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Interplay of Volatility and Geopolitical Tensions in Clean Energy Markets: A Comprehensive GARCH-LSTM Forecasting Approach

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ABSTRACT

In an era dominated by increasing global challenges and market volatilities, this study, firstly, embarks on an in-depth exploration of volatility transmission across clean energy stocks, crude oil and financial markets, emphasizing the underlying currents of geopolitical tensions. By using the advanced multivariate dynamic conditional correlation (MV-DCC) Generalized autoregressive conditional heteroskedasticity (GARCH) model, we unravel a landscape where volatility spillovers exhibit a distinct bidirectional nature, and geopolitical risk exerts a substantial impact, cascading from the oil market to financial markets and ultimately to clean energy stocks. Our findings underline the strategic importance of overweighting clean energy assets in a dual-asset portfolio that includes oil and financial equities to enhance investment strategies in turbulent market conditions. Secondly, we investigate the predictive power of oil and market-implied volatilities in forecasting clean energy market volatility by introducing a novel approach that melds the robustness of GARCH models with the flexibility of long short-term memory (LSTM) networks, creating an innovative hybrid GARCH-LSTM framework. The empirical results demonstrate that this hybrid model significantly outstrips the predictive capabilities of traditional standalone models. Notably, while oil and market-implied volatilities substantially enhance prediction accuracy, the inclusion of historical data does not yield additional predictive value. The implications of our research extend beyond the analytical domain, resonating with financial practitioners and environmentally conscious investors who seek precision in valuation and foresight in market trends. For policymakers, the insights provided offer strategic guidance for developing robust clean energy policies. Overall, our research contributes a fresh perspective to the discourse on renewable energy investment, volatility forecasting, and the interplay between market dynamics and geopolitical risks.

Keywords: Clean Energy, Generalized Autoregressive Conditional Heteroskedasticity Models, Hybrid Generalized Autoregressive Conditional Heteroskedasticity-Long Short-Term Memory Framework, Volatility Forecasting, Portfolio Management
JEL Classifications: G11, G13, Q47, C53, C58

1. INTRODUCTION

With the increasing severity of climate change, the transition to sustainable energy is becoming a priority around the world. That's leads to a growing shift of the global focus from traditional to clean energy sources that are continuously enhancing their capacity to meet energy demands sustainably and cost-effectively. Technological innovations and policy decisions affect the course and pace of this energy transition that progress at different degrees across countries and sectors. Two main reasons stimulate the rapid deployment of renewable energy. First, pollution and climate change, mainly caused by burning oil and coal, represent a real danger for humans and our planet (He et al., 2021). The awareness about these environmental serious concerns and the quest to preserve the universe boost switching to renewable energy[1] as a substitute. Second, clean energy namely, solar energy, wind (WD) energy, ocean energy, geothermal energy, etc., have gained a competitive advantage through technological advancement and increased investment[2] (smart grids, internet of things, big data, artificial intelligence, etc.). The objective is to optimize efficacy and hasten the implementation of sustainable energy in nascent intelligent systems for generating and distributing power. As the cost of renewable energy technologies has fallen, the renewable energy business case becomes a key driver of change (Motyka et al., 2018).

This impulse toward the clean energy also reached the financial market by enhancing the interest to invest in renewable energy stocks especially for environmental friendly investors. The oil market uncertainty supports this investors' attention shift to clean energy stocks (Reboredo, 2015) that become a more attractive investment market. This growing attractiveness explains why one of its leading index, the WilderHill Clean Energy Index (ECO), has recorded an increase of 132.7% over the last 5 years. Therefore, understanding the volatility dynamic and forecasting the risk of renewable energy market becomes crucial to financial practitioners, policy makers and global investors for better decision-making, risk management, and other financial applications (Yahya et al., 2021; Wang et al., 2022). This is, exactly, what we carry out in this paper. More specifically, our study aims to bridge a significant gap in existing literature by, firstly, investigating the interconnections and volatility dynamics between clean energy stocks, crude oil, and financial markets, with a particular emphasis on the role of geopolitical tensions. Moving beyond the siloed approach often seen in previous research, we adopt an integrated perspective, offering a holistic view of these complex interactions. By using a dynamic conditional correlation multivariate (MV-DCC) Generalized autoregressive conditional heteroskedasticity (GARCH) model, we not only analyze these intricate market relationships but also construct optimal portfolio strategies that leverage the hedging potential of clean energy equities against oil and other financial assets. Secondly, in a pioneering step, we introduce an innovative forecasting methodology combining GARCH models with long short term memory (LSTM) with the intention to enhance precision in predicting clean energy market volatility, a key concern for investors and policymakers. We suppose that this hybrid model, blending the volatility clustering strength of GARCH models with LSTM networks' prowess in deciphering long-term dependencies, marks a leap in predictive analytics in our field.

Accordingly, the related literature review reveals three main findings. First, while the topic of the interrelationship between renewable energy market and oil market (Çelik et al, 2022; Dawar et al, 2021; Geng et al., 2021; Tan et al., 2021; He et al., 2021; Yahya et al., 2021; Ahmad, 2017; Dutta, 2017; Bondia et al., 2016; Managi and Okimoto, 2013; Sadorsky, 2012; Kumar et al., 2012; Henriques and Sadorsky, 2008), other commodities market (He et al., 2021; Naeem et al., 2020; Do et al., 2009; Tully and Brian Lucey, 2007), technology and other equities implied market (Shahbaz et al., 2021; Ferreira and Loures, 2020; Nasreen et al., 2020; Maghyereh et al., 2019; Sadorsky, 2012; Kumar et al., 2012; Henriques and Sadorsky, 2008) is widely studied, researches on factors driving to clean energy stocks volatility and its connectedness with other market risks remain sparse. Second, previous studies investigated the volatility transmission between oil and clean energy markets, between oil and financial markets or between oil, technology stock and clean energy markets. However, the volatility spillover between oil, financial stocks and clean energy markets considered jointly remains an under studied topic. Moreover, the impact of geopolitical tensions on this markets interconnection was not considered despite its supposed influence on both the conditional mean (Guidolin and Timmermann, 2008) and the conditional volatility of asset returns (Engle and Rangel, 2008; Engle et al., 2013). Accordingly, previous researches argued that geopolitical risks affect economic conditions (Blomberg et al., 2009[3]) namely the oil price movements (Cunado et al., 2020; Plakandaras et al., 2019; Antonakakis et al., 2017) and also financial markets (Balcilar et al., 2018). Since, this geopolitical risks and associated news impact on oil and financial market (Geng et al., 2021) then we expect that it can affect, in turn, other interconnected markets. The first part of this study aims to fill these gaps. It markedly extends and complements prior literature by investigating the volatility spillover between the three markets by considering the impact of geopolitical tensions. The third finding from related literature review, reveals that prior researches have proposed mixed volatility forecasting models (Kim and Won, 2018; Kristjanpoller and Hernández, 2017; Kristjanpoller and Minutolo, 2016; Kristjanpoller et al., 2014; Hajizadeh et al., 2012; Elgayar et al., 2024; Wang, 2009; Roh, 2007). To enhance the performance of econometric models, particularly GARCH models, researchers have been experimenting with integrating them with neural networks. A common approach has been to employ a single-layer feedforward network. The second part of this paper extends and complements this literature strand by proposing a GARCH-LSTM hybrid model that is supposed to be able (1) to assimilate more sophisticated features and long-term dependency better than flat neural networks and (2) to combine the strengths of different models leading to robust modeling framework as attested by Reston Filho et al. (2014).

Our contributions are manifold. Firstly, we shed light on the previously unexplored territory of volatility transmission among clean energy, oil, and financial markets in the context of geopolitical risks. To our knowledge, no previous study has investigated the volatility transmission between the three markets considered jointly and taking into account the potential impact of geopolitical risk factor. Secondly, our groundbreaking GARCH-LSTM model represents a significant advancement in forecasting the volatility of renewable energy stocks, offering valuable tools for informed decision-making in investment and policy formulation. Our

1 The International Renewable Energy Agency (IRENA) has revealed that the use of renewable energy remedies 90% of the needs necessary to achieve the Paris agreements (IRENA 2018).

2 Clean energy investment could be to exceed 4.5 trillion USD per year by 2030 (compared to 1.8 trillion USD expected in 2023) according to the IEA (International Energy Agency) World Energy Investment 2023 report.

3 According to these authors, the geopolitical risk can have a supply-side implication by affecting the oil demand channel.

purpose is to find the best model and model specification to predict clean energy stocks volatility accurately and reliably.

