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The risk-return relationship in Vietnam's stock market: A weak connection

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ABSTRACT

Vietnam's stock market is one of the fastest-growing in Asia, marked by high volatility and a strong presence of retail investors. This study examines the relationship between volatility, commonly viewed as a measure of risk, and expected returns, challenging the traditional belief that higher risk leads to higher returns. The findings show a statistically significant but economically weak connection, suggesting that volatility has a limited influence on returns. The results highlight the unique characteristics of Vietnam's market, where speculative trading, retail investor behavior, and structural constraints play a larger role than standard risk-return patterns. Instead of aligning with the capital asset pricing model (CAPM), returns are mainly driven by short-term momentum and market sentiment. This study contributes to asset pricing literature by stressing the need for market-specific models in emerging economies and offers insights for investors and policymakers seeking to strengthen market performance and stability.

1. Introduction

Vietnam's stock market has emerged as a dynamic frontier in Asia, driven by rapid growth and a unique investor base. As of March 2025, its total market capitalization reached approximately USD 294 billion, with the Ho Chi Minh Stock Exchange contributing USD 219 billion, the Hanoi Stock Exchange USD 15.1 billion, and the Unlisted Public Company Market (UPCoM) market USD 59.8 billion (AFC, 2025; Goutte et al., 2025). Retail investors dominate, accounting for over 90% of daily trading volume. This injects liquidity but also increases volatility due to their short-term, speculative trading behavior (VIR, 2024). Vietnam's retail-heavy market, combined with rapid economic growth, challenges traditional financial theories. However, it faces issues like price instability, uneven liquidity, and a regulatory framework struggling to match the market's complexity. Macroeconomic shocks, such as oil price fluctuations or monetary policy shifts, further intensify these challenges (Narayan and Narayan, 2010; Truong et al., 2023).

The Capital Asset Pricing Model (CAPM) suggests that higher systematic risk, measured by volatility, should lead to higher expected returns, assuming rational investors and efficient markets (Sharpe, 1964; Lintner, 1965). Nevertheless, Vietnam's high volatility, retail-driven trading, and structural inefficiencies question the applicability of this model. Regulatory constraints, including limited leverage, high transaction costs, and short-selling restrictions, may weaken the risk-return relationship (Nguyen et al., 2015). Despite Vietnam's growing importance, research on its stock market, particularly the link between volatility and expected returns, remains limited. Prior studies often focus on macroeconomic factors or market efficiency (Batten and Vo, 2014), leaving a gap in understanding risk-return dynamics in this context.

This study explores the relationship between volatility and expected returns in Vietnam's stock market. The central research question is: To what extent does volatility influence expected returns? The proposed Hypothesis 1 (H1) suggests that volatility has a positive but weak effect on expected returns. This assumption reflects the speculative behavior and inefficiencies of Vietnam's stock market, which may challenge the assumptions of classical financial theory. The purpose of this study is to provide empirical evidence on the risk–return dynamics in Vietnam, contributing valuable insights for both investors and policymakers. It also aims to broaden the discussion of asset pricing in emerging markets, where market structures often differ from those in developed economies. The article is structured as follows: Section 2 reviews theoretical background, Section 3 describes methodology,

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Section 4 reports findings, Section 5 discusses results, and Section 6 concludes.

2. Theoretical background and hypothesis development

The risk-return relationship is foundational to financial theory, guiding investment decisions under uncertainty. Markowitz (1952) introduced portfolio theory, demonstrating that diversification optimizes the balance between expected returns and risk, measured as variance or standard deviation. Rational investors aim to maximize returns for a given risk level, with volatility as a primary risk metric. The CAPM, developed by Sharpe (1964) and Lintner (1965), formalized this by linking expected returns to systematic risk through beta—the asset's return covariance with the market divided by market variance. CAPM assumes efficient markets where only systematic risk is rewarded, as diversification eliminates idiosyncratic risk, predicting a positive correlation between volatility and returns. Multi-factor models extended this framework: Fama and French (1993) added size and value factors, while Carhart (1997) incorporated momentum, reinforcing that higher volatility drives higher returns. These principles are widely applied in asset pricing and portfolio management in developed markets.

Empirical studies, however, reveal deviations. In developed markets, Ang et al. (2006) identified the low-volatility paradox, where low-volatility stocks outperform high-volatility ones on a risk-adjusted basis, contradicting CAPM. The phenomenon is explained by market frictions and behavioral biases: leverage-constrained investors overbid high-volatile stocks, inflating prices and lowering returns, while arbitrage limits persist (Frazzini and Pedersen, 2014). Baker et al. (2011) attributed this to mispricing from investor preference for lottery-like stocks, weakening the risk-return correlation. In emerging markets, challenges are greater. Harvey (1995) found beta less predictive of returns due to dominant country-specific risks, such as political or macroeconomic instability. Zaremba and Czapkiewicz (2017) confirmed that traditional models struggle in less efficient emerging European markets, where volatility's role in driving returns diminishes. These markets often exhibit higher information asymmetry and liquidity constraints, further complicating risk-return dynamics.

Advancements in machine learning have enhanced risk-return analysis. Extreme gradient boosting (XGBoost), developed by Chen and Guestrin (2016), is an ensemble method using decision trees to model complex, non-linear data patterns. Unlike traditional models like linear regression or generalized autoregressive conditional heteroskedasticity (GARCH), XGBoost captures variable interactions, making it suitable for financial forecasting in volatile markets. It integrates inputs like price trends, volume, and macroeconomic indicators to predict stock returns, offering a flexible alternative to parametric models (Henrique et al., 2019). This approach strengthens risk-return analysis, particularly in emerging markets where traditional assumptions falter, improving forecast accuracy. By addressing non-linearities and incorporating diverse data, machine learning refines risk assessment, enabling more robust investment strategies in both developed and emerging markets.

