ANALYZING THE IMPACT OF GEOPOLITICAL VOLATILITY ON VIETNAMESE OIL AND GAS STOCKS

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Abstract

This study examines the volatility dynamics of Vietnamese oil and gas equities amid rising geopolitical tensions from November 2025 to February 2026. The dataset includes key stocks (GAS, PLX, PVD, PGC, PVT) and 45 technical and statistical variables. Principal Component Analysis reduces dimensionality to 18 components, explaining 95% of total variance. A hybrid GARCH - LightGBM model optimized via a Genetic Algorithm is proposed, integrating conditional variance modeling with nonlinear learning. Out-of-sample results show superior performance over benchmark models, with high accuracy for GAS (R^2 = 0.898; RMSE ≈ 0.045) and stable performance across other stocks. The 21-step forecasts indicate increasing volatility in large-cap stocks, while extreme risk measures reveal heightened tail risk (GAS: VaR5% = 0.925; VaR1% = 1.308; CVaR5% = 1.120; CVaR1% = 1.455). These findings highlight dynamic risk management, conditional risk-based allocation, and portfolio optimization, providing empirical evidence for energy security policy under geopolitical uncertainty.

Keywords: *Energy security, extreme risk, GARCH-LightGBM, geopolitical uncertainty, oil and gas equities, SHAP, volatility forecasting*

PHÂN TÍCH TÁC ĐỘNG CỦA BIẾN ĐỘNG ĐỊA CHÍNH TRỊ ĐẾN CỔ PHIẾU DẦU KHÍ VIỆT NAM

Trần Bá Thuấn

Tóm tắt

Nghiên cứu này phân tích biến động của cổ phiếu dầu khí Việt Nam trong bối cảnh căng thẳng địa chính trị gia tăng từ tháng 11/2025 đến 02/2026. Bộ dữ liệu bao gồm các cổ phiếu chủ chốt (GAS, PLX, PVD, PGC, PVT) cùng 45 biến kỹ thuật và thống kê. Phân tích thành phần chính được sử dụng để giảm chiều dữ liệu xuống còn 18 thành phần, giải thích 95% phương sai tổng thể. Nghiên cứu đề xuất mô hình lai GARCH - LightGBM được tối ưu hóa bằng thuật toán di truyền, kết hợp mô hình hóa phương sai có điều kiện với khả năng học phi tuyến. Kết quả ngoài mẫu chứng minh mô hình vượt trội so với các mô hình chuẩn, với độ chính xác cao đối với GAS (R^2 = 0.898; RMSE ≈ 0.045) và tính ổn định trên các cổ phiếu khác. Dự báo 21 bước chỉ rõ xu hướng gia tăng biến động ở các cổ phiếu vốn hóa lớn, trong khi các thước đo rủi ro cực đoan cho thấy mức rủi ro cực đoan gia tăng (GAS: VaR_5% = 0.925; VaR_1% = 1.308; CVaR_5% = 1.120; CVaR_1% = 1.455). Các kết quả này nhấn mạnh vai trò của quản trị rủi ro động, phân bổ theo rủi ro có điều kiện và tối ưu hóa danh mục, đồng thời cung cấp bằng chứng thực nghiệm cho chính sách an ninh năng lượng trong bối cảnh bất định địa chính trị.

Từ khoá: *An ninh năng lượng, biến động địa chính trị, cổ phiếu dầu khí, GARCH - LightGBM, dự báo biến động, rủi ro cực đoan, SHAP*

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INTRODUCTION

Geopolitical shocks have historically destabilized global energy markets, as shown by the 1973 oil crisis, underscoring vulnerabilities in energy supply chains and security. In late 2025 to early 2026, rising tensions among Iran, the United States, and Israel heightened concerns about disruptions in the Strait of Hormuz, increased volatility in energy markets, and drove declines in energy-related equities. Although Viet Nam produces crude oil and natural gas, it remains heavily dependent on external sources, importing over 80% of its energy from countries such as Kuwait, Nigeria, Brunei, Singapore, and South Korea. This dependence exposes the domestic energy sector to global oil price fluctuations and geopolitical uncertainty, amplifying risks in oil and gas equity portfolios, making volatility and extreme risk forecasting essential.

