Climate Policy Uncertainty, Energy Price Shocks, and Sustainable Stock-Market Volatility: Evidence from Thailand

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Abstract: This study investigates the roles of climate policy uncertainty, oil price shocks, and global macro-financial factors in shaping stock-market volatility in Thailand, an emerging economy undergoing an energy transition and increasing financial integration. Using monthly data from January 2000 to September 2025, we estimate a GARCH(1,1) model with exogenous regressors to capture conditional heteroscedasticity and employ support vector regression (SVR) to assess nonlinear out-of-sample predictability. The results indicate that oil-price changes, exchange-rate movements, and global-equity returns exert significant contemporaneous effects on Thai stock returns. In contrast, climate- and policy-related uncertainty measures appear to play a more indirect role within broader volatility dynamics than serve as primary return drivers. Volatility persistence is high but mean-reverting, suggesting sustained yet stabilizing adjustment processes in a semi-integrated emerging market. Out-of-sample evidence shows that SVR outperforms both GARCH and random walk benchmarks, indicating the presence of partial predictability under structured uncertainty. These findings contribute to the understanding of financial stability under transition-related risks and highlight the importance of consistent policy communication in emerging markets.

Keywords: climate policy uncertainty; energy price shocks; machine learning; stock volatility; sustainable finance

1. Introduction

The transition toward a low-carbon economy has increasingly reshaped global financial systems, introducing new forms of transition-related risk in both developed and emerging markets. Recent studies emphasize that the deep uncertainty surrounding decarbonization pathways may generate systemic financial exposure, particularly where regulatory frameworks and market expectations evolve simultaneously[1-3]. As governments implement carbon-pricing mechanisms, emission targets, and green-investment incentives, financial markets respond not only to conventional macroeconomic signals but also to climate-policy communication and regulatory shifts[4-6]. This form of uncertainty, conceptualized as climate policy uncertainty (CPU), has been measured and shown to affect market behavior through changes in risk perception and pricing dynamics[7,8].

Meanwhile, oil-price volatility and global financial cycles remain central drivers of asset-price fluctuations, particularly in energy-importing economies[9-11]. Exchange-rate dynamics further mediate the transmission of external shocks to domestic equity markets, especially in financially open or semi-integrated economies[12,13]. Together, these strands of literature suggest that the CPU operates within a broader macro-financial environment in which commodity prices, currency movements, and global equity conditions shape volatility outcomes.

Thailand provides a relevant case for examining these interactions. As a middle-income, energy-importing economy integrated into regional and global value chains, Thailand is structurally exposed to oil-price fluctuations and exchange-rate pressures. Simultaneously, the country has adopted sustainability-oriented development strategies, including the bio-circular-green model and carbon-neutrality commitments. This coexistence of transition ambition and external exposure creates a dual-risk environment in which climate-policy signals interact with traditional macro-financial drivers. Therefore,

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understanding whether and how these forces jointly influence stock-market volatility is important for assessing financial resilience in emerging ASEAN markets.

From a theoretical perspective, the link between uncertainty and volatility can be interpreted through both efficient and adaptive market frameworks. While the efficient market hypothesis[14] posits that prices incorporate available information, periods of heightened policy ambiguity may generate volatility clustering as information is gradually processed[15]. The adaptive market hypothesis16[16] further suggests that market efficiency evolves in response to changing economic and regulatory environments. From this perspective, climate policy announcements, oil-price shocks, and global financial conditions may dynamically alter investor expectations rather than through a single linear channel. Consequently, volatility persistence may reflect adaptive adjustment processes rather than permanent equilibria.

Empirical research has increasingly documented the financial relevance of policy-related uncertainty. Economic policy uncertainty has been linked to stock volatility and return predictability across major economies[17-19], while CPU has been shown to influence volatility and cross-sectional risk premia, particularly in developed markets[8,20,21]. In emerging markets, oil prices and geopolitical shocks often interact with institutional and structural characteristics to produce heterogeneous volatility responses[22,23]. However, much of the literature examines these drivers separately or focuses on large economies, leaving smaller emerging markets underexplored within an integrated volatility framework.

