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Quantifying Information Transfer between Commodities and Implied Volatilities in the Energy Markets: A Multi-frequency Approach

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ABSTRACT

We investigate the multi-scale information transmission between two implied volatilities in the energy markets (crude oil volatility and volatility in the energy market) and energy commodities returns (global energy commodity, brent, heating oil, natural gas and petroleum). The Complete Ensemble Empirical Mode Decomposition with Adaptive Noise (CEEMDAN) based Rényi transfer entropy approach is employed to accomplish the research objective. The study's outcome underscores that information flow between implied volatilities and energy commodities is negative with significance being scale-dependent. Especially, significant negative information flow is found at specific intrinsic mode functions (IMFs) such as IMF1, and from IMFs 6-9 suggesting short-, upper medium and long-term energy markets dynamics. Comparatively, we find profound negative information flow with the crude oil implied volatility than the volatility in the entire energy market implying the former's strong hedging benefits. Investors and policymakers should have knowledge about the dynamics of implied volatilities, particularly, the crude oil implied volatility when designing strategies for the energy commodities markets.

Keywords: Crude oil Implied Volatility, Bi-directional Causality, Rényi Transfer Entropy, Heterogeneity
GEL Classifications: G10; G15; G19; O13

1. INTRODUCTION

Energy commodities are traded across international markets. Due to their enormous demand and restricted supply in a few nations, energy commodities' prices are largely influenced by economic, financial, geopolitical, and geological factors (Shaikh, 2018). Geopolitical events as the Arab oil embargo of 1973–1974, the Gulf War of 1990, the Iraq War, and the Ukraine War are to blame for the multiple bouts of price instability (Narayan and Narayan, 2007; Arouri et al., 2011; Baffes and Nagle, 2022). For instance, the price of energy commodities increased in the first quarter of 2022, reflecting the effects of the Ukraine War as well as persistent demand increases and numerous supply constraints.

The commodities most impacted by the current price spike are those that Ukraine and Russia export in greater quantities, such as energy, fertilizers, certain cereals, and metals (Baffes and Nagle, 2022). The commodity price increases in 2022 came on top of a surge in commodity prices that started in the middle of 2020 as a result of concerns about the COVID-19 pandemic. The research has documented significant variations in oil prices prior to COVID-19, during the global financial crisis, and between 2014 and 2015. During the global financial crisis, the price of Brent crude oil rose from 60 to 145 dollars before rapidly falling to 30 dollars. Oil prices fell by about 75% between 2014 and 2015 following the global financial crisis (Degiannakis et al., 2018). Hamilton (1983) asserts that because the crude oil market is oligopolistic, significant disruptions in oil production cause notable price shocks. In addition to causing abnormalities in the energy markets, these price shocks raise prices for importers, exporters, and private consumers.

The conventional method for market participants to protect themselves against changes in the price of oil and disruptions in supply is to purchase crude oil futures. The Crude Oil Volatility Index (OVX) and the Energy Market Volatility Index (EMV), however, are currently used to measure the expected volatility of crude oil. The discussion above informs a strong link between various turbulences in the global environment and uncertainties in the energy commodities market. These indices serve as the benchmark for measuring the amount of fear generated from the market instabilities. As a market benchmark, the indices are important in the decision-making process of emerging market participants to a great degree. This chain can be described as the data-generating process for energy commodities prices in the global marketplace. More importantly, we surmise that this process is analogous to the updating belief system based on information (evidence/data) flowing from economic, financial, geopolitical, and geological disturbances (Shaikh, 2019), to Crude Oil Volatility Index (OVX) and the Energy Market Volatility Index (EMV), and eventually to the prices of energy commodities. This is the foundation of the information theory by Shannon (1948). Hence, the discourse naturally necessitates the investigation of information flow between implied energy volatilities and energy commodities to inform energy market participants about risks, rewards, and strategies.

Several studies investigated the drivers of energy commodity price connectedness and their co-movements (Vacha and Barunik, 2012; Amoako et al., 2022; Umar et al., 2022). Nonetheless, a few studies focused on the information flow between implied energy volatilities and energy returns (Asafo-Adjei et al., 2022). This is despite the role information content plays in market dynamics, especially in the era of one crisis after another. Because economies are interconnected through trade and investments, there is a basic connection between returns and volatility in the energy market. As a result, any information about supply and demand in one country has consequences for others (Hernandez et al., 2014). This study investigates the information content of two implied energy volatilities, OVX and EMV, and the important commodities (Brent, global energy, heat oil, natural gas, and petroleum) returns.

The literature studies document a strong asymmetric negative association between implied volatility index based on other markets such as stock (VIX), Euro (EZV), and Gold (GVZ) and the underlying index returns (Giot, 2005; Car and Wu, 2006; Whaley, 2009; Chiang, 2012; Pathak and Deb, 2020; Amoako et al., 2022) and all reported significant negative relations between the implied volatility indexes and underlying stock index returns. The four papers that come close to the current paper are Chen and Zou (2015), Shaikh (2019), Boateng et al. (2021), and Echaust and Just (2021), and all also identified a significant inverse contemporaneous relationship between the asymmetric relationship between the OVX and energy commodity returns. Different models applied by these studies include GARCH models (Whaley, 2009), Granger causality (Chiang, 2012), Pooled regression models (Chiang, 2012), Kalman filter (Chen and Zou, 2015), Quantile regressions (Boateng et al., 2021; Shaikh, 2019), and Value-at-Risk (Echaust and Just, 2021). While these studies enjoin important findings for both policy and investment, they fail to address the role of information content in the nexus. This is critical because the energy market is largely driven by fear (information) emanating from economic, financial, geopolitical, and geological shifts.