The structure of this paper is designed to guide the reader through a logical progression of concepts and discoveries. Following this introduction, we delve into a comprehensive literature review and formulate our research hypotheses. Subsequent sections detail our data sources, research methodology, and a thorough analysis and discussion of the results. The paper concludes with a synthesis of our findings and their broader implications for the future of renewable energy investments and policy development.

2. LITERATURE REVIEW AND HYPOTHESES DEVELOPMENT

This research is closely related to three strands of literature. The first investigates the volatility transmission between clean energy stocks and oil markets. The possible substitution effect between oil and clean energy (Ahmad, 2017; Managi and Okimoto, 2013; Kumar et al., 2012) and the impact of the crude oil prices' change on clean energy investments and projects (Geng et al., 2021; Ferrer et al., 2018) may explain the dynamic of this interrelationship and the risk spread from oil market to clean energy market. Empirically, related prior studies have used different methodological approaches to analyze the dynamic connectedness between the two markets. Based on the VAR approach, Henriques and Sadorsky (2008) found that rising oil prices have a weak but significant positive effect on clean energy stock returns. Kumar et al. (2012) used the same approach by adding more explanatory variables and by extending the dataset to 2008 to consider the impact of the 2007 financial crisis. According to the findings of Henriques and Sadorsky, there was a notable positive impact of oil and technology stock prices on green energy stock returns. Using a Markov Switching VAR model, Managi and Okimoto (2013) investigated the relationship between oil and clean energy stock prices. They discovered that there was a significant interaction between the two, with the possibility of asymmetric effects. The authors theorized that the change in the relationship between oil and clean energy stock prices was the result of a structural shift that took place in late 2007.

In the same vein, Sadorsky (2012) documented the volatility spillover between oil prices and alternative energy stocks with applying four different multivariate GARCH models (BEKK, Constant Conditional Correlation, Diagonal and Dynamic Conditional Correlation). The results indicate a correlation between the value of clean energy equity and the value of technology and oil shares. In addition, he found that a 1-dollar long position in the clean energy firm is covered by 20 cents by a short position in the crude oil futures market. These findings were confirmed by Bondia et al. (2016) who found a causal relationship between oil and clean energy stocks based on Granger causality and coeintegration model with structural breaks. Reboredo (2015) used the Conditional Value at Risk (CoVar) and the copulas approach. He argued that the dynamic of oil prices contributes approximatively at 30% to the risk change of renewable energy firms. In a later study, based on continuous and discrete wavelets, Reboredo et al. (2017) found a weak dependence in the short term between oil and clean energy returns which strengthens gradually towards the long term.

Another set of related studies have used models based on spillover index. Ahmad (2017) discovered that when energy prices increase, so do the stock prices of alternative energy firms. As a result, oil market volatility, represented by the Oil Price Implied Volatility Index (OVX), holds a crucial place in worldwide renewable energy strategy formulation. Numerous other research projects have employed OVX to assess returns and volatility in the clean energy stock market. Dutta (2017) used this indicator to study the interconnection between oil prices and clean energy stock returns. Based on linear regression models and three distinct range-based realized volatility (RV) estimators, the author uncovered that the clean energy stock market returns are significantly affected by OVX fluctuations. Ahmad et al. (2018) used a multivariate GARCH model to show that the best hedge for clean energy stocks is the measure of financial market volatility over time represented by the implied volatility index (VIX). Other models have been used to investigate the volatility spillover namely the wavelet coherence (Nasreen et al., 2020), the time-varying parameter (Urom et al., 2022) and quantile-based (Tan et al., 2021; Dawar et al., 2021) models. Generally, this first strand of literature agreed that oil and renewable energy markets are interconnected with nonlinear, asymmetric and time varying manner (Tan et al., 2021).

The role of the financial stock market on the dynamic of clean energy market has also emerged as a second stream of literature to which our study is related. Must prior researches has focused on the impact of technology stock prices to explain the clean energy stock prices (Sadorsky, 2012; Kumar et al., 2012; Henriques and Sadorsky, 2008). They reached a consensus that technology stocks has an influence on renewable energy stocks. Maghyereh et al. (2019) added that this causal relationship is rather bidirectional. Otherwise, Nasreen et al. (2020) revealed a transmission volatility effect from technology stocks market to both oil and renewable energy markets over time and considering different frequency scales. Kocaarslan and Soytas (2021) argued that there is a significant asymmetric effect in the dynamic correlation between the three markets. Another set of previous studies focused on the whole financial market. Although previous studies that related to the above strand of literature, investigated the volatility transmission between oil and clean energy markets, between oil and financial markets or between oil, technology stock and clean energy markets, the volatility spillover between oil, financial stock and clean energy markets remain an under studied topic. One of the related study to this area is presented by Ferreira and Loures (2020). The authors used a detrended fluctuation analysis and the detrended cross-correlation analysis and found that the stock market index affects the clean energy index more than oil prices. By using a parametric Granger-causality approach, Shahbaz et al. (2021) found that, the causal relationship from stock market and energy market to clean energy returns depends on the market regime.

Our study is significant because, first, it investigates an under studied topic by previous literature, the volatility dynamic and spillover between oil, financial stock and clean energy markets, jointly. Second, it considers the impact of geopolitical risk that can be explained by a translational effect. The geopolitical risk and namely other economic and financial events may affect the oil market which in turn impacts the renewable energy market. Investigations on the association between oil prices and geopolitical risks, made by Cunado et al. (2020), Plakandaras et al. (2019), and Antonakakis et al. (2017), have revealed much insight. As pointed out by Blomberg et al. (2009), geopolitical risks have a notable effect on economies of both developed and developing countries. Consequently, oil market movements may be impacted by the geopolitical events that arise along the oil demand channel. The geopolitical risks can also have a persistent impact on the supply side, particularly when these risks influence financial markets, which have close ties to oil pricing. This could results in an indirect impact on oil prices through asset markets that's why other studies focus on the impact of various global economic uncertainties on energy prices. Geng et al. (2021) argued that negative news has a more significant impact on the flow of information between oil prices and clean energy stocks returns, compared to positive news. Wang et al. (2022) focused on the respective volatilities of renewable energy and natural gas, using a comprehensive set of predictors, including several global economic conditions and uncertainty indices. They discovered that both global economic conditions and uncertainty indices have the power to predict the volatility of clean energy. Another related study by Liang et al. (2021) assessed the capacity of five uncertainty indicators to forecast the volatility of natural gas futures and concluded that geopolitical risk and equity market volatility can surpass other uncertainty indices. Although the impact of geopolitical risk has always been the focus interest of researchers, little relevant empirical research was available until the development, by Dario and Iacoviello (2018), of a geopolitical risk index based on automated text search results from 11 major newspapers. Besides, while the impact of geopolitical risks on fossil fuels has been widely debated, much less has been done to understand its relationship with renewable energy. Our study seeks to use geopolitical risks as an explanatory variable to model the fluctuating stock volatility of green energy.

The third strand of literature extended and complemented by our study concerns the evolving methodologies for predicting clean energy stock volatility. Traditional models like ARCH and GARCH have provided foundational insights, as discussed by Engle (1982) and Bollerslev (1986). However, with the advent of deep learning techniques, the scope has broadened significantly. Studies leveraging artificial neural network (ANN) and LSTM networks, such as those by Kim and Won (2018) and Wu et al. (2019), demonstrate the utility of these models in capturing complex, non-linear relationships in financial data. LSTM model (Hochreiter and Schmidhuber, 1997) have demonstrated impressive performance in detecting both short-term and long-term dependencies in time series data, making it a valuable tool in predicting volatility due to its persistence over time. In terms of stock market predictions, the LSTM model has been observed to outperform traditional forecasting methods (Chen et al., 2015). A hybrid model of LSTM and GARCH specifications was proposed by Kim and Won (2018) to predict the volatility of the KOSPI200 Index. It showed improved performance over individual models. While so far these mixed models have only been applied in univariate cases, the potential for even better results through the combination of multiple models is intriguing. The combination of an econometric model and a feedforward network, proposed by Hajizadeh et al. (2012), showed improved results and lower errors compared to single models. Boulet (2021) proposed a multivariate GARCH-LSTM model that predict volatility and use it as input for his neural network. He found that adding the above parameters ameliorates the forecasting quality of his model. Our study extends this exploration by integrating GARCH models with LSTM networks, hypothesizing that this hybrid approach can enhance the predictive accuracy for clean energy market volatility.

