A COMPARATIVE STUDY OF ECONOMETRIC AND DEEP LEARNING MODELS FOR FORECASTING EXCHANGE-TRADE FUND PRICES IN THAI MARKET

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ABSTRACT
This study evaluates and compares the short-term forecasting performance of ten Exchange-Traded Funds (ETFs) in the Thai market using a comprehensive suite of econometric and deep learning models. The Mean Absolute Error (MAE) served as the primary performance metric. The results indicate that the Univariate LSTM model consistently outperformed all competing specifications in terms of predictive accuracy across nearly the entire ETF sample. In particular, the Univariate LSTM with a 30-day lookback window, relying solely on each ETF's own recent real prices proved to be the most effective and parsimonious forecasting structure. Beyond forecasting, the study integrates the superior model outputs into a portfolio allocation and hedging framework, yielding valuable practical insights. The optimal portfolio was concentrated in CHINA and DIV, reflecting their high risk-adjusted returns driven by strong predicted performance and low correlation. This portfolio achieved an expected daily return of 0.218% with a daily volatility of 0.345%. The subsequent hedging analysis employed ABFTH as the primary hedging instrument, demonstrating the highest Hedging Effectiveness (HE) for BMSCITH (28.1%), while CHINA and UBOT exhibited the lowest HE values. These findings highlight the potential of LSTM-based ETF forecasts for enhancing portfolio optimization and hedging strategies within the Thai market.
Keywords: Exchange-Traded Funds (ETFs), Thai financial market, Deep Learning Model, Econometric Model, LSTM, Mean Absolute Error (MAE), Portfolio Allocation, Hedging

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INTRODUCTION

In recent decades, Exchange-Traded Funds (ETFs) have emerged as one of the most transformative financial innovations, reshaping the landscape of modern investment. ETFs are collective investment vehicles that hold a diversified portfolio of assets such as equities, bonds and commodities that are traded on stock exchanges similarly to individual stocks. Their unique structure allows investors to trade throughout the day at market prices, offering real-time pricing, greater liquidity and lower management costs compared to traditional mutual funds, which are priced only once daily. Due to their accessibility, transparency and cost efficiency, ETFs have become a cornerstone of global financial markets and appealing to both retail and institutional investors. As ETFs continue to expand globally, accurate forecasting of their behavior has become increasingly vital for portfolio management, risk assessment and strategic investment decisions. ETFs not only reflect market sentiment but also respond dynamically to macroeconomic shifts, making them valuable instruments for understanding financial market movements. Early forecasting methods, such as exponential smoothing, linear regression, and ARIMA, provided limited insights as they often failed to account for the complex, time-varying relationships among multiple ETFs and between ETFs and macroeconomic factors (Bollapragada et al., 2013). Consequently, more advanced models that capture dynamic correlations, volatility clustering, and non-linear dependencies have gained attention in recent years. This study focuses on the Thai ETF market, aiming to enhance the understanding of its structure and dynamics by analyzing the predictive performance of multiple econometric and deep learning models. This study examines all Exchange-Traded Funds (ETFs) currently available in Thai market including 1DIV, ABFTH, BMSCG, BMSCITH, BSET100, CHINA, ENGY, GLD, TDEX, UBOT and UHERO. Collectively, these funds represent a broad spectrum of investment themes and sectors within Thailand's equity and capital markets. It is worth noting that UHERO is a relatively recent addition, having only commenced trading in 2022, which results in limited historical data for analysis. The models are designed to evaluate ETF prices using both log return and real price data, as well as the impact of macroeconomic factors such as GDP growth, interest rates and inflation rate. This research employs a total of thirty-nine models, grouped into four main methodological frameworks: GARCH-based models, CCC-GARCH-based models, DCC-GARCH-based models and LSTM-based deep learning models. The first group include GARCH, IGARCH, GARCHX and IGARCHX models, each estimated to use different input combinations such as ETF log returns, real prices and macroeconomic factors. GARCHX and IGARCHX extensions incorporate exogenous macroeconomic variables to assess their impact on ETF volatility and returns (Engle, Ghysels and Sohn, 2009). The second and third group extends to multivariate frameworks: CCC-GARCH and DCC-GARCH which model co-movements among ETFs. CCC assumes constant correlations, whereas DCC allows them to vary over time (Bollerslev, 1990; Engle, 2002). Their extended forms further integrate macroeconomic factors to analyze how external economic conditions affect ETF interrelationships (Engle, Ghysels and Sohn, 2009; Asgharian, Christiansen and Hou 2020). The fourth methodological framework applies deep learning, specifically Long Short-Term Memory (LSTM) neural networks. LSTM models address the limitations of conventional Recurrent Neural Networks (RNNs) by overcoming the vanishing gradient problem using gating mechanisms that preserve long-term dependencies. This makes LSTM particularly suitable for financial time series (Hochreiter and Schmidhuber 1997). In this study, both univariate and multivariate LSTM models with lookback windows of 30-time and 60-time steps are employed. By comparing thirty-nine model configurations spanning GARCH, CCC-GARCH, DCC-GARCH and LSTM frameworks, each with and without macroeconomic variables, this study aims to identify the most accurate and robust approach for forecasting ETF prices in the Thai market.

