OPTIMIZING VOLATILITY FORECASTING AND RISK MANAGEMENT OF JINKOSOLAR UNDER TARIFF POLICY TENSIONS USING GARCH-XGBOOST

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Abstract: This study forecasts the stock price volatility of JinkoSolar (JKS), a leading renewable energy company, under U.S.-China trade tensions using a hybrid GARCH(2,5)-XGBoost model. Principal Component Analysis (PCA) is applied to reduce dimensionality and enhance model learning. Several algorithms - Lasso, Linear Regression, Elastic Net, Decision Tree, GBM, XGBoost, and traditional GARCH - are compared. Results show that the GARCH(2,5)-XGBoost model achieves the best performance, while traditional GARCH performs poorly, highlighting the limits of linear models in nonlinear markets. Although trading performance is modest, the hybrid model effectively adapts to market signals and short-term volatility. Key technical indicators such as MA_21, EMA_21, CCI, RSI, and VWAP significantly affect forecasts. The study recommends exploring LightGBM and GARCH-LightGBM hybrids to further improve adaptability and forecasting accuracy, with practical value for risk analysis and portfolio optimization in emerging markets like Viet Nam.

Keywords: FDI, GARCH-XGBoost, JinkoSolar (JKS), Reciprocal Tariff, Risk management, Volatility forecasting

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Introduction

The global shift toward carbon emission reduction and sustainable development has positioned the renewable energy supply chain at the center of investment strategies and international policy agendas. Among the leading solar energy manufacturers, JinkoSolar (JKS) plays a pivotal role by integrating across multiple segments of the supply chain-from polysilicon procurement to solar panel distribution. However, the stock performance of companies like JKS remains highly volatile due to global tariff tensions, geopolitical instability, and fluctuations in input costs-posing significant challenges for investors and risk management strategies.

In this context, accurate volatility forecasting is essential not only for asset valuation but also for constructing effective hedging strategies in the clean energy market. Traditional models such as GARCH have long been recognized for modeling conditional variance in financial time series. Nonetheless, these models often fall short when confronted with nonlinear, multidimensional influences or macroeconomic shocks-factors increasingly prevalent in the global renewable energy sector. To address these limitations, this study proposes a hybrid GARCH-XGBoost model, combining the statistical rigor of GARCH with the powerful predictive capabilities of gradient boosting algorithms. By applying this framework to JinkoSolar's stock data, the research aims to improve forecasting accuracy and support more robust risk mitigation strategies amid escalating trade disputes and supply chain disruptions. Ultimately, the findings are expected to contribute to more adaptive and sustainable investment strategies within the renewable energy supply chain.

This study has three main objectives: (1) Analyze the volatility characteristics of JinkoSolar (JKS) stock within the renewable energy supply chain under the influence of global tariff tensions. (2) Develop a GARCH-XGBoost model to optimize JKS stock volatility forecasting by integrating conditional variance modeling with nonlinear machine learning. (3) Apply the forecasting outcomes to financial risk management to enhance investment decision-making in highly volatile renewable energy markets.

Literature review

Related work

In recent years, geopolitical disruptions and global green industrial policies have significantly impacted supply chains, international trade, and financial markets. Three recent studies underscore the close relationship between green industrial policy, renewable energy competition, and escalating U.S.-China trade tensions. Specifically, Li and Du (2025) reveal that although China's green industrial policies promote renewables, they prioritize economic growth over environmental commitments, triggering conflicts with global trade rules. This has fueled trade protectionism and encouraged many countries to implement domestic green policies to rebalance their supply chains. Zeng and Zhang (2025) demonstrate that trade policy uncertainty forces U.S. firms to consider reshoring, yet cost and contractual constraints remain major barriers. Meanwhile, Xia et al. (2019) use a global input–output model to show that U.S.-China trade conflicts cause long-term damage to energy demand and growth for both economies, while weakening the global energy market. Hughes and Meckling (2017) highlight that both the U.S. and China view renewable energy as a strategic sector in addressing climate change. However, since 2011, both countries have been locked in solar panel trade disputes, with the U.S. imposing anti-dumping duties under pressure from domestic manufacturers and Congress.

This trend is now spreading to Southeast Asia, with Viet Nam emerging as a new hotspot. Guarascio (2025) warns that over USD 13 billion in wind and solar investment in Viet Nam is at risk due to retroactive feed-in-tariff (FiT) revisions, raising concerns about legal frameworks and investor confidence. Khue (2025) and VnEconomy (2025) note that the U.S. has imposed up to 542.64% in anti-dumping and countervailing duties on solar panels imported from Viet Nam, significantly higher than other countries, because the U.S. does not recognize Viet Nam as a market economy. Kao (2025) and Ho (2025) report record-high tariffs of 3,521% on solar products from Viet Nam, Cambodia, Thailand, and Malaysia, due to suspected Chinese transshipment. These actions have intensified U.S.-Southeast Asia trade tensions, pushed up clean energy costs in the U.S., and disrupted regional supply chains.