The current study, in contrast to earlier works, uses the Complete Ensemble Empirical Mode Decomposition with Adaptive Noise (CEEMDAN) based entropy approach to investigate the multi-frequency information flow in the energy market. This method decomposes the data time series into intrinsic mode functions (IMFs), which represent time horizons across the short-, intermediate-, and long-run. The strongest characteristics of the CEEMDAN-based entropy approach are its support for asymmetric, nonlinearity relationships, and nonstationary difficulties as well as its removal of noise anchored in the data resulting from market anxiety that encourages irrational behavior by market players (Owusu Junior et al., 2021). We denoise the data to get the fundamental relationship between the variables and cater to different investment horizons (short-, medium-, and long-term) addressing the heterogeneous market hypothesis (HMH) (Müller et al., 1993). Regarding Adaptive Market Hypothesis (AMH), Lo (2004) contends that markets change with varying degrees of efficiency, with the intensity of market efficiency being more influenced by adaptation, innovation, competition, and mutation. In line with CMH of Owusu Junior et al. (2021), this suggests that profit-making chances are a dynamic process that needs optimal timing for implementation and active portfolio management. The HMH assume that investors will study events and news and consider the implications of various time horizons as part of their trading strategy and this is known as intrinsic time.

The authors of the current study can thus comprehend the information flow in light of reduced noise and various investor kinds by using the CEEMDAN-based entropy technique. The closest study to ours is that of Asafo-Adjei et al. (2022) who investigated information transfer between commodities and uncertainties in the COVID-19. Outcome from this study was interesting to reveal the delayed volatility of market competitiveness and external shocks (DVMCES) hypothesis. However, analysis from this study was restricted to the COVID-19 pandemic and considered a cluster of intrinsic mode functions (IMFs) demonstrating high-, medium-, and low-frequencies. This was executed without considering the impulse responses of the distinct IMFs to facilitate the information flow. Additionally, the estimations were performed without incorporating the global implied volatility index from the energy sector. As far as the authors of the current study are aware, no other study has examined the information transfer between implied volatilities and energy commodity returns using the CEEMDAN-based entropy technique while treating each IMFs as distinct; incorporating the implied volatilities from the energy sector, thus, the gap and contribution of our study.

The rest of the research is organized as follows. Data issues and methods are presented in Section 2. In Section 3, the study presents the analysis of the empirical results, and in Section 4, we offer our conclusions and policy recommendations.

2. METHODOLOGY

2.1. Ceemdan

In contrast to wavelet analysis, empirical mode decomposition techniques have gotten a lot of attention from researchers because they use a purely data-driven algorithm to separate scales that aren't defined by predefined basis functions. In spite of this, the EMD strategy resorts to the scale mixing issue. The ensemble empirical mode decomposition method (EEMD), created by Wu and Huang (2009), was used to address this issue by incorporating a randomly produced white-noise series into the original signal. To address the residual noise in the reconstructed signals inside the EEMD, Torres et al. (2011) developed the CEEMDAN by attaching the noise to the residual of the prior iteration rather than the original signal (Peng et al., 2021). In comparison to EMD, EEMD, and perhaps CEEMD, the CEEMDAN reduces the signal reconstruction error to zero, improves completeness, to mention a few (See, Asafo-Adjei et al., 2022).

The CEEMDAN decomposition was performed with the help of the libeemd R package (Helske and Luukko, 2018).

The algorithm's application can be summarised as follows:

Begin the number of realizations N, noise parameters, index for IMF j =1

Perform the EMD for N realizations; $Sm(t) = S(t) + \delta_o Wn(t), i = 1,2,3,\ldots,N$, where n refers to the index for realizations; $Wn(t)$ is the white noise series added to the candidate signal, and δ_o is the noise parameter for the first step.

The ensemble mean IMF are calculated as

$$\overline{IMF_1(t)} = \frac{1}{N}\sum_{n=1}^{N} IMF_n(t) \tag{1}$$

The exclusive first residue can be determined as:

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

Evolve N number of realisations, then the operator $E_j(.)$ produces J^{th} the mode obtained by EMD.

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

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

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

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

2.2. Rényi Effective Transfer Entropy (RETE)

The Shannon entropy (SE) (1948) is a foundation for the Rényi transfer entropy (RTE) (1970), which reveals uncertainty within a system (Behrendt et al., 2019). Several experiments (p_j) are performed due to the investigation of a probability distribution. As provided by Hartley (1928), symbols have the following form if the average information is determined

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

where n is being represented as several symbols' observations based on probabilities P_j.