Given our research goals and based on the above literature, we propose to test three classes of hypothesis. In the first hypothesis class, we will test the volatility spillover between crude oil, financial stock and clean energy markets, jointly.

H1: There is a significant spillover effect from oil market volatility to clean energy market volatility.

H2: The volatility in clean energy market returns is influenced by broader market volatility indicators.

These above hypotheses will be useful to test the hedge role of oil assets regarding the clean energy equities' fluctuations. To test the impact of geopolitical risk on the dynamic of renewable energy stock volatility, we formulate the second hypothesis class.

H3: Geopolitical risks exert a measurable impact on the volatility of clean energy stocks.

In the third class of hypothesis, we will test the driver factors and the best model and model specification to predict clean energy stocks volatility.

H4: The inclusion of oil and market-implied volatilities enhances the predictive accuracy for clean energy stock volatility.

H5: A hybrid model combining GARCH and LSTM approaches yields superior volatility prediction accuracy for clean energy stocks compared to standalone models.

3. DATA AND RESEARCH METHODOLOGY

In our quest to unravel the dynamics of renewable energy market volatility, we concentrated on the top-performing clean energy exchange traded funds (ETFs), with a special focus on the iShares Global Clean Energy ETF (ICLN)[4]. This ETF, which tracks the progress of nearly 100 corporations in the clean energy sector, provides a comprehensive view of market trends and investor sentiments. Our selection also includes prominent companies from sub-sectors like solar (SL), wind (WD), and bioenergy (BIO), identified as market leaders by Reuters (2020)[5]. These firms, chosen for their pioneering roles in their respective fields, offer unique insights into the sector's trajectory. For these four series,

4 ICLN is the Top 1 Clean Energy ETF in terms of size assets and year-to-date returns in 2022 (Source: https://www.nasdaq.com/articles/top-clean-energy-etfs-in-2022).

5 Reuters (2020) uses criteria such as investor confidence, regulatory compliance, financial performance, innovation, and resilience to shocks and geopolitical risks to select which energy companies are global leaders in their respective sub-sectors.

we use daily data spanned from October 06, 2009 to April 08, 2022, reflecting a significant period for clean energy evolution. This dataset, sourced from Yahoo Finance, offers a rich canvas for our analysis. Table 1 provides an exhaustive overview of the stocks and indices used in our study.

We employ the CBOE Volatility Index (VIX)[6] and the Crude Oil ETF Volatility Index (OVX)[7] as proxies for US stock market and oil volatilities. The corresponding data series are extracted from CBOE and Yahoo Finance website from the date January 01, 2010 until May 31, 2022 totaling 3123 data points. Additionally, we use the Geopolitical Risk Index (GPR) by Dario and Iacoviello (2018) to measure geopolitical turbulence. This innovative index, designed by Federal Reserve economists, leverages text-mining techniques to capture the frequency of key terms in news articles from 11 leading publications.

The methodology adopted in this work involves a four-step approach. The first concerns a meticulous data processing and normalization. This phase was crucial for ensuring data integrity and consistency. We tackled missing values, standardized data formats, and normalized the data for comparability. Such rigorous data handling is fundamental for reliable econometric analysis. The second step is the econometric Modeling. Our core analytical tool is the MV-DCC GARCH model (Engle, 2002). This sophisticated model allows us to dissect the volatility spillover effects and time-varying correlations among clean energy, oil, and financial markets. It is instrumental in investigating the complex market interconnections. The third step of our empirical methodology is the portfolio optimization. Using the conditional variance and covariance data from the DCC model, we construct and analyze optimal two-asset portfolios. These portfolios, a blend of oil-clean energy stocks and financial market-clean energy stocks, are examined for their hedging potential and risk-return dynamics. The fourth step, which is a key part of our research, is the forecasting of renewable energy market volatility. Here, we introduced an innovative hybrid GARCH-LSTM model to predict the volatility of the selected renewable energy series (ICLN, FSLR, NEE, REGI). The choice of this approach is justified by the specific nature of our data and the need for clear interpretation. We believe this model adeptly combines the best of both worlds – the traditional GARCH model's reliability and the LSTM's advanced predictive capabilities. We are convinced that such hybrid model, blending the volatility clustering strength of GARCH models with LSTM networks' prowess in deciphering long-term dependencies, marks a leap in predictive analytics in our field. We present below the detailed sequence of our empirical approach steps[8].

3.1. Econometric Modeling

We start by modeling the diagonal through a univariate GARCH approach and estimating the correlations.

$$H_t = D_t' P_t D_t \tag{1}$$

$$D_t = \mathrm{diag}\left(h_{11,t}^{\frac{1}{2}} \ldots\ldots h_{33,t}^{\frac{1}{2}} \right) \tag{2}$$

Where, H_t is a (3×3) matrix with time varying conditional covariances and D_t is a (3×3) diagonal matrix with the square root of the conditional variances on the diagonal.

We use the surrogate variable Q to estimate the conditional correlation matrix P_t:

$$P_t = Q_t^{*-1} Q_t Q_t^{*-1} \tag{3}$$

Where, Q_t^{*-1} is a diagonal matrix containing the square roots of the diagonal elements of Q_t with $Q_t = (q_t^{ij})$ is a (3×3) symmetric positive definite matrix determined as follows:

$$Q_t = (1-\theta_1-\theta_2)\bar{Q} + \theta_1 \eta_{t-1}\eta_{t-1}' + \theta_2 Q_{t-1} \tag{4}$$

Here, $\eta_{it} = \frac{r_{i,t}}{\sqrt{h_{ii,t}}}$ are non-negative scalars with r_{it} denotes the return of asset (i) at time t and $\bar{Q}$ is the (3×3) unconditional variance matrix of η_{t-1}. The parameters θ_1 and $\theta_1$are non-negative with a sum of less than unity.

The correlation estimator is: $\rho_{ij,t} = \frac{q_{ij,t}}{\sqrt{q_{ii,t} q_{jj,t}}}$ (5)

The DCC model starts by estimating the conditional variance for each variable using a univariate GARCH model. Then, it determines the conditionally dependent parameters. This model has the capability to always maintain the positive definiteness of the covariance matrix.

3.2. Portfolio Optimization

We use the results of the DCC model to compute hedge ratios and optimal asset allocation weights. As demonstrated by Kroner and Sultan (1993), hedge ratios can be calculated based on the

6 This up-to-the-minute index mirrors the market's predictions for the fluctuations in the S&P 500's (SPX) near-term value.

7 This index estimates the anticipated 30-day volatility of crude oil based on the United States Oil Fund (USO) rating.

8 To provide a practical insight into our methodology, we included a sample Python code snippet in Appendix A.

Table 1: Clean energy variables details

Stock/Index	Symbol	Sector	Description
iShare	ICLN	EFT	It follows the performance of a global clean energy sector index composed of equity investments in the clean energy sector.
First solar	FSLR	solar	It is one of the world largest grid-connected PV-power plants.
Next era energy	NEE	wind	It is the largest electric utility holding company by market capitalization.
Renewable energy group	REGI	BIO	It is the largest supplier of biofuel.

estimated conditional volatilities. The intuition is to balance out a long position in asset (i) with a short position in another asset (j). The formula for determining the hedge ratio between asset (i) and asset (j) is as follows:

$$\beta_{ij,t} = h_{ij,t} / h_{ii,t} \tag{6}$$

According to Kroner and Ng (1998), the optimal weights of two-assets portfolio are given by:

$$w_{ij,t} = \frac{h_{jj,t} - h_{ij,t}}{\sqrt{h_{ii,t} - 2h_{ij,t} + h_{jj,t}}} \tag{7}$$

$$w_{ij,t} \begin{cases} 0, \text{ if } w_{ij,t} < 0 \\ w_{ij,t}, \ \textit{if} \ \ 0 \le w_{ij,t} \le 1 \\ 1 \ \textit{if} \ w_{ij,t} > 1 \end{cases} \tag{8}$$

Where, $w_{ij,t}$ is the weight of the first asset in the one-dollar portfolio of asset (i) and asset (j) at time t. $h_{ij,t}$ is the conditional covariance of asset i and asset j at time t.

3.3. Hybrid Modeling for Volatility Prediction

The last step of our empirical investigation is the hybrid GARCH-LSTM to predict the return's volatility of the considered four renewable energy series. The calculation of returns is performed using the equation:

$$r_t = 1000 \times \log\left(\frac{P_t}{P_{(t-1)}}\right) \tag{9}$$

Where, r_t represents the return on day t, and P_t and P_{t-1} are the closing prices of the financial series on days t and t-1, respectively.