In this context, modern forecasting models-particularly hybrid approaches combining econometrics and machine learning-are gaining importance. Le et al. (2021) introduced two privacy-preserving variants of FedXGBoost for secure, distributed training. Celestin et al. (2025) show that GARCH and its extensions (EGARCH, TGARCH), when combined with machine learning, significantly enhance the accuracy of high-frequency market volatility predictions. Wang et al. (2024) integrated ARIMA-GARCH-XGBoost to refine residuals and improve stock price forecasting. Cui and Zhao (2023) found that GARCH excels at capturing short-term volatility, while XGBoost is more flexible for direct forecasting. Rz et al. (2020) and Januardi (2025) validated the effectiveness of GJR-GARCH-XGBoost and ETS-ARIMA-XGBoost in exchange rate forecasting and risk hedging. Yan and Li (2024) show that XGBoost, CatBoost, and LightGBM, when applied to volatility-based quantitative strategies, can generate stable annual returns of 5%-10%. Finally, Chen (2024) concludes that GARCH remains central in financial forecasting under high volatility, especially when integrated with AI and machine learning to enhance accuracy and real-world applicability.

This study addresses a significant research gap by applying the GARCH-XGBoost hybrid to forecast stock volatility in the renewable energy supply chain area that has not been sufficiently explored, especially under increasing geopolitical, trade, and technological uncertainties. Novelty: The novelty of this study lies in integrating 34 technical financial indicators with Principal Component Analysis (PCA) and SHAP values to identify key features influencing JKS stock volatility. Furthermore, it employs a Genetic Algorithm (GA) to optimize GARCH parameters and Bayesian Optimization (BO) to fine-tune XGBoost hyperparameters-demonstrating a unique hybrid approach combining econometrics and machine learning. Contribution: The main contribution of this research is the development of a robust quantitative risk management framework tailored for clean energy investors. This is particularly relevant as Viet Nam and Southeast Asia emerge as new global solar manufacturing hubs facing intensified retaliatory tariffs from the United States.

Research methodology

Volatility

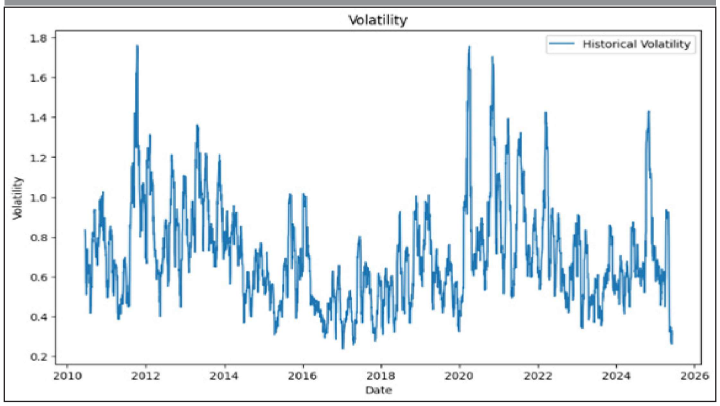
Stock volatility or Historical Volatility (HV) is based on the logarithmic returns (Log Returns) of the stock. First, the Log Returns are calculated using the formula: $r_i = \ln\left(\frac{P_i}{P_{i-1}}\right)$ (1) where is the adjusted closing price on day t. Then, the standard deviation of the Log Returns within a 21-day window is: $(Volatility_t)\ \sigma_t = \sqrt{\frac{1}{N-1}\sum_{i=t-N+1}^{t}(r_t-\bar{r})^2}$ (2) in which, is the average log returns within a 21-day window: $\bar{r} = \frac{1}{N}\sum_{i=t-N+1}^{t} r_i$ (3). And N=21 is the window length (21 days), is the standard deviation of Log returns at day t, representing the price volatility over the last 21 days. The volatility is then annualized as follows: $HV = \sigma_{21} \times \sqrt{252}$ (4).

