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The Impact of Oil Prices on Guyana's Real Exchange Rate: An AlphaFold-Decomposition Analysis

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Abstract: In 2015, Guyana, a small South American country, experienced a major economic turning point after ExxonMobil identified substantial commercial oil reserves in its waters. By 2020, Guyana had started producing and exporting oil commercially, shifting its economy toward oil exports. A key factor shaping Guyana's economic future is the global price of oil, since it directly impacts the country's export income and government revenue from oil. Subsequently, the effect of oil prices on the real exchange rate now becomes an important issue for Guyana due to the potential to affect the country's economic stability and competitiveness. Therefore, the relevant research question is: (i) to what degree have oil prices impacted Guyana's real effective exchange rate? This study created a decomposition technique called AlphaFold-Decomposition, hereinafter referred to as AlphaFold-D, based on the AlphaFold methodology. Drawing inspiration from AlphaFold's ability to model complex folding patterns with high accuracy, the subsequent methodology provides a more accurate means of decomposing time series into its underlying intrinsic modes than empirical mode decomposition. As such, this methodology is characterized by the integration of AlphaFold's attention mechanisms, multi-stage refinement processes, and noise reduction techniques.

Keywords: oil prices, real effective exchange rate, Guyana, Dutch disease, AlphaFold-Decomposition

1. Introduction

Guyana, a South American nation, made a significant economic breakthrough in 2015 when ExxonMobil discovered commercial crude oil reserves within its territory. The country began commercial production and exports in 2020, marking its transition to an oil-exporting economy. Since then, the Government of the Cooperative Republic of Guyana (GoG) has been receiving oil revenues. While Guyana's current production stands at 582,000 barrels per day (bpd) as of 2024, its proven reserves exceed 13 billion barrels of oil equivalent (boe), with production expected to rise steadily in the coming years.

An important factor for Guyana's economic outlook is global oil prices, as they directly determine export earnings and government oil revenues.

The effect of oil prices on the real exchange rate is important for an oil-exporting country like Guyana because it directly influences the country's economic stability and competitiveness. For instance, if oil prices rise, the influx of foreign currency from oil exports is likely to increase. This in turn may facilitate an appreciation of the domestic currency in real terms. If an appreciation does occur, it may make non-oil exports (such as agriculture or manufacturing goods) more expensive and less competitive in global markets, potentially harming other sectors of the economy – a phenomenon referred to as the Dutch disease.

Conversely, if oil prices fall, there is likely to be a decline in export revenues. This may be accompanied by depreciation pressure on the real exchange rate. If this occurs, it may increase the cost of imports (such as machinery, food, and fuel), contribute to inflation, and reduce purchasing power. Since Guyana is a relatively new oil producer with a growing dependence on petroleum revenues, oil price volatility should be of great importance to the country as oil prices could lead to significant swings in the real exchange rate.

While the oil price-exchange rate nexus has continued to be studied by many countries, Guyana, being a developing country, faces a dearth of research on this topic. A few studies, such as works by Bulkan [1], Roopnarine [2], and Leonard [3], have done research on Guyana and its oil industry. However, there is a lack of empirical research on the oil price-exchange rate nexus for Guyana. Therefore, this study's objective is to analyze the impact of oil prices on the real effective exchange rate (REER) of Guyana. The relevant research question is: (i) to what degree have oil prices impacted Guyana's real effective exchange rate?

This study introduces a new decomposition technique named AlphaFold-Decomposition (which can be referred to as AlphaFold-D), derived from AlphaFold, a methodology pioneered by Jumper et al. [4]. AlphaFold-Decomposition (AlphaFold-D) is a proposed time-series decomposition methodology inspired by AlphaFold's neural network architecture. Its goal is to address the limitations of traditional empirical mode decomposition (EMD) and provide a more accurate way to decompose time-series data into intrinsic

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modes. AlphaFold-D achieves this through innovative steps integrating attention mechanisms, multi-stage refinement, and noise reduction.

After decomposing the time series, the dependence between variables is analyzed using the artificial neural network (ANN) causality test proposed by Charles [5] to identify causal relationships. This method is based on the premise that if variable X causes variable Y, incorporating information about X should enhance the accuracy of predictions for Y. In this test, a simple three-layer feedforward neural network is used to predict Y. If including X in the neural network significantly improves the predictive accuracy for Y, it is concluded that X has predictive causality with Y. Conversely, if X does not enhance the predictive accuracy for Y, then X is deemed not to have predictive causality with Y.

The results involved the decomposition of time series, including Brent oil prices, WTI oil prices, and Guyana's REER index. This allowed for the application of the ANN causality test to examine causality between these variables. The test found causality from WTI oil prices to Guyana's REER index at IMF4 and IMF5, which represent high-frequency fluctuations, indicating that the WTI oil prices influenced the REER index in the short run. However, no causality was detected from the WTI prices to the REER index at IMF1 to IMF3, suggesting that oil prices do not have a long-term impact on the REER index. Similar results were found for Brent oil prices relative to the REER.

This study makes the following contributions to the literature. It is the first to quantitatively measure the impact of oil prices on Guyana's real exchange rate using nonlinear and machine learning models, offering an innovative approach to understanding the dynamics of oil price fluctuations. Machine learning models, particularly in this case, excel at identifying complex, nonlinear relationships that traditional econometric models may overlook. This capability is crucial when studying oil prices, which often exhibit sudden price spikes, crashes, and volatility clusters.

The study also contributes to the literature with the development of the AlphaFold-D methodology, which addresses several key limitations found in traditional decomposition techniques like EMD. By overcoming issues such as mode mixing, sensitivity to noise, boundary effects, and difficulties in handling non-stationary time series, AlphaFold-D provides a more accurate and reliable approach to time-series analysis, especially for complex data with abrupt changes.

The rest of this study is structured as follows. Section 2 provides a literature review. Section 3 explores the data and methodology. Section 4 presents the results of the analysis. Section 5 offers a discussion. Section 6 concludes this study.

2. Literature Review

The relationship between exchange rates and oil prices has been investigated in the literature.

2.1. Theoretical transmission channels between oil prices and exchange rates

Several transmission channels explain the relationship between oil prices and exchange rates, primarily demonstrating how oil price movements influence currency values. One key mechanism is the supply-demand channel, where rising oil prices lead to inflationary pressures. In oil-importing nations, higher oil prices increase production costs and consumer prices, driving inflation. Conversely, oil-exporting countries may experience higher revenues, which may stimulate domestic demand, leading to demand-pull inflation. Once inflation occurs, it will subsequently cause real exchange rate appreciation [6].

The impact of oil prices on exchange rates, transmitted through the inflation channel, can be explained as follows. As a globally traded commodity, increases in crude oil prices directly raise production and transportation costs, thereby driving up domestic price levels. At the same time, exchange rate fluctuations further intensify inflationary pressures; when a currency depreciates, it raises the cost of imported goods and increases input expenses for domestic firms reliant on foreign materials. This dual effect, referred to as exchange rate pass-through, can amplify the transmission of global commodity price shocks into domestic inflation, posing persistent challenges for central banks striving to maintain price stability [7].

The Dutch disease theory can also explain the relationship between oil prices and the real exchange rate. Dutch disease is a process in which a boom in the natural resources sector results in a shrinking non-resource tradable sector. This situation often causes an increase in resource and non-tradable sectors due to specialization that makes the economy more vulnerable to resource-specific shocks. Therefore, a boom in the oil sector can cause a rise in oil rents [8–11].

If the Corden and Neary [12] model is applied, an increase in foreign currency inflows from oil exports expands the oil sector. This triggers a resource movement effect, where factors of production (labor and capital) shift from the non-booming tradable sector (e.g., agriculture or manufacturing) to the booming tradable sector (oil and related industries). As workers and businesses benefit from higher incomes and commercial opportunities in the expanding oil sector, a spending effect emerges. The rise in domestic consumption drives up local prices, leading to inflation. Since domestic prices increase faster than foreign prices, this results in an appreciation of the real exchange rate.

Another important mechanism is the terms of trade channel, which suggests that oil price fluctuations alter real exchange rates by affecting trade balances and purchasing power parity. These changes are driven by arbitrage forces in international markets [6].

Another mechanism involves the application of the balance of payments theory. This shows how oil price shifts redistribute wealth between oil-importing and oil-exporting nations. Oil-exporting countries typically see currency appreciation due to increased revenues, while oil-importing nations often face currency depreciation as their trade balances deteriorate [13–15].

It is also possible for the nominal exchange rate to impact international oil prices, especially since oil prices are usually denominated in USD. When the USD appreciates against other major currencies, it effectively increases the price of oil for non-US buyers, reducing their purchasing power. This phenomenon can be explained through the law of one price: as dollar-denominated oil becomes more expensive in local currency terms, demand from foreign markets tends to decline, potentially exerting downward pressure on global oil prices. The same principle works in reverse – a weaker USD makes oil relatively cheaper for international buyers, which may stimulate global demand and support higher oil prices [6].

2.2. Empirical relationship between oil prices and exchange rates

One strand of the literature explores the relationship between oil prices and exchange rates, focusing on specific countries. For instance, Yildirim and Arifli [16] investigate the impact of oil price shocks on the exchange rate of a small oil-exporting economy, specifically Azerbaijan. Using a vector autoregressive (VAR) model and monthly data spanning from 2006 to 2018, their findings reveal that the Azerbaijani economy is negatively affected by declines in oil prices. More precisely, a negative oil price shock leads to currency depreciation, rising inflation, and a decline in economic activity.

