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A Hybrid Mathematical and Deep Learning Framework for Forecasting Volatility Spillovers in Green Finance and Renewable Energy Markets

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Abstract

This study proposes a novel hybrid mathematical framework that integrates the Time-Varying Parameter Vector Autoregression (TVP-VAR) connectedness approach with Long Short-Term Memory (LSTM) deep learning networks to analyze, forecast, and manage volatility spillovers in green financial markets. The framework is motivated by the increasing complexity of risk transmission across sustainable assets, including green bonds, renewable energy stocks, carbon markets, and conventional energy assets. The proposed methodology follows a two-stage structure. First, the TVP-VAR model is employed to quantify dynamic connectedness and time-varying spillover effects across markets. Second, the extracted connectedness measures are used as inputs to an LSTM network to forecast future systemic risk dynamics and generate forward-looking variance-covariance matrices for portfolio optimization and hedging purposes. Using daily data from 2015 to 2025, the empirical results reveal that renewable energy stocks are the dominant transmitters of volatility within the system, exerting substantial spillover effects on green bonds and other sustainable assets. The forecasting evaluation demonstrates that the proposed hybrid TVP-VAR-LSTM framework significantly outperforms traditional econometric models (ARIMA and GARCH) as well as conventional machine-learning benchmarks (SVR, Random Forest, and XGBoost), reducing the Root Mean Squared Error (RMSE) by more than 46% in out-of-sample forecasting. Moreover, the enhanced forecasting accuracy translates into economically meaningful benefits, leading to substantial reductions in realized portfolio risk and improved hedging effectiveness. The findings further highlight the importance of carbon pricing mechanisms and standardized green bond certification in mitigating volatility transmission across sustainable financial markets. Overall, this study contributes to the literature on financial mathematics, systemic risk modeling, and machine learning in green finance by providing a unified framework for volatility spillover analysis, forecasting, and dynamic portfolio optimization.

Received: 9 May 2026
Revised: 13 June 2026
Accepted: 8 July 2026
Published: 10 July 2026

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Keywords: green finance; volatility spillovers; TVP-VAR; LSTM; financial mathematics; machine learning; portfolio optimization; systemic risk

MSC: 91G70, 62M10, 68T07, 91G80

1. Introduction

The escalating threat of climate change has fundamentally altered the landscape of global financial markets. The transition to a low-carbon economy requires massive capital reallocation, driving the exponential growth of green finance instruments such as green bonds and renewable energy stocks. However, these sustainable assets are not immune to market shocks. Understanding how risk—measured as volatility—transmits between green assets and traditional markets is crucial for investors, policymakers, and financial mathematicians aiming to build resilient portfolios. This issue has become increasingly important as regulatory initiatives such as carbon pricing mechanisms and green bond certification standards continue to reshape investment flows and risk transmission patterns across sustainable financial markets.

The literature on financial contagion and volatility spillovers has traditionally relied on econometric models. Diebold and Yilmaz (2012) introduced a seminal variance decomposition framework to measure connectedness [1]. This was later refined by Antonakakis et al. (2020), who incorporated Time-Varying Parameter Vector Autoregression (TVP-VAR) to overcome the limitations of rolling-window sizes and loss of observations [2]. Recent empirical studies, such as Tiwari et al. (2021) and Ringstad and Tselika (2024), have extensively applied these mathematical models to demonstrate significant dynamic spillover effects among green bonds, renewable energy stocks, and carbon prices [3,4].

Despite their explanatory power, these traditional econometric models face challenges when forecasting future volatility, primarily due to the highly non-linear, non-stationary, and noisy nature of financial time series. To address this mathematical limitation, artificial intelligence (AI), specifically deep learning, has emerged as a powerful predictive tool. Long Short-Term Memory (LSTM) networks, introduced by Hochreiter and Schmidhuber (1997), are uniquely designed to capture long-term dependencies in sequential data [5]. Recent advancements in financial mathematics have demonstrated that hybrid models—integrating econometric models like GARCH with LSTM—significantly outperform standalone models in forecasting stock price volatility (Kim and Won, 2018) [6].

While previous hybrid forecasting studies have largely focused on combining volatility models such as GARCH with deep learning architectures, little attention has been paid to integrating connectedness-based systemic risk measures with neural network forecasting frameworks. In particular, the literature lacks a unified approach that combines dynamic spillover extraction and nonlinear forecasting within the context of green financial markets. This gap is particularly important because connectedness measures contain valuable information about risk transmission channels that may improve predictive performance beyond conventional volatility indicators.

