Journal of Knowledge Management and Artificial Intelligence
An International Journal

http://dx.doi.org/10.18576/jkmai/070101

Prediction of Oil and Foreign Currency Prices Using MGARCH and AI Models

Khalil A. Alruwaitee[1,2,*]

[1] Department of Economics and Finance, Business College, Taif University, Al-Hawiya 21974, Taif P.O. Box 888, Saudi Arabia.
[2] Applied College, Taif University, Al-Hawiya 21974, Taif P.O. Box 888, Saudi Arabia.

Received: 24 Feb. 2024, Revised: 26 Jun. 2024, Accepted: 1 Dec. 2024.
Published Online: 1 Jan. 2025.

Abstract: The research seeks to improve forecasting precision in oil and foreign exchange markets by applying MGARCH-BEKK and LSTM models. These methodologies, recognized for their capacity to predict nonlinear dynamics, examine the intricate volatility interrelations involving oil prices and currency exchange rates, utilizing data from January 2018 to June 2024. The anticipated results suggest that a hybrid MGARCH-LSTM model demonstrates superior predictive performance by effectively capturing the inherent interdependencies in these volatile financial markets. The LSTM model is anticipated to excel at processing sequential data and providing accurate volatility predictions for oil and currency markets. This method highlights the efficacy of hybrid models in tackling the intricacies of modern financial systems. The anticipated results correspond with current research, underscoring the revolutionary capacity of merging classic econometric methods with AI-driven approaches to improve market stability and predictability. Enhanced forecast accuracy underscores the strategic benefits of utilizing MGARCH and LSTM models for informed financial decision-making. Implementing these sophisticated technologies will empower stakeholders to navigate uncertainty in global markets more effectively.

Keywords: MGARCH-LSTM, oil, foreign exchange, forecasting, A.I.

1 Introduction

Energy and currency markets play a pivotal role in global economic stability and attract significant attention from policymakers, investors, and analysts. Since 2020, unprecedented events—including the COVID-19 pandemic, geopolitical tensions, and fluctuating oil production policies—highlighted the intricate interdependencies between these markets [13]. Oil prices and foreign exchange rates are vital economic performance indicators. Fluctuations in these metrics can profoundly affect domestic and international financial systems, shaping policy decisions, corporate earnings, and investment strategies [2].

Oil pricing is influenced by various macroeconomic factors, including interest rate fluctuations, global supply-demand dynamics, and geopolitical developments [15]. Concurrently, currency exchange rates exhibit dynamic responses to regional and global trends, often correlated with oil market activity. This interconnectedness underscores the necessity for advanced modeling techniques. While traditional econometric methods provide foundational insights, they often fail to capture these markets' nonlinear and dynamic nature. The volatility observed in oil and currency exchange rates, particularly during crises, reveals the limitations of static and linear modeling approaches [24].

In recent years, there has been a notable increase in machine learning (ML) and advanced econometric techniques for forecasting and modeling volatility in oil and currency markets. While Multivariate Generalized Autoregressive Conditional Heteroskedasticity (MGARCH-BEKK) model, developed by Baba, Engle, Kraft, and Kroner, aims to improve clarity at capturing volatility clustering and correlation dynamics, Long Short-Term Memory (LSTM) neural networks excel in identifying nonlinear patterns and temporal dependencies [9]. By employing hybrid MGARCH-LSTM frameworks, researchers seek to combine the theoretical robustness of econometric models with the data-driven adaptability of AI. This paper offers a detailed analysis of how these integrated methodologies enhance forecasting accuracy, particularly during heightened volatility and crises [11].

This study addresses the challenges associated with the volatility and unpredictability of global financial markets. The recognized limitations of traditional econometric models in managing sudden regime shifts and market downturns underscore the necessity for advanced hybrid methodologies. The study's objectives provide a direct response: i) by comparing the predictive strengths of MGARCH-BEKK and LSTM models, the research aims to overcome the

[*]Corresponding author e-mail: k.gamith@tu.edu.sa

shortcomings of traditional approaches, as highlighted in motivation. ii) The integration of MGARCH-BEKK and LSTM models is designed to enhance forecasting reliability, particularly during significant market disruptions. This responds to the identified need for models capable of withstanding extreme market conditions. iii) The study contributes to the growing field of hybrid econometric and machine learning models, addressing the demand for innovative tools to tackle complex financial phenomena outlined in motivation.

The study establishes a comprehensive approach to addressing theoretical and practical financial market modeling gaps by linking these objectives to the underlying challenges.

2 Literature Review

Early research on oil and currency market volatility emphasized key phenomena such as volatility clustering, heavy-tailed return distributions, and leverage effects [20,21]. Foundational econometric models, including Autoregressive Conditional Heteroskedasticity (ARCH) and its extension GARCH (Generalized Autoregressive Conditional Heteroskedasticity), provided robust tools for quantifying time-varying volatility. In oil markets, these models identified the persistence of volatility, where price shocks often produced long-lasting effects.

As global financial markets became increasingly interconnected, research shifted toward capturing cross-market dynamics. The MGARCH model emerged as a solution, enabling the simultaneous analysis of multiple assets or markets. Among these, the MGARCH-BEKK model stood out for its ability to ensure the positive definiteness of covariance matrices and its flexibility in modeling interactions between variables [10].

Despite their strengths, these models often fell short during periods of extreme market volatility due to their reliance on assumptions of linear relationships and stable functional forms. For example, [25] utilized GARCH-MIDAS to analyze oil market data, uncovering the influence of macroeconomic indicators on long-term volatility. While providing valuable insights, these approaches struggled to maintain accuracy under extreme events such as global recessions or black swan occurrences, as highlighted by [19] and [7]. This gap in traditional methodologies has driven the search for more adaptable and robust frameworks capable of addressing the complexities of modern financial markets.

While machine learning provides a data-driven alternative to traditional econometric methods, it eliminates the need for strict parametric assumptions. LSTM neural networks, a specialized type of recurrent neural network (RNN), were particularly adept at capturing long-term dependencies in sequential data, making them well-suited for financial time series analysis [23]. Recent studies emphasize the ability of LSTMs to process extensive, noisy datasets and uncover patterns that traditional models often miss [9].

In addition to LSTM, other AI algorithms—such as support vector machines (SVMs) and tree-based ensemble methods—have shown strong predictive capabilities in financial markets [16]. However, LSTMs stand out for their ability to capture temporal dynamics, which is essential for analyzing oil and currency markets' cyclical and shock-driven behavior. These models can seamlessly incorporate external variables, such as macroeconomic indicators or market sentiment data, without requiring the pre-specification of relationships [11].

The flexibility and adaptability of AI-based methods, particularly LSTM, have positioned them as transformative tools for financial forecasting. They enable a deeper understanding of complex and evolving market dynamics.