GARCH-XGBoost model

XGBoost (Extreme Gradient Boosting) is a powerful machine learning algorithm within the ensemble learning family, developed from the gradient boosting framework. The model is notable for its ability to handle large-scale datasets, mitigate overfitting through regularization techniques (L1 and L2), and support parallel training, thereby optimizing computational efficiency. XGBoost operates as a boosting algorithm of decision trees, where each subsequent tree is trained to correct the residual errors of the previous one. Given the training dataset $D = \{(x_i, y_i)\}_{i=1}^{n}$ (5), The predictive model is $\hat{y}_i = \sum_{k=1}^{K} f_k(x_i),\ f_k \in F$ (6). The objective function is optimized $\mathrm{L}(\phi) = \sum_{i=1}^{n} l\left(y_i, \hat{y}_i\right) + \sum_{k=1}^{K}\Omega(f_k)$ (7) và $\Omega(f) = \gamma T + \frac{1}{2}\lambda\|w\|^2$ (8). At each step, the loss is approximated $\mathrm{L}^{(t)} \approx \sum_{i=1}^{n}\left[g_i f_t(x_i) + \frac{1}{2}h_i f_t^2(x_i)\right] + \Omega(f_t)$ (9) where $g_i = \partial_{\hat{y}_i^{(t-1)}} l(y_i, \hat{y}_i)$ (10) and $h_i = \partial^2_{\hat{y}_i^{(t-1)}} l(y_i, \hat{y}_i)$ (11). According to Chen & Guestrin (2016), XGBoost also integrates sparsity-aware algorithms, weighted quantile sketch, and enhanced memory access mechanisms, enabling the model to scale efficiently to billions of data samples. Owing to its outstanding performance, XGBoost has been widely applied in nonlinear financial forecasting.

The Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model is widely used to capture time-varying variance, also known as volatility

FIGURE 2: HISTORICAL VOLATILITY OF JKS STOCK



Source: Author's analysis

clustering, which is a common feature in financial time series such as asset return volatility. The general mathematical formulation of the GARCH (p, q) model is as follows: $y_t = \mu + \varepsilon_t$ (12), $\varepsilon_t = z_t \cdot \sigma_t$ (13), $z_t = N(0,1)$ (14), $\sigma_t^2 = \omega + \sum_{i=1}^{q} \alpha_i \cdot \varepsilon_{t-i}^2 + \sum_{j=1}^{p} \beta_j \cdot \sigma_{t-j}^2$ (15). Where, σ_t^2 is the value of the financial time series at time t, μ is the unconditional mean of the series, ε_t is the shock or residual at time t, σ_t^2 is the conditional variance at time t, ω is a constant ensuring positive variance, are the ARCH coefficients capturing the impact of past shocks ε_{t-i}^2 , α_i are the GARCH coefficients representing the persistence of past conditional variances σ_{t-j}^2, z_t is a white noise process, typically assumed to follow a standard normal distribution.

Mechanism of operation: the input data is first demeaned to obtain residuals. Based on previous shocks and past conditional variances, the current conditional variance is calculated. This allows volatility to be modeled dynamically, rather than assuming a constant variance over time. Specifically, in this study, the GARCH(2,5) model is employed to capture and forecast time-varying volatility (conditional variance) in financial time series. In GARCH(2,5), the conditional variance at time depends on the five past squared residuals (ARCH terms) $\left(\varepsilon_{t-i}^2\right)$ and the two previous conditional variances (GARCH terms) (h_{t-j}). This allows the model to reflect the market's "memory" of past shocks. The GARCH (2,5) equation is formulated $h_t = \varpi + \sum_{i=1}^{5} \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^{2} \beta_j h_{t-j}$ (16), where the conditional variance at time t, ε_{t-i} is a function of past errors at time $t-i$ with $\varpi, \alpha_i, \beta_j$ all coefficients being positive and satisfying stationarity conditions. GARCH (2,5) enables the model to capture both short-term shocks and long-term volatility trends in stock price movements.

The hybrid GARCH (2,5)-XGBoost model combines the strength of GARCH in modeling conditional heteroskedasticity with the nonlinear learning capabilities of XGBoost. While GARCH (2,5) estimates time-varying variance and reflects the structural dynamics of financial volatility, XGBoost utilizes this variance output along with extended technical features to accurately forecast future stock prices. This integration is particularly useful in financial forecasting contexts characterized by high volatility and complex nonlinear behavior, enhancing predictive performance and market responsiveness.

Genetic Algorithm (GA) and Bayesian Optimization (BO)

Genetic Algorithm (GA) is an evolutionary optimization technique that simulates the process of natural selection. It is effective in exploring large and non-linear parameter spaces to identify optimal model structures. In this study, GA is applied to determine the appropriate GARCH (p, q) configuration for accurately modeling conditional variance. Meanwhile, Bayesian Optimization (BO) is a global optimization technique that leverages a surrogate function to efficiently search for optimal hyperparameters, particularly when the loss function is non-differentiable or computationally expensive. BO is employed to fine-tune the XGBoost model, enhancing the overall performance of the GARCH-XGBoost hybrid in volatility forecasting.