This paper aims to bridge the gap between traditional financial econometrics and modern artificial intelligence by proposing a hybrid TVP-VAR-LSTM framework. The primary contributions of this study are fourfold. First, we develop a hybrid mathematical framework that extracts dynamic connectedness features using the TVP-VAR approach and integrates them into an LSTM network to forecast future volatility spillovers in green financial markets. Second, we apply the proposed framework to a comprehensive dataset comprising green bonds, renewable energy indices, carbon emission futures, and conventional energy assets, thereby capturing the complex interdependencies within the green financial ecosystem. Third, we derive mathematical formulations for optimal portfolio weights and dynamic hedge ratios based on forecasted volatility and covariance structures, providing practical tools for risk-averse investors and portfolio managers. Fourth, the study evaluates the economic significance of forecasting improvements by linking predictive accuracy to portfolio risk reduction and hedging effectiveness, thereby providing practical insights for sustainable investment management.

The remainder of this paper is structured as follows: Section 2 reviews the relevant literature. Section 3 details the mathematical formulation of the TVP-VAR connectedness approach and the LSTM network. Section 4 describes the data, empirical findings, forecasting evaluation, and portfolio optimization results. Section 5 concludes the paper and discusses policy implications and future research directions.

2. Literature Review

The intersection of green finance, volatility spillovers, portfolio optimization, and machine learning represents a rapidly evolving domain in financial mathematics. The imperative to transition to a low-carbon economy has catalyzed the growth of green assets, simultaneously exposing them to complex, nonlinear risk transmission mechanisms. This section comprehensively reviews the foundational mathematical models and recent empirical advancements (2020–2026) that inform our proposed hybrid framework. The review is structured into four main themes: the mathematical modeling of volatility spillovers, risk transmission in green finance, the safe-haven and hedging properties of green assets, and the application of deep learning in financial forecasting.

2.1. Mathematical Modeling of Volatility Spillovers

The measurement of risk transmission across financial assets has been a central theme in econometrics and financial mathematics. The foundational work by Engle (2002) on Dynamic Conditional Correlation (DCC-GARCH) provided a robust method to model time-varying correlations, allowing researchers to observe how asset relationships evolve over time [7]. However, DCC-GARCH models primarily capture correlations rather than the direction and magnitude of shock transmissions. To address this, Diebold and Yilmaz (2012) proposed a seminal variance decomposition framework utilizing generalized vector autoregression (VAR), where forecast-error variance decompositions are invariant to variable ordering [1].

While the Diebold-Yilmaz approach became the industry standard, its reliance on rolling-window estimation introduced arbitrariness in window size selection and led to a loss of observations. To capture the dynamic nature of these spillovers without such limitations, Antonakakis et al. (2020) introduced the Time-Varying Parameter Vector Autoregression (TVP-VAR) connectedness approach [2]. This method utilizes multivariate Kalman filters to estimate time-varying coefficients and variance–covariance matrices, making it highly robust to outliers and structural breaks. The TVP-VAR model has since become the cornerstone for analyzing dynamic interconnectedness in financial networks.

Furthermore, Baruník and Křehlík (2018) extended this literature by proposing a spectral representation framework to measure the frequency dynamics of connectedness, distinguishing between short-term and long-term shock transmissions [8]. Recent methodological advancements have continued to refine these models [9,10]. For instance, Abdelmalek and Khemakhem (2026) applied a TVP-VAR extended joint connectedness model to investigate time-varying connectedness during recent crises [11], while Yi and Jiang (2025) utilized time-frequency spillovers to demonstrate that return spillovers are predominantly short-term, whereas volatility spillovers exhibit long-term effects [12].

2.2. Risk Transmission in Green Finance and Carbon Markets

Empirical applications of these mathematical models to the green finance ecosystem have yielded significant insights, particularly concerning the nexus of green bonds, renewable energy stocks, and carbon markets. Tiwari et al. (2021) investigated the dynamic spillover effects among these assets, finding that renewable energy acts as a major transmitter of shocks to the green bond market [3]. This finding was corroborated by Zhang and Umair (2023), who demonstrated significant time-varying spillovers across green

bonds, renewables, and carbon markets using the TVP-VAR network connectivity approach [13].

The role of the carbon market, specifically the European Union Allowance (EUA), is increasingly recognized as a critical factor in green asset pricing. Ringstad and Tselika (2024) applied frequency dynamics to show that connectedness among green assets varies significantly across time horizons, with short-term spillovers dominating during periods of financial stress [4]. Chai et al. (2025) examined the dynamic nonlinear connectedness between green bonds, clean energy, and stock prices, highlighting the profound impact of the COVID-19 pandemic on these relationships [14]. More recently, Su et al. (2025) explored the dynamic connectedness within the carbon-clean energy-climate policy-green finance innovation system, emphasizing the lower quantile spillover effects of carbon prices on ESG indices [15].

Geopolitical risk (GPR) and economic policy uncertainty (EPU) have also been identified as significant drivers of volatility in green markets. Yousfi and Bouzgarrou (2024) quantified the contribution of GPR to the dynamic connectedness between clean and conventional energy markets, finding that heightened geopolitical tensions amplify risk spillovers [16–21]. Similarly, Zhu et al. (2026) and Khan (2025) emphasized the portfolio hedging implications of dynamic spillovers between geopolitical risk and energy markets [22–24].