Traditional GARCH/EGARCH models capture volatility clustering but struggle with nonlinear relationships, while machine learning improves predictive accuracy but reduces interpretability. Hybrid approaches achieve superior performance in forecasting financial and energy volatility. Che et al. (2024) combine ARIMA - GARCH with LightGBM, improving accuracy; Araya et al. (2024) integrate

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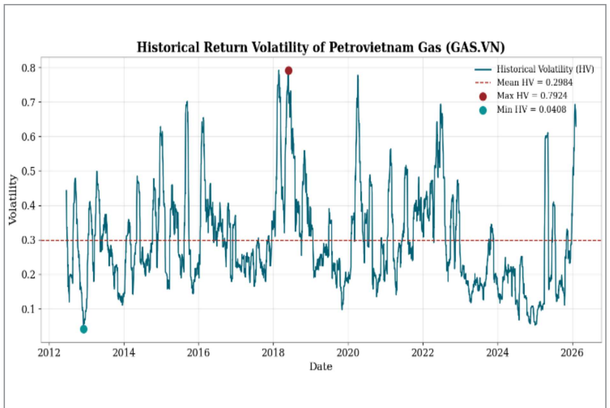
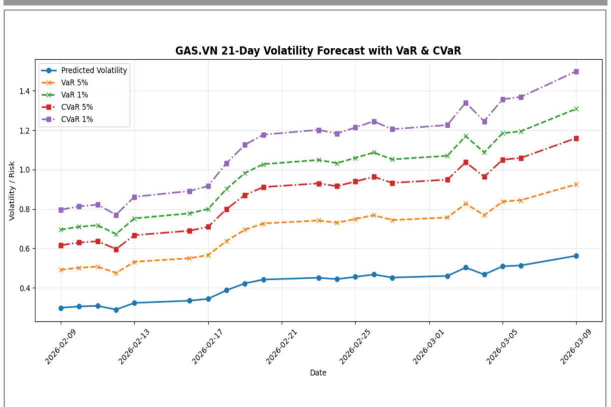
FIGURE 1: HISTORICAL RETURN VOLATILITY OF GAS.VN STOCK



Source: Author

FIGURE 2: FORECAST OF EXTREME RISK FOR GAS.VN



Source: Author

TABLE 1: OPTIMIZED GARCH-LIGHTGBM PARAMETERS

80% Dataset training	GAS.VN	PLX.VN	PVD.VN	PGC.VN	PVT.VN
Best Garch (p,q)	(2,4)	(2,1)	(1,1)	(5,2)	(1,2)
num_leaves	95	79	42	92	47
learning_rate	0.0918	0.0756	0.0383	0.0244	0.0770
n_estimators	261	334	377	441	407
max_depth	10	6	6	10	9
min_child_samples	13	12	10	11	23
min_child_weight	0.0447	0.0938	0.0047	0.0138	0.0474
subsample	0.9622	0.7697	0.6635	0.7643	0.6969
colsample_bytree	0.7392	0.8547	0.9605	0.8503	0.8427
reg_alpha	0.0309	0.0443	0.0008	0.0749	0.1275
reg_lambda	0.8171	0.7893	0.0076	0.5968	0.6855
random_state	42	42	42	42	42
verbosity	-1	-1	-1	-1	-1

Source: Author

CNN, BiLSTM, and ARIMA - GARCH, reducing MAE and RMSE; Feng et al. (2024) apply SHAP-based boosting models to Chinese oil futures, identifying variable contributions and capturing nonlinear dynamics. In asset management, hybrid frameworks incorporating LightGBM, CatBoost, and FFNN with LSTM or EMGNN demonstrate strong performance in both short- and long-term volatility forecasting, thereby improving quantitative investment strategies (Yan & Li, 2024; Zhang, 2022; Zhou et al., 2025; Zhang et al., 2024). Furthermore, models such as GARCH - MIDAS, GARCH - GRU, and TCN-LSTM-LightGBM preserve econometric structures while enhancing predictive performance and risk measurement capabilities (Wang et al., 2020; Wei et al., 2025; Gong et al., 2025). In the energy domain, recent studies emphasize the importance of multidimensional data analytics in supporting policy decision-making (Chinenye, 2024; Patterson & Taylor, 2024; Angleški, 2025).

However, prior research mainly focuses on developed or large markets and rarely integrates Genetic Algorithm-based hyperparameter optimization for LightGBM, while the interpretability of PCA - transformed features remains underexplored in the context of Viet Nam's oil and gas equities. To address these gaps, this study proposes a GA - GARCH - LightGBM–SHAP framework, combined with VaR-CVaR, to provide accurate volatility forecasts and estimate extreme risk at the 5% and 1% levels, thereby supporting robust portfolio risk management in Viet Nam's energy sector.