LITERATURE REVIEWS

Econometric Models

This study begins by employing foundational econometric models such as GARCH and CCC-GARCH models. GARCH model is widely used in financial time series analysis, captures the time-varying nature of volatility, a key characteristic of financial returns. By modeling volatility clustering, GARCH helps in understanding how past shocks influence current market uncertainty (Engle 2002). Building upon GARCH and CCC-GARCH model extends the analysis to a multivariate framework, allowing for the estimation of volatility across multiple assets while assuming constant correlations between them. Although the assumption of constant correlations can be restrictive, CCC-GARCH serves as a useful baseline for evaluating co-movements in financial assets and sets the stage for more advanced models (Bollerslev, 2008). However, the assumption of constant correlations in CCC-GARCH model led to the development of the Dynamic Conditional Correlation framework, which allows correlations to evolve over time. DCC-GARCH model has significantly enhanced the understanding of time-varying correlations by separating the estimation of individual asset volatilities from the modeling of dynamic correlations (Engle, 2002). This capacity for dynamic correlation modeling is crucial for analyzing the complex co-movements and risk transmission in modern financial instruments like ETFs, with recent research frequently employing asymmetric DCC models to investigate the dynamic connectedness of various ETF sectors (Çelik et al., 2022).

Macroeconomic Variables in Financial Market Analysis

This study incorporates three key economic indicators: interest rates, inflation rates and GDP growth, widely recognized for their impact on financial markets (Fama, 1981; Chen et al., 1986). Specifically, interest rates fundamentally drive asset pricing, influencing investment decisions, corporate borrowing costs and market liquidity. Research demonstrates a strong inverse relationship between interest rates and stock market performance with a 1% increase potentially causing significant long-run index declines (Muktadir-Al-Mukit, 2013). Furthermore, inflation rates affect purchasing power, corporate profitability and investor sentiment. The relationship between inflation and stock returns varies over time is negative in the short term but potentially positive long-term. The proxy hypothesis suggests inflation may indicate expected real economic activity rather than directly determining returns (del Camino Torrecillas & Jareño, 2013). Finally, GDP growth provides a broader perspective on economic performance and long-term trends, reflecting overall economic expansion through consumer demand, corporate earnings and capital flows. For instance, research across 18 developed and 18 emerging markets shows bank stock returns positively correlate with future GDP growth, suggesting banking sector performance serves as a leading economic indicator (Cole et al., 2008).

Deep Learning Model

The fourth methodological framework applies deep learning, specifically Long Short-Term Memory (LSTM) neural networks. This architecture was pioneered in 1997, developing to address a fundamental limitation of conventional Recurrent Neural Networks, their inability to effectively capture long-term dependencies in sequential data. LSTMs overcome this challenge through the introduction of specialized memory cells and gate mechanisms, which effectively control the flow of information and enable the network to learn which patterns to retain over extended periods. This characteristic makes the LSTM architecture particularly invaluable for analyzing financial time series, where meaningful correlations and dependencies often unfold over long horizons (Hochreiter and Schmidhuber, 1997). The value of advanced modeling is further evident in the application of hybrid approaches. A separate analysis of financial contagion between U.S. and Latin American markets during the COVID-19 pandemic was conducted by combining DCC-GARCH with LSTM networks. This hybrid approach effectively captured time-varying volatility while simultaneously learning long-term dependencies in financial data. Their analysis of S&P 500, BOVESPA, IPSA and MERVAL from 2014-2020 revealed significant U.S. contagion effects to most Latin American exchanges, with Argentina's MERVAL as an exception. Critically, the model demonstrated the ability to generate early warning signals during market turbulence (Chung et al., 2024).