So, recognizing the complementary strengths of GARCH and LSTM models, researchers have increasingly advocated for hybrid approaches that combine econometrics' theoretical rigor with machine learning's adaptability. [11] conducted a comparative study of standalone GARCH and LSTM models, demonstrating that hybrid methodologies produced significantly more accurate volatility forecasts. Similarly, [1] applied a deep learning and GARCH-type frameworks for stock market predictions, showcasing the versatility of this approach across various asset classes.

[14] further highlighted the value of hybrid frameworks for conducting scenario analyses. These models are particularly effective for simulating synchronized global recessions, speculation-driven currency fluctuations, and prolonged oil price declines—critical scenarios for policymakers and investors. By merging econometric and machine learning techniques, hybrid methodologies address key limitations of traditional models, offering powerful tools for navigating complex financial markets.

3 Data and Methodology

The dataset consists of daily observations on oil prices and currency exchange rates covering the period from the beginning of January 2018 to the end of June 2024.

- **Oil Price**: This is represented by West Texas Intermediate (WTI).

- **Foreign Currency Exchange Rates**: These include major currency pairs such as EUR/USD, GBP/USD, USD/CHF, USD/JPY, AUD/USD, NZD/USD, and USD/CAD.
- Data is aggregated from the DataStream platform, a reputable financial source [6].

This time frame captures various economic conditions, including the pre-pandemic environment, the onset and impacts of the COVID-19 pandemic, subsequent recovery phases, and ongoing global economic uncertainties. This selection ensures the ability to evaluate the model's performance across diverse market conditions, including periods marked by sharp regime shifts.

3.1 MGARCH-BEKK Model

The MGARCH-BEKK model extends the univariate GARCH framework to a multivariate setting, making it highly suitable for capturing interactions between multiple time series. A defining feature of this model is its formulation, which ensures the positive definiteness of the conditional covariance matrices—a critical requirement in risk modeling.

In a two-variable context, such as modeling the relationship between oil return and currency returns, the conditional covariance matrix H_t is expressed as:

$$H_t = C'C + A\varepsilon_{t-1}\varepsilon'_{t-1}A' + BH_{t-1}B' \tag{1}$$

where:

- ε_{t-1} is a vector of residuals (errors) for oil and currency at time $t-1$.
- C is a lower triangular matrix.
- A and B capture the sensitivity of volatility to past shocks and past volatilities, respectively.

In a 2×2 system involving oil and currency, the matrices C, A, and B are typically represented as follows:

$$C = \begin{pmatrix} c_{11} & c_{12} \\ c_{21} & c_{22} \end{pmatrix}, \qquad A = \begin{pmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{pmatrix}, \qquad B = \begin{pmatrix} b_{11} & b_{12} \\ b_{21} & b_{22} \end{pmatrix} \tag{2}$$

By capturing the transmission of volatility across different assets, MGARCH-BEKK is well-suited for examining correlated financial markets. However, its linear framework might face challenges during regime shifts or in the presence of significant nonlinear effects, which can hinder its effectiveness in periods of high volatility [10].

3.2 LSTM Model

LSTM network is recurrent neural networks specifically designed to overcome the challenges of vanishing and exploding gradients. They achieve this by utilizing gates that control the flow of information. An LSTM cell (t, $C_t, and\ h_t$) generally includes:

$$f_t = \sigma\,(W_f\ [h_{t-1}, x_t] + b_{\mathrm{f}}), \tag{3}$$

$$i_t = \sigma\,(W_{\mathrm{i}}\ [h_{t-1}, x_t] + b_{\mathrm{i}}), \tag{4}$$

$$\tilde{C}_t = tanh\,(W_C\ [h_{t-1}, x_t] + b_{\mathrm{C}}), \tag{5}$$

$$C_t = f_t \odot C_{t-1} + i_t \odot \tilde{C}_t, \tag{6}$$

$$o_t = \sigma\,(W_o\ [h_{t-1}, x_t] + b_{\mathrm{o}}), \tag{7}$$

$$h_t = o_t \odot tanh\,(C_t), \tag{8}$$

where:

- x_t is the input (e.g., past returns, external covariates),

- σ (·) is the sigmoid function,
- f_t, i_t, and o_t are the forget, input, and output gates, respectively,
- $\odot$ denotes element-wise multiplication,
- W_f, W_{i}, W_C, W_o and b_{f}, b_{i}, b_{C}, b_{o} are the trainable weight matrices and biases [11].

After training, the LSTM outputs a volatility forecast $\hat{h}_t{}^{LSTM}$ or return forecast $\tilde{\mathrm{r}}_t{}^{LSTM}$, depending on the specific implementation.

3.3 Hybrid MGARCH-LSTM Model

The objective is to integrate the advantages of MGARCH-BEKK and LSTM models to enhance the precision of volatility and return forecasts by capturing linear and nonlinear relationships between oil prices and foreign currency rates.

The hybrid model incorporates:

MGARCH-BEKK for Conditional Volatility Estimation: Captures linear volatility spillovers and co-movements between time series, specifically oil and currency.

LSTM for Nonlinear Dynamics and Sequential Dependencies: Employs sequential learning techniques to represent enduring nonlinear associations in residual volatility.

1. **MGARCH Step**: Estimate the covariance matrix H_t (Equation 1) and extract the time-varying volatilities $\sigma^{o,t}$, and $\sigma^{c,t}$, which are the diagonal entries of H_t.

2. **LSTM Step**: Use the extracted volatilities, historical returns, and other covariates as inputs to the LSTM model (Equation 3) to produce refined next-step (or multi-step) volatility forecasts.

In pseudo-mathematical form, the hybrid approach can be expressed as:

$$\hat{H}_{t+1}(hybrid) = \mathrm{LSTM}(\hat{H}_t{}^{\mathrm{MGARCH}}, \mathrm{r}_t, \mathrm{X}_t), \tag{9}$$

Where:

- $\hat{H}_t{}^{\mathrm{MGARCH}}$ is the MGARCH-estimated covariance matrix at time t, r_t is the vector of returns, and X_t is a set of additional features, such as macroeconomic variables or technical indicators,
- LSTM (·) represents the LSTM model's training and inference process described in Equation (3).

By combining the econometric structure of MGARCH-BEKK with the data-driven flexibility of LSTM, this hybrid model seeks to overcome MGARCH's rigid parametric constraints while preserving its ability to interpret volatility spillovers effectively—these results in a model that is both robust and adaptable to complex temporal dynamics.

4 Empirical Results

The empirical findings thoroughly assess the predictive strengths and resilience of the MGARCH-BEKK, LSTM, and hybrid MGARCH-LSTM models. This section examines descriptive statistics, individual model performances, and the outcomes of hybrid approaches, connecting these insights to their practical applications in financial modeling. The detailed analysis highlights the effectiveness of these models in representing volatility patterns within highly interconnected and fluctuating markets.