2.3. Safe-Haven, Hedging Properties, and Portfolio Optimization

A critical application of volatility spillover analysis is portfolio optimization and risk management. The literature has extensively debated whether green assets, particularly green bonds, act as diversifiers, hedges, or safe havens against conventional market risks. Arif et al. (2022) explored the hedging and safe-haven potential of green bonds for conventional equity and commodity investments, finding substantial diversification benefits [25]. Ren et al. (2023) comprehensively examined green bonds' ability to act as a safe haven against international equity market movements, confirming their utility during periods of extreme market turbulence [26].

Recent studies have integrated ESG (Environmental, Social, and Governance) criteria directly into portfolio optimization models. Ameer et al. (2024) demonstrated that including clean energy and green bond indices in conventional portfolios significantly reduces extreme risk, supporting the superiority of clean energy assets in mean conditional value-at-risk optimization [9]. Abuzayed and Al-Fayoumi (2023) derived optimal portfolio weights and hedging effectiveness strategies for green bonds during the COVID-19 pandemic [10].

Furthermore, advanced optimization frameworks are being developed. Müller and Joubrel (2025) proposed a robust mean-variance portfolio optimization model incorporating ESG risks under Knightian uncertainty [27]. Varmaz et al. (2024) and Taheripour et al. (2025) developed multi-criteria approaches to ESG-based portfolio optimization, taking into account environmental and social responsibility aspects alongside traditional financial metrics [28,29]. These studies rely heavily on calculating dynamic hedge ratios and optimal portfolio weights derived from the variance–covariance matrices of econometric models.

2.4. Deep Learning in Financial Forecasting

While TVP-VAR and GARCH models excel at measuring historical volatility and connectedness, their forecasting accuracy can be constrained by linear assumptions and their inability to capture complex, non-stationary patterns. To address this mathematical limitation, artificial intelligence (AI) and deep learning have emerged as powerful predictive tools.

Long Short-Term Memory (LSTM) networks, introduced by Hochreiter and Schmidhuber (1997), are specialized recurrent neural networks designed to overcome the vanishing gradient problem, enabling them to capture long-term dependencies in sequential data [5]. In the context of financial forecasting, Giantsidi and Tarantola (2025) provided a comprehensive review of deep learning applications, noting the widespread success of LSTM hybrids for stock price prediction [30].

Recent advancements in financial mathematics have demonstrated that hybrid models—integrating econometric models with LSTM—significantly outperform standalone models. Kim and Won (2018) proposed a hybrid model integrating LSTM with multiple GARCH-type models to forecast stock price volatility, demonstrating significant reductions in prediction errors [6]. This approach has been validated by subsequent research. Ben Romdhane and Boubaker (2026) demonstrated that a hybrid HAR-LSTM-GARCH model significantly outperforms benchmark models in forecasting volatility [31]. Similarly, Roszyk and Ślepaczuk (2024) confirmed that LSTM networks outperform traditional GARCH models in forecasting the S&P 500 index's volatility [32].

In the specific domain of green finance, the application of machine learning is gaining traction. Nunes et al. (2026) presented an explainable deep learning approach (LSTM-LagLasso) applied to bond yield forecasting [33]. Furthermore, studies such as those by Hussain et al. (2025) and Ali et al. (2025) have begun to utilize machine learning to model and forecast renewable energy consumption and the impact of the greenium effect in green bond financing [34,35].

Despite these advancements, a significant gap remains in the literature. While TVP-VAR is extensively used for measuring connectedness, and LSTM is proven in forecasting asset prices, the integration of these two methodologies—specifically using LSTM to forecast the dynamic connectedness indices extracted from a TVP-VAR model in the context of green finance—has not been explored. This study aims to fill this gap by proposing a novel hybrid TVP-VAR-LSTM framework for forecasting volatility spillovers and optimizing sustainable portfolios.

3. Methodology

To capture the complex and nonlinear risk transmission mechanisms among green financial assets, this study proposes a hybrid econometric–machine learning framework. The methodology consists of three sequential stages. First, the Time-Varying Parameter Vector Autoregression (TVP-VAR) model is employed to extract dynamic connectedness and volatility spillover measures. Second, these connectedness measures are transformed into time-series features and used as inputs to a Long Short-Term Memory (LSTM) neural network to forecast future spillover dynamics. Finally, the forecasted covariance matrices are utilized for dynamic portfolio optimization.

3.1. Time-Varying Parameter Vector Autoregression (TVP-VAR) Connectedness

Following the framework of Antonakakis et al. (2020) [2], which extends the Diebold and Yilmaz (2012) connectedness approach [1], the TVP-VAR model allows both coefficients and variance–covariance structures to evolve over time, eliminating the need for arbitrary rolling-window estimation.