Vietnam's stock market offers a distinct setting for testing risk-return theories, driven by rapid growth and retail investors dominating over 90% of daily trading volume (VIR, 2024). Unlike developed markets led by institutional investors, Vietnam resembles speculative emerging markets. Batten and Vo (2014) found that liquidity constraints and investor sentiment significantly shape Vietnam's market, indicating returns may not align with CAPM's volatility-return link. Regulatory limits, such as restricted leverage, high transaction costs, and short-selling bans, distort pricing mechanisms (Nguyen et al., 2015). Vo and Phan (2019) observed herding behavior among retail investors chasing short-term gains, potentially decoupling returns from volatility. These structural and behavioral traits make Vietnam a key case for evaluating CAPM's volatility-return correlation in a speculative emerging market.

Research on Vietnam's risk-return dynamics remains sparse. Loc et al. (2006) studied firm efficiency in Vietnam's transitional economy but overlooked stock market risk-return relationships. While Nartea et al. (2017) explored extreme returns in China, Vietnam's retail-driven market and regulatory context are underexplored. The low-volatility paradox, where low-volatility stocks outperform, is established in developed markets (Ang et al., 2006), but its applicability to Vietnam's volatile, speculative market is unclear. This gap, contrasted with extensive research in mature markets and limited studies in other emerging markets, highlights the need to examine Vietnam specifically. CAPM predicts a strong volatility-return link, but Vietnam's market traits suggest this may not hold, requiring a context-specific hypothesis.

Thus, Hypothesis 1 (H1) states: In Vietnam's stock market, volatility has a positive but weak effect on expected returns. This aligns with CAPM's premise but reflects speculative trading and market inefficiencies, echoing the low-volatility paradox and emerging market trends. XGBoost is used to test H1, leveraging its capacity to model non-linear relationships and capture complex signals like price momentum and volume surges, surpassing traditional models (Chen and Guestrin, 2016; Henrique et al., 2019). This study challenges universal risk-based pricing, offering insights into Vietnam's market and contributing to theoretical and practical advancements in an emerging frontier.

3. Methodology

This study uses a dataset from the Vietnam all share (VNAllShare) index, chosen for its broad coverage of Vietnam's equity market, including stocks from the Ho Chi Minh Stock Exchange, Hanoi Stock Exchange, and UPCoM market. The dataset contains 2,475 daily observations from February 4, 2015, to January 24, 2025. It is split into three subsets for analysis: the training set, 70% of the data from February 4, 2015, to May 16, 2022, calibrates model parameters; the validation set, 15% from May 17, 2022, to April 8, 2023, refines parameters; and the test set, 15% from April 9, 2023, to January 24, 2025, evaluates model performance on new data (AFC, 2025; Hastie et al., 2009). Variables include weighted market return from adjusted index values, trading volume, index closing values, total market capitalization, number of stocks, quarterly GDP growth, and monthly CPI-based inflation, reflecting market and economic dynamics.

This study employs the XGBoost algorithm to forecast market returns and test Hypothesis 1, which examines the relationship between forecasted volatility and expected returns. XGBoost constructs an ensemble of decision trees, each correcting prior errors, to predict returns using features such as past returns and trading volume. It optimizes an objective function balancing accuracy and complexity, using squared error loss and regularization to prevent overfitting. A second-order gradient approach captures non-linear patterns, suitable for Vietnam's retail-driven market with complex behavioral dynamics, as noted by Chen and Guestrin (2016).

For volatility forecasting, the study compares four traditional GARCH models: Exponential generalized autoregressive conditional heteroskedasticity (eGARCH), Glosten-Jagannathan-Runkle generalized autoregressive conditional heteroskedasticity (GJR-GARCH), Markov-switching generalized autoregressive conditional heteroskedasticity (MS-GARCH), and Dynamic conditional correlation generalized autoregressive conditional heteroskedasticity (DCC-GARCH), as described by Nelson (1991), Glosten et al. (1993), Haas et al. (2004), and Engle (2002). These models estimate volatility, with eGARCH capturing leverage effects, GJR-GARCH addressing asymmetric shocks, MS-GARCH modeling regime switches, and DCC-GARCH handling dynamic correlations. Models are trained on data from February 4, 2015, to May 16, 2022, validated from May 17, 2022, to April 8, 2023, with grid search for parameter tuning, and tested from April 9, 2023, to January 24, 2025, using hyperparameters such as a tree depth of 4, learning rate of 0.05, and 100 trees for XGBoost, following the approach of Wang and Liang (2024). The XGBoost model is defined as

$$\hat{y}_i = \sum_{k=1}^{K} f_k(x_i) \tag{1}$$

where, $\hat{y}_i$ is the predicted return, x_i is the feature vector, and f_k is the k-th tree's contribution. The eGARCH model is

$$\ln(\sigma_t^2) = \omega + \alpha\left(\frac{|\epsilon_{t-1}|}{\sigma_{t-1}} - \sqrt{\frac{2}{\pi}}\right) + \gamma\frac{\epsilon_{t-1}}{\sigma_{t-1}} + \beta\ln(\sigma_{t-1}^2) \tag{2}$$

where, σ_t^2 is the conditional variance, ϵ_{t-1} is the error, and ω, α, γ, β are parameters. Hypothesis 1 is tested via regression:

$$\text{Forecasted Return}_t = \beta_0 + \beta_1 \text{Forecasted Volatility}_t + \varepsilon_t \tag{3}$$

where, β_1 assesses volatility's effect, reflecting investor decisions in a sentiment-driven market, as noted by Vo and Phan (2019).

4. Empirical results

Table 1 summarizes descriptive statistics for key VNAllShare index variables, revealing a volatile market. The daily weighted return averages 0.1374% with a standard deviation of 1.75%, indicating significant fluctuations typical of emerging markets. Positive skewness at 0.3703 and high kurtosis at 5.2653 suggest frequent extreme returns. The Jarque-Bera test confirms non-normal distribution, consistent with patterns observed in emerging markets by Cont (2001). Trading volume averages 1,945,846 shares but has a median of 202,050, with extreme skewness at 15.31 and kurtosis at 236.31, signaling retail-driven surges tied to market events, as noted by Ané and Geman (2000).