The SE shows a discrete random variable (j). This variable has a probability distribution ($P(j)$). In this case, the average number of bits needed for encoding independent draws at the maximum, according to Behrendt et al. (2019) can be represented as

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

Under the Markov framework, SE took insights from the Kullback-Leibler distance (1951) concept to measure information flows amid two-time series. The study considers two discrete random variables, I and J (which are the equity indices), and corresponding marginal probabilities of $P(i)$ and $P(j)$. Simply, the joint probability of the discrete variables can be seen as $P(i,j)$. It has a dynamic structure that resembles a stationary Markov process of order k (Process I) and I (process J). The Markov property implies that the probability of spotting I at time t+1 in state i dependent on the k prior observations is $p(i_{t+1}|i_t,\ldots,i_{t-k+1}) = p(i_{t+1}|i_t,\ldots,i_{t-k})$. In encoding the observation in t+1, the mean number of bits needed given that the ex-ante k observations are obtained can be offered in the form

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

Where $i_t^{(k)} = (i_t,\ldots,i_{t-k+1})$ (for process J). Under the Kullback-Leibler distance phenomenon in the context of two random variables, the flow of information from process J to process I is estimated through quantification of the deviation from the generalized Markov property $P\left(i_{t+1}|i_t^{(k)}\right) = P\left(i_{t+1}|i_t^{(k)}, j_t^{(I)}\right)$.

Regarding what is presented earlier, the SE is then shown as

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

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

Taking insights from the SE, the RTE can then be presented. An important quality of the RTE is the opportunity to model information flows regarding market conditions. This is conditioned on a weighting factor q, and can be computed as

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

With $q>0$. For $q\rightarrow 1$, RTE converges to SE. For $0<q<1$, hence, extra weights are attributed to low probability events, while for $q>1$ the weights benefit outcomes j with a higher original probability. Consequently, based on factor q, RTE allows for revealing oscillating distribution sections (Behrendt et al., 2019; Adam, 2020).

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

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

It is worthy of note that the computation of the RTE can divulge inverse outcomes. Based on this, having knowledge about the record of J presents remarkably more uncertainty than knowing the record of I only would present. This is ideal for diversification potentials. Since the transfer entropies could be biased (Marschinski and Kantz, 2002) in tiny samples, a rectification factor is necessary with the effective transfer entropy calculated as

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

Where $T_{\text{Jshuffled}\square\text{I}}$ (k,l) represents the transfer entropy using a shuffled version of the time series J; that is, through a random selection of observations from the actual time series J and adjusting them to produce a fresh time series, causing chaos for the dependencies in time series J, but not superintending the statistical reliance between J and I.

This charges $T_{\text{Jshuffled}\rightarrow\text{I}}$ (k,l) to be closer to zero with increases in the sample size. On the other hand, any nonzero value of $T_{\text{Jshuffled}\square\text{I}}$ (k,l) is tantamount to tiny sample impacts. Recurring shuffles and the total replications of the mean of the transfer entropy shuffled estimates act as the small sample bias estimator, which is expunged from the ETE(s) estimated, to yield a bias-adjusted ETE estimate. The information transmission has a null hypothesis devoid of information flows and is determined by recurrent RTE estimations.

2.3. Data Sources and Description

The study's analyses take into account implied volatility in the energy markets as well as prices for seven different energy commodities. Data is available from May 7, 2012, through March 31, 2021. The data were combined to create this period so that the dates were consistent. The variables used for the energy commodity prices include Brent, Global Energy Commodity (GEnergy), Heating Oil (HOil), Natural Gas (Ngas), and Petroleum (Pet) futures markets. Due to their large market capitalization and important role in portfolio diversification with other financial assets, these commodities were chosen (Rehman and Vo, 2021; Dmytrów et al., 2021; Sinha et al., 2022).

The suggested volatilities were selected to demonstrate information flow with global shock transmitters. Particularly, the volatility in the energy markets (VEnergy) and the implied volatility of crude oil (OVX) were chosen as forward-looking proxies relevant to the energy markets but having a similar impact on other financial time series through contagion (Boateng et al., 2021; Dutta et al., 2021; Amoako et al., 2022; Asafo-Adjei et al., 2022). The entire collection of financial time series was taken from investing.com.

3. EMPIRICAL RESULTS

3.1. Preliminary Statistics

Plots of the prices, returns, and implied volatility for energy commodities are shown in Figure 1. Similar trends in the prices and returns of all energy commodities indicate that they are all trending downwards. The graph demonstrates a sharp decline in prices during both the 2016 BREXIT and the 2020 COVID-19 pandemic crises, with the COVID-19 crisis phase appearing to be more severe than the BREXIT era. We see incredibly high implied volatilities during the COVID-19 crisis phase. This suggests that in times of crisis, the implied energy volatilities are inversely correlated with the energy commodities, and as a result, they may provide safe-haven benefits for inverters. In the COVID-19 crisis era, all data returns demonstrate volatility clustering with excessive shocks.

All returns on energy commodities are negative, indicating poor performance. The energy volatilities, however, have positive meanings. With the exception of natural gas, all energy commodities show negative skewness, which indicates a severe lack of performance. In contrast, energy implied volatilities show positive skewness with a high likelihood of success. Leptokurtic distributions are indicated by kurtosis values greater than three. The time series is not normally distributed, according to the Jarque-Bera (JB) Statistics. The unit root tests that were adopted demonstrate that all data returns are stationary (Table 1).

The majority of the energy commodities are substantially positively correlated with one another, as shown by the correlation matrix in Table 2, indicating a high likelihood of the integration of the energy markets. On the other hand, implied volatility in the energy sector is inversely connected with energy commodities. As a result, investors can diversify, hedge, or seek safe haven, depending on the state of the market. The degree of linear relationship is measured using correlation analysis, which does not imply causality.