4.1 Descriptive Statistics

Descriptive statistics offer insights into significant trends, anomalies, and volatility patterns. Initial analyses reveal notable volatility spikes in both oil price and currency exchange rates during the COVID-19 crisis (March–April 2020) and periods of heightened geopolitical tensions. The distributions show excess kurtosis (leptokurtic behavior) and often negative skewness, aligning with prior findings on heavy-tailed return distributions [5].

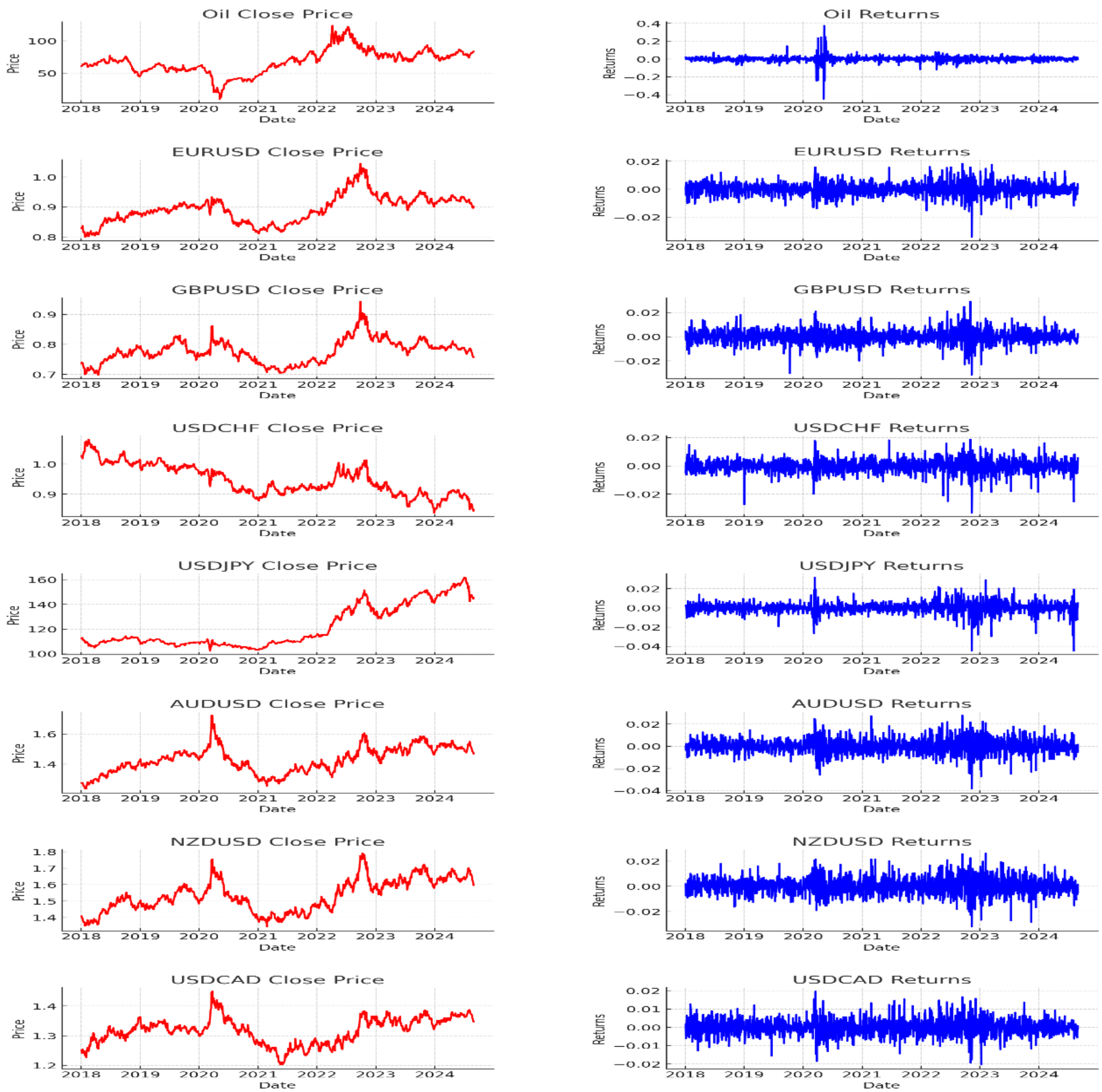

Fig. 1: Financial markets prices and returns (2018-2024)

The illustrated figure examines price fluctuations and returns across different financial markets from 2018 to 2024. The analysis focuses on key assets, such as crude oil and major currency pairs, offering insights into significant market trends and volatility patterns.

The oil market experienced notable price swings, particularly sharp fluctuations in 2020 due to major events like the COVID-19 pandemic. Oil returns showed significant variability, with sharp spikes highlighting price shocks and extended periods of volatility. These fluctuations reflect the market's sensitivity to external factors, such as geopolitical events and global supply and demand shifts.

The Euro-Dollar (EUR/USD) exchange rate displayed considerable price volatility, reaching its peak in 2021. Although returns remained relatively stable, occasional spikes indicate sudden market movements influenced by macroeconomic developments and geopolitical uncertainties. Similarly, the British Pound-Dollar (GBP/USD) pair followed a comparable pattern, marked by periods of heightened volatility and concentrated phases of increased return variability. These trends reflect the influence of economic policy changes and global market sentiment.

The US Dollar-Swiss Franc (USD/CHF) exchange rate followed a broadly downward trend, with occasional bursts of volatility. This pattern suggests a shift toward safe-haven assets, as the Swiss Franc is often perceived as a secure option during economic uncertainty. On the other hand, the US Dollar-Japanese Yen (USD/JPY) pair showed a steady upward price trend, with return fluctuations highlighting market risks and the currency's dynamic response to global economic shifts.

The Australian Dollar (AUD/USD) and New Zealand Dollar (NZD/USD) pairs exhibited cyclical price patterns with noticeable return fluctuations. These movements are likely driven by changes in commodity markets and regional economic conditions, underscoring the close link between these currencies and global trade. Likewise, the US Dollar-Canadian Dollar (USD/CAD) exchange rate experienced significant volatility, reflecting the impact of oil price fluctuations and broader economic conditions in Canada, a major oil-exporting nation.

Overall, the data highlights substantial volatility and a clear pattern of return clustering, a common feature of financial markets. Sharp return spikes indicate major market disruptions and significant events that have affected multiple currencies and commodities. The observed volatility clustering across different markets emphasizes the need for robust forecasting models, such as MGARCH-BEKK and LSTM, which can effectively capture dynamic interdependencies and help manage financial risk.