Let $Y_t = (y_{1t}, y_{2t}, \dots, y_{Nt})'$ denote an $N \times 1$ vector of asset volatility series representing green bonds, renewable energy equities, carbon prices, and conventional energy assets. Here, N is the number of assets in the system. The TVP-VAR model of order p is defined as:

$$Y_t = \beta_t Y_{t-1} + \epsilon_t, \epsilon_t \sim N(0, \Sigma_t)$$

$$\beta_t = \beta_{t-1} + v_t, v_t \sim N(0, R_t)$$

where β_t is the time-varying coefficient matrix, ε_t represents the vector of innovations, Σ_t is the time-varying variance–covariance matrix, v_t captures structural innovations, R_t is the covariance matrix of state innovations, and Y_{t-1} is a lagged endogenous vector (with optimal lag p selected via BIC). Estimation is carried out using the multivariate Kalman filter.

The model can be expressed in its vector moving average (VMA) representation as:

$$Y_t = \sum_{h=0}^{\infty} A_{h,t} \varepsilon_{t-h}$$

Based on this representation, the generalized forecast error variance decomposition (GFEVD) is defined as:

$$\theta_{ij,t}(H) = \frac{\sigma_{jj,t}^{-1} \sum_{h=0}^{H-1} (e_i' A_{h,t} \Sigma_t e_j)^2}{\sum_{h=0}^{H-1} (e_i' A_{h,t} \Sigma_t A_{h,t}' e_i)}$$

where H is the forecast horizon (i.e., the number of steps ahead for the variance decomposition), $\sigma_{jj,t}$ is the standard deviation of the error term for the variable j , and e_i is a selection vector. Since the row sums of the variance decomposition matrix are not necessarily equal to one, normalization is applied:

$$\tilde{\theta}_{ij,t}(H) = \frac{\theta_{ij,t}(H)}{\sum_{j=1}^N \theta_{ij,t}(H)}$$

The Total Connectedness Index (TCI) is then computed as:

$$TCI_t(H) = \frac{\sum_{i,j=1, i \neq j}^N \tilde{\theta}_{ij,t}(H)}{N} \times 100$$

The normalization by N ensures comparability across systems of different dimensions. This is because each row of the normalized variance decomposition matrix sums to one, implying that the total sum of all elements in the $N \times N$ matrix equals N . Therefore, dividing by N appropriately scales the measure into percentage form, making the index invariant to the number of variables in the system.

Directional spillovers are defined as:

$$TO_{i,t}(H) = \sum_{j=1, j \neq i}^N \tilde{\theta}_{ji,t}(H)$$

$$FROM_{i,t}(H) = \sum_{j=1, j \neq i}^N \tilde{\theta}_{ij,t}(H)$$

The net spillover index is:

$$NET_{i,t}(H) = TO_{i,t}(H) - FROM_{i,t}(H)$$

A positive (negative) value indicates that the asset is a net transmitter (receiver) of volatility.

The optimal lag length p is selected using the Bayesian Information Criterion (BIC), where the model minimizing BIC is chosen for estimation. The results are reported in Section 4.2.

3.2. Long Short-Term Memory (LSTM) Forecasting Framework

While the TVP-VAR model provides a rigorous measure of historical connectedness, it does not fully capture nonlinear temporal dependencies in financial time series. To address this limitation, we employ a Long Short-Term Memory (LSTM) neural network introduced by Hochreiter and Schmidhuber (1997) [5].

The LSTM network mitigates the vanishing gradient problem through a gated memory structure consisting of forget, input, and output gates.

LSTM Structure

The LSTM unit is defined as:

$$f_t = \sigma(W_f[h_{t-1}, x_t] + b_f)$$

$$i_t = \sigma(W_i[h_{t-1}, x_t] + b_i)$$

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

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

$$o_t = \sigma(W_o[h_{t-1}, x_t] + b_o)$$

$$h_t = o_t \odot \tanh(C_t)$$

where x_t represents the input vector constructed from the historical TVP-VAR-based connectedness measures (TCI, NET spillovers, and directional indices), h_t is the hidden state, W and b represent trainable weights and biases, $\sigma(\cdot)$ is the sigmoid activation function, and $\odot$ denotes element-wise multiplication.

Input Structure

$$X_t = (TCI_{t-k}, \dots, TCI_t, TO_{t-k}, \dots, TO_t, FROM_{t-k}, \dots, FROM_t, NET_{t-k}, \dots, NET_t)$$

where k is the sequence length.

Prediction Target

$$\hat{y}_t = (TCI_{t+1}, NET_{t+1})$$

Loss Function: The network is trained by minimizing the Mean Squared Error (MSE) loss function:

$$L = \frac{1}{T} \sum_{t=1}^T (y_t - \hat{y}_t)^2$$

where y_t is the observed connectedness measure, $\hat{y}_t$ is the predicted value, and T denotes the number of observations.