We assess the performance of various models by comparing their predicted and realized volatility. The RV_t on day t for T trading days is calculated as follows:

$$RV_t = \sqrt{\frac{1}{\eta_t}\sum_{t}^{\eta_t}\left(r_t - \bar{r}_t\right)} \tag{10}$$

Where, η_t is the number of days remaining after time t. r_t represents the log return rate, and $\bar{r}_t$ is the average of the stock log return rate over η_t after time t.

Standardizing the data prior to inputting it into an LSTM network can enhance the efficiency of predictive models. Outliers in input variables can distort probability distributions and make data scaling through normalization challenging. To address this, outliers can be ignored when calculating the mean and standard deviation and then the data can be standardized using the following equation:

$$X_t = \frac{x_t - median}{P75 - P25} \tag{11}$$

To model time series with properties of volatility clustering or fat-tailed distributions, Bollerslev (1986) proposed a model called the GARCH (p,q) model. This model predicts volatility by taking a weighted sum of past variance forecasts and historically observed volatility. It is defined as follows:

$$r_t = \mu + \mu_t \tag{12}$$

$$\varepsilon_t = \omega_t \sigma_t \tag{13}$$

$$\sigma_t^{\,2} = \alpha_0 + \sum_{i=1}^{p}\alpha_i \varepsilon_{t-i}^{\,2} + \sum_{j=1}^{q}\beta_j \sigma_{t-j}^{\,2} \tag{14}$$

α_0 and α_i for all (i) in [1...p] must be positive, and βj for all (j) in [1...q] must also be positive. Additionally, $\sum_{i=1}^{p}\alpha_i + \sum_{j=1}^{q}\beta_j < 1$.

To comprehend the workings of neural networks, it is important to understand deep feedforward networks (DFN) and ANN models. These models are designed to mimic the structure of neurons in the human brain, with the goal of approximating a given function (υ) through the capacity of its neuron network. Artificial neurons are linked to one another, and they solve problems by adjusting their connection strengths through learning. DFN computes the output layer by successively using the previous layer as input for the next one. The function of the neural network can be described as follows:

$$\upsilon_t = f(f\left(f\left(x_i w_{ji} + b_j\right) w_{mj} + b_m\right) w_{km} + b_k) \tag{15}$$

The input value, X_i is multiplied by a weight w_{ji} and then combined with the bias b_j. This output is then added to the next layer and repeated until the final output layer is reached. The activation function f(.) acts as a processing step to convert the input into an output. The weights in the network are determined by minimizing the discrepancy between the predicted and target values using backpropagation. This model is different from recurrent neural networks (RNNs), as there is no cyclical relationship between nodes, as shown in Figure 1.

RNNs represent a class of neural networks designed for processing sequences by incorporating an internal state or memory. As shown in Figure 1a, RNNs recursively process sequence data $(x_1, x_2, ..., x_n)$, allowing for the retention of information across sequence elements. However, traditional RNNs encounter challenges with long sequences due to the vanishing gradient problem, which impedes the network's ability to learn from data points that are far apart in the sequence. This limitation has been addressed by the introduction of LSTMs, depicted in Figure 1b, which include mechanisms to retain and selectively forget information, thus preserving long-term dependencies in data. Figure 2 illustrates the difference between RNN and LSTM cells.

Figure 2a presents the architecture of a simple RNN structure, emphasizing the recurrent connection that feeds the hidden state from the previous time step back into the network. In contrast, Figure 2b illustrates the intricate structure of an RNN-LSTM network, where each LSTM cell comprises three gates: input,

Figure 1: (a and b) Recurrent neural networks and feedforward neural networks functioning

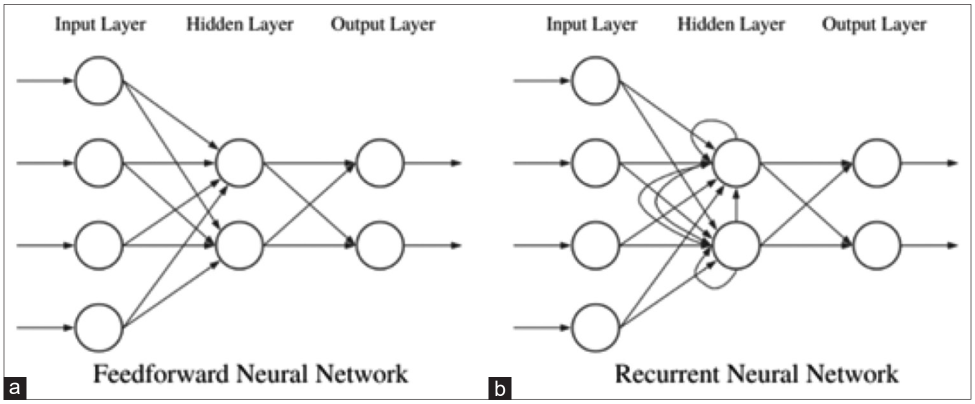
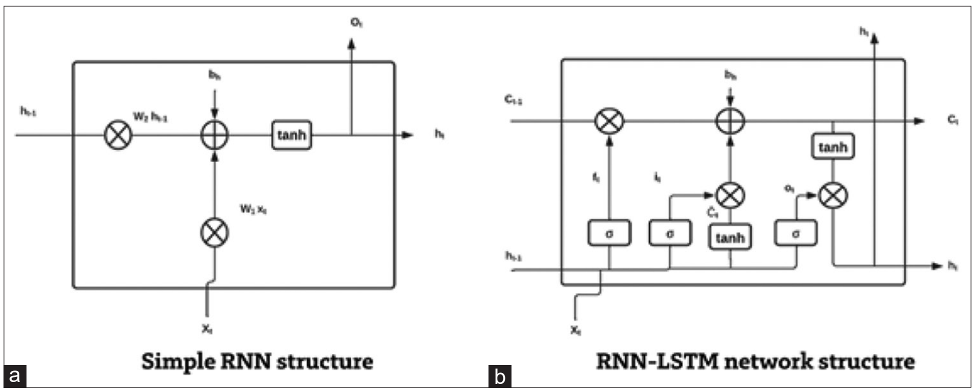


Figure 2: (a and b) Simple recurrent neural networks and recurrent neural networks-long short-term memory network structures



forget, and output, (input I_t, forget G_t, and output o_t) alongside a memory cell C_t. These gates collectively manage the flow of information, enabling the network to learn from extended sequences without the risk of vanishing or exploding gradients. The input gate regulates the amount of new information added to the cell. At any given time, t, the input is represented by x_t and the hidden state by h_t

The equations for the cell state C_t the gates, and the hidden state are given below.

$$G_t = \sigma(U_g x_t + W_g h_{t-1} + b_f) \quad (16)$$

$$I_t = \sigma(U_I x_t + W_I h_{t-1} + b_I) \quad (17)$$

$$O_t = \sigma(U_O x_t + W_O h_{t-1} + b_O) \quad (18)$$

$$C_t = G_t \text{"} C_t + I_t * \text{Ç}_t \quad (19)$$

$$\text{Ç}_t = \text{Tanh}\,(U_c x_t + W_c h_{t-1} + b_c) \quad (20)$$

$$h_t = O_t \text{"} \text{Tanh}\,(c_t) \quad (21)$$

The equations use a bias term b and matrices W and U to signify the weights or importance. The weighted combination of x_t, h_{t-1}, and b is calculated by the forget gate G_t through the application of a sigmoid function, as depicted in equation 16. This results in values between 0 and 1, where 0 means none of the inputs are allowed to pass through the gate, and 1 signifies all inputs are permitted to go through. The forget gate G_t regulates the amount of information that is used to update the current cell state C_t from the previous cell state C_{t-1}, as outlined in equation 19. Equation 20 outlines the computation of new information at time t and its output, which is transformed by the hyperbolic tangent function to generate values ranging from −1 to 1. The new information and past cell information, monitored by the input and forget gates, are combined to determine the cell state C_t at time t, as specified in equation 19. Finally, the output h_t is obtained by passing the cell state C_t through the output gate O_t after being altered by the hyperbolic tangent function, resulting in values between −1 and 1. The output h_t is then derived by multiplying these transformed values by O_t This process updates C_{t-1} by filtering out extraneous information and retaining only pertinent information, yielding h_t as indicated in equation 21.