3.2. Results

In this section, the main findings and their discussions are presented. Particularly, the Rényi transfer entropy was used for the analysis. The conclusions of the study on information transfers between energy commodities and implied energy volatilities are presented. Using the Rényi transfer entropy framework, both negative and positive values are produced (Owusu Junior et al., 2021; Asafo-Adjei et al., 2021; Bossman, 2021; Asafo-Adjei et al., 2022; Bossman et al., 2022; Agyei et al., 2022; Bossman and Agyei, 2022; Bossman et al., 2022). The pairing enables

Figure 1: Time series plots of prices and returns

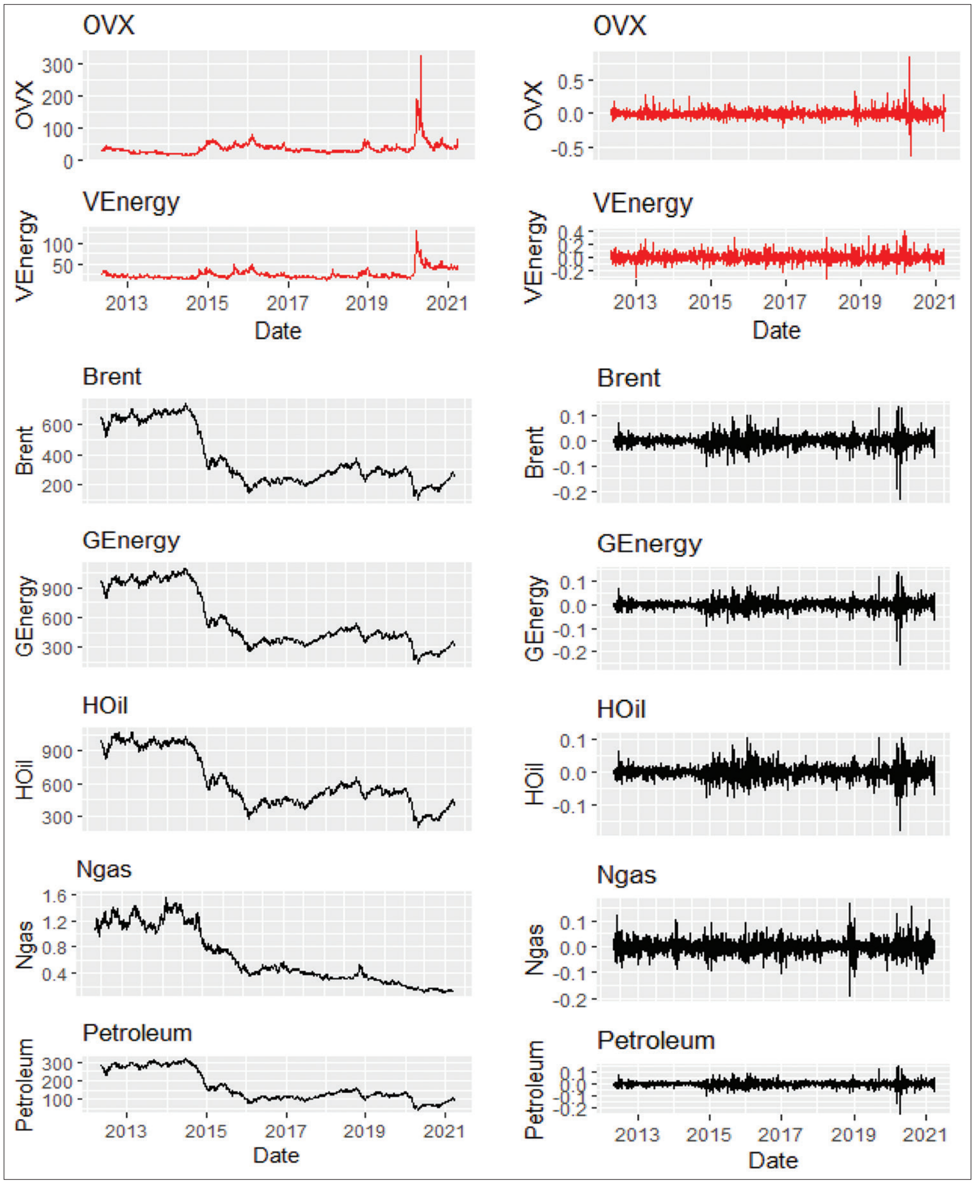


Table 1: Descriptive statistics

	Mean	Median	Max	Min	Std. Dev.	Skewness	Kurtosis	JB Prob.	ADF	KPSS
Energy commodities										
BRENT	–0.0004	0.0005	0.1352	–0.2338	0.0224	–0.6758	14.712	0.00	–31.01***	0.1162
GENERGY	–0.0005	0.0005	0.1373	–0.2564	0.0208	–0.9215	19.8913	0.00	–31.22***	0.0827
HOIL	–0.0004	0.0004	0.1026	–0.177	0.0198	–0.243	9.1655	0.00	–49.08***	0.0873
NGAS	–0.001	–0.001	0.1664	–0.192	0.0264	0.1174	6.9675	0.00	–48.83***	0.1164
PETROLEUM	–0.0005	0.0005	0.146044	–0.24785	0.022191	–0.766	16.57319	0.00	–31.26***	0.0766
Energy volatilities										
VENERGY	0.0002	–0.004	0.3808	–0.3103	0.0592	0.701	7.0651	0.00	–47.92***	0.0334
OVX	0.0002	–0.0036	0.8577	–0.6222	0.0587	1.6427	33.61	0.00	–29.78***	0.0231