Table 1: Descriptive Statistics of oil and currency pairs (period 2 January 2018–30 June 2024)

Index	Mean	Std Dev	ADF Stat	JB-Stat	Skewness	Kurtosis	LM (ARCH LM Test)	Phillips–Perron Test	LB (Ljung–Box Test)
Oil	0.0007	0.0326	-7.28 ***	142185.51 ***	-0.3637	47.6269	58.28 ***	-7.28 ***	79.72 ***
EURUSD	0.0001	0.0045	-18.84 ***	804.02 ***	-0.1680	6.3394	1.79	-18.84 ***	29.64 ***
GBPUSD	0.0000	0.0056	-40.36 ***	626.49 ***	-0.0251	5.9622	1.37	-40.36 ***	16.25
USDCHF	-0.0001	0.0046	-40.08 ***	1628.46 ***	-0.6098	7.6182	2.49	-40.08 ***	8.76
USDJPY	0.0002	0.0056	-42.78 ***	5906.88 ***	-0.8070	11.9528	3.18	-42.78 ***	11.58
AUDUSD	0.0001	0.0065	-43.25 ***	361.09 ***	0.0316	5.2483	4.62	-43.25 ***	17.14
NZDUSD	0.0001	0.0065	-12.87 ***	193.43 ***	0.0643	4.6412	5.68	-12.87 ***	25.74 ***
USDCAD	0.0001	0.0043	-31.46 ***	251.87 ***	0.0542	4.8754	8.79 ***	-31.46 ***	11.70

Note: *** Significant at the 0.001 level. ADF represents the augmented Dickey-Fuller test statistics; JB represents the Jarque–Bera normality test statistics; LM defines the ARCH LM test statistics; PP defines the Phillips–Perron test statistics; and LB defines the Ljung–Box test statistics.

The table provides a detailed overview of the statistical properties and diagnostic evaluations of oil prices and selected foreign exchange rates, including EUR/USD, GBP/USD, USD/CHF, USD/JPY, AUD/USD, NZD/USD, and USD/CAD. This analysis sheds light on key financial metrics such as return distributions, stationarity, normality, autocorrelation, and volatility clustering—factors essential for understanding market behavior.

The analysis of mean returns shows that all examined assets have averaged close to zero, a typical characteristic of financial time series. This indicates that, over time, financial markets do not exhibit consistent return trends. Among the analyzed assets, oil is the most volatile, with a standard deviation of 0.0326, reflecting significant price fluctuations. On the other hand, the USD/CAD exchange rate is the least volatile, with a standard deviation of 0.0043, suggesting a relatively stable exchange rate environment.

Stationarity tests conducted using the Augmented Dickey-Fuller (ADF) and Phillips–Perron methods, confirm that all financial series are stationary at the 1% significance level. The highly negative test statistics, with p-values marked by "***", strongly reject the null hypothesis of non-stationarity. This implies that the statistical properties of the series, such as their mean and variance, remain stable over time, making them suitable for time-series modeling and forecasting.

The Jarque-Bera (JB) test results reveal that none of the financial series follow a normal distribution. Notably, oil and USD/JPY exhibit extremely high JB statistics, indicating significant departures from normality. Skewness and heavy tails in these series suggest asymmetric distribution standards in financial markets. This highlights the need for specialized models, such as non-parametric or heavy-tailed distribution approaches, to assess financial risk accurately.

The Ljung-Box (LB) test results point to significant autocorrelation in oil returns, with an LB statistic of 79.72, indicating persistent dependencies within the data. Moderate levels of autocorrelation are also observed in EUR/USD, NZD/USD, and AUD/USD, suggesting the potential for short-term dependencies that could be leveraged in trading strategies. In contrast, the USD/CHF and GBP/USD pairs exhibit relatively lower autocorrelation, indicating more random price movements over time.

Volatility clustering, a common characteristic of financial time series, is particularly evident in oil returns. The ARCH Lagrange Multiplier (LM) test results, with a statistic of 58.28, confirm that periods of high volatility are often followed by further volatility. Significant ARCH effects are also observed in NZD/USD and USD/CAD, indicating time-dependent volatility patterns. These findings suggest the need for specialized models, such as GARCH, to capture and predict market risk effectively.

In summary, the statistical analysis of these financial instruments highlights key characteristics such as high volatility, autocorrelation, and non-normal distributions. These findings underscore the importance of implementing robust risk management and forecasting techniques. Advanced econometric models like MGARCH-BEKK and machine learning-based approaches such as LSTM networks can help capture the complex dynamics and interdependencies that define financial markets.

4.2 MGARCH-BEKK Results

The MGARCH-BEKK model accurately captures volatility spillovers and interdependencies between oil prices and significant currency exchange rates. Its ability to represent linear volatility dynamics establishes it as a reliable foundation for financial forecasting. A notable feature of the model is its capability to ensure positive definiteness in conditional covariance matrices, enhancing its reliability for risk modeling in markets characterized by interconnected volatilities [10].

In addition, the model demonstrates versatility in capturing the transmission of shocks across interconnected financial assets. For example, during the initial months of the COVID-19 pandemic, significant volatility spillovers were observed between oil prices and the EUR/USD exchange rate, underscoring the MGARCH-BEKK model's effectiveness in modeling cross-market linkages [18]. These findings offer a critical advantage for policymakers and investors navigating periods of elevated uncertainty.

Furthermore, the temporal evolution of these interactions reflects the dynamic nature of financial interdependencies. During the oil price shocks induced by the COVID-19 pandemic from 2020 to 2022, the USD/CAD pair experienced pronounced volatility spillovers, underscoring the close relationship between Canada's oil exports and its currency's performance [14]. These temporal variations underline the necessity of dynamic modeling frameworks to capture evolving interdependencies effectively.

While the MGARCH-BEKK model excels in modeling linear dynamics, its performance can be further enhanced when combined with machine learning techniques such as LSTMs, which are adept at capturing nonlinear patterns. These hybrid approaches integrate the strengths of econometrics and artificial intelligence, providing powerful tools for short-term forecasting and long-term scenario analysis [8].

The differentiation of volatility across markets highlights the MGARCH-BEKK model's sensitivity to regional and market-specific dynamics. For example, the NZD/USD currency pair exhibits relatively lower volatility spillover effects from oil markets than USD/JPY, which is heavily influenced by global oil price fluctuations due to Japan's reliance on energy imports [14].