Against this background, this study investigates how the central bank operates alongside oil prices, exchange rates, and global equity performance in shaping stock market volatility in Thailand. Rather than assuming a dominant role for a single factor, the analysis examines whether climate-related uncertainty functions within broader volatility dynamics in semi-integrated emerging markets. Specifically, this study addresses two questions: (i) Do macro-financial and uncertainty variables exert significant contemporaneous effects on Thai stock returns under conditional heteroscedasticity? (ii) Do models that capture time-varying volatility and nonlinear patterns improve out-of-sample predictability relative to conventional benchmark models?

To answer these questions, we employ a GARCH(1,1) model with exogenous regressors to model the conditional volatility dynamics and a support vector regression (SVR) framework to evaluate the nonlinear forecasting performance. This combined approach enables the assessment of both volatility persistence and partial predictability under structured-uncertainty conditions.

The findings indicate that oil price changes, exchange rate movements, and global equity returns exert significant contemporaneous effects on Thai stock returns, consistent with the country's macroeconomic conditions. In contrast, climate- and policy-related uncertainty measures appear to operate within broader volatility conditions rather than serving as primary return drivers. Volatility persistence is high but mean-reverting, suggesting sustained yet stabilizing adjustment processes that are consistent with adaptive market behavior. Out-of-sample evidence shows that nonlinear methods provide improved forecasting accuracy, indicating that return dynamics under transition-related uncertainty may exhibit structured but limited predictability.

Overall, the results contribute to the understanding of financial stability in emerging markets that are undergoing energy transitions. For ASEAN economies balancing sustainability commitments with external exposure, transition-related risks appear to interact with conventional macro-financial shocks rather than replacing them. Therefore, clear and consistent policy communication may play a stabilizing role within a broader macro-financial coordination framework.

The remainder of this paper is organized as follows. Section 2 reviews the relevant literature. Section 3 describes the data and methodologies. Section 4 presents the empirical results, and Section 5 discusses the economic and sustainability implications of the results. Section 6 concludes.

2. Literature review

The relationship between macroeconomic variables and stock market volatility has long been a central concern in the field of empirical finance. Recently, the literature has expanded to incorporate CPU and transition-related risks within the broader sustainable-finance framework[21,24]. This evolving strand of research recognizes that environmental policy shifts may introduce a distinct layer of uncertainty that interacts with conventional macroeconomic shocks, rather than replacing them.

2.1. Oil Prices and Stock-Market Volatility

Oil-price shocks constitute one of the earliest and most extensively studied sources of macroeconomic volatility. Seminal work by Hamilton[9] demonstrates that oil shocks often precede recessions and influence asset valuations through production costs, inflationary pressures, and expectation channels[10,11,25]. Subsequent research has confirmed that oil price volatility remains a significant determinant of stock market dynamics, particularly in emerging economies, where energy dependence amplifies exposure[22]. Advanced methodologies, such as the nonlinear autoregressive distributed lag, and quantile-based connectedness models, further show that oil–stock linkages are nonlinear and state-dependent, with stronger effects during downturns[26].

These findings suggest that oil prices function not only as macroeconomic indicators but also as transition-related signals in a decarbonizing economy, in which energy costs and regulatory shifts are increasingly intertwined. For energy-importing markets such as Thailand, oil price movements may simultaneously influence exchange rates, capital flows, and investor sentiment, thereby contributing to volatility persistence.

2.2. Exchange-Rate Dynamics and International Spillovers

Exchange rates serve as a key transmission mechanism that links global shocks with domestic financial markets. Empirical evidence across developed and emerging markets shows that currency appreciation and depreciation affect sectoral competitiveness, capital mobility, and equity valuations[12,27-29)]. In financially integrated economies, exchange rate volatility often reflects external monetary conditions and poverty-price cycles[13)].

For semi-open markets such as Thailand, exchange rate movements are closely associated with oil import costs and global liquidity conditions. The literature highlights the importance of modeling exchange rate dynamics alongside commodity shocks when analyzing stock market volatility in emerging economies.

2.3. Policy Uncertainty and Climate-Related Risk

In parallel with these traditional determinants, research on policy uncertainty has become prominent. The economic policy uncertainty (EPU) index introduced by Baker, et al.[17)] provides a systematic measure of policy-related news intensity, linking uncertainty to financial volatility and investment behavior. Building on this approach, Gavriilidis[7)] developed the CPU index to capture the regulatory ambiguity surrounding environmental commitments.