Asterisks ***, **, * represent 1%, 5%, and 10% level of significance

us to assess if diversification benefits exist for that market with the recipients in the situation of heightened uncertainty from a specific asset (Asafo-Adjei et al., 2022; Bossman et al., 2022; Agyei et al., 2022; Bossman and Agyei, 2022). Critical values between 1% and 10% are represented by the black bars' ends. In order to reject the null hypothesis of no information flow, the black bars must be in one of the positive or negative regions.

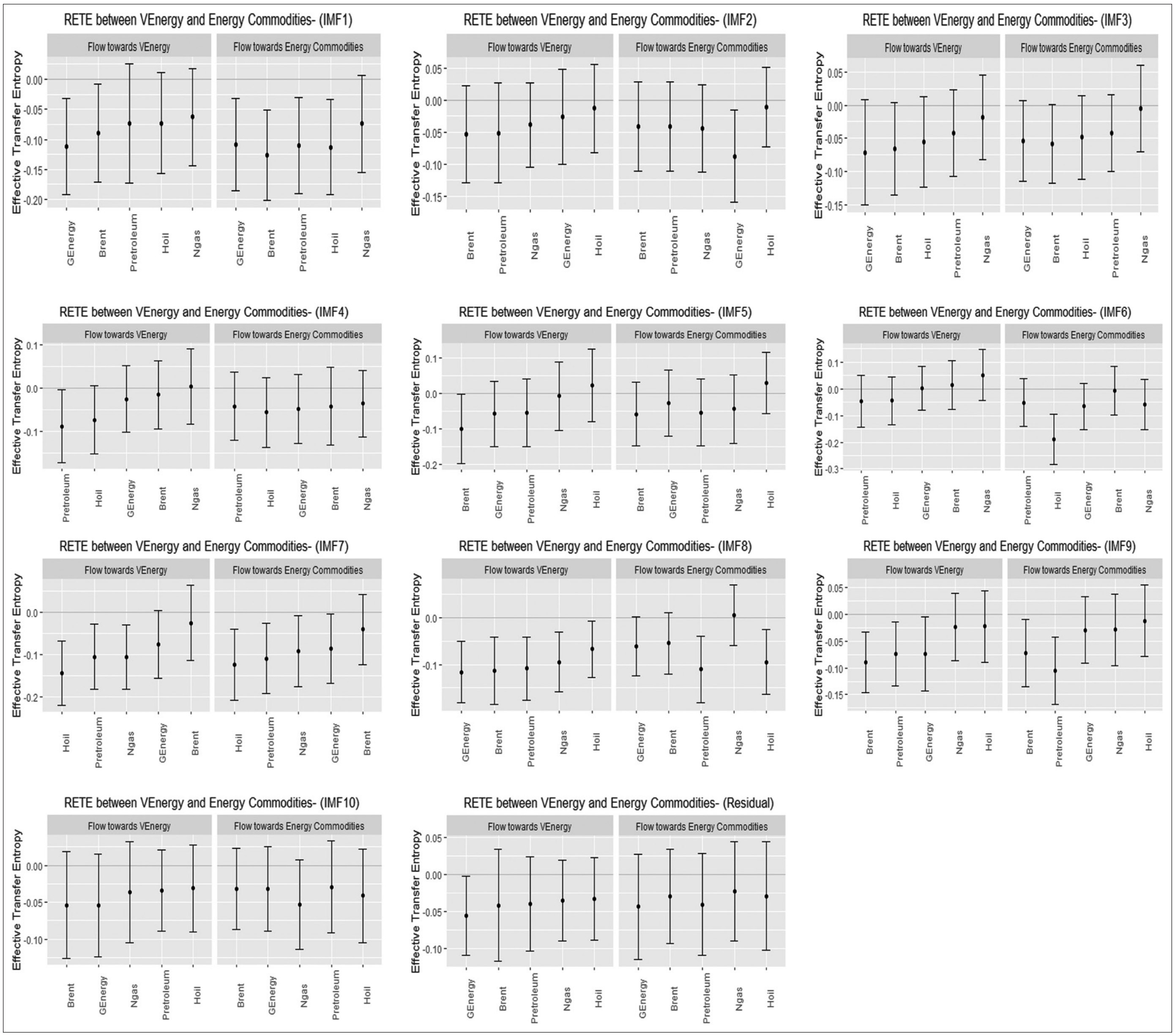
In Figure 2, the information flow between energy commodities and implied volatility in the energy sector in the short- (IMFs 1-4), medium- (IMFs 5-7), and long- (IMFs 8-10) terms, and residue (fundamental feature). Figures 2 and 3 respectively show information flow between volatilities in the energy market (VEnergy) and energy commodities returns, and information flow between OVX and energy commodities returns through the Rényi

Table 2: Unconditional correlation matrix

Probability	BRENT	GENERGY	HOIL	NGAS	PETROLEUM	VENERGY	OVX
BRENT	1.00						
GENERGY	0.98***	1.00					
HOIL	0.94***	0.93***	1.00				
NGAS	0.12***	0.23***	0.14***	1.00			
PETROLEUM	0.99***	0.99***	0.94***	0.13***	1.00		
VENERGY	–0.41***	–0.39***	–0.37***	–0.03	–0.40***	1.00	
OVX	–0.45***	–0.47***	–0.41***	–0.06***	–0.46***	0.49***	1.00

Asterisks ***, **, * represent 1%, 5%, and 10% level of significance

Figure 2: Multi-scale information flow between volatilities in the energy market and energy commodities returns



transfer entropy approach. Table 2 further shows the Rényi transfer entropy estimates.