The total market capitalization shows a slight negative skewness (-0.2365) and negative kurtosis (-1.4661), suggesting occasional declines, likely caused by delistings and indicating structural changes. Together, these features point to the strong role of retail investors and possible market inefficiencies, providing the basis for testing Hypothesis 1.

Table 1: Descriptive statistics of the VNAllShare index

Variable	Mean	Median	SD	Min	Max	Skewness	Kurtosis
Weighted_return	0.001374	0.000839	0.0175	-0.0873	0.1288	0.3703	5.2653
Index	956.61	895.64	280.95	520.13	1,586.29	0.3160	-0.9683
Volume	1,945,846	202,050	24,425,711	45,950	437,150,000	15.31	236.31
Total_marketcap	1,010,176,006	1,069,385,932	600,851,163	91,512,686	1,920,068,234	-0.2365	-1.4661

SD: Standard deviation

Table 2 presents regression results testing Hypothesis 1, analyzing the relationship between forecasted returns from XGBoost and forecasted volatility from GARCH models. The volatility coefficient of 0.141888 is positive and significant at the 5% level with a p-value of 0.012, confirming a positive relationship, but the R^2 of 0.01699 shows volatility explains only 1.7% of return variation. A Pearson correlation coefficient of 0.130 indicates weak linkage, supporting Hypothesis 1.

Fig. 1 depicts this relationship, displaying a positive yet dispersed regression line, consistent with weak risk-return ties in emerging markets (Zaremba and Czapkiewicz., 2017). Fig. 1 shows a scatter plot with a positive but dispersed regression line, reflecting a weak correlation between forecasted volatility and returns. Table 3 compares forecasted and actual Sharpe ratios for Vietnam's market, showing the forecasted ratio at 0.0536 versus an actual ratio of 0.1460, representing a 172% difference.

This significant gap demonstrates that traditional risk-return models substantially underestimate Vietnam's market performance. This finding aligns with the low-volatility paradox documented by Ang et al. (2006), where low-volatility assets outperform high-volatility ones. According to Frazzini and Pedersen (2014) and Baker et al. (2011), this phenomenon in Vietnam is driven by three key factors: speculative trading behaviors, leverage constraints, and regulatory restrictions that shape market dynamics.

Table 2: Regression of forecasted returns on forecasted volatility

Parameters	Coefficients	Standard error	t-statistic	p-value
Constant (β_0)	-0.002197	0.001422	-1.545	0.124
Volatility (β_1)	0.141888	0.056129	2.528	0.012*
R^2	0.01699	-	-	-
Correlation coefficient	0.130	-	-	-

*: Significance at the 5% level

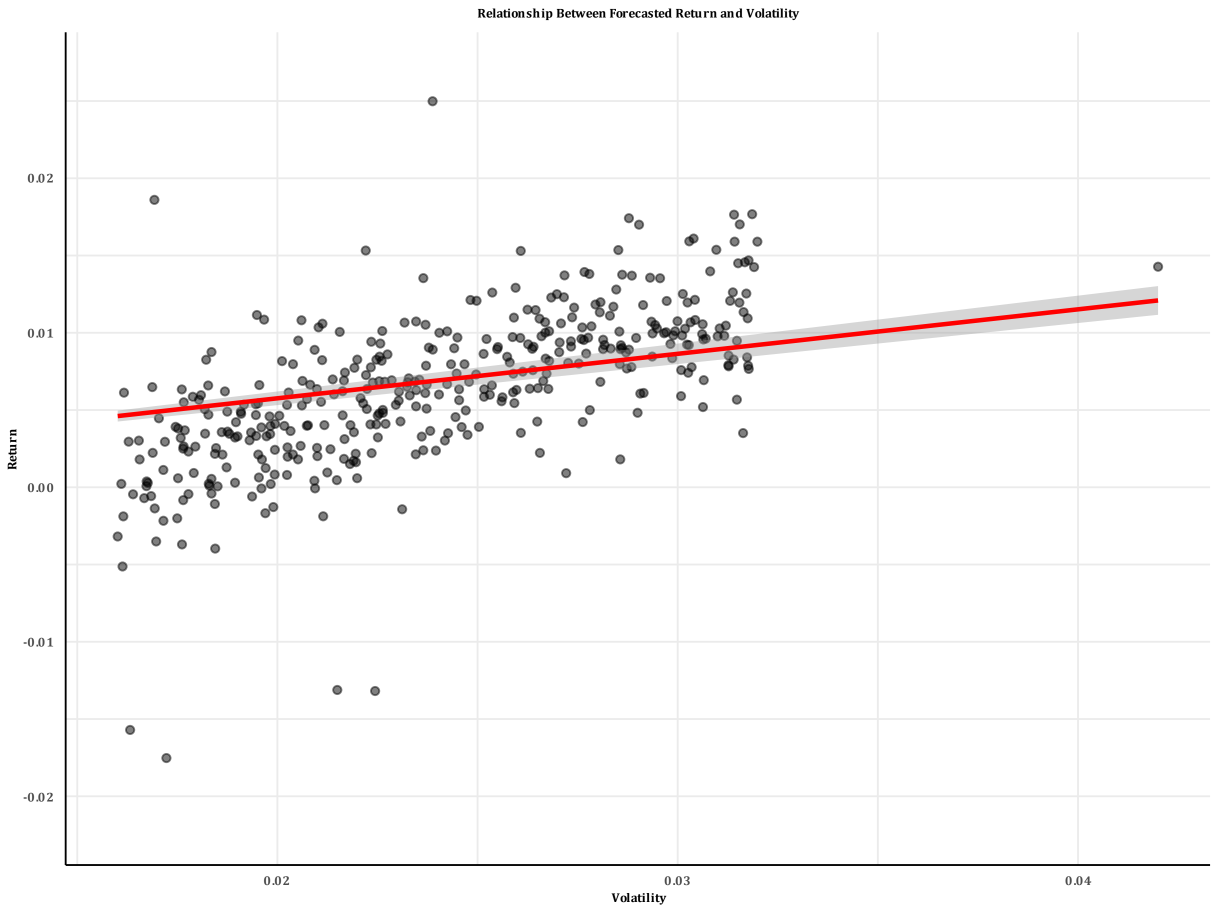

Fig. 1: Relationship between forecasted volatility and forecasted returns

Table 3: Comparison of forecasted and actual Sharpe ratios

Index	Value
Forecasted Sharpe ratio	0.0536
Actual Sharpe ratio	0.1460
Difference	172%