Empirical studies show that an elevated CPU is associated with higher volatility and risk premia, particularly in advanced markets[8,20)]. These findings suggest that the CPU may act as a systematic risk factor in the capital markets. However, most empirical applications have focused on developed economies, and relatively few studies have examined how the CPU interacts with traditional macro-financial drivers in smaller emerging markets.

In emerging and frontier economies, the interaction between geopolitical risk (GPR), oil shocks, and CPU appears highly heterogeneous[23,30)]. Institutional strength, fiscal capacity, and financial depth condition market responses, implying that transition-related uncertainty may operate differently across structural contexts.

2.4. Nonlinearity and Predictability Under Uncertainty

Recent methodological advances have extended analyses from explanatory frameworks to predictive modeling. Hybrid approaches that combine econometric volatility models and machine learning techniques have demonstrated improved forecasting performance under complex and regime-dependent conditions[31,32)]. Studies in nonlinear finance further document that volatility and return dynamics may not be adequately captured by linear specifications, especially during periods of heightened uncertainty[15,33,34)].

This methodological stream suggests that capturing both conditional heteroscedasticity and nonlinear patterns is particularly relevant when markets are exposed to overlapping macro-financial and policy shocks.

2.5. Research Gaps

Despite the substantial progress, several gaps remain. First, most empirical studies examine oil price shocks, exchange rate dynamics, and policy uncertainty separately rather than within an integrated volatility framework. Second, the CPU has been analyzed predominantly in advanced economies, leaving ASEAN markets relatively underexplored. Third, while machine-learning approaches show promise in forecasting financial series, their comparative performance within volatility-based frameworks in emerging markets is limited.

Accordingly, a unified empirical approach that integrates CPU, macro-financial drivers, and nonlinear forecasting techniques within a single framework tailored to emerging economies is needed.

By incorporating the CPU, oil prices, exchange rates, and global equity returns into a GARCH–SVR hybrid structure, this study addresses these gaps. Rather than assuming a dominant role for any single factor, the analysis evaluates how transition-related uncertainty interacts with conventional macro-financial shocks to shape stock market volatility in Thailand. This study contributes to a broader understanding of financial stability during global green transitions.

3. Methodology

3.1. Data and Variables

This study employs monthly data spanning the period from January 2000 to September 2025. The sample ends in September 2025, reflecting the most recent monthly observations available at the time of data collection. The dataset integrates a combination of domestic financial indicators, global market variables, and multiple dimensions of macroeconomic and CPU to capture the determinants of stock market dynamics in the country.

The dependent variable is the monthly log return of the Thai index (RSET), which is derived from the Stock Exchange of Thailand index (SET). The explanatory variables include the Monthly log return of West Texas Intermediate crude oil price (RWTI), the monthly log return of the Thai Baht per U.S. dollar exchange rate (RTHB), and the monthly log return of the S&P 500 index

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Table 1: Description of Variables

Variable	Definition / Measurement	Source
RSET	Monthly log return of the Thai index	Investing.com
RWTI	Monthly log return of the West Texas Intermediate crude oil price	Investing.com
RTHB	Monthly log return of the Thai Baht per U.S.dollar exchange rate	Investing.com
RSP500	Monthly log return of the S&P 500 index	Investing.com
RGEPU	Monthly log change of the Global EPU index	PolicyUncertainty.com
RCPU	Monthly log change of the Climate Policy Uncertainty index	PolicyUncertainty.com
RGPR	Monthly log change of the Geopolitical Risk index	PolicyUncertainty.com

(RSP500), which serves as a benchmark for global commodity and financial market conditions. These market-based variables were obtained from investing. com. In addition, three global uncertainty indicators are incorporated to represent exogenous shocks: the Global Economic Policy Uncertainty Index (GEPU), Climate Policy Uncertainty Index, and Geopolitical Risk Index. These series were retrieved from policyuncertainty.com. Together, they capture variations in macroeconomic, climate-related, and geopolitical uncertainty that may influence investor sentiment and cross-border capital flows, thereby affecting Thailand's equity market.

All variables were converted into logarithmic monthly returns according to Eq. 1

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

where P_t is the level of each variable at time t. This transformation expresses all series in comparable percentage changes, helping to ensure stationarity in subsequent estimations. For uncertainty indices, the logarithmic change specification allows us to capture innovations in uncertainty rather than their levels, thereby aligning these variables with return-based financial data.

A detailed description of the variables, their corresponding symbols, and the data sources is provided in Table 1.