METHODOLOGY

Method

Historical volatility (HV), defined as the 21-day annualized standard deviation of logarithmic returns, is used as a key risk indicator and forecasting target (Jorion, 2010). This study proposes a GARCH - LightGBM framework that integrates GARCH-based conditional variance modeling (Engle, 1982; Bollerslev, 1986) with nonlinear learning via LightGBM (Ke et al., 2017). The feature vector includes historical volatility, GARCH volatility, and 43 technical indicators. A 21-step direct multi-horizon strategy is applied to forecast future volatility paths. Dimensionality is reduced from 45 variables to 18 principal components via PCA, preserving 95% of the variance, and standardized inputs ensure model stability. Genetic Algorithm optimization is used to tune the hyperparameters of GARCH and LightGBM (Holland, 1992). SHAP is employed to interpret feature contributions, while VaR-CVaR at 5% and 1% quantifies extreme risk. Model performance is evaluated using MAE, RMSE, MAPE, R^2, and STD, ensuring robust assessment of predictive accuracy and stability for portfolio risk management.

Data

This study uses daily stock prices of major Vietnamese oil and gas firms, including GAS.VN, PLX.VN, PVD.VN, PGC.VN, and PVT.VN, sourced from Yahoo Finance. Adjusted close prices are used to compute logarithmic returns and historical volatility. The dataset includes technical indicators (MA, EMA, RSI, MACD), liquidity measures (volume, VWAP, OBV), volatility estimators (Parkinson, Garman - Klass, Yang - Zhang), and risk metrics (VaR, ES). It also incorporates temporal features, GARCH-derived volatility, and Markov-switching probabilities. Data are cleaned, standardized, and split into 80% for training and 20% for testing for model development and evaluation in a SHAP-LGBM-GARCH framework.

EMPIRICAL RESULTS

Descriptive statistics and data visualization

The analysis of Vietnamese oil and gas stocks (GAS.VN, PLX.VN, PVD.VN, PGC.VN, PVT.VN) indicates that all tickers deviate from normal distribution ($p < 0.001$, Shapiro-Wilk & D'Agostino - Pearson), exhibiting Phi-Gaussian distributions with heavy tails and extreme fluctuations, reflecting oil price shocks and geopolitical risks. Long historical series for GAS.VN (2012–2026) and PVT.VN (2008-2026) allows stable model assessment, while other stocks capture short-term volatility. Historical volatility (HV) averages range from 0.1566 (PGC.VN) to 0.3867 (PVT.VN), with positive skewness and kurtosis, indicating upward shock tendencies and fat tails.

These results confirm that the Vietnamese oil and gas equity market exhibits asymmetric volatility and extreme variations, consistent with non-Gaussian characteristics. Such features underscore the need to apply GARCH or hybrid LightGBM - GARCH models with SHAP, thereby capturing nonlinear dependencies and effectively forecasting extreme risk.

Optimal GARCH-LightGBM estimation

The GA-optimized GARCH - LightGBM model uses stock-specific (p,q) orders and tuned LightGBM hyperparameters to balance complexity, prevent overfitting, and effectively capture heterogeneous volatility dynamics across Vietnamese oil and gas equities.

Out-of-sample results show GAS.VN achieves the highest R^2 (0.898) with lowest errors, capturing large-cap volatility effectively. PGC.VN records lowest MAE/RMSE but moderate R^2, while PLX.VN and PVT.VN show intermediate performance. PVD.VN has the weakest R^2, reflecting complex dynamics. Collectively, the optimized GARCH - LightGBM model performs best for large-cap stocks and remains robust across equities, supporting portfolio risk management.

Forecasted volatility and tail risk estimation

The GARCH - LightGBM model captures heterogeneous volatility across Vietnamese energy stocks. GAS.VN and PLX.VN show rising 21-day