Another example is Albulescu and Ajmi [6], who analyze changes in the causal relationship between international oil prices and the REER of the US dollar. Their study concludes that oil prices Granger-cause movements in the US dollar exchange rate.

Thus, one group of studies employs Granger causality analyses and focuses on the short-term responses of oil prices (or exchange rates) to shocks in exchange rates (or oil prices), utilizing VAR models to examine these dynamics.

Another group of studies focuses on the long-term relationship between these variables, employing cointegration-based models such as the Vector Error Correction Mechanism (VECM). Some studies concentrate specifically on the relationship between oil prices and exchange rates, while others extend their analysis to include other macroeconomic variables like inflation and Gross Domestic Product (GDP). For instance, Musa and Maijama'a [17] investigate the causal linkages among domestic oil prices, exchange rates, and inflation in Nigeria for the period 1985 to 2019 using a VECM model. The Johansen cointegration test revealed evidence of cointegration among the variables. Their findings indicate unidirectional causality running from domestic oil prices to exchange rates and from inflation to exchange rates, along with evidence of long-run causality.

Another group of studies explores the oil price-exchange rate nexus through the lens of volatility modeling, such as Generalized Autoregressive Conditional Heteroskedasticity (GARCH) models. For example, Lakshmanasamy [18] examined the causality between crude oil prices, exchange rates, and the BSE Sensex, along with their volatilities, in India. Using daily data spanning 14 years from January 2006 to March 2019, they applied a GARCH model to analyze the relationships. The GARCH estimates found that the BSE Sensex is influenced by volatility in crude oil prices and exchange rates. Additionally, Granger causality tests revealed unidirectional causality from crude oil prices to the BSE Sensex and from crude oil prices to the Indian exchange rate.

However, the studies based on VAR, VECM, and GARCH models are based on linear models such as the aforementioned models are linear. VAR, VECM, and GARCH models are linear models and are based on the assumption of linearity and normality. When the linearity and normality assumptions do not hold, it can result in model misspecification, biased parameter estimates, and unreliable forecasts. This can lead to incorrect inferences about the relationships between variables, potentially undermining the validity of the study's conclusions.

Another group of studies employs nonlinear methodologies (such as copulas and decomposition methods) to explore the co-movement and dependence structure between variables. For instance, Yamaka [19] examined the relationship between oil prices and the exchange rates of five countries: the United States, India, China, Japan, and Korea. Using monthly data from January 2007 to December 2020, they applied a copula-based approach to capture structural changes and measure the dependencies between oil prices and exchange rates. Their findings revealed the presence of regime-switching dynamics, highlighting how the co-movement patterns between oil prices and exchange rates vary across different states or regimes.

An example where a decomposition methodology was used to examine the nexus among the exchange rate and oil prices can be seen in Duan et al. [20]. Using wavelet analysis on data spanning 2008 to 2019, their study uncovered evidence of bidirectional causality between these two variables.

This study can contribute to the literature in three key areas. First, this study can quantitatively measure the impact of oil prices on Guyana's real exchange rate using nonlinear and machine learning models to capture complex, nonlinear patterns. There seems to be a dearth of studies on the relationship between oil prices and the exchange rate of Guyana. Second, this study can introduce a methodology, AlphaFold-D, which addresses limitations in traditional decomposition methods like mode mixing, noise sensitivity, and boundary effects. Third, this study can empirically apply a three-layer feedforward neural network to test the predictive causality between variables, which is an improvement beyond the linear Granger causality test.

2.3. Oil prices transmission effect on other economic variables

Some authors note that oil prices have transmission on other economic variables. Hamilton [21], for example, examines the transmission mechanism via which shocks to the price of oil impact actual economic activity, concentrating on the US economy from 1948 to 1980. His empirical research challenges the notion that these shocks were only reflections of larger macroeconomic conditions by focusing on the causative role that rising oil prices play in starting economic recessions.

According to Hamilton, the transmission mechanism mainly operates via three interrelated channels:

1) **Higher input prices for businesses:** Production costs increase when oil prices spike, especially in energy-intensive industries like chemicals, manufacturing, and transportation. Decreases in output and income are directly caused by these higher expenses since they lower profit margins and may result in reductions in employment and production.
2) **Disruption to investment and consumption:** The demand for non-energy goods declines when customers' disposable income declines due to rising energy and transportation costs. Businesses postpone or abandon investment initiatives at the same time because of increased uncertainty, increased operating expenses, and decreased profitability. Aggregate demand is weakened by the simultaneous drop in private investment and consumer spending.
3) **Monetary policy response:** Central banks may tighten monetary policy (by raising interest rates) in reaction to inflationary pressures brought on by oil. This further reduces demand by making borrowing more expensive.

Hamilton's methodology centers on autoregressive distributed lag (ARDL) specifications and Granger causality tests. The model includes real oil prices and real GDP growth. Real GDP growth and real oil prices are included in the model. He adds other controls like money supply growth, interest rates, inflation, and other leading indicators to account for the potential that oil prices are endogenous or just connected with other macroeconomic variables. To determine whether comparable links existed during a time when oil markets were less volatile and more strictly regulated, he focuses especially on the years 1948–1972, which preceded the significant oil shocks of the 1970s. The paper's main conclusions show a statistically significant correlation between rising oil prices and ensuing output drops, usually with a three to four-quarter lag. He finds little evidence to support the idea that past macroeconomic conditions influence oil prices. Rather, it seems that the shocks to the oil price are mostly exogenous, resulting from sector-specific or geopolitical developments.

The ARDL model was appropriate for analysis in the 1980s when Hamilton did the research. However, it is now well known that the ARDL model assumes linearity and normality in the data, which are often violated in real economic data. Consequently, relying on ARDL-based estimates can lead to misleading inferences.

2.4. Oil prices have multiple components that affect other variables

Notably, some authors have realized that oil prices may have multiple components that can affect other variables. In fact, Kilian [22] recognized this. It is noteworthy that Kilian [22] recognized this complexity in their research. Using an Structural Vector Autoregression (SVAR) model, they examine the macroeconomic effects of various oil price shocks on the US economy. Their study spans January 1973 to October 2006, which includes multiple oil market volatility events and a range of macroeconomic circumstances.

Oil prices have historically been regarded as exogenous in empirical research when examining their effects on macroeconomic aggregates like inflation or US GDP. Kilian [22] contested this notion by highlighting the fact that several structural shocks, including disruptions in oil supply (such as geopolitical events), global aggregate demand shocks (connected to the global business cycle), and oil-specific (precautionary) demand shocks (reflecting shifts in market expectations regarding future oil availability), endogenously determine oil prices.

The authors used an SVAR model with economic identification restrictions. Due to these restrictions, changes in the price of oil were divided into three structural innovations:

1) Shocks to the oil supply, which are thought to have an immediate impact on world oil production.
2) Aggregate demand shocks, which are determined by a real activity index based on dry cargo shipping rates and represent worldwide economic activity.
3) Demand shocks unique to oil that reflect shifts in market expectations or precautionary demand unrelated to supply or output at the moment.

Kilian [22] evaluates the effects of each structural oil price shock on the real Gross Domestic Product (GDP) and the Consumer Price Index (CPI), two US macroeconomic aggregates, using impulse response functions:

1) Real GDP temporarily and statistically significantly declines as a result of oil supply shocks, particularly during the first two years. They don't really affect the pricing level, though.
2) Because there is a greater demand for American goods abroad, aggregate demand shocks – which reflect global economic expansion – first marginally increase US GDP. However, as time goes on, the inflationary consequences of rising oil prices take over, delaying the recession and causing the CPI to rise steadily.
3) Particularly over a three-year horizon, oil-specific demand shocks are linked to a substantial, long-lasting increase in consumer prices and a steady, statistically significant decline in real GDP.

Despite being a popular tool in macroeconomic analysis, the SVAR model has some significant drawbacks. It is based on the assumptions of linearity and normalcy, which frequently do not hold true for real economic data. The assumption of normalcy is often violated by skewness, large tails, or structural discontinuities in financial or commodity price data, such as oil prices, and by the nonlinearity of economic linkages. Due to this, SVAR-based inference may be misleading, as variance decompositions and impulse response functions may not adequately represent the system's actual dynamics. These limitations can be overcome by employing decomposition-based techniques like wavelet transforms, EMD, and the proposed AlphaFold-D, which divide complex time series into easier-to-analyze components.

3. Data and Methodology

The primary variables of interest in this study are Guyana's Real Effective Exchange Rate (REER), Brent oil prices, and West Texas Intermediate (WTI) oil prices. Data for Guyana's REER was sourced from the Economic Commission for Latin America and the Caribbean online database (ECLAC and CEPALSTAT). This data was available at the monthly frequency over the January 2013 to September 2024 period, producing 141 observations.

Data pertaining to Brent oil prices and WTI oil prices were obtained from the US Energy Information Administration (USEIA) online database [23]. The same time period was selected to match the REER data.

3.1. Methodology-pretesting

Before any analysis is conducted, some pretesting is performed. The pretests are conducted to determine if there are structural breaks in the data and whether the data is normally distributed. These tests are necessary because if the data is not normally distributed or if there are structural breaks, traditional models based on the assumptions of linearity and normality may not produce accurate parameters.

Additionally, tests are performed for stationarity. This is because if the data is non-stationary and structural breaks are found, the non-stationarity could be attributed to the presence of structural breaks. Likewise, the structural breaks could be responsible for the non-stationarity. Therefore, tests for stationarity with structural breaks are also conducted.