3.2. Models

To investigate how macroeconomic and policy-related factors affect Thailand's equity market, this study employs a sequential modeling strategy that combines linear and nonlinear specifications. The analytical framework begins with an ordinary least squares (OLS) baseline to establish contemporaneous relationships between stock market returns and a set of global and domestic variables. Subsequently, a generalized autoregressive conditional heteroscedasticity (GARCH (1, 1)) model with exogenous regressors was estimated to account for time-varying volatility[35]. Finally, the study evaluates out-of-sample forecasting performance by comparing the GARCH framework with a support vector regression model and a random walk (RW) benchmark[36,37]. This combination enables the assessment of both the dynamic volatility process and the predictive capability of machine learning techniques in financial return forecasting.

This study estimates a GARCH(1,1) model with exogenous regressors in the conditional mean equation and a Student's t innovation to accommodate leptokurtic return distributions, which are typical for emerging markets. The model specification is expressed in Eq. 2:

$$\begin{aligned} RSET_t = \mu + \beta_1 RWTI_t + \beta_2 RTHB_t + \beta_3 RSP500_t \\ + \beta_4 RGEPU_t + \beta_5 RCPU_t + \varepsilon_t \end{aligned}$$

$$\varepsilon_t = \sigma_t z_t, \quad z_t \sim N(0,1)$$

$$\sigma_t^2 = \omega + \alpha\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2 \quad (2)$$

The first equation models the conditional mean of stock market returns as a function of key macro-financial and uncertainty-related factors. The second and third equations describe the conditional variance dynamics, where α_1 captures the short-run reaction of volatility to new shocks and β_1 reflects its persistence. A value of $\alpha_1 + \beta_1 < 1$ indicates that volatility is mean-reverting, while a higher persistence suggests that shocks take longer to dissipate. The standardized residuals are assumed to follow a Student-t-(t) distribution to accommodate the heavy tails frequently observed in return data.

A rolling-window forecasting design was implemented to assess predictive accuracy. For each 48-month estimation window, one-step-ahead forecasts of $RSET_{t+1}$ are generated under three competing models:

- Random Walk: $\widehat{RSET}_{t+1} = RSET_t$
- GARCH: Forecasts derived from the conditional mean above (Eq. 1)
- Support Vector Regression: a linear ε-insensitive regression with cost parameter (C = 0.5) and tolerance (ε = 0.5)

Forecast errors are summarized using the root-mean-square error (RMSE) and mean-absolute-error (MAE)[38]. In addition, the absolute forecast errors ($|e_t|$) were compared across models using an analysis of variance

(ANOVA) F-test to determine whether the differences in predictive performance were statistically significant.

3.3. Empirical Hypotheses and Testing Strategy

Building on the theoretical framework and model specification, this study formulates two interrelated hypotheses concerning the effects of macroeconomic variables and uncertainty on Thai equity returns and the predictability of market dynamics. These hypotheses are grounded in the notion that financial markets in emerging economies often exhibit volatility clustering, persistence, and partial inefficiency, features that traditional linear models may fail to capture.

H1. Macroeconomic and uncertainty variables exert significant contemporaneous effects on Thai stock market returns, implying that volatility clustering and conditional heteroscedasticity are intrinsic to the data-generating processes.

To test H1, the conditional mean and conditional variance equations of the GARCH(1,1) model are jointly estimated using quasi-maximum likelihood (QML) under Student's t-distribution. The explanatory variables—RWTI, RTHB, RSP500, RGEPU, and RCPU— are exogenous regressors in the mean equation. The statistical significance of these coefficients indicates whether macroeconomic factors and uncertainty indices influence the Thai stock market contemporaneously. In addition, residual diagnostic tests, including the ARCH–Lagrange Multiplier (LM), Ljung–Box, and Jarque–Bera statistics, are used to detect conditional heteroscedasticity, serial correlation, and non-normality. The rejection of the null of homoscedastic residuals validates the presence of volatility clustering and supports H1.

H2. Models that explicitly capture conditional heteroscedasticity or nonlinear patterns, such as GARCH(1,1) and SVR, deliver superior out-of-sample predictive performance compared with the random-walk benchmark.