3.2.1. LSTM Architecture and Training Procedure

To ensure reproducibility and address hyperparameter sensitivity, the model is trained as follows:

- Optimizer: Adam
- Loss function: Mean Squared Error (MSE)

- Sequence length: $k = 10$
- Hidden units: 50
- LSTM layers: 1
- Learning rate = 0.001
- Batch size: 32
- Epochs: 100
- Data split: 70% training, 15% validation, 15% testing

Hyperparameters are selected using validation-based tuning to avoid overfitting and ensure out-of-sample robustness.

3.2.2. Integration of TVP-VAR and LSTM

The proposed framework adopts a sequential hybrid design. First, the TVP-VAR model extracts time-varying connectedness measures that reflect the evolving structure of volatility transmission among assets. Second, these measures are used as inputs to the LSTM model, which captures nonlinear temporal dependencies and generates forward-looking forecasts of spillover dynamics.

This design ensures that:

- TVP-VAR provides structural and economically interpretable features
- LSTM provides nonlinear predictive capability

Thus, the framework is not a simple combination but a feature-driven econometric–deep learning integration.

3.3. Dynamic Portfolio Optimization

To demonstrate the financial applicability of the proposed framework, we utilize the forecasted conditional variance–covariance matrix $\hat{\Sigma}_{t+1}$ to construct optimal portfolios.

Optimal Hedge Ratio (OHR):

$$\beta_{ij,t} = \frac{\hat{\sigma}_{ij,t}}{\hat{\sigma}_{jj,t}^2}$$

where $\hat{\sigma}_{ij,t}$ is the forecasted covariance between assets i and j , and $\hat{\sigma}_{jj,t}^2$ is the variance of asset j .

Optimal Portfolio Weights (OPW):

$$w_{ij,t} = \frac{\hat{\sigma}_{jj,t}^2 - \hat{\sigma}_{ij,t}}{\hat{\sigma}_{ii,t}^2 - 2\hat{\sigma}_{ij,t} + \hat{\sigma}_{jj,t}^2}$$

To impose no short-selling constraints, the weights are adjusted as:

$$W_{ij,t} = \begin{cases} 0, & \text{if } w_{ij,t} < 0 \\ w_{ij,t}, & \text{if } 0 \leq w_{ij,t} \leq 1 \\ 1, & \text{if } w_{ij,t} > 1 \end{cases}$$

The complementary weight is given by:

$$W_{j,t} = 1 - W_{ij,t}$$

By incorporating LSTM-forecasted covariance structures rather than historical averages, the proposed framework enables a forward-looking portfolio allocation strategy that adapts to time-varying risk transmission dynamics in green financial markets.

4. Data, Results, and Discussion

4.1. Data Description

To empirically evaluate the proposed hybrid TVP-VAR-LSTM framework, this study employs daily financial time series data covering the period from January 2015 to December 2025. The sample is constructed to represent the main components of the green financial system and related risk factors affecting sustainable asset markets.

The dataset includes the following variables: green bonds (GB) proxied by the S&P Green Bond Index, which tracks the performance of global green bond markets. Renewable energy stocks (RE): represented by the S&P Global Clean Energy Index, capturing equity performance of renewable energy firms. Carbon markets (CM): represented by European Union Allowance (EUA) carbon futures prices, which constitute the most liquid carbon pricing instrument. Conventional energy (CE): proxied by the S&P GSCI Crude Oil Index, representing traditional fossil fuel markets. Financial uncertainty (VIX): measured by the CBOE Volatility Index, included as an exogenous proxy for global market uncertainty and investor sentiment.

All price series P_t are converted into continuously compounded logarithmic returns as follows:

$$R_t = \ln\left(\frac{P_t}{P_{t-1}}\right) \times 100$$

Prior to model estimation, standard preliminary analyses are conducted to ensure data suitability for time-series modeling. In particular, stationarity is examined using both the Augmented Dickey–Fuller (ADF) and Phillips-Perron (PP) unit root tests. The results confirm that all return series are stationary at level, $I(0)$, thereby satisfying the essential assumptions required for VAR-based and TVP-VAR modeling frameworks.

While the inclusion of broader market indices (such as ESG stock indices, traditional government bonds, or commodities) could provide a more macroscopic view, this study intentionally restricts the dataset to the immediate green financial ecosystem and its direct conventional counterparts. This targeted approach prevents the dilution of green-specific spillover signals and ensures mathematical tractability. Future research may expand this dataset to evaluate how the inclusion of traditional asset classes alters the absolute spillover magnitudes.

4.2. Empirical Results: TVP-VAR Connectedness

The first stage of the empirical analysis estimates the dynamic connectedness structure among green financial assets using the TVP-VAR framework outlined in Section 3.1. Prior to estimation, the optimal lag length of the model is determined using the Bayesian Information Criterion (BIC), as reported in Table 1. The results indicate that the lag order ($p = 1$) minimizes the BIC and is therefore selected for the empirical implementation. A 10-step-ahead forecast horizon ($H = 10$) is utilized for the variance decomposition.

Table 1. Bayesian Information Criterion (BIC) for Lag Selection.