A feature importance analysis of the XGBoost model reveals that short-term momentum factors dominate predictive power, contributing 74.8% of total importance, with the 5-day rolling mean at 41.5%, followed by 1-day and 2-day lagged returns. Lagged volatility contributes merely 1.8%, further confirming the weak risk-return relationship in this market. Fig. 2 visually illustrates this dominance, highlighting momentum's critical role in Vietnam's inefficient market as documented by Rouwenhorst (1999). The analysis shows a rapid decline in lagged return importance, indicating a short information half-life of approximately 5 days, suggesting market participants quickly incorporate new information but primarily focus on recent price movements rather than fundamental factors.

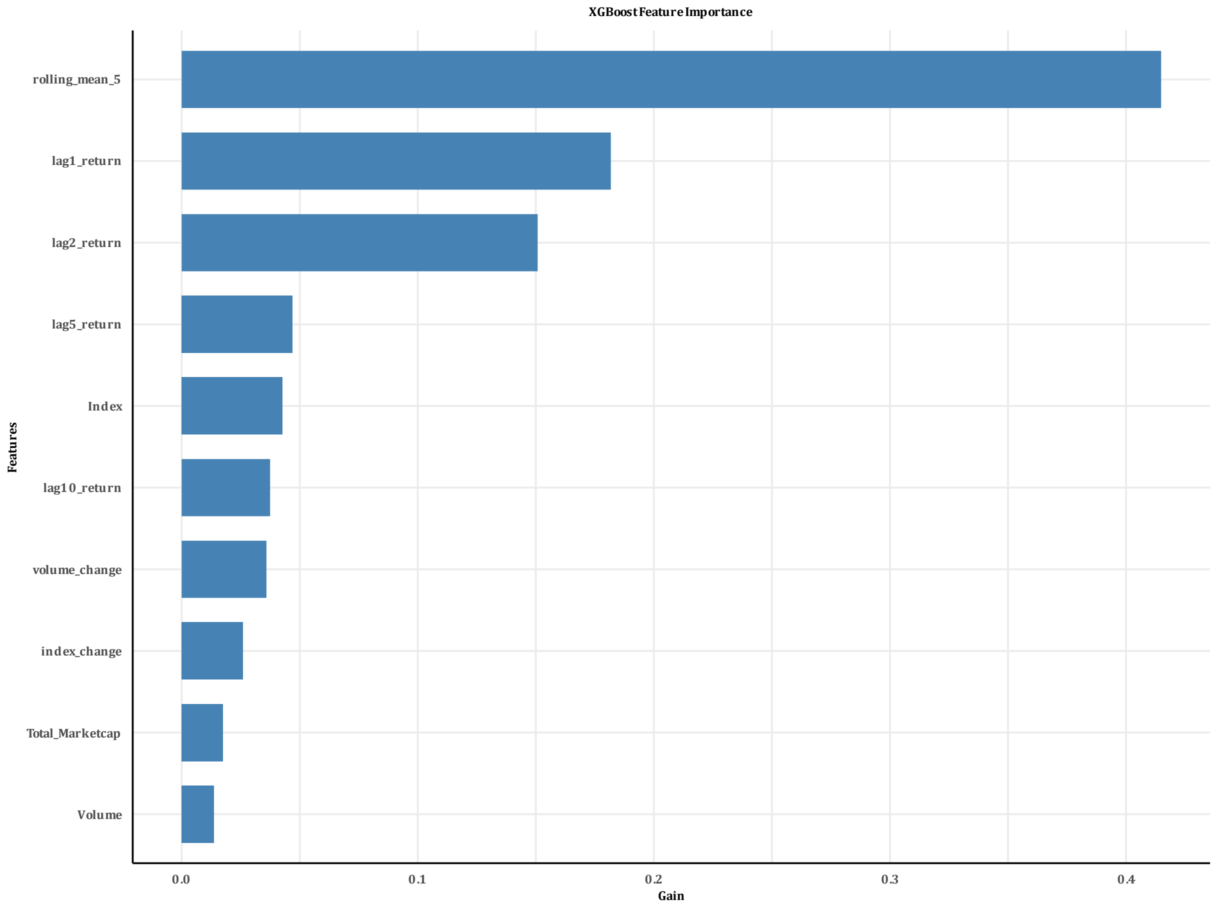

Fig. 2: Feature importance in the XGBoost model

Based on the feature importance analysis shown in Fig. 2, we evaluate forecasting accuracy for VNAllShare index daily returns and volatility during the test period spanning April 9, 2023, to January 24, 2025. Table 4 presents performance metrics comparing XGBoost with traditional models, including GARCH(1,1) as our benchmark and four GARCH variants: eGARCH, GJR-GARCH, MS-GARCH, and DCC-GARCH. For return forecasting, XGBoost demonstrates superior performance with Root mean square error (RMSE) at 0.008706, mean absolute error (MAE) at 0.006529, and R^2 at 0.235, significantly outperforming eGARCH with RMSE at 0.0120, which ranks as the best among GARCH models.