In this research, we aim to study the outcomes of using both the GARCH (1,1) and LSTM models, as well as a hybrid model, on renewable energy stock returns. The process of forecasting volatility, illustrated in Figure 3, starts with the calculation of returns from daily financial data, followed by GARCH estimation. The GARCH model captures the time-varying volatility, which is then used as an input feature for the LSTM model. The LSTM model, benefitting from the GARCH output, proceeds to predict future volatility, considering additional features such as implied market volatilities.

3.4. Prediction Performance Evaluation

To evaluate the performance of the forecasting models, we base on standard metrics that are commonly used in literature namely Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and Absolute Percentage Error (MAPE), as defined below, to ensure a robust and comprehensive assessment (Kim and Won, 2018; Kristjanpoller et al., 2014; Fuertes et al., 2009).

$$\text{RMSE} = \sqrt{1/n\sum_{i=1}^{n}\left(\text{PV}_t - \text{RV}_t\right)^2} \quad (22)$$

$$\text{MAPE}=1/\text{N}\sum_{i=1}^{\text{N}}\left|\text{PV}_t - \text{RV}_t\right| \quad (23)$$

$$\text{MAPE}=1/\text{N}\sum_{i=1}^{\text{N}}\left|1 - \text{PV}_t / \text{RV}_t\right| \quad (24)$$

Where, PV and RV are respectively, predicted volatility and realized volatility.

4. EMPIRICAL RESULTS

4.1. Descriptive Statistics

Table 2 presents the statistical properties for the daily return series of pivotal variables, including the iShares Global Clean Energy ETF (ICLN), benchmark renewable energy stocks (FSLR, REGI, NEE), market volatility indices (VIX, OVX), and the Geopolitical Risk Index (GPR). It reports key metrics namely, mean, variance, skewness, and kurtosis. It also includes results from statistical tests (Jarque-Bera, ADF, PP, KPSS, ARCH LM) that affirm the non-normality and stationarity of the series. Furthermore, our findings align with the patterns noted in studies like Kumar et al. (2012), where similar assets exhibit distinct skewness, indicating the peculiar risk-return profiles in renewable energy investments.

The Table 2 shows that ICLN, NEE, and REGI have negative skewness, suggesting a higher likelihood of extreme losses, a phenomenon that has been explored in the context of renewable energy markets by Dutta (2017). This is complemented by positive skewness in other series, reflecting a more diverse risk landscape. The observation of high kurtosis values, especially in REGI and OVX, resonates with Gabaix and Ibragimov (2011) insights, highlighting the prevalence of extreme values in financial distributions. These ‘fat tails’ suggest more frequent extreme outcomes than a normal distribution would predict. However, despite initial concerns about infinite variance raised by these high kurtosis values, our comprehensive analysis, rooted in methodologies from Engle (2002), confirms the finiteness of these variances within our study’s timeframe. This conclusion is deduced from a combination of statistical tests and robustness checks, ensuring that the extreme values observed do not lead to infinite variance or invalidate our model’s results. The descriptive statistics underscore the necessity of adopting robust econometric models able to handle such complex distributions, which explain why our choice of hybrid GARCH (1,1) and LSTM model can be particularly relevant. The GARCH model, known for effectively managing data with ‘fat tails’ as corroborated in Engle et al. (2013), is complemented by the LSTM’s ability to understand long-term dependencies in time series data, a synergy that can be especially beneficial in the context of geopolitical uncertainty.

Figures B1 and B2 in Appendix B visualize the GPR’s evolution and the interplay of return transmissions among ICLN, VIX, and OVX. These visual representations corroborate the volatility clustering and leverage effects observed which constitutes a financial markets’ specificity as discussed in-depth in Ahmad (2017). The significant skewness and kurtosis values validate our

Figure 3: Forecasting volatility using generalized autoregressive conditional heteroskedasticity and long short-term memory models

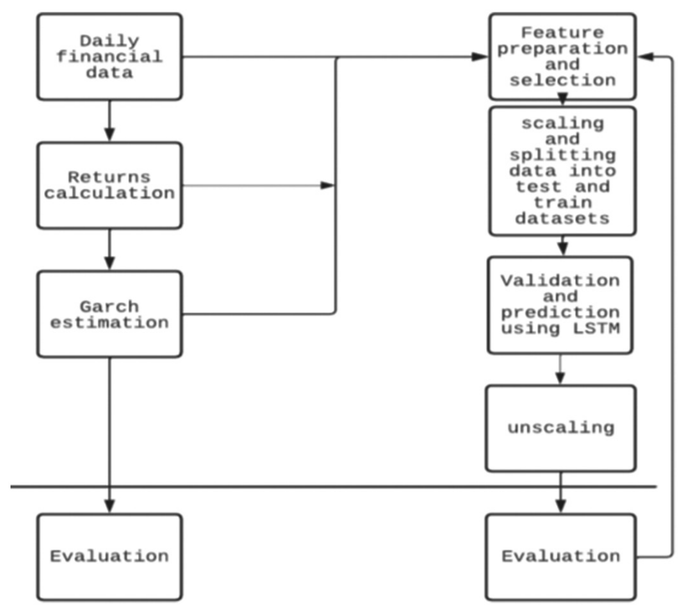


Table 2: Descriptive statistics of daily returns

Variables	Mean	Variance	Skewness	Kurtosis	JB	ADF	KPSS	PP	ARCH LM P-Value
FSLR	−0.0003	0,00115	0.1953	11.121	16200.13	−57.63***	-	-	0.000
REGI	0.0007	0,00136	−0.5921	17.235	3.1321	−53.52***	-	-	0.008
NEE	0.0006	0,00017	−0.3494	14.812	27988.23	−12.54***	-	-	0.000
ICLN	−0.0236	1.2899	−0.3121	4.631	3040.82***	−39.142***	0.096	−57.2511***	0.000
OVX	−0.0113	3.9214	0.9756	16.824	38836.12***	−29.147**	0.024	−56.6231**	-
VIX	−0.0091	6.4521	1.3652	11.931	20278.75***	−29.048**	0.008	−61.6547	-
GPR	−0.0061	38.45	0.2812	2.962	1229.14***	−36.524**	0.002	−89.2547**	-

Table 2 presents the descriptive statistics of the daily closing returns of the iShares Global Clean Energy ETF (ICLN); 3 renewable energy stock series of companies leading the solar, WD and bioenergy subsectors: First Solar (FSLR) Renewable Energy Group (REGI) and Next era energy (NEE); the CBOE Volatility Index (VIX); the CBOE Crude Oil ETF Volatility Index (OVX); and the Geopolitical Risk Index (GPR). JB is the Jarcque-Bera test of normality. ADF (Augmented Dickey fuller), PP (Phillips and Perron) and KPSS (Kwiatkowski Phillips Schmidt Shin) are unit-roots tests that are used to test stationarity and to detect the order of integration for the series. ARCH LM is the test for autoregressive conditional heteroscedasticity. ***, ** and * indicate statistical significance at a level of 1%, 5% and 10% respectively model choice. Table 3, following the Scott Hacker and Hatemi (2005) Multivariate ARCH effect test methodology, reveals significant ARCH effects in our chosen series ICLN, VIX, OVX and GPR, substantiating the use of the VAR(p)-GARCH(1,1) model in capturing the complex volatility dynamics of our data set.

4.2 Volatility Spillover Between Crude Oil, Financial and Clean Energy Markets in the Presence of Geopolitical Tension

Our exploration of the volatility transmission among the crude oil, financial, and clean energy markets is based on a sophisticated multivariate DCC GARCH model able to capture the complex interdependencies in volatile markets. We present the quasi-maximum likelihood estimates for this model in Table 4.