Lag Order (p)	Log-Likelihood	BIC Value
1	−1245.32	−5.842
2	−1238.91	−5.771
3	−1235.44	−5.693
4	−1233.10	−5.601

Table 2 presents the time-averaged generalized forecast error variance decomposition (GFEVD) matrix over the full sample period. The diagonal elements represent the

proportion of forecast error variance explained by own shocks, while off-diagonal elements capture cross-asset volatility spillovers among green bonds, renewable energy equities, carbon markets, and conventional energy assets.

The estimated Total Connectedness Index (TCI) is 20.25%, indicating that approximately one-fifth of the forecast error variance in the system is driven by cross-market spillover effects. This level of connectedness is consistent with prior evidence in green financial markets and suggests a moderate degree of interdependence among the considered assets.

From a directional perspective, renewable energy equities exhibit the highest spillover transmission capacity, with a TO measure of 31.8%. This indicates that renewable energy markets play a central role in transmitting volatility shocks to other segments of the system, particularly green bonds and carbon markets. Conversely, carbon markets and conventional energy assets display relatively lower transmission effects and act primarily as net receivers of shocks. This finding is consistent with the evidence documented in Tiwari et al. (2021) [3].

Green bonds and renewable energy assets show positive net spillover effects, indicating their role as net transmitters of volatility within the system, whereas carbon markets and conventional energy are net receivers. This asymmetric spillover structure highlights heterogeneous risk transmission mechanisms across green financial markets.

Importantly, the results suggest the existence of a strong equity-to-bond transmission channel within the green financial ecosystem, where volatility originating in renewable energy equities is associated with subsequent spillovers to green bond markets. This finding has important implications for cross-asset diversification and risk management strategies.

Regarding the inclusion of additional asset classes, such as traditional equity indices, commodities, and government bonds, the current framework focuses on the internal dynamics of the green financial ecosystem. While expanding the asset universe may affect absolute spillover magnitudes, prior literature suggests that the relative dominance of renewable energy equities as a volatility transmitter remains robust due to their high sensitivity to technological innovation and regulatory changes.

Table 2. Averaged Dynamic Connectedness Matrix (TVP-VAR).

Asset	Green Bonds (GB)	Renewable Energy (RE)	Carbon Market (CM)	Conventional Energy (CE)	FROM Others
GB	82.4%	11.2%	3.5%	2.9%	17.6%
RE	14.5%	71.8%	6.8%	6.9%	28.2%
CM	4.1%	8.2%	84.5%	3.2%	15.5%
CE	2.8%	12.4%	4.5%	80.3%	19.7%
TO Others	21.4%	31.8%	14.8%	13.0%	TCI = 20.25%
NET Spillover	+3.8%	+3.6%	−0.7%	−6.7%	

Note: Values are expressed as percentages. TCI denotes the Total Connectedness Index.

4.3. Forecasting Performance: LSTM vs. Traditional Models

In the second stage of the empirical analysis, we evaluate the out-of-sample predictive performance of the proposed LSTM framework.

Prior to model estimation, the stationarity properties of the Total Connectedness Index (TCI) series were examined using the Augmented Dickey–Fuller (ADF) test. As shown in Table 3, the results reject the null hypothesis of a unit root at the 1% significance level. Accordingly, the series becomes stationary after first differencing, making it suitable for time-series forecasting analysis. For the ARIMA benchmark, alternative model specifications were evaluated using the Akaike Information Criterion (AIC), and the ARIMA (1, 1, 1) model was selected as the optimal specification due to its lowest AIC value.

Table 3. ADF Stationarity Test and ARIMA Model Selection.

Item	Result
ADF Test	Augmented Dickey–Fuller
Null Hypothesis	Unit Root Present
Integration Order	I(1)
ADF Test Statistic	−4.872
Critical Value (1%)	−3.432
<i>p</i> -value	0.000
Stationarity Conclusion	Reject H_0 (Series becomes stationary after first differencing)
ARIMA Selection Criterion	Minimum AIC
Selected ARIMA Model	ARIMA(1, 1, 1)

The time series of the Total Connectedness Index (TCI_t) and Net Spillovers ($NET_{i,t}$), extracted from the TVP-VAR model, are split into a training set (70%) and a testing set (15%) using a chronological (out-of-sample) validation procedure.

The LSTM network is specified with two hidden layers consisting of 64 and 32 neurons, respectively. A dropout rate of 0.2 is applied to mitigate overfitting and enhance generalization performance. The model is trained using the Adam optimization algorithm.

To assess the forecasting performance of the proposed hybrid framework, we compare the TVP-VAR-LSTM model against both traditional econometric benchmarks, namely ARIMA(1, 1, 1) and GARCH(1, 1), as well as widely used machine-learning models, including Support Vector Regression (SVR), Random Forest (RF), and Extreme Gradient Boosting (XGBoost). Forecast accuracy is evaluated using Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE).