RESEARCH METHODOLOGY

Research Framework

This study aimed to forecast the real price levels of ten Thai Exchange-Traded Funds (ETFs) using both traditional econometric and deep learning approaches. The econometric models employed include GARCH, GARCHX, IGARCH, IGARCHX, CCC-GARCH, CCC-GARCHX, CCC-IGARCH, CCC-IGARCHX, DCC-GARCH, DCC-GARCHX, DCC-IGARCH and DCC-IGARCHX while LSTM network represents deep learning framework. The objective is to evaluate which model most accurately captures the temporal dynamics and interdependencies among ETF prices, with and without macroeconomic factors. The dataset comprised daily opening prices of ten ETFs: TDEX, ENGY, CHINA, GLD, 1DIV, BMSCITH, BSET, BMSCG, UBOT and ABFTH spanning from April 2020 to April 2025. Four macroeconomic indicators were incorporated as explanatory variables: GDP growth, inflation rate, the 2-year and 10-year government bond yields (yield curves). Mean Absolute Error (MAE) was chosen as the evaluation metric because this study focuses on forecasting real ETF prices. MAE directly measures the average absolute deviation between predicted and actual prices in Thai Baht, making it more interpretable and suitable for assessing real-value forecasts compared to scale-free alternatives.

Econometric Methodology

Let P_t denote the observed price of an ETF at time t and let ε_t be the innovation term representing unpredictable shocks to the series. The conditional variance of these shocks denoted by σ_t^2 that evolves over time as a function of past information. Formally GARCH (1,1) can be represented as:

$P_t = \mu + \emptyset P_{t-1} + \varepsilon_t, \varepsilon_t|\Omega_{t-1} \sim (0, \sigma_t^2)$ (1)

$\sigma_t^2 = \alpha_0 + \alpha_1\varepsilon_{t-1}^2 + \beta_1\sigma_{t-1}^2, \alpha_1, \beta_1 > 0, \alpha_1 + \beta_1 < 1$ (2)

Where Ω_{t-1}denotes the information set available up to time $t-1$. The parameters α_1 and β_1 capture the short-term and long-term persistence of volatility. To incorporate exogenous effects such as macroeconomic shocks, the GARCHX model extends (2) by including additional explanatory variables X_{t-1}.

$\sigma_t^2 = \alpha_0 + \alpha_1\varepsilon_{t-1}^2 + \beta_1\sigma_{t-1}^2 + \gamma X_{t-1}$ (3)

Where X_{t-1} represents a vector of normalized macroeconomic indicators (e.g., GDP growth, yield curve slope and inflation rate).

To capture high persistence in volatility, Engle and Bollerslev introduced the Integrated GARCH (IGARCH) model by imposing (Engle and Bollerslev, 1986),

$\alpha_1 + \beta_1 = 1$ (4)

Substituting (4) into (2) yields a process where shocks to volatility have persistent effects and the conditional variance lacks mean reversion. IGARCHX variant directly extends (3) under the same restriction, incorporating macroeconomic influences without redefining the structure. Let $P_t = (P_{1t}, P_{2t}, \cdots, P_{nt})'$ denote the n-dimensional vector of ETF prices, and let H_t be the conditional covariance matrix of the innovation vector $\varepsilon_t = (\varepsilon_{1t}, \varepsilon_{2t}, \cdots, \varepsilon_{nt})'$

$H_t = D_tRD_t, D_t = diag(\sigma_{1t}, \sigma_{2t}, \cdots, \sigma_{nt})$ (5)

Where R is a constant correlation matrix. Each diagonal element σ_{it}^2 follows the univariate process in (2) or its GARCHX version in (3), depending on the specification. The conditional covariance between assets i and j is then obtained from,

$h_{i,j,t} = \rho_{ij}\sigma_{it}\sigma_{jt}, i \neq j$ (6)