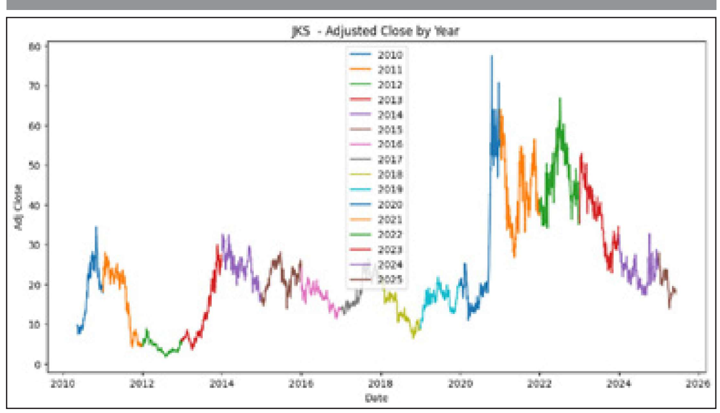
Data

The dataset used in this study comprises the stock prices of JinkoSolar Holding Co., Ltd. (JKS), retrieved from Yahoo Finance. The analysis focuses on the 'Adj Close' column to compute log-returns and construct the volatility time series. To enhance interpretability and predictive capability, the dataset is enriched with 33 technical indicators, including:

(i) Trend and momentum indicators: MA_21, EMA_21, MACD, Momentum, Trend_Slope, Trix, TSF, ROC.

(ii) Volatility and distribution metrics: Volatility_GARCH_Scaled, ATR, BB_upper, BB_lower, BB_width,

FIGURE 1: THE ADJUSTED CLOSING PRICE HISTORY OF JKS STOCK



Source: Author's analysis

Skewness, Kurtosis. Volume and money flow indicators Volume, VWAP, OBV, MFI, CMF. Popular oscillators RSI, %K, %D, CCI, Williams_%R, Ultimate_Oscillator, ADX.

(iii) Seasonality features: Day_of_Week, Month_of_Year, Fourier_Week, Fourier_Month, Seasonal_Residual.

(iv) Price range composite: Donchian_Width. The data were cleaned, missing values imputed, outliers removed and normalized using MinMaxScaler before analysis with the hybrid GARCH-XGBoost model. The integration of technical and statistical features enables the model to capture both short-term dynamics (price shocks) and long-term patterns (cycles and seasonality) in stock volatility behavior.

General evaluation of the model

GARCH optimized by GA and XGBoost optimized by BO, evaluated using MAE, MSE, RMSE, MAPE, R^2, and STD, ensure accurate analysis. MAE and MSE measure deviations, RMSE emphasizes large errors, MAPE normalizes the error, R^2 evaluates the explanatory power, and STD reflects the stability of the forecast.

$$MAE = \frac{\sum_{i=1}^{n}\left|y_i - \hat{y}_i\right|}{n} \quad MSE = \frac{1}{n}\sum_{i=1}^{n}\left(y_i - \hat{y}_i\right) \quad RMSE = \sqrt{\frac{\sum_{i=1}^{n}\left(y_i - \hat{y}_i\right)}{n}}$$

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{y_i - \hat{y}_i}{y_i}\right| \quad R^2 = 1 - \frac{\sum_{i=1}^{n}\left(y_i - \hat{y}_i\right)^2}{\sum_{i=1}^{n}\left(y_i - \bar{y}\right)^2}$$

$$STD = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(\mathrm{error}_i - \overline{\mathrm{error}}\right)^2}$$

Evaluating trading strategies using the Sharpe Ratio, Sortino Ratio, and Maximum Drawdown provides a comprehensive assessment of performance and risk. The Sharpe Ratio measures return relative to overall risk, the Sortino Ratio focuses specifically on downside risk, and Maximum Drawdown quantifies the largest observed loss from a peak. Together, these metrics offer a practical and well-rounded view of both profitability and risk exposure.

$$\text{Sharpe Ratio} = \frac{R_p - R_f}{\sigma} \quad \text{Sortino Ratio} = \frac{R_p - R_f}{\sigma_d} \quad \text{Max Drawdown} = \frac{P_{peak} - P_{trough}}{P_{peak}}$$

Empirical research

Data visualization

Since its listing in 2010 at an adjusted price of approximately \$9.75, JinkoSolar (JKS) stock has experienced several periods of significant volatility. Following an initial sharp decline, JKS recorded a remarkable growth phase between 2021 and 2023, reaching nearly \$80. However, by 2025, the stock price had plummeted to around \$18.5, reflecting a pronounced downward trend that may be attributed to escalating U.S.-China trade tensions and intensifying retaliatory tariff policies.