Table 3: Multivariate ARCH effect test

Returns	Squared returns
98.52***	91.95***

Table 3 reports the Scott Hacker and Hatemi (2005)' Multivariate Arch effect test for ICLN, VIX, OVX and GPR series. *** indicates statistical significance at a level of 1%. ARCH: Autoregressive conditional heteros

Table 4: VAR-generalized autoregressive conditional heteroskedasticity estimation

Mean equations	Coefficient value	P-Value
Mean model (ICLN)	−0.003	0.000
Mean model (OVX)	−0.058	0.000
Mean model (VIX)	−0.041	0.000
Variance equations	**Coefficient value**	**P-Value**
C1,1	1.921	0.000
C1,2	5.325	0.000
C1,3	25.782	0.000
A1,1	0.941	0.000
A1,2	−0.0089	0.000
A1,3	0.001	0.000
A2,1	1.0487	0.000
A2,2	0.204	0.000
A2,3	−0.015	0.000
A3,1	−0.482	0.000
A3,2	−0.061	0.000
A3,3	0.512	0.000
B1,1	0.901	0.000
B1,2	0.013	0.000
B1,3	−0.003	0.000
B2,1	−0.312	0.000
B2,2	0.900	0.000
B2,3	0.025	0.000
B3,1	−0.671	0.000
B3,2	0.059	0.000
B3,3	0.927	0.000
k1,1	0.035	0.000
k1,2	0.289	0.000
k1,3	0.789	0.000
ϴ1	0.008	0.000
ϴ2	0.961	0.000
Residual diagnostics		
ARCH test statistic	7.676224	
P-Value	0.660429	

Table 4 presents the quasi-maximum likelihood estimations for the MV-DCC GARCH model. The Ai, j and Bi, j parameters reflect the respective ARCH and GARCH effects. The lag dependence and persistence of fluctuations in the conditional variance equations are apprehended by the GARCH variable Bi, i. The B1, 1 coefficient is associated with the GARCH term of the ICLN equation returns, while B2, 2 and B3, 3 are related to the GARCH term of the OVX and VIX equation returns. The Ki, j coefficients highlight the impact of geopolitical risk on markets' volatility

Significantly at the 1% level, the Bi,i estimates demonstrate robust connections of current conditional variance to the GARCH term, a finding that is in concordance with Dutta's (2017) insights on the asymmetric impact of oil market uncertainty on clean energy stock returns. The statistical significance of parameters Ai,i, at the 5% level, reveals the influence of past ARCH coefficients on actual conditional variance, underlining the relevance of historical volatility in shaping current market conditions (Engle et al., 2013). The estimated values of Ai,i are smaller than the estimated Bi,i values, indicating that the long-term persistence of volatility is greater than its short-term persistence. The off-diagonal components of matrices A and B capture the cross-market effects of shocks and volatility spillovers. A multi-directional volatility spillover among the three markets is evident (significant parameters of A1,2; A2,1; A1,3; A3,1; B1,2; B2,1; B1,3; B3,1), indicating both short and long-term persistence of volatility spillovers. This implies that crude oil and financial market implied volatility information embedded in the price innovations transmit into the volatility of clean energy stocks. However, crude oil volatility appears to have a higher degree of volatility spillover, as evidenced by the higher values of A2,1; A2,3; B2,1; and B2,3.

When examining the direct effect of geopolitical risk on each market's volatility separately, the results demonstrate that the coefficients k1,1; k1,2; and k1,3 are all statistically significant and positive, suggesting that geopolitical risk affects the three markets' volatility positively. The results reveal a statistically significant positive impact of heightened geopolitical tensions and risks on the time-dependent conditional covariance between ICLN and VIX (k1,3) and ICLN and OVX (k1,2). These findings quantify the impact of geopolitical risk on diversification and market volatility in the renewable energy market. They suggest that the emergence of geopolitical tensions and risks increases reliance on diversification in the renewable energy market rather than crude oil, and shocks in geopolitical risk may alter the renewable energy stock market through investor sentiment reflected by implied volatility index. The direct impact of geopolitical risk on the time-varying conditional covariance is illustrated in Figure B3 in Appendix B. The graph highlights a negative dynamic correlation between ICLN and OVX when crucial geopolitical events occur (e.g. the Arab Spring, Libyan conflict, Iranian nuclear issue, EU embargo on Iranian oil, etc.). Notably, ICLN/VIX and ICLN/OVX show a significant jump in dynamic conditional correlation during 2014, which was marked by a significant decline in crude oil and equity market prices.

To check the model appropriateness and the robustness of our findings, we perform additional diagnostic tests, including a multivariate ARCH test on the model's residuals. The absence of significant ARCH effects in the residuals, as indicated by the ARCH test statistic and P-value in Table 4, validates the suitability of our model, and aligns with the advanced analytical techniques discussed in the literature.

4.3. Optimal Portfolio Weighting and Hedging Strategies

Leveraging the outputs from the MV-DCC GARCH model, we constructed hedge ratios and optimal portfolio weights following the methodologies of Kroner and Sultan (1993) and Kroner and Ng (1998). Table 5 presents the descriptive statistics of the hedge ratios (Panel 1) and optimal two-asset portfolio weights (Panel 2).

The hedge ratios in Panel 1, particularly for ICLN/VIX and ICLN/OVX, indicate a prevalent trend of long positions driven by negative conditional correlations. This observation is consistent with Sadorsky's (2014) findings on the dynamic nature of hedging costs in volatile markets. Panel 2 shows the optimal portfolio weights, suggesting a predominant allocation towards ICLN/VIX and ICLN/OVX pairs, reflecting a strategic diversification approach in the face of changing market conditions. Figures B4 and B5 in Appendix B depict the evolution of these hedge ratios and portfolio weights. The fluctuations observed, especially post-2018, can be attributed to shifts in energy policies and geopolitical events (e.g. Russia's invasion of Ukraine in 2022) which have significantly influenced global energy markets.

4.4. Clean Energy Volatility Prediction

4.4.1. GARCH estimation

Initiating our predictive modeling, we estimated the GARCH (1,1) model using the generalized error distribution. This choice, guided by the Akaike criterion, effectively captures the asymmetries and excess kurtosis in the data. Findings, reported in Table 6, show that the generalized error distribution slightly outperforms the normal distribution, indicating its suitability for our model. Parameters alpha plus beta are close to one, which reflect persistent volatility in our data series.

Table 5: Summary statistics of hedge ratios and optimal portfolio weights

Asset Pair/Ratio	Mean	Standard deviation	Min	Max
Panel 1: Summary statistics of hedge ratios (long/short position)				
ICLN/VIX	−0.15	0.08	−0.58	−0.05
ICLN/OVX	−0.14	0.06	−0.42	−0.04
VIX/ICLN	−1.07	0.29	−3.03	−0.26
VIX/OVX	0.29	0.08	0.04	1.12
OVX/ICLN	−2.83	0.77	−6.49	−1.39
OVX/VIX	0.79	0.21	0.18	3.86
Panel 2: Summary statistics of the two-assets optimal portfolio weights				
ICLN/VIX	0.80	0.06	0.35	0.94
ICLN/OVX	0.86	0.03	0.65	0.94
VIX/OVX	0.88	0.11	0.00	1.00

4.4.2. LSTM Model Estimation

In order to enhance prediction accuracy, we incorporate gradually in our hybrid GARCH-LSTM model a set of variables including implied volatilities (VIX, OVX) and historical data (HD)[9]. Moreover, we scale the input data using the normalization method described in the methodology section. Then, we train our multiple regression model based on the three dimensions of data structure: the sequence, the time step (mini-batch) and the feature. Figure 4, reporting combining volatility estimates from GARCH and LSTM models, illustrates the data transformation process for neural network training, a crucial step in our structured approach to maximize training time and enhance model accuracy.

The LSTM model's architecture and parameters, detailed in Table 7, were optimized for maximum efficacy in volatility prediction. We note that the process of training a machine learning model involves various hyper-parameters, such as batch size, number of epochs, and learning rate, that affect the performance of the model. The batch size determines the number of samples that the model processes before updating its internal parameters. The number of epochs defines how often the learning algorithm trains on the entire dataset, allowing each sample to update the internal parameters. An epoch may consist of one or more batches. The learning rate determines the extent to which the model's weights change when the estimated error is used to update them.

To assess the forecast accuracy of our models, we initially employ three loss function metrics (RMSE, MAE, and MAPE)[10]. Our results in Table 8, demonstrate that the hybrid model significantly outperformed the simple GARCH model across all clean energy sub-sectors, evidenced by substantial decreases in error rates. Notably, the MAE for ICLN significantly decrease (from 7% to 0.4%), affirming the efficacy of integrating GARCH results into the LSTM model. Additionally, we observe that incorporating both market and oil implied volatilities in the model led to optimal results, with MAPE rates consistently below 10%. We also discover that biofuel energy is more affected by oil implied volatility than

9 We consider the daily differences between the open and close prices, daily differences between the high and low prices, and volume.

10 Figures C in Appendix C provide further insights into the model's performance and prediction accuracy, highlighting the robustness of our hybrid GARCH-LSTM approach in volatile market conditions influenced by geopolitical factors.