3.2. Empirical mode decomposition methodology

EMD is a widely used technique for analyzing nonlinear and non-stationary time-series data [24–26]. The core idea behind EMD is to decompose a time series into a set of intrinsic mode functions (IMFs) that capture the underlying oscillatory modes present in the data. The EMD process starts by identifying the local extrema (peaks and troughs) of the original time series. These extrema are then utilized to construct upper and lower envelopes through interpolation. The mean of these envelopes is computed, and the original time series is subtracted from this mean to derive the first IMF. This procedure is repeated iteratively, using the residue from the previous step as the new input, until a specified stopping criterion is reached.

One of the main advantages of EMD is its data-driven approach, enabling it to adaptively extract IMFs without the need for a predefined basis function [27]. This adaptability makes EMD particularly effective in capturing complex patterns across various datasets, including financial and economic signals. However, EMD also has its drawbacks. A significant concern is mode mixing, where the resulting IMFs may contain oscillatory modes of different frequencies, which can lead to inaccuracies in the decomposition. Additionally, EMD is sensitive to noise, and the presence of outliers can greatly affect the quality of the resulting IMFs. Furthermore, the method struggles with non-stationary signals that exhibit abrupt changes [28].

Due to these limitations, an improvement to EMD is being sought.

3.3. Methodology: AlphaFold

AlphaFold is a methodology developed by Jumper et al. [4] to make accurate predictions. The method involves employing advanced neural network architectures, particularly deep learning techniques. Jumper et al. [4] applied their novel methodology to predict protein structures and sought to determine the three-dimensional structures of proteins from their amino acid sequences, addressing one of biology's most significant challenges. The methodology is built upon a neural network that utilizes the attention mechanism, allowing it to effectively process and learn from sequence data. AlphaFold integrates a series of complex architectures, including convolutional neural networks (CNNs) and attention-based models, enabling the model to capture long-range interactions and intricate patterns within the protein sequence. Through analyzing the spatial relationships and interactions between amino acids, Jumper et al. [4] used AlphaFold to generate highly accurate structural predictions that significantly outperform traditional methods.

However, the AlphaFold methodology created by Jumper et al. [4] was designed to make predictions, not to decompose time series. As such, elements from the AlphaFold methodology can be extracted to develop a method for time-series decomposition that is stronger than the EMD.

3.4. AlphaFold-D methodology

The AlphaFold-Decomposition (hereinafter referred to as AlphaFold-D) is proposed as a time-series decomposition methodology designed to overcome the limitations associated with traditional EMD. It is inspired by the neural network architecture of AlphaFold. The main goal of AlphaFold-D is to provide a more accurate means of decomposing time-series data into its underlying intrinsic modes than the EMD. As such, this methodology is characterized by the integration of AlphaFold's attention mechanisms, multi-stage refinement processes, and noise reduction techniques. Therefore, it should be better able to handle complex time-series data.

The AlphaFold-D Methodology proceeds via the following steps.

1) Step 1: data preprocessing layer

Step 1 involves creating a data preprocessing layer. This step entails the application of convolutional filters to suppress random noise while retaining significant patterns within the time-series data. The convolutional filtering is applied using a Gaussian window to smooth out the random noise. This is represented by:

$$\overline{\mathrm{d}}\,(\mathrm{n}) = \sum_{\mathrm{k}=-\mathrm{K}}^{\mathrm{K}} \omega\,(\mathrm{k})\,.\,\mathrm{d}(\mathrm{n}-\mathrm{k}) \tag{1}$$

where $d(n)$ is the original time series at point n, $\overline{d}\,(n)$ is the smoothed version of the original time series at point n, K is the half-width of the Gaussian window, and $\omega\,(k)$ is the Gaussian window (or kernel) that is centered around zero (0) and applied over the range (−K, K).

Note, the Gaussian window $\omega\,(k)$ is given by:

$$\omega\,(k) = \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left(-\frac{k^2}{2\sigma^2}\right) \tag{2}$$

where σ is the standard deviation of the Gaussian window, which controls the spread or width of the window and determines the degree of smoothing.

Note, the application of the convolutional filter is to enhance the clarity of the original signal or time series $d(n)$ and generate a more accurate decomposition process than EMD. Additionally, this step includes the application of wavelet transforms to analyze and reconstruct the signal with localized frequency analysis, allowing for primary frequency bands to be identified.

The wavelet transform can be expressed as:

$$W_\psi\,(s,\tau) = \int_{-\infty}^{\infty} y\,(t)\,\psi\,*\left(\frac{t-\tau}{s}\right) dt \tag{3}$$

where $W_\psi\,(s,\tau)$ refers to the wavelet coefficients, $y\,(t)$ is the original time series, s is the scaling parameter, τ is the translation parameter, and ψ is the mother wavelet.

The wavelet transform is particularly effective as it allows for localized frequency analysis, enabling the identification of primary frequency bands. Establishing these bands is necessary as they form a baseline for subsequent processing stages, ensuring that the decomposition captures the essential characteristics of the data without being influenced by noise or irrelevant fluctuations.

2) Step 2: attention-based mode isolation layer

Following the preprocessing phase, Step 2 introduces the attention-based mode isolation layer. The step in this model code doesn't directly follow AlphaFold's exact approach but rather takes inspiration from the general concept of multi-head attention, which is used in AlphaFold and is commonly used in transformers.

In AlphaFold, multi-head attention is used to allow the model to focus on different parts of the protein sequence and learn complex relationships in the spatial and temporal structure of amino acids. This model applies a similar idea to using adaptive multi-head filters with different cutoff frequencies, where each "head" isolates unique frequency components. Therefore, this model involves the creative application of attention concepts to time-series decomposition.

A simplified attention mechanism, which may be applied to frequency decomposition, may be given by:

$$\mathrm{Mode_i}\,(\mathrm{t}) = \sum_{\mathrm{k}=1}^{\mathrm{N}} \alpha_{\mathrm{i,k}}\,(\mathrm{t})\,.\,\mathrm{F_k}(\mathrm{t}) \tag{4}$$

where $Mode_i\,(t)$ is the i-th isolated mode at time t; N is the total number of attention heads; $\alpha_{i,k}\,(t)$ is the adaptive attention weight for the i-th mode, k-th frequency, and time t; and $F_k(t)$ is the k-th frequency filtered version of the input signal.

The filters effectively isolate different modes in the data, which reduces the likelihood of mode mixing, which is a common problem that is encountered in traditional EMD.

Note, the traditional attention mechanism found in transformer models is expressed as follows:

$$\mathrm{Attention}\ (\mathrm{Q},\ \mathrm{K},\ \mathrm{V}) = \mathrm{softmax}\left(\frac{\mathrm{QK^T}}{\sqrt{\mathrm{d_k}}}\right)\mathrm{V} \tag{5}$$

where Q, K, and V represent the query, key, and value matrices. d_k is the dimensionality of the keys.

Standard attention mechanisms in transformers seek to compute attention scores between elements within sequences. This is typically performed through a query-key-value framework, involving calculating weights based on similarities between queries and keys.

3) Step 3: recursive prediction layer for boundary correction

Step 3 involves the implementation of a recursive prediction layer focused on boundary correction. One of the notable challenges in traditional EMD techniques is the end effect. This end effect is where data boundaries can affect the decomposition and the corresponding IMFs. To address this, the recursive prediction layer performs boundary correction by extrapolating values at the beginning and end of each mode to ensure smooth transitions. This is expressed by:

$$\hat{y}(t) = \begin{cases} \text{Extrapolation } (y(t)), & t \in \text{boundary region} \\ \text{Smoothing } (y(t)), & t \notin \text{boundary region} \end{cases} \tag{6}$$

where $y(t)$ is the mode or signal at time step t and $\hat{y}(t)$ is the smoothed signal after boundary correction.

4) Step 4: frequency-specific layer

In Step 4, the methodology includes a frequency-specific layer aimed at enhancing the accuracy of mode detection. In this step, there is an application of a frequency-specific layer function to enhance mode differentiation by filtering each mode with a frequency-specific band, with each band-pass filter focused on a distinct frequency range. This comes from the idea that neurons in a transformer can be used to extract different features from the input data. Thus, the frequency-specific layer extracts distinct frequency bands from the signal.

The frequency-specific filtering process is given by:

$$y_i(t) = F^i_{band-pass}(x(t);\, f_{low,i},\, f_{high,i}) \tag{7}$$

where $x(t)$ represents the original time series, $F^i_{band-pass}$ is the band-pass on the i-th frequency band, and $f_{low,i}$ and $f_{high,i}$ are the corresponding frequency cutoffs for the i-th filter.

5) Step 5: adaptive sifting and decomposition process

Step 5 introduces an adaptive sifting and decomposition process designed to enhance the reliability of the decomposition results. This step replaces the subjective stopping criteria typically employed in EMD with a learned stopping criterion that is data-driven.

So if $x(t)$ is the original time series that is being considered for decomposition, the sifting process can be expressed as:

$$IMF_i(t) = Sifting(x(t), i) \tag{8}$$

where $Sifting$ is the adaptive sifting process and i is the i-th IMF.

6) Step 6: dynamic adjustment for short data segments

In cases where the time series is short, the traditional EMD tends to struggle due to the need for a sufficient number of extrema. To overcome this problem, Step 6 is applied only to short time series (where there are fewer than 30 observations) and lengthens the dataset. For simplicity, an autoregressive moving average (ARMA) (1,1) process can be used. The order of the AR p process is 1, and the order of the MA q process is 1.