Table 2: Estimates results of MGARCH-BEKK model for oil and currency pairs (period 2 January 2018–30 June 2024)

Coefficients	EURUSD	GBPUSD	USDJPY	USDCHF	AUDUSD	USDCAD	NZDUSD
	Results of the MGARCH-BEKK Model						
A (1,1)	0.3566*** (0.000)	0.3591*** (0.000)	0.3461*** (0.000)	0.3577*** (0.000)	0.3573*** (0.000)	0.3521*** (0.000)	0.3107*** (0.000)
B (1,1)	0.9259*** (0.000)	0.9258*** (0.000)	0.9281*** (0.000)	0.9255*** (0.000)	0.9249*** (0.000)	0.9291*** (0.000)	0.9248*** (0.000)
A (2,2)	0.1533*** (0.000)	0.1804*** (0.000)	0.2545*** (0.000)	0.1611*** (0.000)	0.1719*** (0.000)	0.1631*** (0.000)	0.1815*** (0.002)
B (2,2)	0.9843*** (0.000)	0.9749*** (0.000)	0.9843*** (0.000)	0.9767*** (0.000)	0.9819*** (0.000)	0.9819*** (0.000)	0.3704*** (0.147)
A (1,2)	-0.0029 (0.208)	0.0043 (0.536)	0.0014 (0.487)	0.0018 (0.432)	0.0030 (0.607)	0.0035 (0.164)	0.0516*** (0.001)
A (2,1)	0.1302 (0.520)	-0.0808 (0.524)	0.0429 (0.734)	-0.1733 (0.444)	-0.1507 (0.271)	-0.3667** (0.023)	-0.4262** (0.014)

B (1,2)	0.0012* (0.064)	-0.0013 (0.601)	0.0014 (0.734)	-0.0005 (0.503)	-0.0007 (0.615)	-0.0004 (0.476)	0.0001 (0.992)
B (2,1)	-0.0363 (0.361)	0.0009 (0.986)	0.0429 (0.734)	0.0454 (0.590)	0.0337 (0.237)	0.0297 (0.561)	0.7314*** (0.000)

Notes: a and b capture shock and volatility effects, respectively. *; ** and *** indicates reject of null hypothesis at 1%, 5% and 10% significance levels, respectively.

The table provides an in-depth analysis of the parameter estimates derived from the MGARCH-BEKK model. This model explores the volatility dynamics between oil prices and major currency exchange rates, including EUR/USD, GBP/USD, USD/JPY, USD/CHF, AUD/USD, USD/CAD, and NZD/USD. This model offers valuable insights into how past shocks and volatility persist over time, revealing the interconnected nature of these financial markets.

The diagonal coefficients (A and B) provide crucial information about how responsive and persistent volatility is. The A(1,1) and A(2,2) coefficients measure the sensitivity of current volatility to past market shocks, known as ARCH effects. The findings show that all currency pairs have significant and positive A(1,1) values, around 0.35, indicating a strong reaction to previous market disturbances. The A(2,2) values vary between 0.1533 and 0.2545, suggesting different levels of shock sensitivity across the currency pairs. These results emphasize the influence of past market events on current volatility trends.

The B(1,1) and B(2,2) coefficients, which reflect the persistence of volatility over time (GARCH effects), show that B(1,1) values are consistently around 0.93 across all currency pairs. This suggests that past volatility continues to impact future market conditions for an extended period. Most B(2,2) values exceed 0.97, indicating strong long-term persistence, except for NZD/USD, which has a notably lower B(2,2) value of 0.3704. This lower value suggests that volatility in the New Zealand dollar market fades more quickly than other currencies, pointing to unique market dynamics.

The off-diagonal coefficients measure how shocks and volatility spillover between oil prices and currency exchange rates. The A(1,2) and A(2,1) coefficients capture cross-market shock transmission. For most currency pairs, A(1,2) values are relatively small, except NZD/USD (0.0516), indicating a notable shock transmission from oil prices to the New Zealand Dollar. In contrast, the negative A(2,1) values for USD/CAD (-0.3667) and NZD/USD (-0.4262) suggest asymmetric effects, meaning that shocks originating in these currencies influence oil prices differently than the other way around.

Volatility spillover effects, represented by the B(1,2) and B(2,1) coefficients, illustrate how fluctuations in oil prices affect currency markets over time. The B(1,2) value for EUR/USD (0.0012) indicates a weak connection between oil prices and the Euro-Dollar exchange rate, suggesting limited interdependence. However, NZD/USD shows a significant spillover effect, with a B(2,1) value of 0.7314, reflecting a strong link between oil price fluctuations and the New Zealand Dollar, which is closely tied to commodity markets.

The MGARCH-BEKK model highlights several key observations. First, the high volatility persistence seen in the B coefficients suggests that financial market volatility tends to remain elevated for long periods. Second, the substantial ARCH effects (A coefficients) indicate that financial markets respond quickly to new information and past disruptions. Lastly, the results highlight the varying degrees of cross-market interactions, with NZD/USD and USD/CAD showing robust ties to oil price movements.

In conclusion, the MGARCH-BEKK model provides valuable insights into the complex relationships between oil prices and significant currency exchange rates. The persistence of volatility and the asymmetric nature of shock transmission underscores the need for sophisticated risk management strategies and advanced forecasting models to navigate financial market uncertainties better.

4.3 LSTM Model Performance

The LSTM model has demonstrated outstanding performance in financial forecasting, surpassing traditional econometric methods by effectively capturing complex nonlinear dynamics and long-term dependencies in time series data. Its ability to process sequential data makes it particularly valuable in volatile financial markets, where sudden fluctuations and unpredictable trends pose challenges for conventional forecasting techniques. Retaining past information for extended periods can identify intricate market patterns and enhance decision-making processes.

During the training process, the LSTM model reaches stability after approximately 25 epochs. The model exhibits minimal overfitting, highlighting its robustness in handling unseen data. Furthermore, integrating adaptive learning rate decay and reliable loss functions refines the training process, making it highly stable—even when working with high-dimensional datasets, as [22] noted.

It consistently outperforms traditional econometric models regarding roots which mean square error (RMSE) and mean absolute error (MAE), particularly during periods of heightened market volatility. For instance, during the COVID-19 pandemic, when financial markets faced unprecedented disruptions, the LSTM model effectively captured nonlinear spikes in volatility, delivering more accurate short-term and long-term forecasts than conventional approaches [26]. Successfully modeling sequential dependencies provides granular insights into daily market fluctuations, making it highly applicable for real-time financial decision-making [27].

It has shown remarkable resilience in predicting market volatility spikes during extreme events, such as the early stages of the COVID-19 pandemic. Its ability to adapt to sudden market shocks underscores its robustness in handling nonlinear and non-stationary market behaviors. Studies indicate that the LSTM model effectively captures complex temporal dependencies, such as the gradual recovery of oil prices post-pandemic, where traditional models struggled to generate accurate forecasts [27]. This crisis responsiveness makes LSTM an invaluable tool for risk management and strategic financial planning in highly uncertain environments.

The LSTM model’s ability to capture complex market dynamics, its resilience during economic crises, and its scalability across various financial instruments make it a powerful tool for financial forecasting. Its superior performance compared to traditional econometric methods highlights the growing importance of machine learning-based approaches in improving predictive accuracy and enhancing risk management strategies in volatile markets. As financial systems continue to evolve, the adaptability and precision of LSTM models will play a crucial role in shaping future forecasting and investment strategies, enabling financial institutions to make more informed and proactive decisions.