From Figure 2, significant negative information is transmitted from the VEnergy to most of the energy commodity returns, except for Ngas in the short-term (IMF1). We find a bi-directional relationship between VEenergy and two energy commodities (GEnergy and Brent). At IMF2, negative significant information is only transmitted to GEnergy. As the investment horizon is prolonged (from IMF3-IMF5), the negative information flows become insignificant for all assets. Contrarily, bi-directional causality is pronounced from IMFs 7-9 representing upper medium and long-term dynamics of the market. A saturated market in the very long-term expressive of the residual of a deterministic trend demonstrates no information flow between VEnergy and energy commodities returns. Hence, information flow between VEnergy and energy commodities are scale-dependent. Investors of energy commodities can hedge against excess fluctuations in the short-term (IMF1), medium-, and long-terms (IMFS 7-9). Nonetheless, portfolio diversification would be worthwhile across investment horizons due to most insignificant information flow, but prone to being negative. The significant impact of VEnergy on energy commodities at certain frequencies and quantile confirm the studies of Amoako et al. (2022), Alssubaie et al. (2022).

On the other hand, significant information flow is noticeable with OVX as shown in Figure 3 at most intrinsic times. For instance, in the short-term (IMF1), except for Ngas, negative significant information is transmitted between OVX and the energy commodities returns. The dynamics of information flow continues for IMF2. For IMFs 3-5, information flows are negative but insignificant. Increase in the investment horizon from IMFs 6-9 lends to a bidirectional causality of negative information flow between OVX and energy commodities returns. This confirms the findings of Asafo-Adjei, Frimpong et al. (2022) in the multi-frequency (high-, medium-, and low) assessment of information flow between uncertainties and commodities during the COVID-19 pandemic. Similar to the VEnergy, no significant information is found at IMF 10 and the fundamental feature as the investment horizon is prolonged. The unpredictable patterns of information flow in this way succumbs to the efficient market hypothesis of Fama (1970).

Notwithstanding, the presence of a simultaneous unpredictable information flow and the significant information flow at varying investment horizons confirm the heterogeneous market hypothesis (Müller et al., 1993). This provides that the relentlessness search for competing risks and rewards by investors induce competitiveness (Owusu Junior et al., 2021) among the selected energy commodities facilitated by the irrational behaviour of market participants in line with the behavioural market hypothesis. Accordingly, it is not absolutely appropriate to assume that information flow between energy commodities returns and implied volatilities within the energy market is negative and significant across investment horizons of a stressed market outcome.

Figure 3: Multi-scale information flow between OVX and energy commodities returns