Notably, the AlphaFold-D method is employed in this study to examine the intertemporal relationships between the key variables under consideration.

Decomposition-based approaches are particularly suited to analyzing such interdependencies because they allow for the simultaneous modeling of the variables' past values, capturing the feedback effects and causal relationships without the need for an exhaustive list of all possible external factors. The approach does not claim to provide a comprehensive model of all oil price determinants but rather focuses on the key drivers that are most relevant to the study's objectives.

3.4.1. Justification of AlphaFold-D

Jumper et al. [4] created AlphaFold, a methodology that learns long-range spatial dependencies to predict the three-dimensional structure of proteins from amino acid sequences. CNNs, attention-based models, and iterative refinement procedures are all used to accomplish this. Despite being initially designed for biological data, these same components provide strong tools for deciphering time-series data patterns, which also necessitate the discovery of complex relationships and multi-scale dynamics across time.

The proposed AlphaFold-D methodology selectively repurposes the attention-based architecture and refinement processes for time-series decomposition. This helps to overcome important EMD drawbacks such as mode mixing, sensitivity to noise, and inadequate boundary handling. For instance, AlphaFold-D's attention-based mode isolation layer uses the multi-head attention mechanism from AlphaFold to concentrate on various spatial relationships. Through adaptively weighting various filtered representations, it is re-designed to isolate frequency components within the time series and minimize mode mixing. Similarly, the proposed AlphaFold-D's boundary correction reduces the end effects that frequently distort empirical mode functions in conventional EMD by utilizing a recursive prediction layer that was inspired by AlphaFold's iterative updates.

Additionally, AlphaFold-D improves EMD by using other methods like adaptive sifting with data-driven stopping criteria and frequency-specific filtering to increase mode separation.

3.5. ANN causality test

To determine a causal relationship between the variables, causality testing was applied. The causal relationship between variables is often determined through the use of the Granger causality test. However, the Granger causality test is based on the assumption of linearity. In fact, in the Granger causality test, a linear regression is specified between a dependent variable Y and an independent variable X. The variable X is found to have a causal impact on variable Y if the information from X improves the predictive accuracy of Y more than a regression with Y alone. Thus, variable X is said to be Granger-cause Y if X improves the predictive accuracy of Y in a linear regression.

It is well known that many time series are not linear. Therefore, the application of the Granger causality test would be limited to a linear predictive accuracy test. As such, the test is constrained by the assumption of linearity.

The linearity constraint is overcome in this study by using the ANN causality test proposed by Charles [5] to determine the causality between the variables.

Applying the same logic used in the Granger causality test, a causal relationship should exist between variables X and Y if, in a regression with Y as the dependent variable and X as the independent variable, including X in the regression improves the predictive accuracy of Y compared to a univariate regression of Y. However, rather than applying a linear regression, a three-layer feedforward neural network is used for the regression, as neural networks can model nonlinear relationships. Therefore, if the inclusion of the variable X in the three-layer feedforward neural network improves the prediction of Y, then X is said to have predictive accuracy and a causal relationship with Y. Conversely, if the inclusion of the variable X in the three-layer feedforward neural network does not improve the prediction of Y, then X is said to lack predictive accuracy and a causal relationship with Y.

Since the Charles [5] causality test involves the application of a neural network, it requires training the data to learn patterns. As such, the model is trained on the training set and validated against the test set. This training and validation process results in the generation of a mean squared error (MSE). The MSE generated from the regression of $Y = f(X, Y_{t-1})$ is called MSE 1.

This MSE 1 is compared to the MSE of a univariate model ($Y = f(Y_{t-1})$).

Causality is determined when the MSE 1 is less than the MSE 2. Moreover, a ratio can be calculated as MSE 1/ MSE 2. If $\frac{\text{MSE 1}}{\text{MSE 2}} < 1$, then causality exists from variable X to variable. If $\frac{\text{MSE 1}}{\text{MSE 2}} > 1$, then no causality exists from variable X to variable Y.

The next step of the Charles [5] ANN causality test involves statistically testing to see if the ratio $\frac{\text{MSE 1}}{\text{MSE 2}}$ is statistically significantly less than 1.

The corresponding null and alternative hypotheses are as follows:

1) H_0: MSE 1/ MSE 2 < 1 (this means that there is predictive causality from variable X to Y).
2) H_1: MSE 1/ MSE 2 > 1 (this means that there is no predictive causality from variable X to Y).

Essentially, the null hypothesis investigates if MSE 1 < MSE 2. As such, the corresponding alternative hypothesis investigates if MSE 1 > MSE 2.

Therefore, the null hypothesis should be rejected in favor of the alternate hypothesis if the value of MSE 1/MSE 2 is significantly different from the hypothesized value of less than 1.

The corresponding test statistic is as follows:

$$\frac{\left(\frac{\text{MSE1}}{\text{MSE2}}\right)}{\text{SE}} \tag{9}$$

where SE is the standard error or $\frac{\sigma_{xy}}{\sqrt{n}}$;

σ_{xy} is the covariance of the variables X and Y.

The decision rule for this right-tailed test[1] is based on comparing the test statistic to a critical value of $\frac{1}{\text{SE}}$. If the test statistic does not exceed the critical value, then the null hypothesis should not be rejected. Conversely, if the test statistic exceeds the critical value, the null hypothesis should be rejected in favor of the alternative hypothesis.

The non-rejection of the null hypothesis implies that MSE 1 is less than MSE 2, indicating that variable X has predictive causality over variable Y. On the other hand, rejecting the null hypothesis suggests that MSE 1 is greater than MSE 2, implying that variable X does not exhibit predictive causality with respect to Y.

The code for the AlphaFold-D methodology and the ANN causality test is made available on Github.

3.6. Combination of the methodologies

This study follows an approach used by Jiang and Yoon [29]. Jiang and Yoon [29] used the wavelet transform methodology to decompose oil prices and stock prices, then used a linear causality test to investigate the relationship between the variables. Instead, this study used the proposed AlphaFold-D methodology to decompose the time series. Then it uses the ANN causality test to investigate the relationship between the variables.

[1]The test is right tailed because the rejection region is on the right.

Notably, the traditional elasticity-based approach can be applied. For example, a linear regression can be applied. The model can be of the form

$$Y_t = \alpha_0 + \beta_t X_t + \varepsilon_t \tag{10}$$

where Y_t is the dependent variable and can be oil prices, X_t can be the matrix of the independent variables, α_0 is the vector with the constants that are estimated, β_t is the vector with the estimated parameters, and ε_t is the error term.

However, the approach in Equation (10) is a linear-based approach, which has the limitations of linear regression. A key limitation of linear regression is that it is not designed to handle time-varying, non-stationary data, where the mean and variance of the series change over time. This is a significant issue for oil prices, which often exhibit large fluctuations.

Decomposition-based methods, such as wavelet transform, EMD, and the proposed AlphaFold-D, overcome this limitation by decomposing the time series into subcomponents like IMFs. Each IMF is designed to capture specific oscillations in the data without requiring stationarity. This decomposition effectively isolates short-term fluctuations caused by geopolitical events.

Linear regression requires a predefined set of independent variables, meaning any relevant exogenous variables must be explicitly included in the model. If important factors are omitted or misspecified, the results can be biased or incomplete, leading to large standard errors, serial correlation, and other statistical issues.

Decomposition-based methodologies, such as wavelet transform, Fourier transform, EMD, and the proposed AlphaFold-D, are data-driven and do not require the researcher to specify a functional form or predefined relationships between variables. Instead, these methods allow the data itself to guide the decomposition process, making them more effective in capturing complex patterns that may not be immediately apparent or predictable through linear modeling.[2]

This study applies a nonlinear and decomposition-based approach, similar to Jiang and Yoon [29], Reboredo and Rivera-Castro [30], and Zhang et al. [31]. In these approaches, a decomposition method is used to break a time series into multiple subcomponents (such as wavelets or IMFs), and a dependence method is then applied to analyze the relationships between the subcomponents of each variable.

4. Results

Before any inferential analysis is applied, some pretests are performed.[3] First, the Jarque-Bera test for normality is performed. The null hypothesis of the Jarque-Bera test is that the data follows a normal distribution. Specifically, it tests whether the skewness and kurtosis of the data are consistent with those expected in a normal distribution. The results are displayed in Table 1.

4.1. Normality pretest results

The probability of the Jarque-Bera test statistic for the REER index was 0.0000. This would lead to the rejection of the null

[2]Notably, time-frequency studies such as Bouri et al. [32] and Soni et al. [33] use wavelet transforms to decompose time series for analysis and use them with correlation. While this is acceptable, the author does not use wavelet transforms because they produce wavelet decompositions of different lengths, which is a problem already overcome by EMD. In EMD, all the IMFs are of the same length. Second, correlation is a method of estimating the linear association between variables, but it is not causality.

[3]The pretests are performed in EViews.

Table 1
Descriptive statistics results

	REER	WTI	BRENT
Mean	101.1879	67.60163	72.40723
Median	100.5000	65.17000	71.23000
Maximum	108.3000	114.8400	122.7100
Minimum	97.30000	16.55000	18.38000
Std. Dev.	2.331660	21.44394	23.39106
Skewness	1.382459	0.222009	0.212192
Kurtosis	4.454210	2.174091	2.205801
Jarque-Bera	57.33703	5.165753	4.763761
Probability	0.000000	0.075556	0.092377
Sum	14267.50	9531.830	10209.42
Sum Sq. Dev.	761.1295	64377.97	76599.81
Observations	141	141	141

hypothesis that the REER index was normally distributed at the 10% significance level.