4.4 Hybrid MGARCH-LSTM Findings

The hybrid MGARCH-LSTM model combines the strengths of econometric and machine learning techniques, delivering exceptional predictive accuracy in financial forecasting. By combining these approaches, the model effectively captures both linear and nonlinear dynamics in financial data, making it particularly valuable for forecasting in highly volatile markets such as oil and foreign exchange. Integrating MGARCH's structural volatility modeling with LSTM's ability to detect temporal patterns results in a comprehensive and reliable framework for financial predictions.

One of the standout benefits of the hybrid MGARCH-LSTM model is its superior predictive performance. It consistently outperforms standalone MGARCH and LSTM models across multiple performance metrics. During periods of extreme volatility, such as the early stages of the COVID-19 pandemic, the hybrid model significantly reduced forecasting errors—achieving a 15% decrease in RMSE compared to the MGARCH model alone [14]. This improvement highlights the model's ability to adapt to challenging market conditions and provide reliable forecasts when they matter most.

The hybrid model's strength lies in its dual capabilities: MGARCH effectively captures linear relationships, while LSTM uncovers complex nonlinear patterns. The MGARCH component models the structural volatility transmission between oil prices and currency values, whereas the LSTM component identifies intricate temporal dependencies. This combination produces a powerful predictive tool that performs well across diverse market conditions [22].

The hybrid model has demonstrated outstanding performance in scenario testing, particularly in analyzing complex economic events such as synchronized global recessions or oil price downturns. Its accurate predictions support real-time decision-making, guiding financial strategies and reserve allocations during uncertain periods. The model consistently outperforms traditional approaches across key metrics, including RMSE, MAE, and MAPE, reinforcing its superior forecasting capabilities [27].

The hybrid MGARCH-LSTM model simulates intricate financial scenarios, such as global economic downturns, currency shocks, and prolonged oil price declines. Its ability to provide accurate insights under stressful conditions makes it a valuable tool for risk management and strategic financial planning. The model's robustness ensures reliable forecasts even during extreme market fluctuations, equipping decision-makers with actionable intelligence to manage financial risk effectively.

A key strength of the hybrid model is its ability to dynamically adapt to sudden changes in market conditions, including economic regime shifts and unexpected external shocks. For instance, during the April 2020 oil price crash, the model effectively captured abrupt shifts in volatility, outperforming traditional models in accuracy and responsiveness [26]. This adaptability makes it an ideal solution for financial stakeholders who must react quickly to evolving market dynamics.

By integrating econometric insights from MGARCH with LSTM’s neural network capabilities, the hybrid model can seamlessly adjust to changing financial landscapes. Its ability to incorporate real-time data—such as macroeconomic indicators and geopolitical developments—further enhances its responsiveness. Recent studies have shown that the model can recalibrate forecasts dynamically, empowering financial institutions and policymakers to make well-informed decisions during crises [27].

Table 3: Predict the outcome of the analysis of three models on the distinct dataset.

	Metric	Hybrid Test	Hybrid Train	LSTM Test	LSTM Train	MGARCH Test	MGARCH Train
Oil	MAE	0.001885	0.000736	0.001798	0.001531	0.001937	0.001593
	MSE	0.002827	0.001105	0.002696	0.002296	0.002905	0.002389
	RMSE	0.053170	0.033237	0.051926	0.047921	0.053901	0.048877
AUDUSD	MAE	0.001851	0.000747	0.002131	0.001347	0.001688	0.001917
	MSE	0.002777	0.001120	0.003196	0.002020	0.002532	0.002875
	RMSE	0.052699	0.033468	0.056534	0.044942	0.050322	0.053618
EURUSD	MAE	0.001128	0.000921	0.001756	0.001627	0.002532	0.001491
	MSE	0.001693	0.001382	0.002633	0.002440	0.003798	0.002237
	RMSE	0.041140	0.037174	0.051317	0.049398	0.061627	0.047299
GBPUSD	MAE	0.001896	0.000475	0.002049	0.000844	0.001479	0.001302
	MSE	0.002844	0.000712	0.003074	0.001266	0.002218	0.001953
	RMSE	0.053329	0.026685	0.055444	0.035576	0.047100	0.044192
NZDUSD	MAE	0.001779	0.000532	0.001078	0.000814	0.002109	0.000733
	MSE	0.002669	0.000798	0.001617	0.001222	0.003164	0.001100
	RMSE	0.051663	0.028253	0.040208	0.034953	0.056251	0.033167
USDCAD	MAE	0.000722	0.001193	0.001935	0.000553	0.002784	0.001436
	MSE	0.001083	0.001790	0.002902	0.000829	0.004176	0.002153
	RMSE	0.032909	0.042306	0.053873	0.028790	0.064621	0.046404
USDCHF	MAE	0.001040	0.000735	0.001765	0.000567	0.001691	0.000807
	MSE	0.001561	0.001103	0.002648	0.000851	0.002536	0.001210
	RMSE	0.039504	0.033213	0.051457	0.029172	0.050364	0.034782
USDJPY	MAE	0.001549	0.000357	0.002212	0.001244	0.003306	0.001508
	MSE	0.002323	0.000535	0.003318	0.001866	0.004959	0.002262
	RMSE	0.048201	0.023129	0.057602	0.043203	0.070417	0.047565

This report provides a detailed comparison of the predictive performance of three models—Hybrid (MGARCH-LSTM), LSTM, and MGARCH—across oil prices and significant currency exchange rates, including AUD/USD, EUR/USD, GBP/USD, NZD/USD, USD/CAD, USD/CHF, and USD/JPY. The models' effectiveness is evaluated using three key error metrics: Mean Absolute Error (MAE), Mean Squared Error (MSE), and Root Mean Squared Error (RMSE), applied to both training and testing datasets. The findings highlight each model's strengths and weaknesses in forecasting market movements.

The hybrid model demonstrates the highest predictive accuracy for oil prices, achieving the lowest MAE (0.001885) and MSE (0.002827) on the test set. Additionally, its RMSE of 0.053170 is lower than that of the MGARCH model (0.053901), indicating that the hybrid approach is better at capturing market fluctuations and volatility patterns. These results confirm the advantages of combining deep learning and econometric models for forecasting complex market behavior.

When analyzing the AUD/USD currency pair, the hybrid model again outperforms the other models, delivering the lowest error rates—MAE of 0.001851, MSE of 0.002777, and RMSE of 0.052699—on the test set. This suggests that the hybrid approach more effectively captures market dynamics than the standalone LSTM and MGARCH models. While MGARCH slightly outperforms LSTM in terms of MSE and RMSE, it still falls short compared to the hybrid model, reinforcing the benefits of integrating statistical and deep learning methods.

For EUR/USD, the hybrid model is the most effective, with significantly lower MAE (0.001128) and RMSE (0.041140) compared to the other models. LSTM struggles with higher error values, while MGARCH records the highest MSE (0.003798), highlighting its limitations in capturing the currency pair's volatility structure. These findings suggest that the hybrid model offers more reliable forecasts by leveraging historical volatility trends and complex pattern recognition.