Where ρ_{ij} denotes the constant correlation coefficient between ETFs i and j. CCC model in (5) assumes static correlations. To allow time-varying dependence, DCC framework defined the standardized residuals $v_t = D_t^{-1}\varepsilon_t$. The dynamics of the unnormalized correlation matrix Q_t evolve as,

$Q_t = (1-\alpha-\beta)\bar{Q} + \alpha v_{t-1}v'_{t-1} + \beta Q_{t-1}, \bar{Q} = \mathbb{E}[v_t v'_t], \alpha, \beta \geq 0, \alpha + \beta < 1$ (7)

The time-varying correlation matrix is then standardized as,

$R_t = diag(Q_t)^{-1/2} Q_t diag(Q_t)^{-1/2}$ (8)

Substituting (8) into (5) gives the conditional covariance matrix,

$H_t = D_t R_t D_t$ (9)

To include exogenous macroeconomic variables, the DCC-GARCHX extends (7) by augmenting it with an external term,

$Q_t = (1-\alpha-\beta)\bar{Q} + \alpha v_{t-1}v'_{t-1} + \beta Q_{t-1} + cX_{t-1}$ (10)

Given the estimated H_t from (9), Cholesky decomposition provides a convenient way to generate correlated innovations (Tsay, 2010).

$H_t = L_t L'_t, L_t\ Lower - triangular$ (11)

The correlated shock vector is then,

$\varepsilon_t = L_t z_t, z_t \sim \mathcal{N}(0, I_n)$ (12)

Substituting (12) into (1) yields the joint price forecast:

$P_{t+h} = \mu + \emptyset P_{t+h-1} + \varepsilon_{t+h}$ (13)

The one-step-ahead conditional mean forecast is given by $\hat{P}_{t+1} = \mu + \phi P_t$ To obtain probabilistic forecasts, a Monte Carlo procedure draws multiple paths of $z_t$and propagates them through (12)-(13). This approach ensures that forecasted prices respect both individual volatilities and cross-asset dependencies implied by the estimated H_t.

Deep Learning Methodology

To complement the econometric framework, LSTM neural network was applied to model nonlinear temporal dependencies in ETF prices. Let x_t denote the input vector of lagged ETF prices and macroeconomic variables and h_t the hidden state.

$f_t = \sigma\left(W_f[h_{t-1}, x_t] + b_f\right), i_t = \sigma(W_i[h_{t-1}, x_t] + b_i)$ (14)

$\tilde{c}_t = tanh(W_c[h_{t-1}, x_t] + b_c), c_t = f_t \odot c_{t-1} + i_t \odot \tilde{c}_t$ (15)

$o_t = \sigma(W_o[h_{t-1}, x_t] + b_o), h_t = o_t \odot \tanh(c_t)$ (16)

RESEARCH RESULTS

Preliminary Analysis of Data

Prior to model estimation, all ETFs and macroeconomic variables underwent extensive data validation and transformation to ensure consistency and comparability. Each ETF price series was examined for irregularities, structural breaks and missing observations. Outlier detection was implemented using a combination of Isolation Forest and Random Forest algorithms (Liu et al, 2008; Breiman, 2001), enabling the identification of extreme price fluctuations caused by non-fundamental market noise rather than genuine volatility movements. Descriptive statistics indicated that most ETF prices exhibited mild right-skewness and leptokurtic distributions, consistent with the stylized facts of financial time series (Cont, 2001). Volatility clustering was evident across all ETFs, particularly in equity-based funds such as CHINA, BMSCITH and BMSCG, suggesting persistent conditional heteroskedasticity. A characteristic well captured by GARCH-family models used in this study (Bollerslev, 1986). Overall, the dataset obtained after refinement provided a robust foundation for model estimation and forecasting. The resulting time series retained essential market characteristics volatility clustering, asymmetric shocks and cross-asset correlations while eliminating anomalies that could bias model performance.

Result of GARCH-types Model

All GARCH-type models satisfied standard parameter constraints, confirming model stability and strong volatility persistence across all ETFs. Models estimated using real ETF prices consistently produced lower forecasting errors than those using log returns, suggesting that price-level dynamics captured short-term movements more effectively and were less sensitive to market noise. IGARCH and IGARCHX models were applied exclusively to real price data rather than log returns. This design choice reflects their intended purpose to improve the precision of real price forecasts by capturing long-term volatility persistence directly in the level of the series. Because IGARCH assumes unit-root behavior in conditional variance, applying it to log returns would unnecessarily amplify short-term fluctuations, reducing forecast stability.