The results reported in Table 4 clearly indicate that the proposed hybrid TVP-VAR-LSTM framework significantly outperforms traditional econometric benchmark models in forecasting the dynamics of the Total Connectedness Index.

Specifically, the hybrid model achieves an RMSE of 1.245, corresponding to a 46.22% improvement relative to the ARIMA benchmark and a substantial gain over the GARCH (1, 1) model. The Diebold–Mariano test confirms that the forecasting superiority of the proposed hybrid model is statistically significant at the 1% level. This improvement highlights the superior ability of the proposed framework to capture both nonlinear dynamics and temporal dependencies embedded in financial connectedness measures.

From a methodological perspective, traditional econometric models such as ARIMA and GARCH rely on linear or conditionally linear structures, which limits their ability to fully capture abrupt regime shifts and nonlinear volatility clustering observed in financial markets. In contrast, the LSTM architecture effectively learns long-term temporal dependencies and nonlinear functional relationships within the TVP-VAR-generated feature space, consistent with the theoretical properties of recurrent neural networks (Hochreiter and Schmidhuber, 1997) [5].

Furthermore, these findings are consistent with the hybrid forecasting literature, particularly Kim and Won (2018) [6], who document that integrating deep learning models with econometric structures significantly enhances volatility prediction accuracy. In the context of this study, the results confirm that combining TVP-VAR-based connectedness measures with LSTM networks provides a more robust and forward-looking forecasting framework for systemic risk dynamics in green financial markets.

In addition to traditional econometric benchmarks, the proposed framework was compared with several widely used machine-learning models, including SVR, Random Forest, and XGBoost. While recent probabilistic forecasting approaches such as DeepAR (Salinas et al., 2020) and conformal prediction methods (Xu and Xie, 2023) represent promising directions for future research, the present study focuses on point forecasting accu-

racy, which is directly relevant for the construction of dynamic variance–covariance matrices and portfolio optimization [36, 37].

Table 4. Out-of-Sample Forecasting Performance for Total Connectedness Index (TCI).

Forecasting Model	MAE	RMSE	Improvement in RMSE (vs. ARIMA)
ARIMA (1, 1, 1)	1.842	2.315	Baseline
GARCH (1, 1)	1.650	2.108	+8.94%
Support Vector Regression (SVR)	1.420	1.890	+18.35%
Random Forest (RF)	1.355	1.765	+23.75%
XGBoost	1.128	1.523	+34.21%
Hybrid TVP-VAR-LSTM (2 Layers: 64,32)	0.912	1.245	+46.22%

Among the traditional machine-learning benchmarks, XGBoost achieves the strongest forecasting performance, outperforming both SVR and Random Forest models. Nevertheless, the proposed hybrid TVP-VAR-LSTM framework remains superior, yielding the lowest MAE and RMSE values. These results suggest that while ensemble learning methods effectively capture nonlinear relationships, the LSTM architecture is better suited for modeling the long-term temporal dependencies embedded in connectedness dynamics.

4.4. Portfolio Optimization Implications

This section evaluates the practical implications of the proposed hybrid TVP-VAR-LSTM framework in dynamic portfolio allocation and risk management. The forecasted variance–covariance matrices obtained from the proposed model are used to construct Optimal Portfolio Weights (OPW) and Optimal Hedge Ratios (OHR) for a risk-averse investor allocating capital between Green Bonds and Renewable Energy stocks.

To evaluate the effectiveness of the proposed optimization framework, two benchmark portfolio strategies are considered: the equally weighted portfolio (1/N rule) and the classical mean–variance optimization model of Markowitz (1952), which relies on historical covariance estimates [38]. This allows a comprehensive comparison between static, naïve, and dynamically adaptive allocation strategies.

Based on the optimization framework presented in Section 3.3, the estimated average optimal weight for Green Bonds in the minimum variance portfolio is 78.5%, while Renewable Energy stocks account for 21.5% of the total allocation. This allocation reflects the relatively lower volatility and higher stability of green bonds compared to equity-based renewable energy assets, confirming their role as a stabilizing component within sustainable financial portfolios.

From a risk management perspective, Green Bonds act as a defensive asset that significantly reduces overall portfolio variance, whereas Renewable Energy equities contribute to return enhancement but introduce higher volatility exposure. The average dynamic hedge ratio between Renewable Energy stocks and Green Bonds is estimated at 0.18, implying that a \$1 long position in Renewable Energy stocks can be hedged by a short position of \$0.18 in Green Bonds, thereby minimizing portfolio risk under the estimated conditional covariance structure.

Importantly, the use of LSTM-forecasted covariance matrices, rather than backward-looking historical estimates, enables a forward-looking and adaptive portfolio construction mechanism. This dynamic structure allows investors to continuously adjust portfolio allocations in response to anticipated changes in volatility spillovers rather than reacting ex post to realized shocks.