The probability of the Jarque-Bera test statistic for Brent oil prices was 0.0924. This would lead to the rejection of the null hypothesis that Brent oil prices were normally distributed at the 10% significance level.

The probability of the Jarque-Bera test statistic for WTI prices was 0.0756. This would lead to the rejection of the null hypothesis that WTI prices were normally distributed at the 10% significance level.

Since the results suggest that Brent and WTI oil prices and the REER index are not normally distributed, then models based on the assumption of normality would produce inaccurate results. This justifies the use of models that do not rely on the normality assumption.

Next, structural break tests are applied to determine if the time series is linear.

4.2. Structural breaks pretest results

The Sequential L + 1 breaks test is a methodology used to identify structural breaks in time-series data. It sequentially tests for the presence of an additional break by comparing the test statistic at each hypothesized number of breaks with a critical value. In this right-tailed test, if the test statistic exceeds the critical value, the null hypothesis of no further break is rejected, indicating the presence of another structural break.

The Sequential L + 1 breaks test is applied to Brent oil prices, WTI oil prices, and the REER index. The results are displayed in Tables 2–4.

In Table 2, the Sequential L + 1 breaks test is applied to Brent oil prices to determine the presence of structural breaks in the time series. Under the null hypothesis of zero breaks, the test statistic was 93.87697, while the critical value was 8.58. Since the test statistic was greater than the critical value, the null hypothesis was rejected in favor of the alternative hypothesis. This test is continued for up to four breaks. Under the null hypothesis of four breaks, the test statistic was 0.000000, which was less than the critical value of 12.25. Therefore, the null hypothesis of four breaks was not rejected in favor of the alternative hypothesis of more than four breaks. This suggests that Brent oil prices have four structural breaks.

In Table 3, the Sequential L + 1 breaks test is applied to WTI oil prices to determine the presence of structural breaks in the time series. The null hypothesis of two breaks generates a test statistic of 7.860423, which is less than the critical value of 11.14. This suggests that WTI oil prices have two structural breaks.

In Table 4, the Sequential L + 1 breaks test is applied to the REER index to determine the presence of structural breaks in the time series. Under the null hypothesis of zero breaks, the test statistic was 192.2454, while the critical value was 8.58. Since the test statistic was greater than the critical value, the null hypothesis of zero breaks was rejected in favor of the alternative hypothesis of

Table 2
Structural breaks test results for Brent oil prices

Sequential F-statistic determined breaks:			4
Break Test	F-statistic	Scaled F-statistic	Critical Value**
0 vs. 1 *	93.87697	93.87697	8.58
1 vs. 2 *	183.0320	183.0320	10.13
2 vs. 3 *	13.47193	13.47193	11.14
3 vs. 4 *	26.98559	26.98559	11.83
4 vs. 5	0.000000	0.000000	12.25
* Significant at the 0.05 level.			
** Bai-Perron (*Econometric Journal*, 2003) critical values.			
Break dates:			
	Sequential	Repartition	
1	2014M11	2014M12	
2	2021M06	2017M11	
3	2017M09	2019M08	
4	2019M08	2021M06	

Table 3
Structural breaks test results for WTI oil prices

Sequential F-statistic determined breaks:			2
Break Test	F-statistic	Scaled F-statistic	Critical Value**
0 vs. 1 *	84.25783	84.25783	8.58
1 vs. 2 *	225.9761	225.9761	10.13
2 vs. 3	7.860423	7.860423	11.14
* Significant at the 0.05 level.			
** Bai-Perron (*Econometric Journal*, 2003) critical values.			
Break dates:			
	Sequential	Repartition	
1	2014M11	2014M12	
2	2021M06	2021M06	

Table 4
Structural breaks test results for REER index

Sequential F-statistic determined breaks:			1
Break Test	F-statistic	Scaled F-statistic	Critical Value**
0 vs. 1 *	192.2454	192.2454	8.58
1 vs. 2	6.784403	6.784403	10.13
* Significant at the 0.05 level.			
** Bai-Perron (*Econometric Journal*, 2003) critical values.			
Break dates:			
	Sequential	Repartition	
1	2023M01	2023M01	

more than zero breaks. Under the null hypothesis of one break, the test statistic was 6.784403, which was less than the critical value of 10.13. Thus, the null hypothesis of one break is not rejected in favor of the alternative hypothesis. This suggests that the REER index has one structural break.

Therefore, Brent and WTI oil prices, and Guyana's REER index are not linear. Subsequently, a linear model is not appropriate for modeling these variables.

4.3. Stationarity pretest results

Table 5 shows the stationarity test results. The null hypothesis for the Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) stationarity tests is that the time series contains at least one unit root. For the variables Brent oil prices, WTI oil prices, and the REER index, the null hypothesis of possessing a unit root was not rejected at level at the 5% significance level.

However, at first difference, the null hypothesis of possessing a unit root was rejected at the 10%, 5%, and 1% significance levels. This suggests that the variables (Brent, WTI, and REER index) have a unit root.

The Perron Stationarity with structural break test has a null hypothesis that the time series is non-stationary (i.e., has at least one unit root) and has a structural break. For the variables (Brent oil prices, WTI prices) at level, the probability of the test statistic was greater than the 10% significance level. This led to the conclusion that the variables are non-stationary and contain at least one unit root. However, for the REER index, at level, the probability of the test statistic was less than 10%, 5%, and 1% significance levels. This suggested the rejection of the null hypothesis of non-stationarity with a structural break. Thus, it implies that the REER index may be stationary (does not have a unit root) but exhibits a structural break in its trend or mean.

The existence of non-stationarity in the variables, as well as the presence of a unit root, justifies the use of a nonlinear model to analyze the time series.

4.4. Results of the AlphaFold-D

The proposed AlphaFold-D methodology was used to decompose each time series (Brent oil prices, WTI oil prices, and Guyana's REER index) into multiple IMFs.[4] The author labeled the frequencies as follows:

1) IMF5 represents the highest-frequency component. It is supposed to capture very short-term fluctuations, which represent oscillations in the range of 1–2 months in the monthly dataset.

Table 5
Stationarity test results

	ADF	PP	Stationarity with break
Brent (level)	0.0969	0.1850	0.5820
Brent (1st difference)	0.0001	0.0001	0.01
WTI (level)	0.1387	0.2352	0.5612
WTI (1st difference)	0.0001	0.0001	0.01
REER (level)	0.1087	0.1264	0.01
REER (1st difference)	0.0000	0.0000	0.01

[4]The proposed AlphaFold-D methodology was run in MATLAB 2021a.

2) IMF4 represents a slightly lower-frequency fluctuation than IMF5, generally reflecting short-term patterns that last around 2–4 months.
3) IMF3 represents medium-term patterns, in the range of 4–8 months. This is associated with seasonal effects or other short-term trends.
4) IMF2 represents lower-frequency trends, capturing fluctuations over a span of 8–12 months.
5) IMF1 represents the lowest-frequency IMF and captures long-term trends that are in excess of 12 months. For this 34-month time series, IMF1 is supposed to show a trend or cyclical behavior, essentially representing any persistent long-term trend present in the data.

The decomposed time series are presented in Figures 1–3.

The IMFs for Brent deconstructed using AlphaFold-D are displayed in Figure 1. A layered structure of dynamic behavior over time horizons is seen in the breakdown of Brent oil prices. Market microstructure noise and transient speculative movements are captured by IMF5 (1–2 months). Market corrections and temporary demand/supply mismatches are shown in MF4 (2–4 months). IMF3 (4–8 months) probably correlates with hedging activity, inventory adjustment cycles, and sentiment in international business. The effects of energy policy, strategic changes in output, or cycles of monetary tightening that progressively affect oil prices over quarters may be captured by IMF2 (8–12 months). Brent pricing's structural trend is seen by the IMF1 (>12 months).

Similar to analysis on Brent, the AlphaFold-D decomposition of WTI oil prices reveals a multi-layered frequency structure that reflects different market forces at work throughout time periods. See Figure 2. Short-term volatility caused by speculative trading, inventory surprises, and quick reactions to geopolitical events is captured by IMF5 (1–2 months). IMF4 (2–4 months) accounts for transient shocks and short-term demand-supply mismatches. IMF3 (4–8 months) corresponds with production movements that are medium-term. IMF2 (8–12 months) might be able to capture longer-lasting macroeconomic effects. Lastly, the structural trend in WTI pricing, including long-term trends, is reflected in IMF1 (>12 months).

Figure 3 shows the IMFs for the REER index decomposed with AlphaFold-D. IMF5 (1–2 months) captures high-frequency exchange rate volatility and immediate financial market reactions. IMF4 (2–4 months) reflects short-run misalignments or market corrections. IMF3 (4–8 months) indicates medium-term currency pressures. IMF2 (8–12 months) may embody more persistent real exchange rate adjustments. IMF1 (>12 months) captures the long-term trend in the REER, reflecting deep structural factors.

After the time series have been decomposed, the ANN causality test is applied to determine the causal relationships between the IMFs.

4.5. Results of the ANN causality test

The ANN causality test is applied from Brent oil prices to the REER index. In other words, it tests whether Brent oil prices have a causal impact on Guyana's REER index. This test was applied to both the full time series and the IMFs. The results of the test are displayed in Table 6.