TABLE 2: COMPARISON OF OPTIMIZED GARCH-LIGHTGBM WITH OTHER MODELS

Model/Metric	MAE	MSE	RMSE	MAPE	R_2	STD
Performance on the GAS.VN test set						
Garch (1;2)	0.1280	0.0231	0.1520	62.56%	-0.4297	0.1066
Elastic Net	0.0655	0.0078	0.0886	25.12%	0.6035	0.1101
LightGBM	0.0397	0.0030	0.0456	11.45%	0.8816	0.1277
Garch-Elastic Net	0.0550	0.0060	0.0774	20.61%	0.6978	0.1180
Garch-LightGBM	0.0299	0.0020	0.0449	10.66%	0.8980	0.1254
Performance on the PLX.VN test set						
Garch(1;1)	0.1753	0.0326	0.1807	72.61%	-0.4965	0.0438
Elastic Net	0.0376	0.0024	0.0493	16.24%	0.7017	0.0841
LightGBM	0.0266	0.0014	0.0376	11.20%	0.8340	0.0869
Garch-Elastic Net	0.0361	0.0022	0.0476	15.61%	0.7199	0.0840
Garch-LightGBM	0.0249	0.0011	0.0343	10.65%	0.8613	0.0856
Performance on the PVD.VN test set						
Garch(1;2)	0.2506	0.0632	0.2515	64.74%	-9.5239	0.0220
Elastic Net	0.0360	0.0020	0.0456	10.79%	0.6352	0.0703
LightGBM	0.0263	0.0011	0.0346	8.99%	0.7434	0.0682
Garch-Elastic Net	0.0365	0.0021	0.0461	11.00%	0.6258	0.0706
Garch-LightGBM	0.0205	0.0003	0.0301	8.51%	0.7669	0.0640
Performance on the PGC.VN test set						
Garch(1;1)	0.0687	0.0078	0.0884	47.84%	-0.1631	0.0645
Elastic Net	0.0173	0.0005	0.0228	18.59%	0.7354	0.0392
LightGBM	0.0138	0.0013	0.0291	14.83%	0.8061	0.0397
Garch-Elastic Net	0.0171	0.0005	0.0228	18.19%	0.7355	0.0386
Garch-LightGBM	0.0134	0.0003	0.0198	13.84%	0.8034	0.0376
Performance on the PVT.VN test set						
Garch(1;2)	0.2233	0.0692	0.2630	61.32%	-2.2717	0.1649
Elastic Net	0.0509	0.0046	0.0683	15.36%	0.7176	0.1122
LightGBM	0.0327	0.0019	0.0442	9.83%	0.8817	0.1169
Garch-Elastic Net	0.0506	0.0047	0.0686	15.26%	0.7155	0.1123
Garch-LightGBM	0.0323	0.0018	0.0434	9.85%	0.8846	0.1158

Source: Author

TABLE 3: FORECAST PERFORMANCE AND GENERALIZATION ASSESSMENT

Metric	GAS.VN	PLX.VN	PVD.VN	PGC.VN	PVT.VN
Cross-validation Mean R^2	0.883	0.783	0.711	0.707	0.875
Cross-validation Std R^2	0.006	0.046	0.062	0.053	0.010
Test R^2	0.897	0.861	0.7690	0.803	0.885
MAE	0.030	0.025	0.0269	0.013	0.032
RMSE	0.045	0.034	0.0360	0.019	0.043
Training time	31.95 s	1.20 s	0.94 s	0.82 s	22.27 s
Generalization	Very stable	Moderately stable	Fairly stable	Stable	Very stable
Most sensitive parameters	learning_rate, num_leaves	reg_alpha, learning_rate	colsample_bytree, min_child_samples	learning_rate, min_child_samples	reg_lambda, reg_alpha, learning_rate
ΔR² impact	≈ 0.11–0.13%	≈ 0.17–0.21%	≈ 0.29–0.49%	≈ 0.30–0.31%	≈ 0.06–0.13%

Source. Author

volatility, indicating macroeconomic sensitivity. PVD.VN remains high but stable, PGC.VN increases from a low base, and PVT.VN shows moderate smooth dynamics. The model effectively distinguishes conditional volatility, supporting short- to medium-term portfolio management.

Tail risk estimation: Extreme risk is rising from February to early March 2026. For GAS.VN, volatility increased from ~0.30 to above 0.56, accompanied by substantial growth in VaR and CVaR at 5% and 1%, highlighting a pronounced tail risk (CVaR_1% ≈ 1.50). PLX.VN and PVT.VN exhibits similar but milder trends, whereas PVD.VN remains high but stable, and PGC.VN shows the fastest relative increase in risk, signaling a potential transition from safe to a higher-risk state. This implies that investors should prioritize low-CVaR assets or diversify to mitigate extreme losses.