Table 6: GARCH model coefficient estimation

Asset	Normal distribution				Generalized error distribution			
	σ	β	α	AIC	σ	β	α	AIC
ICLN	8	0.89	0.1	−18214	8	0.88	0.01	−9150
	(0.00)	(0.00)	(0.01)		(0.03)	(0.00)	(0.00)	
FSLR	3	0.94	0.05	−13214	3	0.94	0.05	−14150
	(0.00)	(0.00)	(0.01)		(0.00)	(0.00)	(0.00)	
REGI	1.2	0.8	0.1	−10214	1.2	0.8	0.01	−10400
	(0.00)	(0.00)	(0.00)		(0.00)	(0.00)	(0.00)	
NEE	3.9	0.88	0.1	−19214	3.6	0.88	0.05	−20150
	(0.00)	(0.00)	(0.01)		(0.00)	(0.00)	(0.35)	

Table 6 presents the results of the GARCH (1.1) model estimation considering both generalized error distribution and normal distribution. α measures the impact of the current volatility shock on future volatility and β is a persistence parameter. AIC corresponds to Akaike criterion values. Values in parentheses indicate the P-values solar energy, as incorporating OVX improved the biofuel energy volatility forecasts. In Table 9, different time windows (7 and 22 days) and forecasting horizons (1, 14, and 21 days) are analyzed to understand the model's nonlinear behavior over time. This analysis confirms that the hybrid model's accuracy declined with longer forecasting horizons, while longer window lengths reduced out-of-sample prediction errors. The results indicate a trade-off between forecasting horizon and accuracy, a crucial consideration for investors and analysts in the clean energy sector.

Table 8 presents the different prediction error evaluation metrics including the RMSE, the MAE, the MAPE calculated for each considered feature set.

Table 7: Hyper-parameters selection

Best parameters selected	
Numbers of epochs	50
Learning rate	0.05
Dropout rate	0.3

Table 9 presents an analysis of different time windows (7 and 22 days) and forecasting horizons (1, 14, and 21 days) to understand the model's nonlinear behavior over time.

To check the robustness of the approach used above to evaluate the performance of our forecasting models and to overcome its possible limitations, we incorporate additional forecast accuracy tests, including the stepwise multiple testing procedure of Romano and Wolf (2005) and the Superior Predictive Ability (SPA) test of Hansen (2005). The SPA test results, reported in Table 10, are particularly enlightening, revealing that our GARCH-LSTM hybrid model outperforms standalone GARCH and LSTM models in terms of predictive ability. This over performance is evident from the test statistics and corresponding P-values for each model. This finding not only validates our methodological choice but also highlights the hybrid model's robustness in capturing the dynamics of volatility spillover, especially under geopolitical tensions. This analysis ensures the validity of our results and

Table 8: Results with out of sample forecasts

Features set	ICLN			FSLR			REGI			NEE		
	RMSE	MAE	MAPE (%)	RMSE	MAE	MAPE (%)	RMSE	MAE	MAPE (%)	RMSE	MAE	MAPE (%)
GARCH	0.08	0.07	36.88	0.139	0.13	79.97	0.22	0.19	12.26.2	0.061	0.03	19.57
LSTM	0.009	0.005	3.73	0.0072	0.0058	2.78	0.023	0.0102	15.6	0.0109	0.0051	3.27
LSTM GARCH	0.0063	0.0041	2.7	0.0069	0.0043	2.48	0.023	0.0107	15.6	0.0122	0.0062	3.9
LSTM GARCH VIX	0.0061	0.0039	2.5	0.0096	0.0041	1.48	0.023	0.0105	15.612	0.013	0.0062	4.089
LSTM GARCH OVX	0.0065	0.004	2.58	0.0072	0.0044	2.53	0.022	0.01	15.26	0.009	0.0052	3.68
LSTM GARCH VIX OVX	0.0063	0.039	2.57	0.0068	0.0041	2.41	0.022	0.009	15.17	0.0095	0.0052	3.39
LSTM GARCH HD VIX OVX	0.0064	0.0038	2.53	0.0071	0.0042	2.475	0.023	0.0107	9.6	0.0091	0.0053	3.57

Table 9: Out-of-sample forecasting with different windows

Forecasting Horizon	1 day ahead prediction		14 days ahead prediction		21 days ahead prediction	
Window Size	7d window	22d window	7d window	22d window	7d window	22d window
MAPE (%)	3	2.38	12.81	12.9	16.42	14.839
MAE	0.0048	0.0036	0.0203	0.0201	0.0263	0.0237
RMSE	0.0083	0.0061	0.0286	0.0282	0.037	0.0358

Figure 4: Sliding window

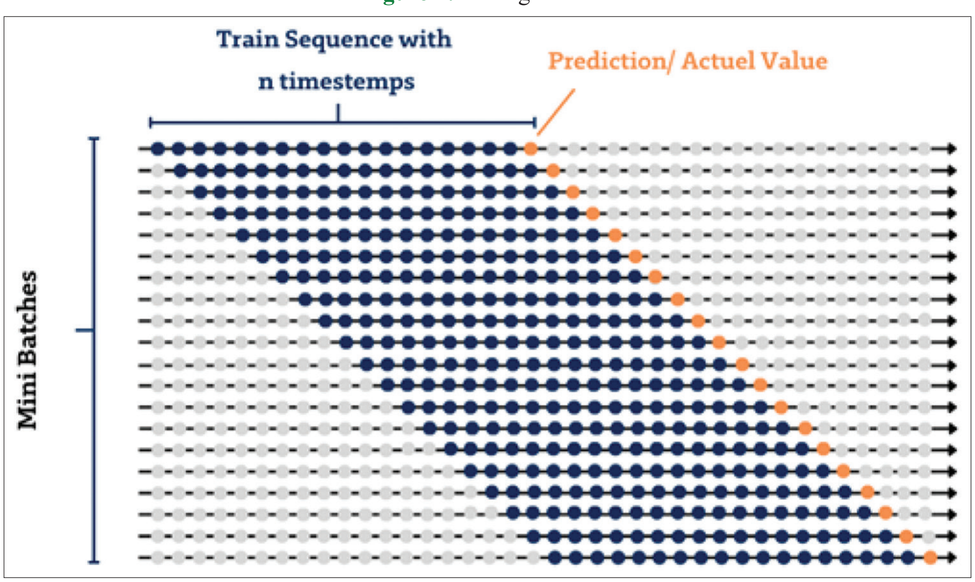


Table 10: Model Comparison: SPA Test Results

Model	SPA test statistic	P-value
GARCH	0.257400	0.016357
LSTM	−0.908481	0.042957
Hybrid GARCH-LSTM	−0.378503	0.033305

illustrates the nuances of predictive accuracy in complex market conditions. It highlights the effectiveness of our selected hybrid model, which adeptly captures the complex dynamics observed in the clean energy market.

5. CONCLUSION

In an era marked with several challenges such as the ongoing ramifications of the climate change, the COVID-19 pandemic and various ecological crises, our study gains critical relevance. These global issues, casting a long shadow over socio-economic stability, emphasize the urgency of a decisive shift towards clean energy sources. This transition, far from being a simple reaction to crises, emerges as a strategic imperative for sustainable development. Our analysis, in this context, becomes an indispensable tool for stakeholders, given the growing interest in renewable energy investments and the need for a nuanced understanding of market volatilities for informed decision-making and effective risk management.

The primary objective of our research was to examine the volatility spillover effects between the crude oil, the financial, and the clean energy stock markets, especially in times of heightened geopolitical tensions. Using the multivariate Dynamic Conditional Correlation (MV-DCC) GARCH model allowed us to determine conditional variances and covariances, enabling to estimate optimal portfolios and hedge ratios that shed light on potential investment strategies. Our findings reveal not just the transmission of volatility across these markets, but also a bidirectional influence, highlighting their deep interconnectedness. The impact of geopolitical risks emerged as direct and significant, altering conditional covariances and reshaping market dynamics. Our second objective in this paper is to forecast the volatility of renewable energy stocks by using a pioneering approach combining the analytical prowess of GARCH models with the predictive power of LSTM networks. This hybrid GARCH-LSTM model establishes a new benchmark in volatility forecasting since it show exceptional performance, significantly reducing prediction error rates. This advancement in predictive analytics marks a turning point for quantitative investing and algorithmic trading, providing a more refined means to anticipate market behaviors.