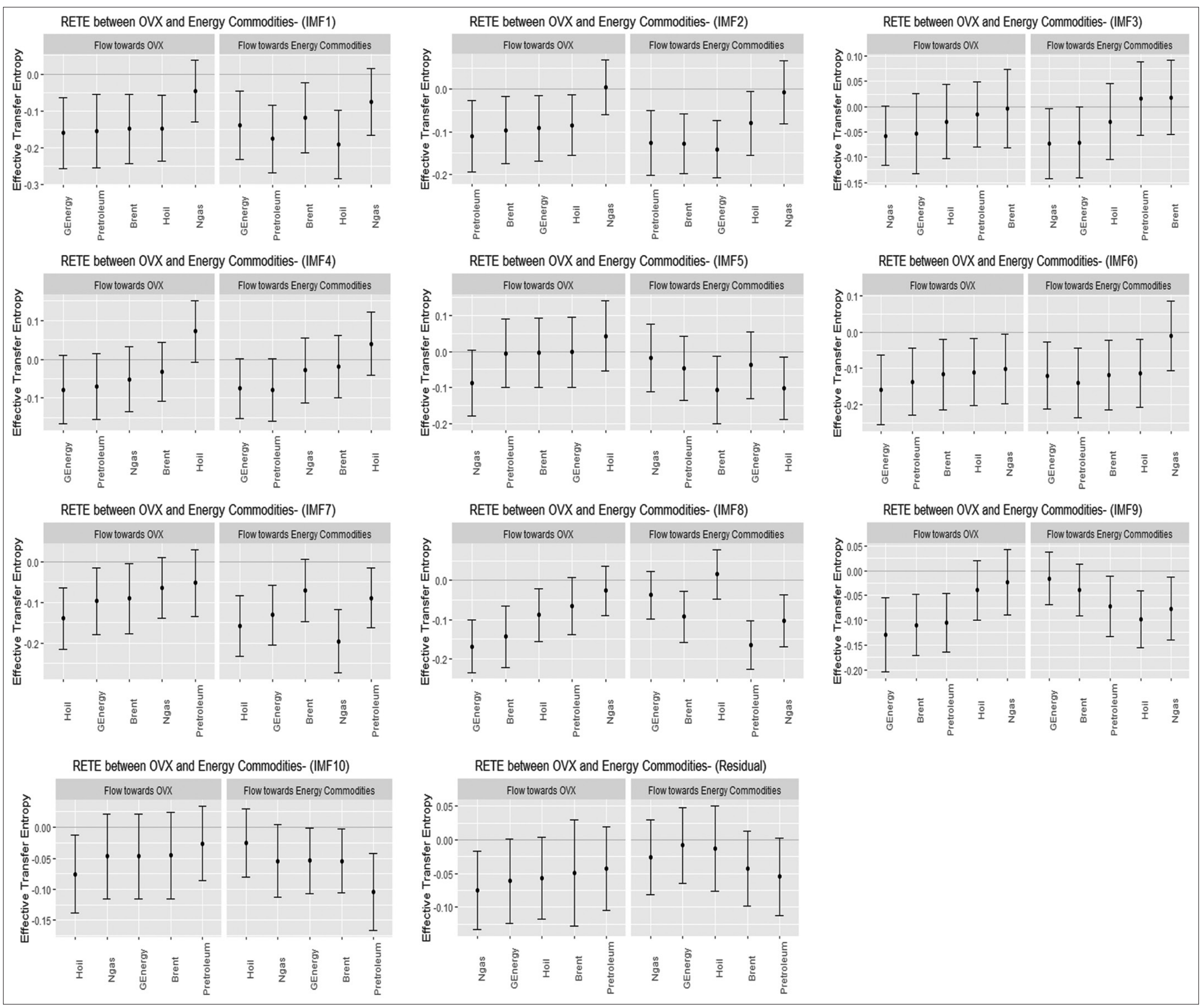


Table 3: Entropy estimates of information flows between implied volatilities (VEnergy and OVX) and energy commodities