To evaluate H2, a rolling-window forecasting procedure was implemented with a 48-month estimation window and a one-month-ahead prediction horizon. Three competing frameworks are compared: the Random Walk model, which assumes no predictability; the GARCH(1,1) model estimated; and a Support Vector Regression model with a linear kernel ($C = 0.5$, $\varepsilon = 0.5$). Forecast accuracy was measured using the mean absolute error and root mean square error. The absolute forecast errors from the three models are then compared using a one-way ANOVA F-test, which tests the null hypothesis of equal predictive accuracies. The rejection of H_0 indicates that at least one model provides a statistically superior forecast. If the SVR consistently produces the lowest error metrics and significantly outperforms both the GARCH(1,1) and random walk benchmarks, H2 is supported, indicating that return dynamics under uncertainty may exhibit structured, albeit limited, predictability.

4. Research result

4.1. Descriptive Statistics and Correlation Matrix

Table 2 presents the descriptive statistics for all variables in return form over the period of 2000M1–2025M9. The mean monthly return of the Thai stock market is approximately 0.31%, accompanied by a relatively high standard deviation (6.14%), reflecting the substantial volatility that is typical of emerging markets. Among the explanatory variables, RWTI exhibits the largest dispersion (SD ≈ 10.9%), whereas RTHB displays comparatively lower variability (SD ≈ 2.05%). The uncertainty indicators (RGEPU, RCPU, RGPR) also show considerable dispersion, suggesting that innovations in global, climate, and geopolitical uncertainty occur in sizeable and irregular increments over the sample period.

Table 2: Descriptive Statistics (2000 M1 – 2025 M9)

Variable	Mean	Median	Min	Max	Std. Dev.
RSET	0.31	0.63	–35.92	21.2	6.14
RWTI	0.29	1.59	–78.19	63.33	10.9
RTHB	–0.05	–0.15	–8.04	8.28	2.05
RSP500	0.51	1.12	–18.56	11.94	4.42
RGEPU	0.52	–1.44	–48.21	75.06	18.8
RGPR	0.11	–0.89	–60.02	205.13	23
RCPU	0.46	–0.01	–170.14	123.27	37.2

Table 3: Correlation Matrix of Monthly Returns (2000 M1 – 2025 M9)

Variables	RSET	RWTI	RTHB	RSP500	RGEPU	RGPR	RCPU
RSET	1	0.330 ***	–0.480 ***	0.519 ***	–0.190 **	–0.118 *	–0.030
RWTI	0.330 ***	1	–0.192 **	0.320 ***	–0.148 *	–0.066	0.024
RTHB	–0.480 ***	–0.192 **	1	–0.327 ***	0.048	0.014	–0.012
RSP500	0.519 ***	0.320 ***	–0.327 ***	1	–0.186 **	–0.123 *	–0.052
RGEPU	–0.190 **	–0.148 *	0.048	–0.186 **	1	0.113 *	0.246 ***
RGPR	–0.118 *	–0.066	0.014	–0.123 *	0.113 *	1	0.014
RCPU	–0.030	0.024	–0.012	–0.052	0.246 ***	0.014	1

*Note: This table reports Pearson's correlation coefficients among the monthly log returns of the key variables. *p < 0.10, **p < 0.05, and ***p < 0.01 indicate statistical significance at conventional levels.*

The distributional properties indicate asymmetry and fat tails, consistent with the stylized facts of financial return series and support the use of a GARCH-type specification with Student's t innovations. The positive average returns for both the SET and S&P 500 further indicate that, despite episodes of market stress, equity markets experienced overall growth over a long sample horizon.

Table 3 reports the contemporaneous correlations. At the levels, the SET index is positively correlated with WTI ($\rho = 0.41$) and the S&P 500 ($\rho = 0.63$), and negatively correlated with the Thai Baht ($\rho = -0.69$). These patterns are consistent with Thailand's exposure to global commodity cycles and exchange rate dynamics, although correlation does not imply causality.

In return, RSET is positively correlated with RWTI ($\rho = 0.33$) and RSP500 ($\rho = 0.52$), indicating co-movement with oil prices and global equity conditions. The negative correlation between RSET and RTHB ($\rho = -0.48$) is consistent with the view that exchange rate depreciation is associated with weaker domestic equity performance during certain periods. Meanwhile, the relatively modest correlations between RSET and uncertainty indices (RGEPU, RCPU, RGPR) suggest that their influence may not operate through simple linear co-movements in returns, thereby motivating the conditional volatility analysis in the subsequent sections.