TABLE 1: THE ARCHITECTURE OF THE OPTIMAL GARCH-XGBOOST

Hyperparameters	Values	Hyperparameters	Values
Best GARCH (p, q)	(2, 5)	min_child_weight	1.8819
colsample_bytree	0.7589	n_estimators	132
gamma	0.0	reg_alpha	0.1227
learning_rate	0.2129	reg_lambda	0.7497
max_depth	12	subsample	0.8661

Source: Author's analysis

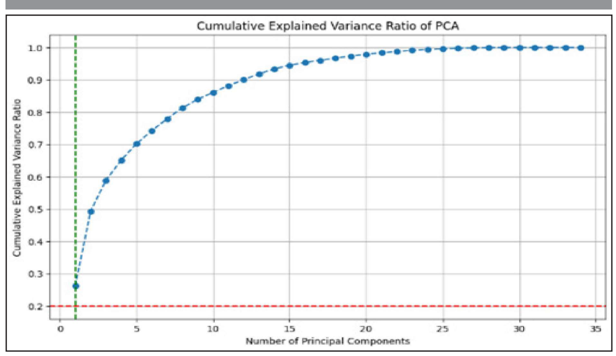
The most recent Historical Volatility (HV) data for JinkoSolar (JKS) stock indicates that price fluctuations remain elevated, with HV values ranging from 0.26 to 0.33 over the past five trading days. This suggests that the market is currently experiencing instability and heightened sensitivity to information, potentially driven by macroeconomic factors such as U.S.-China trade tensions, retaliatory tariff policies, or uncertain prospects in the renewable energy sector. Elevated volatility implies greater risk, but also presents potential investment opportunities if accurately forecasted.

In this analysis, Principal Component Analysis (PCA) is employed to reduce the dimensionality of the dataset by eliminating redundant information and minimizing noise, while retaining a significant portion of the original variance from the complex set of technical indicators. The use of 34 principal components preserves approximately 30% of the total variance, enhancing the efficiency of machine learning models by mitigating overfitting and shortening training time. PCA also improves the visualization of data structure and facilitates the evaluation of each component's contribution, thereby supporting the selection of important features for volatility forecasting models.

Construction of the optimized GARCH-XGBoost model

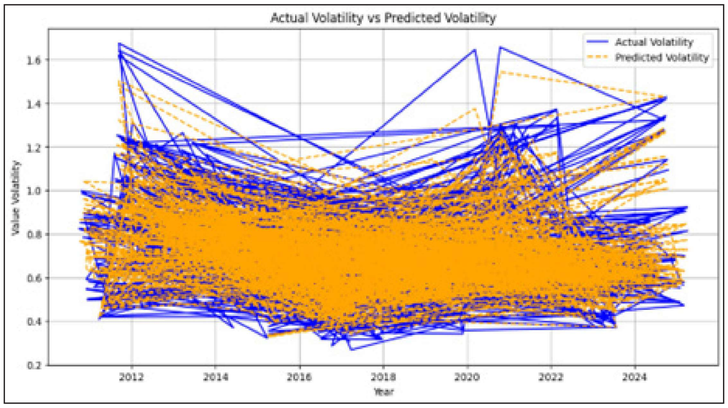
The hybrid GARCH(2,5)-XGBoost model integrates

FIGURE 3: ILLUSTRATING THE DATA DIMENSIONALITY REDUCTION PROCESS USING PCA



Source: Author's analysis

FIGURE 4: COMPARISON OF ACTUAL AND FORECASTED VOLATILITY



Source: Author's analysis

the time-varying conditional variance modeling capability of GARCH with the powerful nonlinear learning ability of XGBoost. Specifically, the GARCH(2,5) configuration captures the influence of five past squared residuals (ARCH terms) and two previous conditional variances (GARCH terms), enabling the model to retain both short-term shocks and long-term trends in market volatility. The XGBoost hyperparameters are optimized as follows: colsample_bytree = 0.7589 and subsample = 0.8661, which reduce variance by randomly sampling columns and rows during training, thereby helping to prevent overfitting.

Gamma is set to 0.0, allowing for flexible tree branching, while a learning rate of 0.2129 ensures efficient convergence during training. A max_depth of 12 enables the model to capture deep nonlinear relationships, and a min_child_weight of 1.8819 helps control tree complexity. The model utilizes 132 estimators (n_estimators), with L1 and L2 regularization parameters set to 0.1227 and 0.7497, respectively, to enhance generalization performance. Overall, this configuration strikes a balance between predictive accuracy and model stability.