	Flows towards VEnergy											Flows towards Energy Commodities										
	IMF1	IMF2	IMF3	IMF4	IMF5	IMF6	IMF7	IMF8	IMF9	IMF10	RS	IMF1	IMF2	IMF3	IMF4	IMF5	IMF6	IMF7	IMF8	IMF9	IMF10	RS
Bt	–0.09	–0.05	–0.07	–0.02	–0.10	0.02	–0.02	–0.11	–0.09	–0.05	–0.04	–0.13	–0.04	–0.06	–0.04	–0.06	–0.01	–0.04	–0.05	–0.07	–0.03	–0.03
	(0.05)	(0.05)	(0.04)	(0.05)	(0.06)	(0.06)	(0.05)	(0.04)	(0.03)	(0.04)	(0.05)	(0.05)	(0.04)	(0.04)	(0.05)	(0.05)	(0.06)	(0.05)	(0.04)	(0.04)	(0.03)	(0.04)
GE	–0.11	–0.03	–0.07	–0.03	–0.06	0.00	–0.08	–0.12	–0.07	–0.05	–0.06	–0.11	–0.09	–0.05	–0.05	–0.03	–0.07	–0.09	–0.06	–0.03	–0.03	–0.04
	(0.05)	(0.05)	(0.05)	(0.05)	(0.06)	(0.05)	(0.05)	(0.04)	(0.04)	(0.04)	(0.03)	(0.05)	(0.04)	(0.04)	(0.05)	(0.06)	(0.05)	(0.05)	(0.04)	(0.04)	(0.03)	(0.04)
Ho	–0.07	–0.013	–0.06	–0.07	0.02	–0.05	–0.14	–0.07	–0.02	–0.03	–0.03	–0.11	–0.01	–0.05	–0.06	0.03	–0.19	–0.12	–0.09	–0.01	–0.04	–0.03
	(0.05)	(0.04)	(0.04)	(0.05)	(0.06)	(0.05)	(0.05)	(0.04)	(0.04)	(0.04)	(0.03)	(0.05)	(0.04)	(0.04)	(0.05)	(–0.05)	(0.06)	(0.05)	(0.04)	(0.04)	(0.04)	(0.04)
Ng	–0.06	–0.04	–0.02	0.01	–0.01	0.05	–0.11	–0.09	–0.02	–0.04	–0.04	–0.07	–0.04	–0.001	–0.04	–0.04	–0.06	–0.09	0.00	–0.03	–0.05	–0.02
	(0.05)	(0.04)	(0.04)	(0.05)	(0.06)	(0.06)	(0.05)	(0.04)	(0.04)	(0.04)	(0.03)	(0.05)	(0.04)	(0.04)	(0.05)	(0.06)	(0.06)	(0.05)	(0.04)	(0.04)	(0.04)	(0.04)
Pet	–0.07	–0.04	–0.04	–0.09	–0.06	–0.05	–0.11	–0.11	–0.07	–0.03	–0.04	–.0.11	–0.04	–0.04	–0.04	–0.05	–0.05	–0.11	–0.11	–0.11	–0.03	–0.04
	(0.06)	(0.04)	(0.04)	(0.05)	(0.06)	(0.06)	(0.05)	(0.04)	(0.04)	(0.03)	(0.04)	(0.05)	(0.04)	(0.03)	(0.05)	(0.06)	(0.05)	(0.05)	(0.04)	(0.04)	(0.04)	(0.04)
	Flows towards OVX											Flows towards Energy Commodities										
Bt	–0.15	–0.10	–0.00	–0.03	–0.00	–0.12	–0.09	–0.14	–0.11	–0.05	–0.05	–0.12	–0.13	0.02	–0.02	–0.11	–.012	–0.07	–0.09	–0.04	–0.05	–0.04
	(0.06)	(0.05)	(0.05)	(0.05)	(0.06)	(0.06)	(0.05)	(0.05)	(0.04)	(0.04)	(0.05)	(0.06)	(0.04)	(0.04)	(0.05)	(0.06)	(0.06)	(0.05)	(0.04)	(0.03)	(0.03)	(0.03)
GE	–0.16	–0.09	–0.05	–0.08	–0.00	–0.16	–0.10	–0.17	–0.13	–0.05	–0.06	–0.14	–014	–0.07	–0.08	–0.04	–0.12	–0.13	–0.04	–0.02	–0.05	–0.01
	(0.06)	(0.05)	(0.05)	(0.05)	(0.06)	(0.06)	(0.05)	(0.04)	(0.05)	(0.05)	(0.04)	(0.06)	(0.04)	(0.04)	(0.05)	(0.06)	(0.06)	(0.04)	(0.037)	(0.03)	(0.03)	(0.03)
Ho	–0.15	–0.08	–0.03	0.07	0.04	–0.11	–0.14	–0.09	–0.04	–0.08	–0.06	–0.19	–0.08	–0.03	0.04	–0.10	–0.11	–0.16	0.02	–0.10	–0.03	–0.01
	(0.05)	(0.04)	(0.04)	(0.05)	(0.06)	(0.06)	(0.05)	(0.04)	(0.04)	(0.04)	(0.04)	(0.06)	(0.05)	(0.05)	(0.05)	(0.05)	(0.06)	(0.05)	(0.04)	(0.03)	(0.03)	(0.04)
Ng	–0.05	0.00	–0.06	–0.05	–0.09	–0.10	–0.06	–0.03	–0.02	–0.05	–0.08	–0.08	–0.01	–0.07	–0.03	–0.02	–0.01	–0.20	–0.10	–0.08	–0.05	–0.03
	(0.05)	(0.04)	(0.04)	(0.05)	(0.06)	(0.06)	(0.04)	(0.04	(0.04)	(0.04)	(0.04)	(0.06)	(0.04)	(0.04)	(0.05)	(0.06)	(0.06)	(0.05)	(0.04)	(0.04)	(0.04)	(0.03)
Pet	–0.15	–0.11	–0.02	–0.07	–0.05	–0.14	–0.14	–0.07	–0.10	–0.03	–0.04	–0.18	–0.13	0.02	–0.08	–0.05	–0.14	–0.16	–0.16	—0.07	–0.10	–0.05
	(0.06)	(0.05)	(0.04)	(0.05)	(0.05)	(0.06)	(0.05)	(0.04)	(0.04)	(0.04)	(0.04)	(0.06)	(0.05)	(0.04)	(0.05)	(0.05)	(0.06)	(0.05)	(0.04)	(0.04)	(0.04)	(0.03)

RETE estimates with standard errors in brackets

Thus, despite the fact that information flow or spillover effects between implied volatilities and other financial assets are prone to being negative, and quantile or scale dependent (Boateng et al., 2021; Pham and Do, 2022; Asafo-Adjei et al., 2022; Li, 2022; Chen et al., 2022; Amoako et al., 2022), investors need to be informed on the specific period assets redeployment, rebalancing, reallocation, to mention a few, is appropriate to enhance diversification or safe haven benefits in a stressed market outcome. It can be concluded that integration among energy commodities should not be entirely ignored but considered in tandem with implied volatilities, especially during markets stress of information flow (Table 3).

4. CONCLUSIONS

In this study, we explored the multiple frequency information transfer between selected energy commodities and implied volatilities using CEEMDAN-based Rényi transfer entropy. The unique contribution of this study to literature is the investigation of information flow between energy commodities returns and implied volatilities at investment horizons detailing the degree of heterogeneity and competitiveness at stressed market outcome (quantile = 0.3). It further addressed the susceptibilities of energy commodities to shocks from two implied volatilities to identify the specific implied volatility that exhibits more significant information flow.

We found bi-directional negative information flow between implied volatilities and energy commodities, but scale-dependent. This was revealed at specific IMFs such as IMF1, and from IMFs 6-9 suggesting short-, upper medium and long-term energy markets dynamics. Hence, information flow at investment horizons of energy commodities and implied volatilities are heterogeneous. Also, noticeable negative information flow was found with the crude oil implied volatility than the volatility in the energy sector suggesting the former's strong hedging benefits.

We come to the conclusion that, especially when markets are under information flow stress, integration among energy commodities should not be completely disregarded and should instead be taken into account alongside implied volatilities. It is advised that a portfolio that includes energy commodities and crude oil implied volatility be taken into account in comparison to implied volatilities from the overall energy market. When developing strategies for the energy commodities markets, investors and policymakers alike need be knowledgeable about the dynamics of implied volatilities, particularly the implied volatility of crude oil.

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