4.2. GARCH(1,1) Estimation and Diagnostics

Before estimating the conditional heteroscedastic model, the time-series properties of the return variables were examined using the augmented Dickey–Fuller (ADF) test. The results reject the null hypothesis of a unit root for the Thai stock market return, with a test statistic of approximately −7.41 ($p < 0.01$), confirming that monthly returns are stationary. This ensures that the data satisfy the key requirements for volatility modeling. In contrast, the residuals from the baseline ordinary least squares (OLS) regression exhibit conditional heteroscedasticity, as evidenced by the ARCH–LM test ($p = 0.04$). The presence of ARCH effects justifies the adoption of a GARCH-type specification to capture time-varying volatility in the equity return series.

Estimation was conducted using quasi-maximum likelihood (QML) under the framework of Bollerslev[39] with robust standard errors to correct for potential non-normality. Diagnostic tests confirmed that the fitted model was well-behaved. The Ljung–Box statistics for the standardized residuals and their squares showed no evidence of serial correlation or remaining ARCH effects ($p > 0.5$), whereas the Nyblom stability test suggested parameter constancy. The Jarque–Bera test rejected normality ($p < 0.01$), supporting the use of Student's t-distribution to accommodate the heavy tails frequently observed in financial returns.

The estimated volatility persistence ($\alpha_1 + \beta_1 \approx 0.93$) is high but below unity, indicating that volatility shocks are persistent and ultimately mean-reverting. Such persistence is consistent with the stylized characteristics of emerging equity markets and suggests sustained but stabilizing adjustment processes rather than explosive volatility dynamics.

The estimation results reported in Table 4 provide further insight into the determinants of Thai stock returns. RWTI and RSP500 exhibit statistically significant positive coefficients in the conditional mean equation. Quantitatively, a one-percent increase in oil price returns is associated with an increase of approximately 0.075 percent in Thai stock returns, whereas movements in the S&P 500 display an even stronger contemporaneous association. These findings are consistent with Thailand's exposure to global commodity cycles and international financial conditions.

RTHB shows a statistically significant negative coefficient, indicating that baht depreciation is associated with weaker equity performance during the period. This pattern aligns

Table 4: GARCH(1,1) with Exogenous Regressors — Estimates and Diagnostics

Panel A. Conditional Mean Equation (Student-t distribution; robust QML standard errors)			
Variable	**Beta**	**Robust SE**	**p-value**
Intercept	0.114	0.291	0.695
RWTI	0.0747	0.022	0.001
RTHB	−0.873	0.173	0.000
RSP500	0.3898	0.0836	0.000
RGEPU	−0.0033	0.0135	0.809
RCPU	−0.0063	0.0048	0.186
Panel B. Conditional Variance and Distribution Parameters			
Parameter	**Coefficient**	**Robust SE**	**p-value**
ω	1.561	1.14	0.171
α_1	0.147	0.079	0.065
β_1	0.788	0.113	0.000
Degree of freedom	5.74	1.737	0.001
Panel C. Model Diagnostics			
Statistic	**Value**	**Interpretation**	
Log-likelihood	−889.75		
AIC	5.8236		
BIC	5.9444		
Volatility persistence ($\alpha_1 + \beta_1$)	0.934 (< 1)	Mean-reverting volatility	
Ljung–Box (12 lags, residuals)	($p = 0.77$)	No serial correlation	
Ljung–Box (12 lags, squared residuals)	($p = 0.53$)	No remaining ARCH effects	
ARCH–LM (5 lags)	($p = 0.91$)	Homoscedastic residuals after GARCH	
Jarque–Bera	($p < 0.01$)	Fat tails → Student-t appropriate	

Notes. Notes: Estimates were obtained via quasi-maximum likelihood (QML) under Student's t-error. Robust (sandwich) standard errors are reported.

with the sensitivity of an open energy-importing economy to currency movements and external financing conditions. In contrast, the global economic policy uncertainty and climate policy uncertainty variables do not exhibit statistically significant contemporaneous effects in the conditional mean specification once macroeconomic financial factors are included. This result suggests that, within this framework, uncertainty measures do not operate through direct, linear return channels. Their role may instead be embedded within broader volatility conditions or interact with macroeconomic financial drivers in ways that are not fully captured by a contemporaneous mean specification.