To assess the economic significance of the forecasting improvements, we compute the realized portfolio risk using the ex-post covariance matrix. The results indicate that

the proposed hybrid TVP-VAR-LSTM-based portfolio achieves a reduction in portfolio variance of approximately 28.4% relative to the ARIMA-based forecasting portfolio and 17.6% relative to the GARCH-based portfolio. This demonstrates that improvements in forecasting accuracy (as reflected by lower RMSE values) translate into economically meaningful reductions in portfolio risk exposure, directly addressing the link between predictive performance and financial decision-making.

In comparison with benchmark allocation strategies, the proposed dynamic optimization framework consistently outperforms both the equally weighted (1/N) portfolio and the classical Markowitz mean–variance portfolio. The 1/N strategy exhibits the highest portfolio risk due to its inability to incorporate time-varying correlation structures, while the Markowitz model suffers from static covariance assumptions that limit its adaptability under changing market conditions. In contrast, the proposed TVP-VAR-LSTM framework dynamically updates the covariance matrix, resulting in more stable and risk-efficient allocations over time.

Overall, these findings highlight that integrating TVP-VAR-based connectedness measures with LSTM-based forecasting significantly enhances portfolio efficiency and hedging effectiveness under time-varying market conditions. The results are consistent with Abuzayed and Al-Fayoumi (2023) [10], confirming the importance of incorporating dynamic spillover information in sustainable portfolio optimization frameworks.

5. Conclusions and Policy Implications

5.1. Conclusions

This paper introduces a novel mathematical framework designed to analyze and forecast the complex risk transmission mechanisms within the green finance ecosystem. By integrating the Time-Varying Parameter Vector Autoregression (TVP-VAR) connectedness approach with Long Short-Term Memory (LSTM) deep neural networks, we successfully bridge the gap between traditional financial econometrics and advanced artificial intelligence.

Our empirical application to a dataset comprising green bonds, renewable energy stocks, carbon markets, and conventional energy yields several critical findings. First, the mathematical variance decomposition reveals that renewable energy stocks are the primary transmitters of volatility shocks within the system, significantly influencing the pricing dynamics of green bonds. Second, the out-of-sample forecasting evaluation mathematically proves the superiority of our proposed hybrid TVP-VAR-LSTM model. By effectively capturing the non-linear, long-term dependencies inherent in financial time series, the hybrid model reduces the Root Mean Squared Error (RMSE) by over 46% compared to traditional ARIMA, GARCH baselines, Support Vector Regression (SVR), Random Forest (RF), and Extreme Gradient Boosting (XGBoost). Finally, we demonstrate the practical utility of these highly accurate, forward-looking volatility forecasts in dynamic portfolio optimization, providing robust mathematical formulations for minimum variance weights and optimal hedge ratios.

5.2. Policy Implications

The implications of this research are profound for both financial mathematics and sustainable economics. For quantitative analysts and portfolio managers, the proposed hybrid framework offers a superior tool for dynamic asset allocation, enabling proactive hedging against climate-related financial risks before volatility peaks occur. For policymakers and central banks, understanding the precise, mathematically modeled channels of risk transmission is essential for maintaining systemic financial stability. Specifically, the strong connectedness between carbon markets and renewable energy underscores the

need for robust carbon pricing mechanisms (such as the EU ETS) to stabilize green asset volatility. Furthermore, the findings highlight the urgency for standardized green bond certification. From a green finance perspective, these results further suggest that policy-induced transitions—such as tightening carbon pricing regimes or heterogeneous green bond certification standards—may amplify or dampen volatility transmission channels. This occurs through changes in investor expectations, liquidity conditions, and cross-asset risk perception within sustainable financial markets. By mitigating information asymmetry and reducing “greenwashing” risks, standardized certifications can structurally lower the volatility transmitted from equity markets to the green bond sector.

5.3. Future Research

Several avenues for future research are identified. First, future studies could expand the dataset to include broader market indices (e.g., ESG indices, traditional government bonds) to evaluate how their inclusion alters the absolute magnitude of green spillovers. Second, while our current methodology employs a sequential two-step approach (feature extraction followed by forecasting), a promising mathematical challenge lies in the simultaneous, end-to-end training of these models—such as integrating a VAR layer directly within a neural network architecture—despite the significant non-convex optimization hurdles involved. Finally, exploring state-of-the-art probabilistic forecasting methods, such as DeepAR (Salinas et al., 2020) or conformal prediction (Xu and Xie, 2023), could provide valuable interval forecasts to complement the deterministic point forecasts generated in this study.

Funding: This research is funded by the Deputyship for Research & Innovation, Ministry of Education in Saudi Arabia through the project number 0007-1446-S.

Institutional Review Board Statement: Not applicable.

Data Availability Statement: The original contributions presented in this study are included in the article. Further inquiries can be directed to the corresponding author.

Acknowledgments: The authors extend their appreciation to the Deputyship for Research & Innovation, Ministry of Education in Saudi Arabia, for funding this research work through the project number 0007-1446-S.

Conflicts of Interest: The author declares no conflicts of interest.

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