Training and evaluation of the optimized GARCH-XGBoost model

The GARCH-XGBoost model was trained using the optimal hyperparameters (best_params) on the PCA-transformed training dataset (X_train_pca, y_train) to maximize forecasting performance. The model achieved optimal evaluation metrics, with a Mean Absolute Error (MAE) of 0.0858, reflecting a low average deviation between predicted and actual values. The Mean Squared Error (MSE) of 0.0135 and Root Mean Squared Error (RMSE) of 0.1163 indicate strong control over squared prediction errors and robustness against outliers. The Mean Absolute Percentage Error (MAPE) reached 12.82%, demonstrating a high level of forecasting accuracy in a highly volatile financial environment.

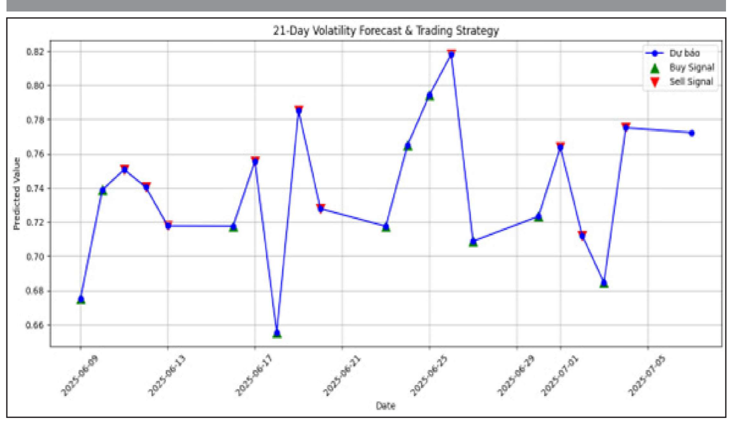
The coefficient of determination (R^2) reached 0.7788, indicating that nearly 78% of the variance in the dependent variable is explained by the input features-demonstrating the model's strong goodness of fit. The standard deviation of the predictions was 0.2017, reflecting the model's stability and consistency in forecasting outcomes. The integration of GARCH, known for modeling time-varying conditional variance, with XGBoost, renowned for its nonlinear learning capacity and ability to handle complex technical features, results in a forecasting framework capable of deeply capturing financial data structures. This makes it highly applicable for real-world use cases in risk analysis and portfolio management.

Application of the optimized GARCH-XGBoost model in forecasting

The optimized GARCH(2,5)-XGBoost model was applied to forecast stock volatility over the next 21 trading sessions. The model demonstrated its capability to generate dynamic trading signals with 11 buy recommendations, 8 sell recommendations, and 1 hold signal. The alternating pattern of these signals reflects the model's ability to detect short-term fluctuations and adjust strategies accordingly. The predicted volatility values ranged from 0.73 to 0.93, illustrating a clear divergence in trading signals and the model's responsiveness to evolving market conditions. The continuous updating of forecast signals based on changing inputs reinforces the hybrid model's practical utility in enhancing short-term investment decisions and adapting to high-frequency shifts in financial markets.

The above results indicate that the GARCH-XGBoost trading model exhibits low performance, with a Sharpe Ratio of 0.095 and a Sortino Ratio of 0.138-both below the threshold of 1-suggesting that returns are not