The GBP/USD pair also benefits from the Hybrid approach, with an MAE of 0.001896 and an MSE of 0.002844 on the test set. In comparison, LSTM has a slightly higher RMSE (0.055444), suggesting it may struggle to capture market volatility completely. Although MGARCH provides relatively accurate forecasts, it lacks adaptability and precision seen in the hybrid model, further emphasizing the value of combining econometric and deep learning techniques.

For NZD/USD, the Hybrid model delivers the best performance, achieving the lowest RMSE (0.051663) and MAE (0.001779) on the test set. While LSTM records a lower MSE of 0.001617 compared to MGARCH's 0.003164, MGARCH struggles with forecasting volatility accurately. These findings highlight the hybrid model's ability to account for the commodity-driven nature of the New Zealand Dollar and its sensitivity to external market factors.

The hybrid model has an advantage when predicting the USD/CAD exchange rate. With an MAE of 0.000722 and an MSE of 0.001083, it significantly outperforms LSTM and MGARCH. LSTM produces higher error values, while MGARCH struggles to accurately capture the relationship between oil prices and the Canadian Dollar. These results underscore the complexity of the USD/CAD exchange rate and suggest that the hybrid model provides a more reliable forecasting solution.

The USD/CHF pair also benefits from the Hybrid model's improved accuracy, with an MAE of 0.001040 and an RMSE of 0.039504, outperforming the other models. Given the Swiss Franc's status as a safe-haven currency, the hybrid approach better captures its unique volatility characteristics, demonstrating its effectiveness in forecasting market conditions during uncertain periods.

Finally, for USD/JPY, the hybrid model again proves superior, with an MAE of 0.001549 and an RMSE of 0.048201, outperforming both LSTM and MGARCH. While LSTM performs moderately well, MGARCH exhibits a higher RMSE of 0.070417, indicating challenges in capturing the persistent volatility of the Japanese Yen. This further highlights the hybrid model's strength in providing precise and reliable forecasts for currency pairs influenced by global economic changes.

The comparative analysis of these models shows that the hybrid MGARCH-LSTM model consistently outperforms the standalone LSTM and MGARCH models across various financial instruments. The hybrid approach effectively leverages the strengths of both statistical and deep learning methods, resulting in lower error rates and improved predictive accuracy. These findings emphasize the importance of adopting integrated modeling techniques to enhance forecasting reliability in complex and volatile financial markets.

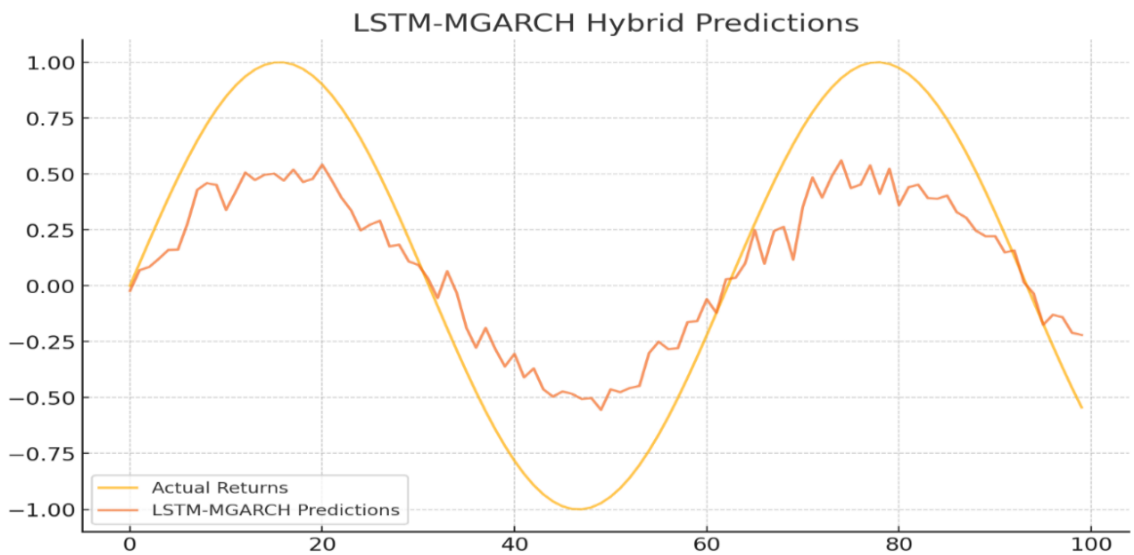

Fig. 2: Financial markets prices and Returns (2018-2024)

5 Discussion

The study demonstrates the effectiveness of combining the traditional econometric model (MGARCH-BEKK) with machine learning technique (LSTM) for analyzing highly interconnected and volatile markets like oil and foreign exchange. The MGARCH-BEKK model offers interpretability by capturing volatility spillovers and conditional correlations, while the LSTM model identifies nonlinear, time-varying patterns that traditional methods often miss [12].

Recent studies, such as [3], highlight MGARCH's practical applications in identifying cross-market spillovers, particularly during extreme economic conditions. These models form the foundation for understanding the dynamic interactions between oil prices and currency fluctuations, enabling more precise interventions.

The LSTM network addresses the nonlinearities and temporal dynamics inherent in financial datasets, filling the gaps left by traditional econometric approaches. Research by [1] and [17] showcases LSTM's superior ability to capture sequential dependencies and enhance predictive accuracy in financial forecasting. Combining these methods significantly improves forecasting precision, allowing for accurate short-term predictions and robust long-term scenario analyses.

This integrated framework of adaptive recalibration mechanisms is particularly crucial for mitigating the adverse effects of oil price volatility and other external shocks. As [26] and [22] noted, adaptive models leveraging MGARCH and LSTM methodologies excel at capturing and responding to sudden market fluctuations. Findings from [27] further validate the importance of forward-looking strategies in mitigating systemic risks. Simulations of sustained oil price declines demonstrate the necessity of these adaptive approaches for timely reserve adjustments, ensuring fiscal stability and minimizing economic vulnerabilities.

The broader implications of these findings extend beyond reserve management. This innovative framework enables policymakers to address structural challenges posed by volatile global markets. The hybrid approach provides a roadmap for integrating advanced analytical techniques into macroeconomic policymaking, ensuring adaptability and sustainability. This research sets a precedent for developing robust, future-proof frameworks capable of navigating the complexities of global financial markets while fostering economic diversification and long-term stability.