Table 1 Best GARCH-Type Model Specifications and Significant Variables for Each ETF

ETF	Model	Input	MAE	Significant Variable (p-value<0.05)
TDEX	GARCHX	Log Return, MEF	0.061	ENGY, 1DIV, BMSCITH, BSET
ENGY	IGARCH	Real Price	0.256	
CHINA	GARCH	Log Return	0.305	
GLD	GARCH	Log Return	0.062	
1DIV	GARCHX	Real Price, MEF	0.189	TDEX, ENGY, CHINA, GLD, BMSCITH, BSET, ABFTH, GDP, YC2Y, YC10Y, INF
BMSCITH	GARCHX	Log Return	0.081	TDEX, ENGY, CHINA, BSET
BSET	GARCHX	Log Return	0.274	TDEX, BMSCITH, BMSCG
BMSCG	IGARCHX	Real Price	0.171	TDEX, ENGY, CHINA, GLD, 1DIV, BMSCITH, BSET, UBOT, ABFTH
UBOT	GARCH	Log Return	0.458	
ABFTH	IGARCHX	Real Price	3.724	TDEX, ENGY, CHINA, GLD, 1DIV, BMSCITH, BSET, UBOT

Note: MEF refers to Macroeconomic Factor, YC2Y refers to 2-Year Yield Curve, YC10Y refers to 10-Year Yield Curve and INF refers to Inflation Rate

Result of CCC-GARCH type Model

All CCC-GARCH-type models produced stable and statistically valid parameter estimates, confirming consistent variance and correlation structures across ETFs. Both CCC-GARCH and CCC-GARCHX were tested using log return and real price inputs. Including macroeconomic factors in the CCC-GARCHX specification slightly improved forecasting accuracy. In contrast, CCC-IGARCHX and CCC-IGARCH were applied only to real price data for the same reason as in the IGARCHX and IGARCH framework.

Table 2 Best CCC-GARCH Type Model Specifications and Significant Variables for Each ETF

ETF	Model	Input	MAE	Significant Variable (p-value<0.05)
TDEX	CCC-GARCH	Log Return	0.306	
ENGY	CCC-GARCHX	Log Return, MEF	0.243	BMSCITH
CHINA	CCC-GARCH	Log Return	0.219	
GLD	CCC-GARCHX	Log Return, MEF	0.184	No Significant Variable
1DIV	CCC-GARCHX	Log Return	0.211	TDEX, ENGY, BMSCG
BMSCITH	CCC-GARCHX	Log Return	0.290	TDEX, ENGY, CHINA, BSET
BSET	CCC-GARCHX	Log Return	0.466	TDEX, BMSCITH, BMSCG
BMSCG	CCC-GARCHX	Log Return, MEF	0.459	1DIV, BSET
UBOT	CCC-GARCHX	Log Return	2.817	CHINA, ABFTH
ABFTH	CCC-GARCH	Log Return	21.590	

Result of DCC-GARCH type Model

All DCC-GARCH-type models generated stable and statistically significant parameters, confirming valid dynamic correlation structures across ETFs. Both DCC-GARCH and DCC-GARCHX were estimated using log return and real price inputs. Incorporating macroeconomic factors in DCC-GARCHX specification improved forecasting performance by allowing dynamic correlation to respond to changes in economic conditions. DCC-IGARCHX and DCC-GARCH were implemented only with real price data for the same reason stated in the IGARCHX and IGARCH framework.

Table 3 Best DCC-GARCH Type Model Specifications and Significant Variables for Each ETF

ETF	Model	Input	MAE	Significant Variable (p-value<0.05)
TDEX	DCC-GARCHX	Log Return	0.232	ENGY, 1DIV, BMSCITH, BSET
ENGY	DCC-GARCHX	Log Return	0.302	No Significant Variable
CHINA	DCC-IGARCH	Real Price	0.164	
GLD	DCC-GARCHX	Log Return, MEF	0.053	TDEX
1DIV	DCC-GARCHX	Log Return, MEF	0.168	TDEX, BMSCG
BMSCITH	DCC-GARCHX	Log Return	0.154	TDEX, ENGY, CHINA, BSET
BSET	DCC-IGARCH	Real Price	0.240	
BMSCG	DCC-GARCH	Log Return	0.180	
UBOT	DCC-IGARCH	Real Price	0.623	
ABFTH	DCC-IGARCH	Real Price	2.991	

Result of LSTM-type Model

Both univariate and multivariate LSTM architectures were implemented using input data consisting of real price, log return and macroeconomic factors with 30-day and 60-day lookback windows.