In volatility forecasting, eGARCH achieves the highest accuracy with RMSE at 0.009167, MAE at 0.006781, and R^2 at 0.312, substantially better than the GARCH(1,1) benchmark with RMSE at 0.0143. These findings, in conjunction with the correlation analysis in Table 2, provide strong support for Hypothesis 1, confirming the weak relationship between returns and volatility in this market, with return predictability predominantly driven by momentum factors as previously documented by Vo and Phan (2019).

Table 4: Forecasting performance for returns and volatility

Model	Return RMSE	Return MAE	Return R^2	Volatility RMSE	Volatility MAE	Volatility R^2
XGBoost	0.008706	0.006529	0.235	N/A	N/A	N/A
GARCH (1,1)	0.0150	0.0110	0.12	0.0143	0.0103	0.185
eGARCH	0.0120	0.0090	0.18	0.009167	0.006781	0.312
GJR-GARCH	0.0140	0.0105	0.14	0.014258	0.010243	0.187
MS-GARCH	0.0160	0.0120	0.10	0.017621	0.012945	0.128
DCC-GARCH	0.0145	0.0108	0.13	0.014302	0.010294	0.185

The GARCH family of models captures different patterns of market volatility. The eGARCH model is particularly effective in describing the reverse leverage effect, where positive shocks raise volatility more than negative shocks. This phenomenon is linked to retail investor overreaction, as noted by Nelson (1991) and Vo and Phan (2019). The GJR-GARCH and DCC-GARCH models are well-suited for modeling asymmetric shocks and dynamic correlations between assets. The MS-GARCH model identifies high-volatility regimes that occur in 33.77% of the sample period, marked by strong shock impacts but weak persistence. Fig. 3 shows these regimes, illustrating transitions between high- and low-volatility states, consistent with Haas et al. (2004).

Fig. 4 presents the stable return forecasts of XGBoost, while Fig. 5 compares forecast stability across models. These results confirm that XGBoost produces more consistent forecasts than traditional

GARCH models, supporting the findings related to Hypothesis 1.

Specifically, Fig. 3 illustrates the volatility regime shifts in the VNAllShare index based on the MS-GARCH model. Fig. 4 highlights the stability of XGBoost return forecasts across different market conditions. Fig. 5 contrasts the performance of XGBoost return forecasts with GARCH volatility forecasts, emphasizing the superior consistency of XGBoost.