Portfolio implications: Risk-based portfolio differentiation suggests CVaR-driven allocation strategies across Vietnamese oil and gas equities. PVD.VN exhibits the highest tail risk ($CVaR_1\%$ = 1.217), making it suitable for high-risk, high-return satellite positioning with limited portfolio weight. PGC.VN shows the lowest downside risk ($CVaR_1\%$ = 0.347), serving as a defensive hedge. GAS.VN and PLX.VN, characterized by moderate-to-high systemic risk, functions as a core holding aligned with market exposure. PVT.VN provides diversification benefits across sectoral dynamics. An optimal portfolio structure combines core assets (GAS, PLX), a defensive allocation (PGC), and satellite exposure (PVD), with weights dynamically adjusted by CVaR to enhance risk - return efficiency under extreme market conditions.

Feature importance analysis using SHAP-PCA

SHAP analysis from the LGBM–GARCH framework shows that volatility is the dominant driver of Vietnamese oil and gas equity dynamics, with Parkinson, Garman - Klass, Yang-Zhang, and GARCH-based measures exhibiting strong predictive power and confirming pronounced volatility clustering and sensitivity to price shocks. Liquidity indicators (Amihud illiquidity, VWAP, OBV) further amplify return fluctuations, reflecting market frictions. Tail-risk measures (VaR, Expected Shortfall) and regime-switching probabilities (MS_prob) capture extreme market states and structural breaks, indicating significant nonlinear and state-dependent risks. These results support macroprudential supervision, stress testing, and dynamic capital allocation. Overall, SHAP - PCA evidence confirms that volatility, liquidity, and regime factors jointly drive predictive behavior, providing empirical support for risk management, price stabilization, and energy security policy in Viet Nam's oil and gas sector.

Performance evaluation, stability, and generalization of the optimized GARCH - LightGBM model

The results highlight that GARCH - LightGBM significantly reduces prediction errors while achieving higher R² values than both traditional GARCH and standard machine learning models (Table 2). For GAS.VN and PLX.VN, the model demonstrates the best performance with low errors and high explanatory power, indicating its capability to capture complex market dynamics. In contrast, individual GARCH models show limited predictive ability, reflecting their reliance solely on conditional variance structures. Similar patterns are observed for PVD.VN, PGC.VN, and PVT.VN. The hybrid model consistently yields lower MAE/RMSE and higher R² than single models, while also improving forecast stability relative to pure LightGBM. This confirms the advantage of combining statistical volatility modeling with machine learning in financial applications.

The results in Table 3 demonstrate that GA-optimized LightGBM provides consistent forecasting across PVD.VN, PGC.VN, and PVT.VN, with low test errors and strong generalization. Notably, PVT.VN achieves the highest performance, whereas PVD.VN remains more challenging to predict due to greater volatility and complexity. The cross-validation and sensitivity analyses further confirm the model's robustness.

Policy implications & discussion

The findings of this study provide critical policy implications for energy security and financial stability in Viet Nam.

Firstly, the hybrid GARCH - LightGBM model's effective volatility forecasts indicate that market shocks can be identified early using volatility and liquidity indicators. This implies that regulatory authorities should build strategic reserves, implement flexible price-stabilization mechanisms, and strengthen market risk monitoring, particularly for leading firms such as GAS.VN and PLX.VN.

Secondly, the estimated volatility and Value-at-Risk highlight the significant presence of tail risks during periods of high market turbulence, underscoring the importance of extreme risk measures, such as Expected Shortfall, in systemic risk management. Extending the analysis to portfolio-level assessment can further capture the risk contagion across the oil and gas sector.

Moreover, from a research perspective, these results illustrate the potential of hybrid models and advanced machine learning approaches in improving forecasting accuracy, especially in increasingly nonlinear and volatile financial markets. Overall, the study offers both practical guidance for policymakers and methodological insights for future research in energy finance.

CONCLUSION

This study proposes a GA-optimized GARCH - LightGBM framework for forecasting volatility in Viet Nam's oil and gas equities. Empirical results show consistent outperformance over benchmark models, with lower forecast errors and improved robustness, particularly for GAS.VN and PVT.VN. Volatility and liquidity variables are identified as key drivers of market dynamics, enabling early detection of shocks and high-risk regimes. VaR and Expected Shortfall confirm significant tail risk and conditional heteroskedasticity during periods of financial stress. The findings support dynamic risk management, strategic energy reserve allocation, flexible pricing policies, and liquidity monitoring, alongside risk-based capital allocation to enhance financial stability. Limitations include the single-country focus and limited incorporation of global spillover effects. Future research should extend to multi-market settings and more advanced hybrid architectures to improve generalizability and forecasting performance in complex financial environments.

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