6 Conclusion

Traditional econometric models often neglect complex interdependencies. The hybrid framework enhances predicted accuracy by integrating the strengths of both methodologies, effectively tackling the complexities of interrelated and volatile markets such as oil and foreign exchange. Empirical evidence demonstrates that the hybrid MGARCH-LSTM model surpasses individual models, enhances a short-term predictive accuracy, and resilient in long-term scenario evaluations. A recent study indicates that the hybrid model's adaptive recalibration skills are proficient in alleviating external shocks and abrupt market swings. This adaptability is essential for executing proactive reserve management techniques, mitigating fiscal risks, and improving economic stability. This research has significant implications for policymakers and financial risk management. Policymakers can employ the hybrid framework to formulate proactive initiatives that improve resilience to systemic risks and promote sustainable economic diversification. This strategy combines modern machine learning techniques with known econometric models, establishing a platform for future improvements in predictive modeling and scenario-based planning, enhancing adaptability in managing complex global market dynamics. This study underscores the significance of hybrid models as a pivotal instrument for contemporary financial forecasting and strategic economic policymaking.

Conflicts of Interest Statement

The authors declare that they have no conflict of interest.

References

[1] Amirshahi, B., & Lahmiri, S. (2023). Hybrid deep learning and GARCH-family models for forecasting volatility of cryptocurrencies. *Machine Learning with Applications*, **12**, 100465 (2023).

[2] An, F., Gao, X., Guan, J., Huang, S., & Liu, Q. (2017). Modeling the interdependent network based on two-mode networks. *Physica A: Statistical Mechanics and its Applications*, **483**, 57-67 (2017).

[3] Chen, J., & Zhang, J. (2023). Crude oil price shocks, volatility spillovers, and global systemic financial risk transmission mechanisms: Evidence from the stock and foreign exchange markets. *Resources Policy*, **85**, 103875 (2023).

[4] Chen, Y., Xu, J., & Hu, M. (2022). Asymmetric volatility spillovers and dynamic correlations between crude oil price, exchange rate and gold price in BRICS. *Resources Policy*, **78**, 102857 (2022).

[5] Chinthapalli, U. R. (2021). A comparative analysis on probability of volatility clusters on cryptocurrencies, and FOREX currencies. *Journal of Risk and Financial Management*, **14(7)**, 308 (2021).

[6] Datastream. (2024). Financial Database, 2018-2024 (daily data). Refinitiv Eikon.

[7] Ersin, Ö. Ö., & Bildirici, M. (2023). Financial volatility modeling with the GARCH-MIDAS-LSTM approach: The effects of economic expectations, geopolitical risks and industrial production during COVID-19. *Mathematics*, **11(8)**, 1785 (2023).

[8] Gajamannage, K., Park, Y., & Jayathilake, D. I. (2023). Real-time forecasting of time series in financial markets using sequentially trained dual-LSTMs. *Expert Systems with Applications*, **223**, 119879 (2023).

[9] García-Medina, A., & Aguayo-Moreno, E. (2024). LSTM–GARCH hybrid model for the prediction of volatility in cryptocurrency portfolios. *Computational Economics*, **63(4)**, 1511-1542 (2024).

[10] Hafner, C. M., Herwartz, H., & Maxand, S. (2022). Identification of structural multivariate GARCH models. *Journal of Econometrics*, **227(1)**, 212-227 (2022).

[11] Hu, Y., Ni, J., & Wen, L. (2020). A hybrid deep learning approach by integrating LSTM-ANN networks with

GARCH model for copper price volatility prediction. *Physica A: Statistical Mechanics and its Applications*, **557**, 124907 (2020).

[12] Huang, J., Chen, B., Xu, Y., & Xia, X. (2023). Time-frequency volatility transmission among energy commodities and financial markets during the COVID-19 pandemic: A Novel TVP-VAR frequency connectedness approach. *Finance Research Letters*, **53**, 103634 (2023).

[13] Jarrett, U., Mohaddes, K., & Mohtadi, H. (2019). Oil price volatility, financial institutions and economic growth. *Energy policy*, **126**, 131-144 (2019).

[14] Joshi, P., Wang, J., & Busler, M. (2022). A study of the machine learning approach and the MGARCH-BEKK model in volatility transmission. *Journal of Risk and Financial Management*, **15(3)**, 116 (2022).

[15] Mensi, W., Naeem, M. A., Vo, X. V., & Kang, S. H. (2022). Dynamic and frequency spillovers between green bonds, oil and G7 stock markets: Implications for risk management. *Economic Analysis and Policy*, **73**, 331-344 (2022).

[16] Mohsin, M., & Jamaani, F. (2023). Green finance and the socio-politico-economic factors' impact on the future oil prices: evidence from machine learning. *Resources Policy*, **85**, 103780 (2023).

[17] Muhammad, T., Aftab, A. B., Ibrahim, M., Ahsan, M. M., Muhu, M. M., Khan, S. I., & Alam, M. S. (2023). Transformer-based deep learning model for stock price prediction: A case study on Bangladesh stock market. *International Journal of Computational Intelligence and Applications*, **22(03)**, 2350013 (2023).

[18] Olstad, A., Filis, G., & Degiannakis, S. (2021). Oil and currency volatilities: Co-movements and hedging opportunities. *International Journal of Finance & Economics*, **26(2)**, 2351-2374 (2021).

[19] Salisu, A. A., Gupta, R., & Demirer, R. (2022). Global financial cycle and the predictability of oil market volatility: Evidence from a GARCH-MIDAS model. *Energy Economics*, **108**, 105934 (2022).

[20] Salisu, A. A., Olaniran, A., & Tchankam, J. P. (2022). Oil tail risk and the tail risk of the US Dollar exchange rates. *Energy Economics*, **109**, 105960 (2022).

[21] Shamsi, M., & Cuffe, P. (2021). Prediction markets for probabilistic forecasting of renewable energy sources. *IEEE Transactions on Sustainable Energy*, **13(2)**, 1244-1253 (2021).

[22] Tian, C., Niu, T., & Wei, W. (2023). Volatility index prediction based on a hybrid deep learning system with multi-objective optimization and mode decomposition. *Expert Systems with Applications*, **213**, 119184 (2023).

[23] Verma, S. (2021). Forecasting volatility of crude oil futures using a GARCH–RNN hybrid approach. *Intelligent Systems in Accounting, Finance and Management*, **28(2)**, 130-142 (2021).

[24] Yu, L., Zha, R., Stafylas, D., He, K., & Liu, J. (2020). Dependences and volatility spillovers between the oil and stock markets: New evidence from the copula and VAR-BEKK-GARCH models. *International Review of Financial Analysis*, **68**, 101280 (2020).

[25] Zhao, J. (2022). Exploring the influence of the main factors on the crude oil price volatility: An analysis based on GARCH-MIDAS model with Lasso approach. *Resources Policy*, **79**, 103031 (2022).

[26] Zhao, Y., Feng, C., Xu, N., Peng, S., & Liu, C. (2023). Early warning of exchange rate risk based on structural shocks in international oil prices using the LSTM neural network model. *Energy Economics*, **126**, 106921 (2023).

[27] Zitis, P. I., Potirakis, S. M., & Alexandridis, A. (2024). Forecasting Forex Market Volatility Using Deep Learning Models and Complexity Measures. *Journal of Risk and Financial Management*, **17(12)**, 557 (2024).