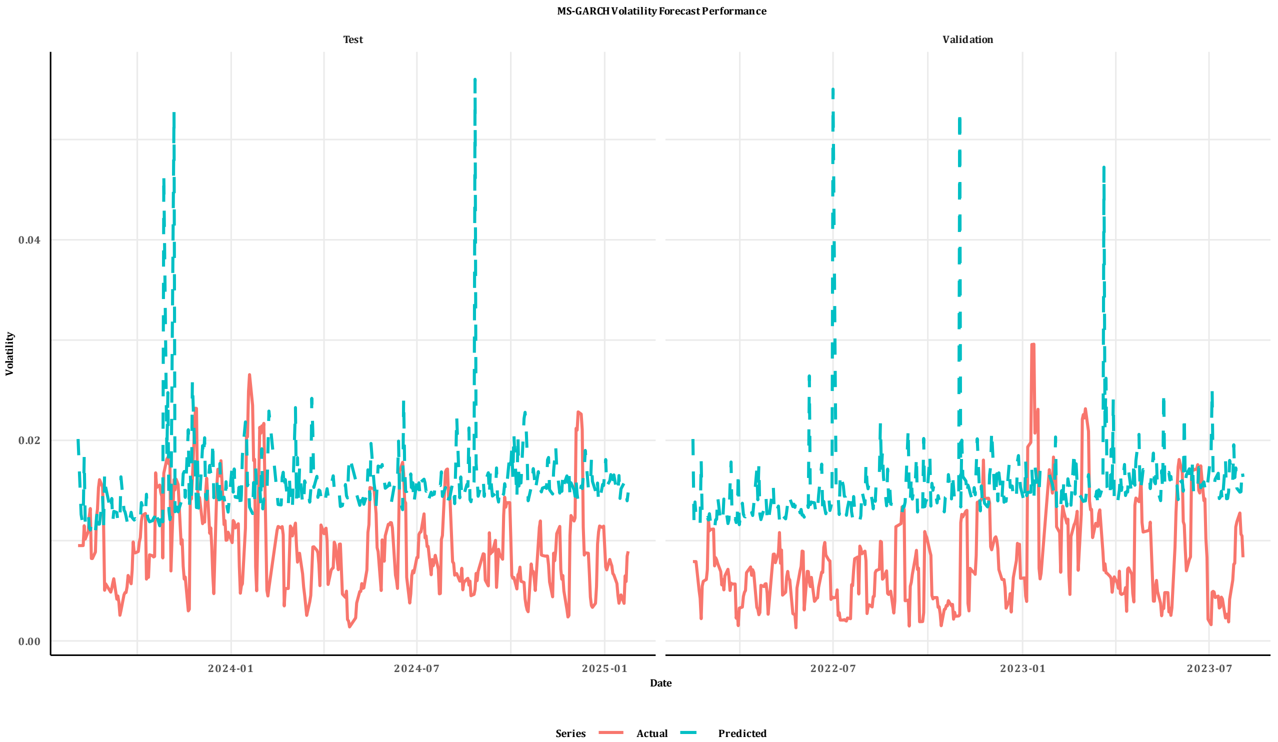

Fig. 3: Volatility regimes over time

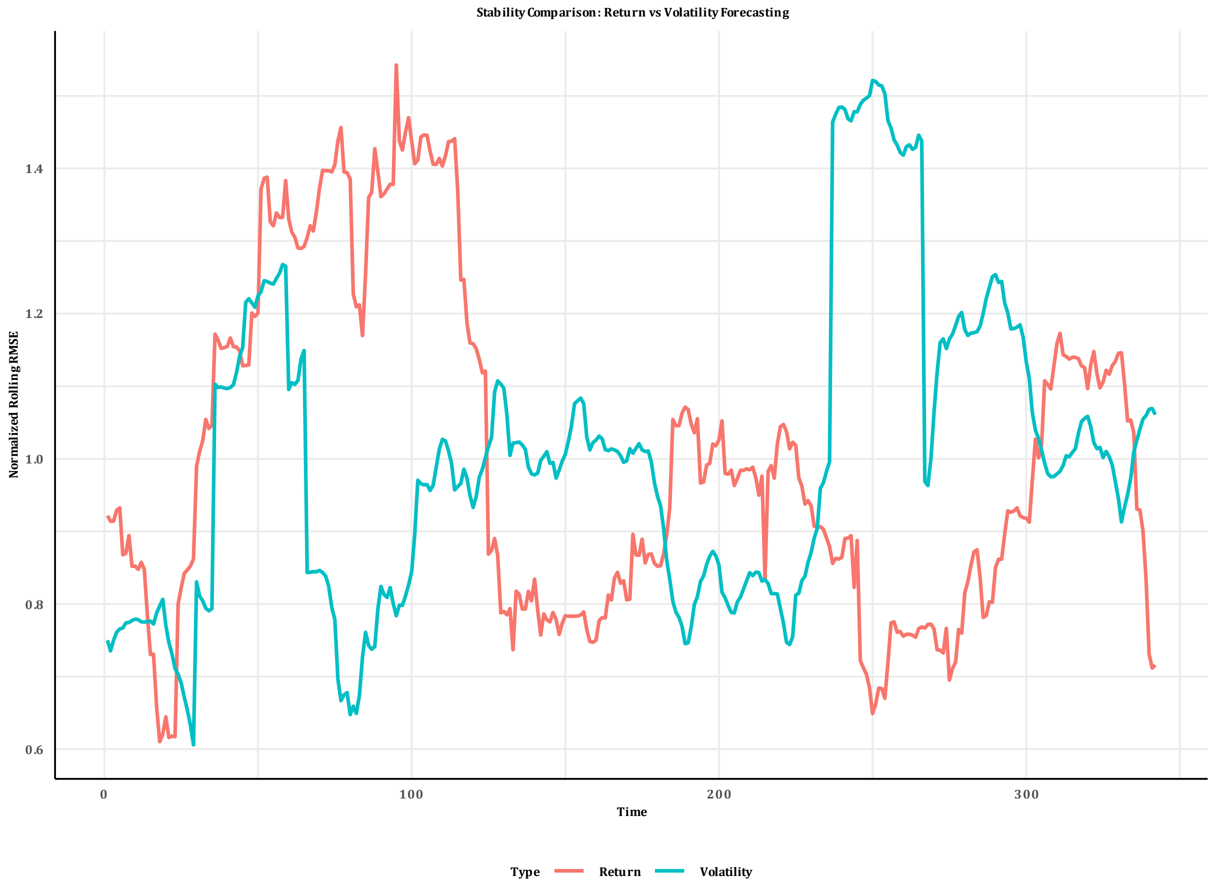

Fig. 4: Stability of return forecasts

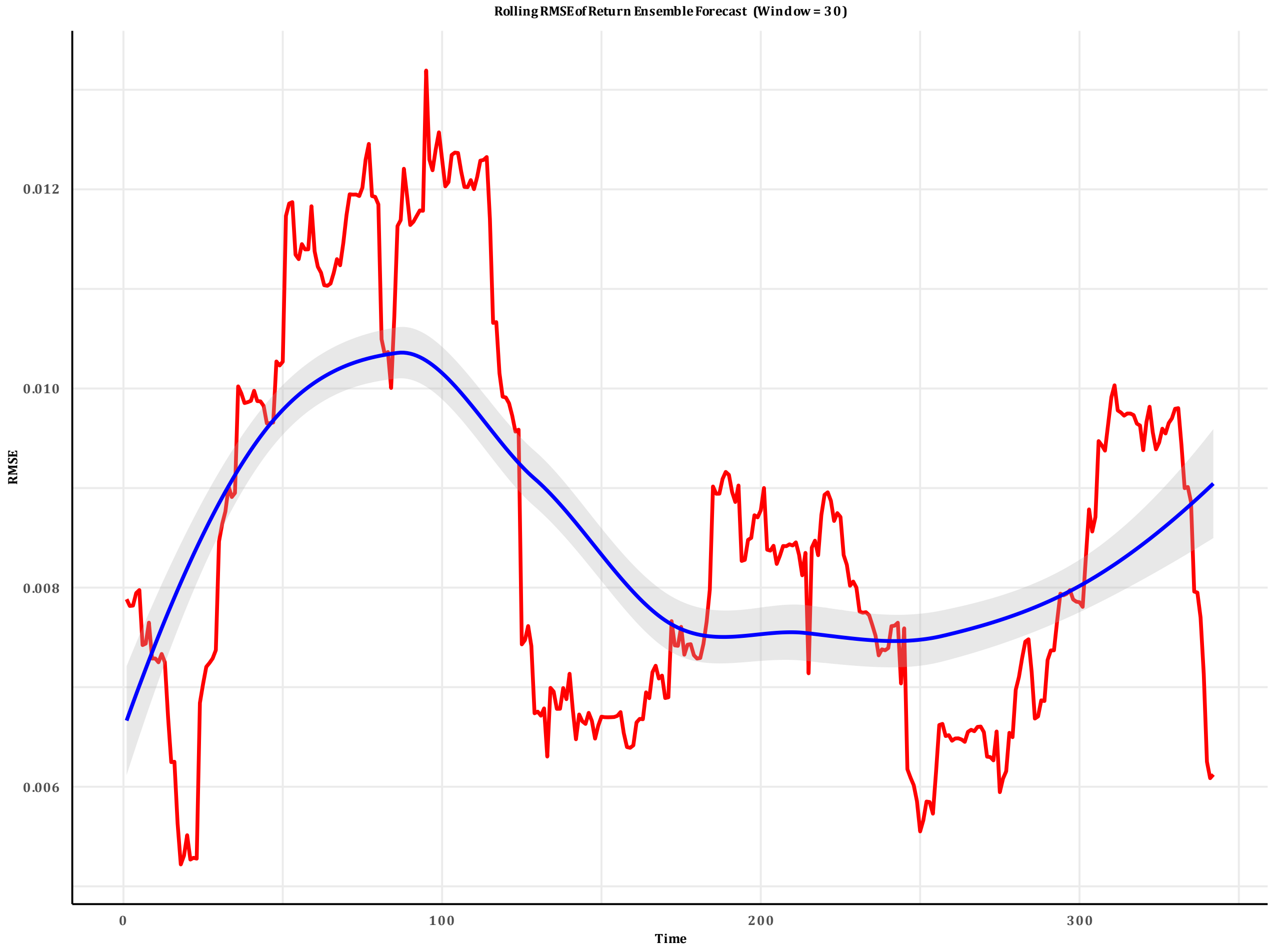

Fig. 5: Comparison of stability between return and volatility forecasts

To verify the stability of our findings, we analyze the volatility-return relationship and forecasting performance across the pre-COVID period from February 4, 2015, to December 31, 2019, and the post-COVID period from January 1, 2022, to January 24, 2025. Table 5 reports regression results extending to Table 2 and RMSE, MAE for XGBoost for returns, and eGARCH for volatility. The volatility coefficient remains positive and significant in both periods, with pre-COVID at 0.132, p = 0.018, and post-COVID at 0.150, p = 0.009, but demonstrates consistently weak explanatory power with R^2 at 0.020 and 0.014, respectively, further supporting Hypothesis 1. XGBoost maintains robust return forecasting performance with pre-COVID RMSE at 0.0083 and post-COVID RMSE at 0.0091, while eGARCH continues to excel in volatility forecasting with pre-COVID RMSE at 0.0088 and post-COVID RMSE at 0.0096.

These results reflect remarkably stable performance despite the increased market uncertainty in the post-COVID environment, as documented by Vo and Phan (2019) and Nguyen (2023).

Table 5: Robustness check across pre- and post-COVID periods

Period	Volatility coefficient	p-value	R^2	XGBoost return RMSE	XGBoost return MAE	eGARCH volatility RMSE	eGARCH volatility MAE
Pre-COVID	0.132	0.018	0.020	0.0083	0.0062	0.0088	0.0064
Post-COVID	0.150	0.009	0.014	0.0091	0.0069	0.0096	0.0071

To analyze XGBoost's return forecasting drivers, we utilize Shapley additive explanations (SHAP) values on the test set spanning April 9, 2023, to January 24, 2025. Unlike Fig. 2's feature importance, Fig. 6's SHAP summary plot reveals how specific feature values influence predictions, with red indicating high values, blue indicating low values, and positive/negative SHAP values showing directional impact. The 5-day rolling mean dominates, with high values boosting predicted returns by up to 0.35 SHAP units and low values reducing them by approximately 0.10 units, demonstrating strong short-term momentum effects. High 1-day and 2-day lagged