FIGURE 5: VOLATILITY FORECASTING AND TRADING STRATEGY FOR THE NEXT 21 DAYS



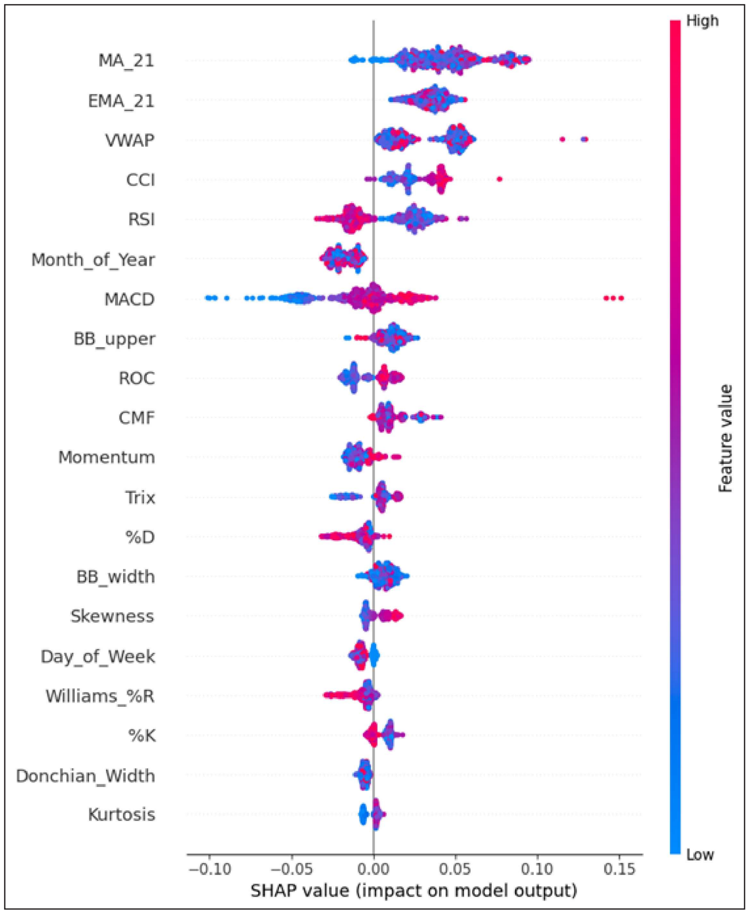
Source: Author's analysis

commensurate with the associated risks. A maximum drawdown of nearly -98% further highlights the severity of potential losses, implying that the strategy lacks robustness and carries high risk exposure.

Based on the ranked importance of input features in the GARCH(2,5)-XGBoost model, several key insights can be drawn regarding the model's ability to forecast JKS stock volatility under the influence of U.S.-China retaliatory tariff tensions. Technical indicators such as MA_21, EMA_21, VWAP, CCI, and RSI emerge as dominant contributors. These variables capture medium-term trends, price momentum, and investor sentiment-factors that are particularly sensitive to macroeconomic policy changes, especially in politically and commercially unstable environments like the current one.

The variables Month_of_Year and Day_of_Week reflect the impact of seasonality and cyclical trading behaviors, which tend to become more pronounced when markets are influenced by geopolitical news and sentiment. Other technical indicators, such as MACD, ROC, CMF, Momentum, and Trix, capture shifts in momentum and capital flow factors that can fluctuate sharply in response to tariff expectations or counter-policy announcements. Descriptive indicators like Skewness, Kurtosis, %K, %D, Williams %R, and BB_width characterize distributional asymmetries and volatility, enabling the model to identify latent risks arising from policy shocks, especially during periods of market instability. The model demonstrates strong sensitivity to trend signals, momentum changes, and seasonal factors-making it highly suitable for tracking and forecasting JKS stock price volatility amid intensifying trade tensions between the world's two largest economies.

FIGURE 6: ESTIMATING FEATURE IMPORTANCE



Source: Author's analysis based on model interpretation using SHAP

TABLE 2: COMPARISON OF THE PERFORMANCE OF GARCH-XGBOOST WITH OTHER MODELS

Model\Metrics	MAE	MSE	RMSE	MAPE	R2	STD
Garch	1.8428	3.4630	1.8609	313.13%	-50.66	0.2590
Lasso	0.2059	0.0680	0.2609	33.48%	-0.0002	0.0
Linear Regression	0.1730	0.0501	0.2238	27.77%	0.2636	0.1313
Elastic Net	0.1733	0.0501	0.2238	27.83%	0.2635	0.1297
Decision Tree	0.1441	0.0384	0.1961	22.25%	0.4347	0.2084
GBM	0.0940	0.0157	0.1253	14.96%	0.7692	0.1848
XGBoost	0.0930	0.0163	0.1278	14.47%	0.7602	0.1972
Garch-XGBoost	0.0858	0.0135	0.1163	12.82%	0.7788	0.2017

Source: Author's analysis

Results and discussion

In this study, PCA was employed to reduce dimensionality, eliminate noise, and improve model training efficiency. The results demonstrate that the hybrid GARCH(2,5)-XGBoost model significantly outperforms other methods, achieving MAE = 0.0858, RMSE = 0.1163, and R^2 = 0.7788, indicating high predictive accuracy and strong explanatory power. The GARCH(2,5) configuration effectively captures short-term shocks and long-term trends, while XGBoost successfully learns nonlinear relationships. Although the model's trading performance remains limited (Sharpe Ratio = 0.095), it shows flexibility in detecting market signals.

Key technical indicators such as MA_21, EMA_21, VWAP, CCI, and RSI play a vital role and are particularly sensitive to fluctuations driven by trade policies. These findings suggest that the GARCH-XGBoost model is well-suited for risk analysis and volatility forecasting in uncertain financial environments. Performance comparison across models reveals that the traditional GARCH model performs the worst, with MAE = 1.8428, RMSE = 1.8609, and R^2 = -50.66, indicating poor forecasting ability. Linear regression models such as Lasso, Linear Regression, and Elastic Net yield moderate results, with MAE values ranging from 0.17 to 0.20 and R^2 between -0.0002 and 0.26. Decision Tree models offer substantial improvement, reaching MAE = 0.1441 and R^2 = 0.4347. Boosting models like GBM and XGBoost demonstrate clear advantages, achieving MAE below 0.094 and R^2 exceeding 0.76.