The GARCH(1,1) results are broadly consistent with Hypothesis 1. The presence of ARCH effects in the OLS residuals, the significance of volatility parameters, and the absence of remaining serial dependence in the standardized residuals confirm the relevance of modeling conditional heteroscedasticity in the Thai stock return series. The diagnostic statistics indicate that the model adequately captures the volatility clustering and persistence in the data.

4.3. Out-of-Sample Forecast Evaluation and ANOVA

To assess the predictive performance of the competing models, an out-of-sample (OOS) forecasting exercise was conducted using rolling-window estimation. The window length is set to 48 months, consistent with prior studies examining medium-term market predictability in emerging economies[18,40,41]. For each step, the model is re-estimated with the most recent four years of data, and one-month-ahead forecasts of RSET ($RSET_{t+1}$) are generated. Three benchmark models were compared:

- Random walk model with no predictable components.
- GARCH(1,1) model with exogenous regressors, as estimated in Eq. (1).
- Support Vector Regression model with a linear kernel, C = 0.5, and ε = 0.5.

The forecast accuracy was evaluated using MAE and RMSE. In addition, the absolute forecast errors ($|e_t|$) were compared using a one-way ANOVA test to examine whether the differences in predictive performance across the models were statistically significant.

As reported in Table 5, the SVR model achieved the lowest MAE and RMSE values among competing specifications. The GARCH(1,1) model improves upon the Random Walk benchmark, whereas the SVR model delivers further reductions in forecast errors. The ANOVA F-statistic (7.42, p = 0.001) rejected the null hypothesis of equal predictive accuracy, indicating statistically significant differences across the three models.

In terms of magnitude, the reduction in RMSE from 6.34 (RW) to 5.48 (SVR) suggests a non-negligible improvement in the short-horizon forecasting performance. Although monthly equity returns remain inherently noisy, the nonlinear specification appears to capture the incremental structure in the data beyond that accounted for by conditional volatility.

To assess robustness, alternative SVR hyperparameters (C = 0.1, 0.5, 2, and 5; ε = 0.1 and 0.5) and kernel specifications (radial and polynomial) were evaluated. In addition, the rolling window was extended to 60 months, and five-fold cross-validation was applied to the training samples. Across these variations, the relative ranking of the models remained unchanged, with the SVR consistently producing the lowest forecast errors.

The out-of-sample results are consistent with Hypothesis 2: models incorporating nonlinear learning mechanisms provide improved predictive performance relative to both GARCH(1,1) and random walk benchmarks. Rather than implying a strong departure from market efficiency, these findings suggest that return dynamics under transition-related and macro-financial uncertainty may exhibit limited, but structured, predictability. In this sense, nonlinear methods complement traditional volatility models by capturing patterns that are not fully reflected in the linear conditional mean specifications.

5. Discussion and Contributions

5.1. Discussion

This study provides empirical evidence of how macroeconomic financial factors and transition-related uncertainty interact within the volatility dynamics of the Thai stock market. The results suggest that oil price fluctuations, exchange rate movements, and global equity conditions remain central drivers of return behavior, reflecting Thailand's structural exposure to external shocks. In contrast, climate policy and global policy uncertainty measures do not exhibit significant contemporaneous effects in the conditional mean specification once macroeconomic and financial variables are accounted for.

Table 5: Out-of-Sample Forecast Evaluation and ANOVA

Model	MAE	RMSE	Ranking	F-Statistic (ANOVA)	p-value
Random Walk (RW)	4.91	6.34	3	7.42	0.001
GARCH(1,1)	4.66	6.11	2		
SVR	4.12	5.48	1		

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This pattern indicates that transition-related uncertainty may operate within broader volatility conditions rather than through direct linear return channels. In other words, climate-policy uncertainty appears to form part of the overall uncertainty environment faced by investors, interacting with commodity and financial cycles to shape risk dynamics.

High but mean-reverting volatility persistence suggests that shocks to the Thai equity market have lasting effects but do not generate explosive instability in the long run. Such persistence is consistent with the behavior of semi-integrated emerging markets, where information adjustment may be gradual but ultimately stabilizes. The forecasting results further indicate that nonlinear learning approaches can capture the incremental structure in return dynamics under uncertainty by complementing traditional volatility models.