The ANN causality test found causality from Brent oil prices to the REER index for the full series. This suggests that there is a causal relationship between oil prices and the REER index. When the decompositions were performed, causality was found in IMF4 and IMF5. Recall that, as specified by the author, IMF5 represents very short-term fluctuations, which correspond to oscillations in the

Figure 1
IMFs for Brent (decomposed with AlphaFold-D)

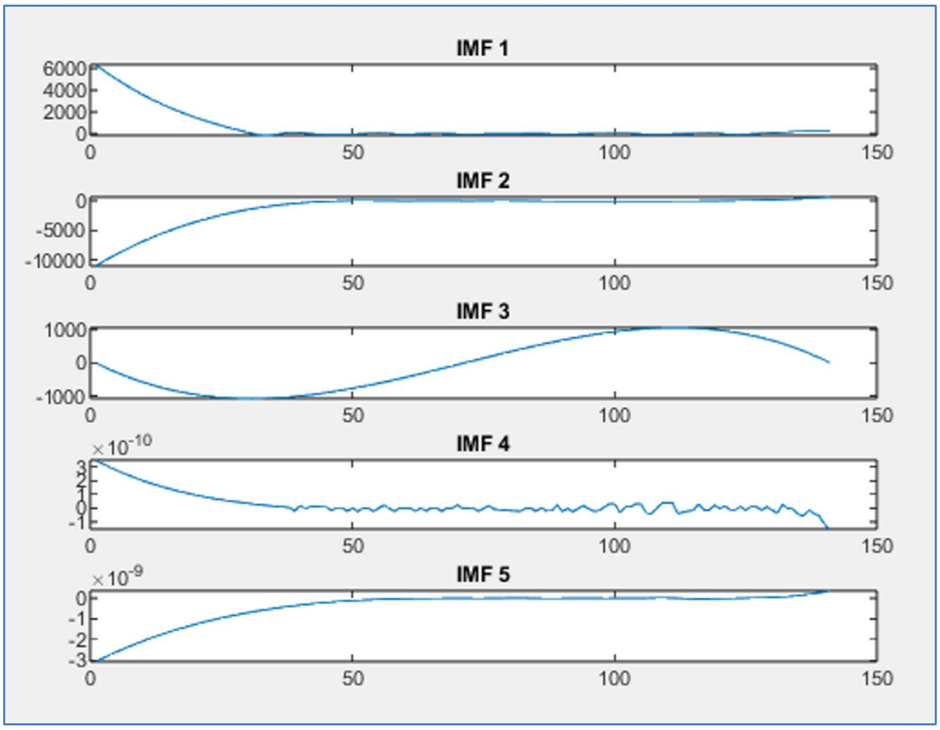

Figure 2
IMFs for WTI (decomposed with AlphaFold-D)

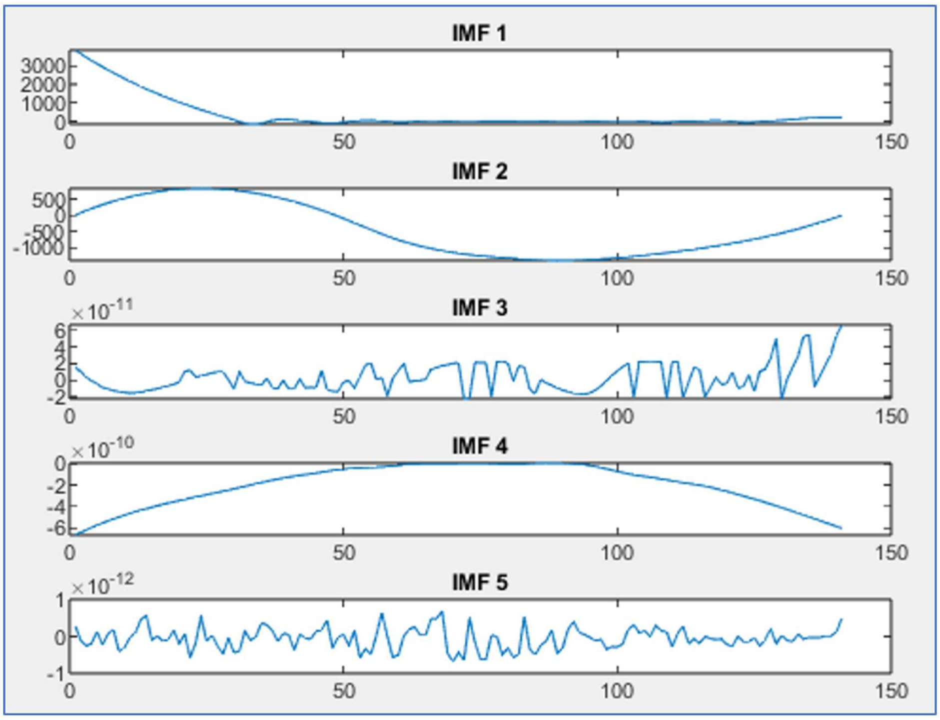

Figure 3
IMFs for REER index (decomposed with AlphaFold-D)

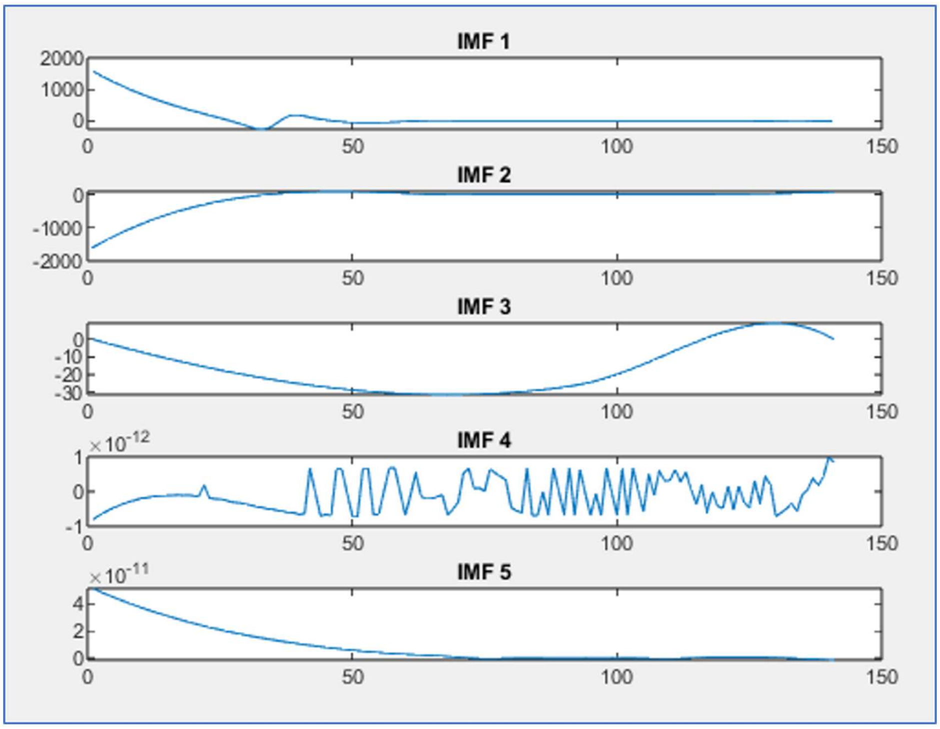

Table 6
ANN causality test from Brent to REER

Brent to REER	Test statistic	Critical value	Decision
IMF1 to IMF1	–4.89E–05	–9.78E–05	Reject the null. There is no causality
IMF2 to IMF2	–4.19E–05	–9.78E–05	Reject the null. There is no causality
IMF3 to IMF3	–5.56E–05	–9.78E–05	Reject the null. There is no causality
IMF4 to IMF4	1.09E+24	1.29E+24	Accept, there is causality
IMF5 to IMF5	3.17E+25	5.56E+25	Accept, there is causality
Full series (Brent to REER)	1.97E–09	2.18E–04	Accept, there is causality

range of 1–2 months in the monthly dataset. Additionally, IMF4 represents slightly lower-frequency fluctuations than IMF5, generally reflecting short-term patterns that last around 2–4 months. This indicates that Brent oil prices typically have short-run effects on Guyana's REER.

The ANN causality test found no causality from Brent oil prices to the REER index at IMF3, IMF2, and IMF1. Recall that the author labeled IMF1 as the lowest-frequency component, capturing long-term fluctuations exceeding 12 months. IMF2 represents a low-frequency component in the span of 8–12 months, while IMF3 represents medium-term patterns in the range of 4–8 months. Therefore, these results suggest that Brent oil prices had no effect on the REER index over the long term. Thus, these results suggest that a causal relationship exists in the short run but not in the long run.

Next, the ANN causality test is applied from WTI oil prices to the REER index. In other words, it tests whether WTI oil prices have a causal impact on Guyana's REER index.

As shown in Table 7, the ANN causality test identified a causal relationship between WTI oil prices and the REER index for the full series, indicating that oil prices influence Guyana's REER. When the data was decomposed, causality was detected at IMF4 and IMF5. According to the classification used in this paper, IMF5 represents very short-term fluctuations, corresponding to oscillations within 1–2 months in the monthly dataset. Similarly, IMF4 captures slightly lower-frequency fluctuations, typically spanning 2–4 months. These findings suggest that WTI oil prices primarily affect the REER index in the short run.

The ANN causality test did not find any causal relationship between WTI oil prices and the REER index at IMF3, IMF2, and IMF1. IMF1, as the lowest-frequency component, represents fluctuations exceeding 12 months, while IMF2 covers 8–12 months, and IMF3 represents medium-term variations lasting 4–8 months. This indicates that WTI oil prices had no significant effect on the REER index within these time frames.