returns also increase predictions with SHAP values of 0.15 and 0.12, respectively, capturing price persistence. Volume change and index value show moderate, mixed effects with SHAP values ranging from 0.08 to -0.03. Notably, lagged volatility's minimal impact, with SHAP values averaging -0.01 for high values, confirms Hypothesis 1's weak volatility-return relationship, contributing merely 1.8% to predictions. Macroeconomic indicators like GDP growth and CPI inflation show negligible SHAP values near zero.

5. Discussion

This study provides significant insights into the unique dynamics of Vietnam's stock market, revealing that volatility has a limited impact on expected returns, while short-term price trends, particularly recent movements, dominate return predictability. These findings challenge the applicability of traditional risk-return models, such as the CAPM, in a retail-driven, speculative market. By leveraging advanced machine learning techniques, the research underscores the need for tailored approaches to understand emerging markets. This section explores the implications for investors, policymakers, and asset pricing scholarship, addressing the practical and theoretical significance of these results.

5.1. Implications for investors

The marginal influence of volatility on returns indicates that strategies relying solely on risk assessment may yield suboptimal outcomes in Vietnam's stock market. With volatility explaining only a small fraction of return variation, investors should prioritize momentum-based strategies that capitalize on recent price trends. For instance, portfolios targeting stocks with strong performance over the past five days could outperform those focused on minimizing volatility. Analysis of model outputs reveals that the 5-day rolling mean is the primary driver of return predictions, suggesting that investors can exploit short-term price persistence to enhance returns. However, the market's sensitivity to sentiment-driven fluctuations necessitates robust risk management, such as stop-loss mechanisms, to mitigate sudden price drops. Additionally, minimum-variance portfolios, which reduce exposure to high-volatility stocks, may offer superior risk-adjusted returns, aligning with the low-volatility paradox observed in other markets.