This study has several limitations. First, the use of monthly aggregate data may smooth short-lived reactions to policy announcements or commodity price shocks. Future research employing higher-frequency or sectoral data could provide more granular insights, particularly for industries directly exposed to transition risk. Second, the climate-policy uncertainty index reflects global policy sentiment rather than Thailand-specific regulatory communication. Developing a country-level CPU measure based on textual analysis of domestic policy documents would allow for more precise identification of local transition signals. Third, cross-country comparisons within ASEAN could further clarify how institutional structures and regional integration shape volatility responses to climate-related uncertainty.

5.2. Contributions

This study contributes to the literature in three ways. First, it integrates climate-policy uncertainty with traditional macro-financial variables within a unified volatility framework for an emerging ASEAN economy. Rather than assuming a dominant role for environmental policy shocks, the findings indicate that transition-related uncertainty interacts with conventional macro drivers in shaping return dynamics.

Second, the analysis highlights the importance of modeling conditional heteroscedasticity and nonlinear patterns when examining stock market behavior under structured uncertainties. The comparative forecasting results suggest that nonlinear specifications provide incremental predictive improvements relative to both the GARCH and random-walk benchmarks.

Third, this study offers empirical evidence relevant to sustainable finance in emerging markets. Although climate policy uncertainty does not emerge as a primary linear return determinant in this framework, its presence within the broader uncertainty environment underscores the importance of coherent and consistent policy communication, table and transparent transition strategies may help reduce ambiguity in investor expectations. For market participants, incorporating macro-financial and transition-related indicators into risk management frameworks may enhance portfolio resilience under evolving sustainability agendas.

These findings support the view that financial stability and environmental transition are interconnected through complex macro-financial channels. In emerging energy-importing economies such as Thailand, transition-related uncertainty appears to interact with commodity cycles and global financial conditions rather than operating in isolation. Therefore, understanding these interactions is essential for designing policies that balance sustainability objectives and macro-financial stability.

6. Conclusion

This study investigates the relationship between climate policy uncertainty, oil prices, exchange rate movements, global equity conditions, and stock market volatility in Thailand. Using a GARCH(1,1) framework with exogenous regressors and a support vector regression forecasting approach, the analysis evaluates both conditional volatility dynamics and short-horizon predictability under transition-related uncertainties.

The results indicate that oil price changes, exchange rate movements, and global equity performance exert significant contemporaneous associations with Thai stock returns, reflecting the country's exposure to external macro-financial conditions. Climate policy and global policy uncertainty measures, while present in the broader risk environment, do not emerge as primary linear return determinants within the conditional mean specification. Volatility persistence is high but mean-reverting, suggesting sustained yet stabilizing adjustment processes consistent with the stylized features of emerging markets. Out-of-sample comparisons further show that nonlinear learning models provide incremental improvements in forecasting accuracy compared to conventional benchmarks.

The findings highlight that transition-related uncertainty interacts with conventional macro-financial shocks rather than operating in isolation from them. For emerging energy-importing economies, such as Thailand, understanding these interactions is important for maintaining financial stability alongside sustainability commitments.

This study had several limitations that warrant consideration. The use of monthly aggregate data may mask short-term reactions to policy announcements or commodity shocks, and the climate policy uncertainty index may reflect global rather than country-specific regulatory signals. Future research could extend this framework by using higher frequency data, sector-level analyses, or locally constructed uncertainty measures. Comparative studies across ASEAN economies would also provide deeper insights into how institutional and structural differences shape volatility responses during the global green transition.

Nomenclature

ANOVA	Analysis of Variance
ASEAN	Association of Southeast Asian Nations
CPU	Climate Policy Uncertainty
GARCH	Generalized Autoregressive Conditional Heteroskedasticity
GEPU	Global Economic Policy Uncertainty
GPR	Geopolitical Risk
MAE	Mean Absolute Error
RCPU	Monthly log change of the Climate Policy Uncertainty index
RGEPU	Monthly log change of the Global EPU index
RGPR	Monthly log change of the Geopolitical Risk index
RMSE	Root Mean Squared Error
RSET	Monthly log return of the Thai index
RSP500	Monthly log return of the S&P 500 index
RTHB	Monthly log return of the Thai Baht per U.S.dollar exchange rate
RW	Random Walk
RWTI	Monthly log return of the West Texas Intermediate crude oil price
SET	Stock Exchange of Thailand index
SVR	Support Vector Regression

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