Next, the ANN causality test is applied from the REER index to the Brent oil prices, then from the REER index to WTI prices. This was done to determine if there was a feedback causality between Guyana's REER index and the oil prices. The results of the test are displayed in Table 8.

The ANN causality test found no causality from the REER index to Brent oil prices or WTI oil prices for the full series, or any

Table 7
ANN causality test from WTI to the REER

WTI to REER	Test statistic	Critical value	Decision
IMF1 to IMF1	–7.62E–06	–1.05E–04	Reject the null. There is no causality
IMF2 to IMF2	8.58E+22	8.54E+22	Reject the null. There is no causality
IMF3 to IMF3	2.38E+27	3.56E+26	Reject the null. There is no causality
IMF4 to IMF4	8.48E+28	8.76E+28	Accept, there is causality
IMF5 to IMF5	2.71E+27	4.06E+27	Accept, there is causality
Full series (WTI to REER)	0.028495	0.033439	Accept, there is causality

Table 8
ANN causality test from REER to Brent and from REER to WTI

REER to Brent			
	Test statistic	Critical value	Decision
IMF1 to IMF1	–7.46E–06	–1.04E–04	Reject the null. There is no causality
IMF2 to IMF2	–2.05E–05	–9.78E–05	Reject the null. There is no causality
IMF3 to IMF3	–1.16E–05	–1.10E–04	Reject the null. There is no causality
IMF4 to IMF4	–9.63E–06	–1.09E–04	Reject the null. There is no causality
IMF5 to IMF5	–7.08E–06	–1.16E–04	Reject the null. There is no causality
Full series (REER to Brent)	–1.01E–05	–1.11E–05	Reject the null. There is no causality
REER to WTI			
IMF1 to IMF1	–7.61E–06	–1.07E–04	Reject the null. There is no causality
IMF2 to IMF2	–2.49E–05	–1.09E–04	Reject the null. There is no causality
IMF3 to IMF3	–1.30E–05	–1.17E–04	Reject the null. There is no causality
IMF4 to IMF4	–9.83E–06	–1.10E–04	Reject the null. There is no causality
IMF5 to IMF5	–7.26E–06	–2.13E+27	Reject the null. There is no causality
Full series (REER to WTI)	–1.23E–05	–1.24E–05	Reject the null. There is no causality

of the decompositions. This suggests that there is no causation from Guyana's REER index to the oil prices.

5. Discussion

The ANN causality test results reveal that Brent oil prices have a short-term causal effect on Guyana's REER, specifically impacting high-frequency fluctuations (IMF4 and IMF5, corresponding to 1–4 months), but no significant long-term causality (IMF1-IMF3, representing fluctuations beyond four months). This suggests that oil price shocks lead to rapid but temporary adjustments in the REER, consistent with the short-run spending effect described in Dutch disease theory. When oil prices rise, increased foreign currency inflows boost domestic demand, driving up prices of non-tradable goods and causing a temporary REER appreciation. This could squeeze competitiveness in non-oil tradable sectors, such as agriculture and manufacturing, in the short run.

The short-term causation between Brent oil prices and high-frequency REER components (IMF4 and IMF5) in the instance of Guyana implies that oil windfalls cause the real exchange rate to rise immediately, most likely as a result of higher capital inflows and expenditure. The pricing competitiveness of non-oil exports, such as light manufacturing or agricultural, may be undermined by this short-term appreciation, which would lower their profitability and deter investment in these industries. The lack of long-term causality (in IMF1 to IMF3) would suggest that Guyana has not yet encountered the more profound structural changes linked to chronic Dutch disease. This can be the situation as a result of policy intervention.

The findings suggest that while Guyana experiences short-term Dutch disease-like pressures – where oil-driven REER appreciation could temporarily weaken non-oil export competitiveness – the absence of long-term causality indicates the economy may be mitigating the structural imbalances characteristic of Dutch disease. This resilience likely stems from prudent fiscal policies, particularly the sterilization of oil revenues through sovereign wealth mechanisms. In 2021, Guyana established the Natural Resource Fund Act, which provides a framework for managing the country's resource wealth effectively. The fund serves several important purposes, namely: (i) insulating public spending from revenue volatility; (ii) preventing the erosion of economic competitiveness; and (iii) ensuring intergenerational equity in resource wealth distribution. Therefore, it appears that the present institutional framework is safeguarding and successfully containing the typical Dutch disease transmission channels, allowing Guyana to benefit from oil revenues while maintaining macroeconomic stability.

Nevertheless, results do imply that the short-term REER fluctuations from oil shocks warrant monitoring.

For instance, in April 2025, the United States imposed tariffs on many countries. It also imposed tariffs on China, which rose to 104% on April 8, 2025. Subsequently, oil prices, both Brent and WTI, fell sharply, with both oil prices dropping below US$60 per barrel on April 8, 2025. However, when news emerged that the United States would pause tariff implementation for three months for countries that did not retaliate, WTI prices surged to US$62.63 per barrel on April 9, 2025. Subsequently, when China retaliated by imposing an 84% tariff on US imports, the United States responded by raising its tariffs on Chinese goods to 145%, prompting another downturn in WTI prices to US$58.86 per barrel. This recent price action reflects the volatility of international oil prices.

If there are short-term fluctuations in oil prices, and their impacts are felt within 1 to 4 months, it stands to reason that Guyana could experience consecutive waves of REER appreciation and depreciation in rapid succession. This volatility would be bad for the economy, as it can undermine investor confidence and delay the implementation of investment projects. Moreover, it introduces significant uncertainty into business planning across all sectors. Exporters, in particular, face a shifting landscape, one month struggling with an overvalued REER that makes their goods more expensive in foreign markets, and the next contending with a depreciated REER that increases the cost of imported inputs.

To mitigate the damaging effects of short-term oil price volatility on Guyana's REER and broader economy, the Natural Resource Fund Mechanism can be strengthened. The policy actions that can be implemented are as follows.

1) **Establishing a liquidity buffer for foreign exchange intervention.** Creating a dedicated liquidity buffer would allow Guyana's central bank to actively smooth excessive REER fluctuations by intervening in foreign exchange markets during periods of extreme volatility. This buffer, funded through oil revenues, could be deployed to sell foreign currency when the REER appreciates too rapidly (preventing Dutch disease symptoms) or buy reserves when the REER depreciates sharply (avoiding inflationary import costs). This approach would provide stability without requiring full pegging.
2) **Adopting a velocity rule for the Natural Resource Fund.** A velocity rule would adjust how the Natural Resource Fund saves or spends oil revenues based on both the magnitude and speed of oil price changes. Unlike static price-based rules, this would account for how rapidly prices are rising or falling. This is important given the modeling shows impacts manifest within 1–4 months. For example, if prices drop by more than 25% within a month, the rule could automatically allow for more withdrawals, whereas gradual changes in oil prices would trigger smaller adjustments. This creates a shock absorber mechanism that responds proportionally to the urgency of market conditions.
3) **Developing a REER-Oil price dashboard.** Another tool that can be implemented is an integrated monitoring dashboard that uses real-time oil price data and the REER data. Oil prices are used as a leading and warning indicator of potential threats to the REER. The dashboard could be designed to flag when Brent/WTI movements exceed volatility thresholds, which in turn alerts policymakers to prepare contingency measures.

The next section concludes this study.

6. Conclusion

Recall, this study research question was:

> "To what degree have oil prices impacted Guyana's real effective exchange rate?"

This study used the proposed AlphaFold-D methodology to decompose the following time series, namely, Brent oil prices, WTI oil prices, and Guyana's REER index. The IMFs were extracted, and the ANN causality test was applied to determine the causality between the variables. Causality was found from Brent oil prices to the REER index at IMF4 and IMF5. Since these IMFs represented the highest frequencies, it is suggested that Brent oil prices had a causal impact on Guyana's real exchange rate in the short run.

The ANN causality test found no causality from Brent oil prices to the REER index at IMF1 to IMF3. Similar results were found for the relationship between WTI oil prices and the REER index. Since these were the lower-frequency IMFs, it is suggested that the oil prices did not have a long-run impact on Guyana's REER. Therefore, the long-run trend for Guyana's REER remains unaffected by Brent and WTI oil prices.

The contributions of this study are as follows. First, this study makes a methodological contribution as it proposes the methodology, AlphaFold-D, to perform the decompositions. AlphaFold-D can be used in place of EMD as it overcomes several limitations. The methodological improvements are as follows.

1) **Addressing mode mixing.** EMD often produces IMFs that contain oscillations of different frequencies within a single mode, leading to inaccurate decompositions. The proposed AlphaFold-D has an adaptive multi-head attention mechanism, which applies frequency-specific filters, helping to isolate unique frequency components and reduce mode mixing.
2) **Addressing sensitivity to noise and outliers.** EMD is highly sensitive to noise, and outliers can distort IMFs. The proposed AlphaFold-D includes a convolutional filtering layer with a Gaussian window that smooths out noise and suppresses random fluctuations, ensuring a clearer signal for accurate decomposition.
3) **Addressing boundary effects.** EMD struggles with artifacts at the beginning and end of the data, known as boundary effects, which distort decomposition results. AlphaFold-D implements a recursive prediction layer for boundary correction, extrapolating values at the boundaries to maintain smooth transitions and reduce boundary-related distortions.
4) **Addressing non-stationary time series.** EMD has limitations in handling non-stationary time series with abrupt changes. AlphaFold-D's frequency-specific filtering layers enhance localized frequency analysis, providing flexibility to capture varying frequencies and adapt to non-stationary characteristics in the data.
5) **Addressing the subjective stopping criteria.** EMD typically relies on subjective stopping criteria for sifting. The proposed AlphaFold-D introduces an adaptive, data-driven stopping criterion in its sifting and decomposition process, improving reliability and consistency in the decomposition results.