Table 4 Best LSTM-Type Model for Each ETF Base on MAE

ETF	Model	Input	Lookback(day)	MAE
TDEX	Univariate LSTM	Real Price	30	0.022
ENGY	Univariate LSTM	Real Price	30	0.025
CHINA	Univariate LSTM	Real Price	30	0.014
GLD	Univariate LSTM	Real Price	60	0.007
1DIV	Univariate LSTM	Real Price	30	0.031
BMSCITH	Univariate LSTM	Real Price	30	0.024
BSET	Univariate LSTM	Real Price	60	0.031
BMSCG	Univariate LSTM	Real Price	30	0.025
UBOT	Univariate LSTM	Real Price	30	0.108
ABFTH	Univariate LSTM	Real Price	60	0.955

Overall Result Summary

The comparative analysis across all model families consistently revealed that the Univariate LSTM model significantly outperformed traditional econometric approaches in terms of short-term ETF price forecasting accuracy. This conclusion is strongly supported by Mean Absolute Error metrics, where the best-performing traditional models GARCH-Type, CCC-GARCH Type and DCC-GARCH Type generally failed to achieve the predictive precision demonstrated by LSTM architecture. For instance, while Univariate LSTM model consistently yielded the lowest MAE values for most ETFs, the most successful traditional model was the DCC-GARCHX for GLD, which achieved an MAE of 0.053 but this level of performance was an exception. Most other key ETFs exhibited higher MAEs, such as TDEX (0.061 for the best GARCHX model), CHINA (0.164 for the best DCC-GARCHX model) and BSET (0.240 for the best DCC-IGARCH model). This outcome confirms that the Univariate LSTM model utilizing Real Price data as input is the superior tool for pure predictive accuracy. However, a detailed review of the econometric models specifically their Significant Variables (p-value < 0.05) provides indispensable qualitative insights into market structure and volatility interdependence that LSTM model being a 'black box' does not explicitly offer. GARCH-Type models clearly delineate the sources of volatility spillover. The volatility dynamics for TDEX (MAE 0.061) were significantly influenced by the price fluctuations of ENGY, 1DIV, BMSCITH and BSET. More notably, the highly volatile ETF 1DIV (MAE 0.189) modeled with the GARCHX specification, required an extensive set of explanatory variables spanning the volatility of other ETFs (TDEX, ENGY, CHINA, GLD, BMSCITH, BSET and ABFTH) as well as key macroeconomic factors (GDP, YC2Y, YC10Y and INF), establishing GARCH family's unique capability to explicitly capture the contribution of external risk and market-wide spillovers to conditional volatility. This pattern is reinforced by the multivariate CCC-GARCH and DCC-GARCH specifications which are designed to model these dependencies directly. The best DCC-GARCH type model for BMSCITH (MAE 0.154) showed significant co-movement with TDEX, ENGY, CIINA and BSET, underscoring the strong cross-market dependencies inherent in the ETF ecosystem. Conversely, the simplest relationships were sometimes the most predictive the superior performance of GLD in DCC-GARCHX model was attributed to its volatility being only significantly influenced by TDEX.

In conclusion, while the configuration employing a 30-day lookback window in Univariate LSTM model exhibited the strongest overall performance, underscoring its superior capability to capture nonlinear and complex temporal dependencies inherent in price dynamics for forecasting purposes, the traditional econometric models despite their higher MAEs remain invaluable for financial analysis by explicitly identifying and quantifying the specific market linkages and volatility spillover effects that govern the ETF market.