Nevertheless, our research is not without limits. The data scope, while extensive, may not encompass all nuances of global markets. Dependencies on historical data, inherent assumptions in econometric modeling, and potential enhancements through integrating broader datasets, such as sentiment analysis, highlight areas for future research. These limitations underscore the need for ongoing investigation to further refine and expand the applicability of predictive models. In summation, our study stands as a guiding light for those navigating the complexities of clean energy investments amidst a dynamic market environment. It offers a strategic framework for understanding market volatilities and introduces an innovative predictive model with significant potential benefits for practitioners. As we progress towards a renewable energy future, the insights from this research will prove invaluable in shaping investment strategies and informing policy decisions, while also acknowledging the imperative for continual methodological innovation and adaptation.

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APPENDIX A

This sample Python code snippet demonstrates the basic structure of our analysis. It exemplifies the foundational structure of our analysis, demonstrating the application of sophisticated programming techniques and statistical models to our comprehensive dataset. This integration of advanced computational methods and robust data sets the tone for the reliability and forward-thinking nature of our research.

```
# Importing necessary libraries
import pandas as pd
import numpy as np
from arch import arch_model
from keras.models import Sequential
from keras.layers import LSTM, Dense

# Load and preprocess data
data = pd.read_csv('financial_data.csv')
returns = np.log(data/data.shift(1)).dropna()

# DCC-GARCH Model
# [Insert DCC-GARCH model code here]

# LSTM Model for Volatility Forecasting
lstm_model = Sequential()
lstm_model.add(LSTM(units=50, return_sequences=True, input_shape=(...)))
lstm_model.add(LSTM(units=50))
lstm_model.add(Dense(1))

lstm_model.compile(optimizer='adam', loss='mean_squared_error')
# [Insert code for training LSTM model here]
```

APPENDIX B

Figure B1: Time series plots of GPR index from 1985 to February 2023

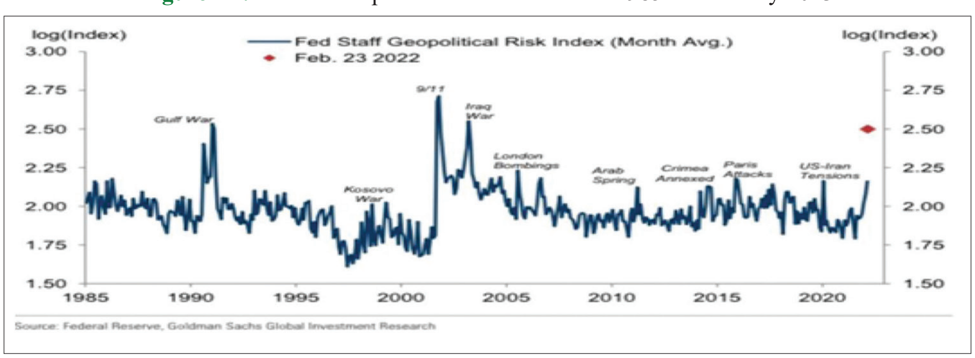


Figure B2: Time series plots of ICLN, VIX and OVX returns

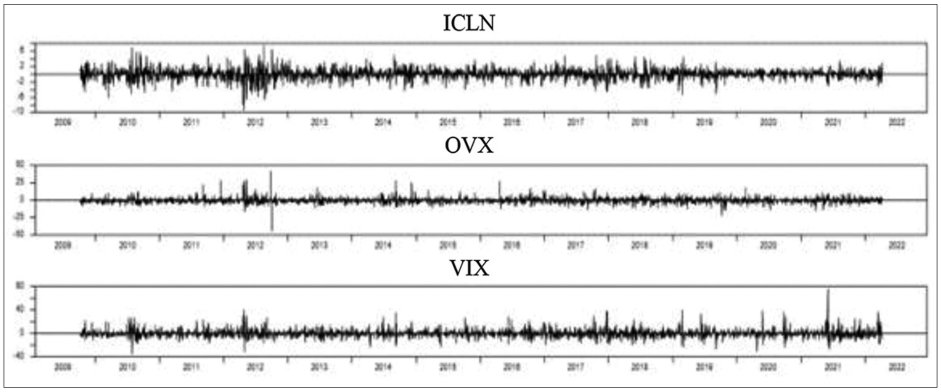


Figure B3: Impact of geopolitical risk on the time-varying correlations between ICLN/VIX and ICLN/OVX

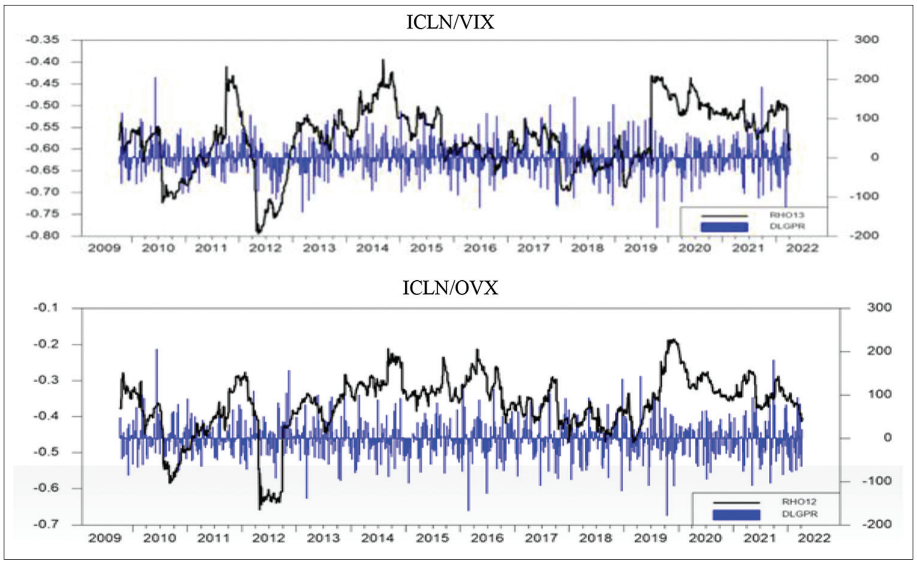


Figure B4: Time-varying hedge ratios computed from DCC model

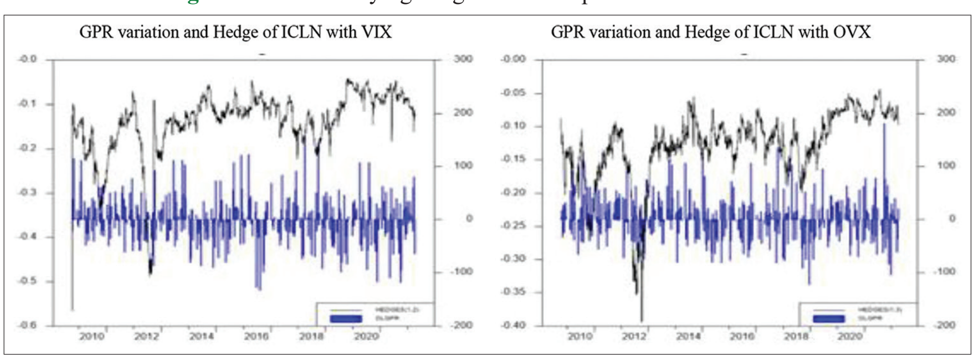
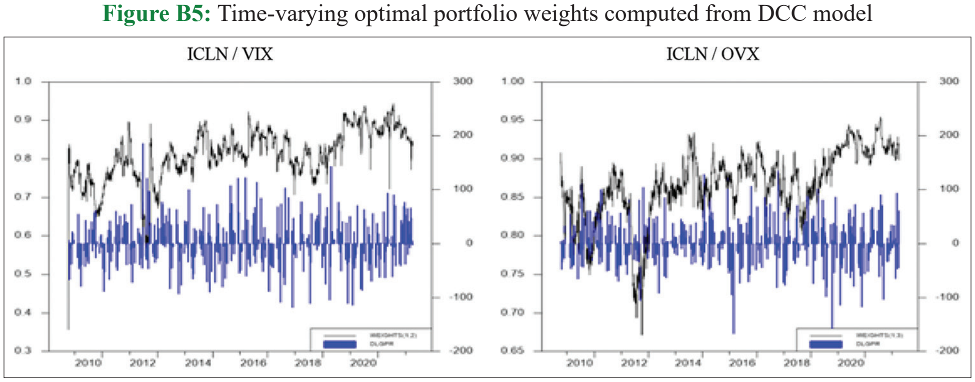


Figure B5: Time-varying optimal portfolio weights computed from DCC model



APPENDIX C

Figure C: Hybrid model forecasting of ICLN, FSLR, REGI and NEE respective volatility