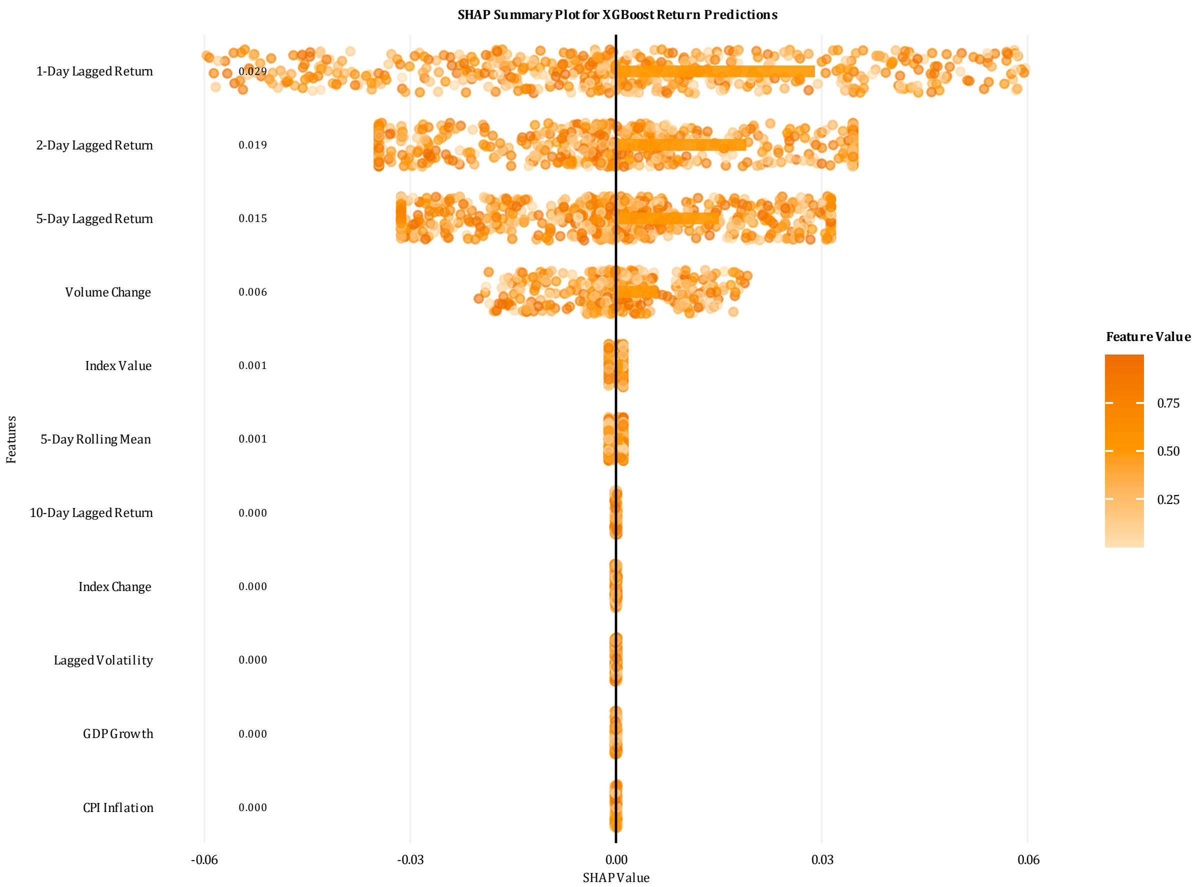

Fig. 6: SHAP summary plot for XGBoost return predictions

5.2. Policy recommendations to address speculative trading

The limited role of volatility and the prevalence of speculative trading highlight structural inefficiencies in Vietnam's stock market, driven by its retail-heavy composition. To curb excessive speculation and enhance market efficiency, policymakers should implement targeted reforms. First, relaxing margin trading restrictions, with a maximum leverage ratio of 2:1 for qualified investors, could improve liquidity while limiting systemic risks. Second, introducing short-selling for large-cap stocks, with a 20% margin requirement, would enable price corrections and reduce speculative bubbles caused by retail investor overreactions. Third, the State Securities Commission should launch investor education programs, such as workshops on fundamental analysis offered through partnerships with universities and brokerage firms, to encourage long-term investment strategies. These measures would foster a more balanced market, attract institutional investors, and align Vietnam with global financial standards.

5.3. Contributions to asset pricing scholarship

The subdued volatility-return relationship and the dominance of short-term momentum challenge the universality of traditional asset pricing models. This study contributes to the literature by demonstrating that behavioral factors, such as retail investor psychology, outweigh systematic risk in shaping returns in emerging markets. The application of XGBoost, which outperformed benchmark models like GARCH and simpler linear regression in forecasting returns, highlights the value of machine learning in capturing complex market patterns. Interpretability analysis, including SHAP values, clarifies that recent price trends drive predictions, while volatility plays a minimal role. These findings advocate customized models that incorporate local market dynamics, advancing the discourse on asset pricing in speculative environments. The robustness of these results across pre- and post-COVID periods further validates their reliability, offering a foundation for future research.

5.4. Limitations and future research directions

While the findings provide robust insights, the study's reliance on the VNAllShare index limits its ability to capture sector-specific dynamics. Future research could analyze industries like banking or real estate to identify distinct risk-return profiles. Incorporating sentiment indicators from social media or news analytics could further elucidate the role of investor psychology in price movements. Additionally, exploring high-frequency trading data or intraday volatility may reveal short-term dynamics not captured in daily data. These directions would complement the current findings, offering a more granular understanding of Vietnam's financial landscape.

6. Conclusion

This study confirms that short-term momentum factors, driven by speculative retail investor behavior, primarily determine return predictability in Vietnam's stock market, reflecting its retail-driven nature and supporting Hypothesis 1. Volatility has a marginal effect on expected returns, challenging conventional risk-return frameworks. These findings emphasize the need to develop asset pricing models tailored to behavioral dynamics in emerging markets.

To enhance market efficiency, policymakers should consider easing margin trading restrictions, introducing short selling with safeguards, and implementing investor education programs to reduce speculative trading and encourage long-term strategies. Future research should investigate alternative risk measures and sector-specific factors to better understand return drivers in Vietnam's evolving market.

List of abbreviations

CAPM	Capital asset pricing model
CPI	Consumer price index
DCC-GARCH	Dynamic conditional correlation generalized autoregressive conditional heteroskedasticity
eGARCH	Exponential generalized autoregressive conditional heteroskedasticity
GDP	Gross domestic product
GJR-GARCH	Glosten-Jagannathan-Runkle generalized autoregressive conditional heteroskedasticity
GARCH	Generalized autoregressive conditional heteroskedasticity
MAE	Mean absolute error
MS-GARCH	Markov-switching generalized autoregressive conditional heteroskedasticity
RMSE	Root mean square error
SHAP	Shapley additive explanations
UPCoM	Unlisted public company market
VNAllShare	Vietnam all share index
XGBoost	Extreme gradient boosting

Compliance with ethical standards

Conflict of interest

The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

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