Second, this study makes an empirical contribution as it applies the ANN causality test created by Charles [5] to assess the causality between the variables.

Third, this study makes an empirical contribution as it investigates the impact of oil prices on Guyana's real exchange rate using nonlinear and machine learning models, offering an innovative approach to understanding the dynamics of oil price fluctuations.

Future research can apply the AlphaFold-D methodology to analyze the economic impact of other economic variables.

Ethical Statement

This study does not contain any studies with human or animal subjects performed by the author.

Conflicts of Interest

The author declares that he has no conflicts of interest to this work.

Data Availability Statement

The data that support the findings of this study are openly available in https://github.com/doncharles005/AlphaFoldDandtheexchangerate and https://statistics.cepal.org/portal/databank/index.html?lang=en&indicator_id=1901.

Author Contribution Statement

Don Charles: Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Resources, Data curation, Writing – original draft, Writing – review & editing, Visualization, Supervision, Project administration.

References

[1] Bulkan, J. (2021). The limits of state territorialisation: Geopolitics and petroleum in Guyana. *Social and Economic Studies*, *70*(3/4), 72–105.

[2] Roopnarine, L. (2022). Managing Guyana's newfound oil and gas wealth: Controversy and challenge. *Caribbean Studies*, *50*(1), 3–33. https://doi.org/10.1353/crb.2022.0000

[3] Leonard, C. (2025). Oil exploration in Guyana and its impact: A closer look at the labor sector & the environmental policies. *Ohio Northern University International Law Journal*, *3*(1), 4.

[4] Jumper, J., Evans, R., Pritzel, A., Green, T., Figurnov, M., Ronneberger, O., ..., & Hassabis, D. (2021). Highly accurate protein structure prediction with AlphaFold. *Nature*, *596*(7873), 583–589. https://doi.org/10.1038/s41586-021-03819-2

[5] Charles, D. (2023). The lead-lag relationship between international food prices, freight rates, and Trinidad and Tobago's food inflation: A support vector regression analysis. *Green and Low-Carbon Economy*, *1*(2), 94–103. https://doi.org/10.47852/bonviewGLCE3202797

[6] Albulescu, C. T., & Ajmi, A. N. (2021). Oil price and US dollar exchange rate: Change detection of bi-directional causal impact. *Energy Economics*, *100*, 105385. https://doi.org/10.1016/j.eneco.2021.105385

[7] Ding, S., Zheng, D., Cui, T., & Du, M. (2023). The oil price-inflation nexus: The exchange rate pass-through effect. *Energy Economics*, *125*, 106828. https://doi.org/10.1016/j.eneco.2023.106828

[8] Oberholzer, B. (2021). Managing commodity booms: Dutch disease and economic performance. *PSL Quarterly Review*, *74*(299), 307–323. https://doi.org/10.13133/2037-3643/17671

[9] Oludimu, S., & Alola, A. A. (2022). Does crude oil output aid economy boom or curse in Nigeria? An inference from "Dutch disease". *Management of Environmental Quality*, *33*(2), 185–201. https://doi.org/10.1108/MEQ-03-2021-0049

[10] Udemba, E. N., & Yalçıntaş, S. (2022). Unveiling the symptoms of Dutch disease: A comparative and sustainable analysis of two oil-rich countries. *Resources Policy*, *79*, 102949. https://doi.org/10.1016/j.resourpol.2022.102949

[11] Yaqub, K. Q. (2024). Fluctuations of the real exchange rate and the structure of the Iraqi economy. *International Journal of Research and Innovation in Social Science*, *8*(10), 622–640. https://dx.doi.org/10.47772/IJRISS.2024.8100052

[12] Corden, W. M., & Neary, J. P. (1982). Booming sector and de-industrialisation in a small open economy. *The Economic Journal*, *92*(368), 825–848. https://doi.org/10.2307/2232670

[13] Togonidze, S., & Kočenda, E. (2022). Macroeconomic responses of emerging market economies to oil price shocks: An analysis by region and resource profile. *Economic Systems*, *46*(3), 100988. https://doi.org/10.1016/j.ecosys.2022.100988

[14] Bunce, A., & Carrillo-Maldonado, P. (2023). Asymmetric effect of the oil price in the ecuadorian economy. *Energy Economics*, *124*, 106876. https://doi.org/10.1016/j.eneco.2023.106876

[15] Akbar, S., Munir, F., & Iqbal, M. (2024). Asymmetric dynamics between exchange rates and crude oil prices: A cross-country assessment. *Pakistan Journal of Humanities and Social Sciences*, *12*(4), 3141–3152. https://doi.org/10.52131/pjhss.2024.v12i4.2566

[16] Yildirim, Z., & Arifli, A. (2021). Oil price shocks, exchange rate and macroeconomic fluctuations in a small oil-exporting economy. *Energy*, *219*, 119527. https://doi.org/10.1016/j.energy.2020.119527

[17] Musa, K. S., & Maijama'a, R. (2021). Causal relationship among domestic oil price, exchange rate and inflation in Nigeria: An application of VECM Granger causality procedure. *Asian Journal of Economics, Finance and Management*, *3*(2), 1–13.

[18] Lakshmanasamy, T. (2022). The causal relationship between volatility in crude oil price, exchange rate, and stock price in India: GARCH estimation of spillover effects. *Indian Journal of Research in Capital Markets*, *8*(3), 8–21. https://doi.org/10.17010/ijrcm/2021/v8i3/167954

[19] Yamaka, W. (2025). Analyzing shifts in structural dependence between oil prices and exchange rates in oil-importing economies. *Asian Journal of Economics and Banking*, *9*(1), 48–63. https://doi.org/10.1108/AJEB-05-2024-0057

[20] Duan, W., Khurshid, A., Rauf, A., Khan, K., & Calin, A. C. (2021). How geopolitical risk drives exchange rate and oil prices? A wavelet-based analysis. *Energy Sources, Part B: Economics, Planning, and Policy*, *16*(9), 861–877. https://doi.org/10.1080/15567249.2021.1965262

[21] Hamilton, J. D. (1983). Oil and the macroeconomy since World War II. *Journal of Political Economy*, *91*(2), 228–248. https://doi.org/10.1086/261140

[22] Kilian, L. (2009). Not all oil price shocks are alike: Disentangling demand and supply shocks in the crude oil market. *American Economic Review*, *99*(3), 1053–1069. https://doi.org/10.1257/aer.99.3.1053

[23] Energy Information Administration. (2025). *Petroleum & other liquids*. https://www.eia.gov/dnav/pet/hist/RBRTED.htm

[24] Al-Jawarneh, A. S., Ismail, M. T., & Awajan, A. M. (2021). Elastic net regression and empirical mode decomposition for enhancing the accuracy of the model selection. *International Journal of Mathematical, Engineering and Management Sciences*, *6*(2), 564–583. https://doi.org/10.33889/IJMEMS.2021.6.2.034

[25] Ge, S., & Lin, A. (2025). An adaptive selection decomposition hybrid model for stock time series forecasting. *Nonlinear Dynamics*, *113*(5), 4647–4669. https://doi.org/10.1007/s11071-024-10404-5

[26] Suo, R., Wang, Q., & Han, Q. (2024). Driver analysis and integrated prediction of carbon emissions in China using machine learning models and empirical mode decomposition. *Mathematics*, *12*(14), 2169. https://doi.org/10.3390/math12142169

[27] Eriksen, T., & Rehman, N. U. (2023). Data-driven nonstationary signal decomposition approaches: A comparative analysis. *Scientific Reports*, *13*(1), 1798. https://doi.org/10.1038/s41598-023-28390-w

[28] Faysal, A., Ngui, W. K., & Lim, M. H. (2021). Noise eliminated ensemble empirical mode decomposition for bearing fault diagnosis. *Journal of Vibration Engineering & Technologies*, *9*(8), 2229–2245. https://doi.org/10.1007/s42417-021-00358-y

[29] Jiang, Z., & Yoon, S.-M. (2020). Dynamic co-movement between oil and stock markets in oil-importing and oil-exporting countries: Two types of wavelet analysis. *Energy Economics*, *90*, 104835. https://doi.org/10.1016/j.eneco.2020.104835

[30] Reboredo, J. C., & Rivera-Castro, M. A. (2013). A wavelet decomposition approach to crude oil price and exchange rate dependence. *Economic Modelling*, *32*, 42–57. https://doi.org/10.1016/j.econmod.2012.12.028

[31] Zhang, Q., Hu, Y., Jiao, J., & Wang, S. (2024). The impact of Russia–Ukraine war on crude oil prices: An EMC framework. *Humanities and Social Sciences Communications*, *11*(1), 8. https://doi.org/10.1057/s41599-023-02526-9

[32] Bouri, E., Nekhili, R., & Todorova, N. (2023). Dynamic co-movement in major commodity markets during crisis periods: A wavelet local multiple correlation analysis. *Finance Research Letters*, *55*, 103996. https://doi.org/10.1016/j.frl.2023.103996

[33] Soni, R. K., Nandan, T., & Chatnani, N. N. (2023). Dynamic association of economic policy uncertainty with oil, stock and gold: A wavelet-based approach. *Journal of Economic Studies*, *50*(7), 1501–1525. https://doi.org/10.1108/JES-05-2022-0267

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