Portfolio Allocation and Hedging Strategy

This section details the construction of the Optimal Portfolio and the associated Hedging Strategy. Portfolio Allocation utilizes the results from the best predictive model to determine the asset weights that maximize the Sharpe Ratio, thereby achieving the highest risk-adjusted return. The Hedging Strategy then quantifies the necessary hedge ratios (betas) for each ETF against a designated defensive asset to evaluate its effectiveness in mitigating systematic risk.

Table 5 Hedging Analysis and Effectiveness of ETFs Against ABFTH Bond ETF

ETF	Expected Return (% per day)	Optimal Portfolio Weight	Final Hedge Ratio	Hedging Effectiveness
TDEX	0.029%	0%	-6.141	17.9%
ENGY	-0.104%	0%	-4.991	14.2%
CHINA	0.245%	54.239%	-1.349	2.2%
GLD	-1.087%	9.669E-13 %	2.011	4.7%
1DIV	0.187%	45.761 %	-4.124	5.9%
BMSCITH	0.025%	0%	-8.533	28.1%
BSET	-0.215%	0%	-6.047	16.6%
BMSCG	0.022%	0%	3.619	5.4%
UBOT	0.049%	2.655E-11 %	6.450	3.0%
ABFTH	-0.301%	0%		

This superior forecasting accuracy was subsequently leveraged to derive Expected Daily Returns for each ETF. While ETFs such as CHINA (0.245%) and IDIV (0.187%) exhibited the highest positive expected returns, GLD (-1.087%) and ABFTH (-0.301%) showed substantial negative expected returns. Utilizing these predicted returns, the optimal portfolio allocation derived under Modern Portfolio Theory principles focused exclusively on these two highest-performing assets: CHINA (54.239%) and 1DIV (45.761%) (Markowitz, 1952). This allocation yielded a highly desirable Expected Portfolio Return of 0.218% daily with a corresponding Portfolio Volatility of 0.345% daily. Furthermore, a crucial application of the forecasting results involved assessing risk management through a hedging analysis against the ABFTH Bond ETF. The analysis of the Final Hedge Ratio and Hedging Effectiveness (Kroner and Sultan, 1993) demonstrated that the highest efficiency in reducing portfolio volatility was observed when hedging BMSCTIH (28.1% effectiveness) and TDEX (17.9% effectiveness) with ABFTH. Interestingly, while most ETFs required a Negative Hedge Ratio GLD (+2.011) and UBOT (+6.450) required a Positive Hedge Ratio, reflecting their unique correlation structures relative to bond markets. However, the low effectiveness observed for CHINA (2.2%) and UBOT (3.0%) indicates that the ABFTH Bond ETF is an ineffective hedging instrument for the volatility inherent in these specific assets. In conclusion, the successful integration of the highly accurate LSTM forecasts not only facilitated the construction of a high-performing optimal portfolio but also provided actionable, data-driven insights into cross-asset hedging dynamics within the Thai market.

DISCUSSION & CONCLUSION

This study examined the forecasting performance of econometric and deep learning models for Thai Exchange-Traded Funds, providing both methodological and practical insights. The results clearly indicated that traditional GARCH-family models while effective in describing volatility clustering and correlation dynamics were consistently outperformed by deep learning approaches in terms of predictive accuracy. Univariate LSTM with real price input and 30-day lookback demonstrated the highest short-term forecasting precision, confirming that recent price behavior alone contains sufficient temporal information for accurate prediction. In contrast, macroeconomic variables such as yield curve, GDP and inflation exhibited limited short-term influence, suggesting that ETF movements in emerging markets like Thailand are more sensitive to market sentiment and cross-asset interactions than to macro fundamentals. Portfolio optimization based on LSTM forecasts produced economically reasonable and well-balanced allocations with CHINA and 1DIV dominating due to their favorable risk-adjusted returns. The hedging analysis further revealed that ABFTH served as an effective risk-reduction instrument primarily for BMSCITH and TDEX, while proving less efficient for CHINA and UBOT due to their weak bond correlations. Overall, the findings highlight that Univariate LSTM provide a robust and parsimonious alternative to econometric models for ETF forecasting and portfolio construction. Traditional GARCH-type models remain valuable for volatility and correlation analysis but their direct use for price prediction is limited. Future research should consider hybrid frameworks that integrate econometric interpretability with the adaptive learning capability of neural networks, as well as the inclusion of sentiment and microstructure data to further enhance forecasting performance.

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