Notably, the integrated GARCH-XGBoost model delivers the best performance with MAE = 0.0858, RMSE = 0.1163, and R^2 = 0.7788, highlighting the effectiveness of combining financial volatility modeling with advanced machine learning techniques. This suggests a promising approach for enhancing forecasting quality in highly uncertain financial environments. Future research should therefore focus on the application of LightGBM and hybrid GARCH-LightGBM models to further improve predictive performance, accuracy, and adaptability to market volatility.

JinkoSolar has made significant investments in Viet Nam, particularly in Quang Ninh, with two major FDI projects totaling nearly USD 865 million. This strategy aims to diversify its global supply chain, reduce reliance on China, and enhance production stability. However, the renewable energy sector in Viet Nam, despite strong FDI inflows, is facing several critical challenges: the outdated FiT pricing mechanism, complex administrative procedures, overloaded transmission infrastructure, and opaque payment policies. These factors have affected over USD 13 billion in investment and are hindering the country's green development commitments. Nguyen (2022) warned that sustaining Viet Nam's rapid clean energy expansion depends heavily on its ability to attract international capital. Urgent reforms are needed, including implementing a transparent bidding mechanism to replace FiT, encouraging direct PPA agreements, upgrading transmission infrastructure, offering tax and land incentives, and enacting a Renewable Energy Law. These reforms would help sustain FDI inflows, improve market reliability, and reassure major investors like JinkoSolar in expanding their operations in Viet Nam.

Conclusion

This study demonstrates the effectiveness of integrating PCA with the GARCH(2,5)-XGBoost model for forecasting stock volatility of JinkoSolar. PCA contributes to dimensionality reduction, noise elimination, and optimization of the training process. Comparative analysis reveals that the traditional GARCH model performs poorly (R^2 = -50.66), while linear regression models yield average results. The Decision Tree model shows notable improvements, whereas GBM and XGBoost exhibit superior performance. Notably, the GARCH-XGBoost model achieves MAE = 0.0858, RMSE = 0.1163, and R^2 = 0.7788, highlighting the strength of combining volatility modeling and nonlinear machine learning in volatile financial environments. Although its trading performance remains limited, the model demonstrates flexible responsiveness to market signals. Future research is recommended to explore the application of LightGBM and a hybrid GARCH-LightGBM model to enhance predictive accuracy and adaptability. As JinkoSolar expands its investment in Viet Nam, energy policy reform and FDI attraction become critical. Optimizing financial market forecasting will contribute to supporting long-term green and sustainable development strategies.

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References:

1. *Celestin, M., Vasuki, M., & Kumar, A. D. (2025). Applications of GARCH models for volatility forecasting in high-frequency trading environments. International Journal of Applied and Advanced Scientific Research, 10(1), 12-21. https://doi.org/10.5281/zenodo.14904200.*
2. *Chen, T., & Guestrin, C. (2016). XGBoost: A scalable tree boosting system. In Proceedings of the 22nd ACM SIGKDD (785-794). https://doi.org/10.1145/2939672.2939785.*
3. *Guarascio, F. (2025). Over $13 billion in solar, wind investment at risk in Vietnam, industry letter says. https://www.reuters.com/business/energy/over-13-billion-solar-wind-investment-risk-vietnam-industry-letter-says-2025-03-10/.*
4. *Ho, S. (2025). New record-high US solar tariffs leave uneven impact across Southeast Asia's solar industry. https://www.eco-business.com/news/new-record-high-us-solar-tariffs-leave-uneven-impact-across-southeast-asias-solar-industry/.*
5. *Li, X., & Du, M. (2025). China's green industrial policy and world trade law. East Asia. https://doi.org/10.1007/s12140-025-09447-1.*
6. *Nguyen, V. (2022, September 1). Vietnam: Foreign investors in dire need of incentives for renewable energy. https://www.energymonitor.ai/tech/renewables/vietnam-foreign-investors-in-dire-need-of-incentives-for-renewable-energy.*
7. *Xia, Y., Kong, Y., Ji, Q., & Zhang, D. (2019). Impacts of China-US trade conflicts on the energy sector. China Economic Review, 55, 101360. https://doi.org/10.1016/j.chieco.2019.101360.*
8. *Yan, K., & Li, Y. (2024). Machine learning-based analysis of volatility quantitative investment strategies for American financial stocks. Quantitative Finance and Economics, 8(2), 364-386. https://doi.org/10.3934/QFE.2024014.*
9. *Zeng, K., & Zhang, H. (2025). U.S.-China supply chains under stress: Trade policy uncertainty and production reallocation. Journal of International Business Studies. https://doi.org/10.1057/s41267-025-00458-3.*

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