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Research Article

A Heterogeneous Multi-Task Deep Learning Approach for Geopolitical Risk Prediction and Cross-Country Heterogeneity in ASEAN Equity Markets

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Abstract: Modeling the asymmetric transmission of geopolitical shocks across structurally diverse emerging markets presents a severe computational challenge. Traditional homogeneous deep learning approaches often suffer from negative transfer and base-rate bias when applied to cross-country financial prediction. To address this, we propose the Heterogeneous Multi-Task Spatiotemporal Network (HMT-STN), a structurally adaptive framework that integrates country-specific embeddings, heterogeneous task decoupling, and a Focal Loss mechanism. Evaluated on a daily panel dataset of ASEAN-4 equity markets (2016–2026), the HMT-STN is designed to simultaneously optimize directional return classification and volatility regression. Comprehensive evaluations using Precision, Recall, F1-score, and AUC-ROC demonstrate the framework's superior discriminative power, notably achieving 66.21% accuracy and an AUC-ROC of 0.68 in Thailand, a highly volatile transitional market. Rigorous ablation studies confirm that Focal Loss prevents catastrophic performance collapse in noisy environments, while country embeddings successfully isolate market-specific idiosyncrasies. Furthermore, SHAP (SHapley Additive exPlanations) analysis reveals a tripartite spectrum of cross-country heterogeneity, providing model-based feature attributions that are consistent with established economic theories of market segmentation and geopolitical risk sensitivity. Collectively, this study demonstrates that explicitly modeling cross-country heterogeneity through heterogeneous multi-task learning offers a robust, interpretable, and computationally efficient paradigm for geopolitical risk assessment in fragmented global economies.

Keywords: ASEAN Equity Markets; Cross-Country Heterogeneity; Deep Learning; Emerging Financial Markets; Explainable AI (SHAP); Geopolitical Risk Prediction; Heterogeneous Multi-Task Learning; Volatility Forecasting.

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1. Introduction

The Association of Southeast Asian Nations (ASEAN) has transitioned from a peripheral emerging market to a central node in the global "China+1" supply chain restructuring, amplifying its exposure to a complex sequence of geopolitical and macroeconomic shocks [1]. Recent events including the Russia-Ukraine conflict, Middle East tensions, and Red Sea disruptions (2024–2026) have triggered significant volatility spillovers across international financial systems [1], [2]. For emerging economies, geopolitical risk does not transmit uniformly; it cascades through specific channels such as the VIX (global risk sentiment) and Brent Oil prices, impacting commodity-exporting nations fundamentally differently than financial hubs. Understanding this asymmetric transmission carries profound implications for global portfolio diversification, monetary policy coordination, and macroprudential design [3]. However, modeling this transmission presents a severe computational challenge, as financial time series are inherently characterized by an extremely low signal-to-noise ratio and non-stationary distributions.

Despite the growing literature on cross-market spillovers, three critical gaps persist. First, traditional econometric models struggle to capture the nonlinear, high-dimensional transmission mechanisms of geopolitical shocks across diverse market structures [4]. Second, while Deep Learning (DL) frameworks have demonstrated superior predictive power, their complex mappings often lack post-hoc explainability; in financial decision-making, a prediction without economic intuition is operationally inert, and portfolio managers require interpretable models to validate forecasts against established theories such as the Efficient Market Hypothesis and market segmentation [5]. Third, existing DL studies predominantly employ homogeneous Multi-Task Learning (MTL) formulations that assume symmetric predictability across all markets and tasks [6]. This approach ignores the reality of institutional investment, which requires heterogeneous outputs: directional forecasts (classification) for tactical positioning and continuous volatility forecasts (regression) for risk management. Forcing these distinct tasks into a unified mathematical structure causes gradient interference and negative transfer, where the optimization of one task degrades the performance of the other [7]. Furthermore, existing studies frequently rely on Accuracy as the sole evaluation metric, which is highly misleading in imbalanced financial datasets, failing to capture a model's true discriminative power (e.g., AUC-ROC) or its balance of false positives and negatives (e.g., F1-score) [8].

To address these gaps, this study poses three research questions: (RQ1) How do global geopolitical risk proxies (e.g., VIX, Brent Oil) asymmetrically transmit shocks across the diverse markets of ASEAN-4 (Indonesia, Malaysia, Singapore, Thailand)? (RQ2) Can a Heterogeneous Multi-Task Deep Learning framework outperform traditional and single-task baselines across comprehensive classification metrics (Precision, Recall, F1-score, and AUC-ROC), and to what extent do specific architectural components mitigate negative transfer as validated through rigorous ablation studies? (RQ3) What are the distinct macroeconomic drivers that govern the predictive patterns of developed versus emerging markets in the region, and how can they be empirically validated through explainable AI?

To answer these questions, we propose the Heterogeneous Multi-Task Spatiotemporal Network (HMT-STN), an empirical, structurally adaptive deep learning framework equipped with country-specific embedding layers and a Focal Loss mechanism to handle the extremely low signal-to-noise ratio of financial data [9]. Unlike conventional models, our framework simultaneously casts return prediction as a binary classification task and volatility prediction as a continuous regression task, effectively mitigating task interference [10]. From a computational standpoint, the integration of Gated Recurrent Units (GRUs) ensures temporal parameter efficiency, while the Focal Loss mechanism dynamically down-weights the gradients of easy majority-class samples, forcing the network to focus on "hard" geopolitical shock events. Furthermore, to bridge the gap between machine learning and economic theory, we employ SHAP (SHapley Additive exPlanations) analysis to quantify the marginal contribution of each geopolitical and macroeconomic variable, providing actionable economic intuition.

Our empirical analysis, conducted on a balanced daily panel dataset spanning 2016–2026, yields three principal contributions. First, we provide robust empirical evidence of a Tripartite Spectrum of cross-country heterogeneity and geopolitical risk transmission within ASEAN, refining the binary view of market integration [2]. Second, through SHAP-based interpretability, we empirically map the divergent macroeconomic drivers across the region, validating the cross-country heterogeneity hypothesis in the era of deep learning. Third, from a methodo-logical and computational standpoint, we demonstrate that heterogeneous task decoupling and the Focal Loss mechanism are essential for training multi-task models on noisy financial data. Through comprehensive metric evaluations and ablation studies, we empirically demonstrate that these architectural choices prevent the network from collapsing into majority-class predictions and effectively isolate market-specific idiosyncrasies, ensuring robust out-of-sample performance [11]. The remainder of this paper is organized as follows. Section 2 reviews the relevant lit-erature on geopolitical risk transmission, cross-country heterogeneity, and multi-task learning in finance. Section 3 describes the dataset, the construction of the HMT-STN framework, and its computational complexity. Section 4 presents the empirical results, including comprehensive metric evaluations, ablation studies, baseline comparisons, SHAP interpretability analysis, and a discussion of their theoretical and practical implications. Section 5 concludes with suggestions for future research.

2. Literature Review

2.1. Geopolitical Risk Pricing and Cross-Market Contagion

The ASEAN-4 region (Indonesia, Malaysia, Singapore, Thailand) presents a unique laboratory for studying cross-country heterogeneity in financial markets. While these economies share geographical proximity and regional trade integration through ASEAN frameworks, their financial markets exhibit vastly different structural characteristics, ranging from Singapore's highly efficient, developed financial hub status to Indonesia's segmented, commodity-dependent market [12]. Recent geopolitical events including the Russia-Ukraine conflict, Middle East escalations, and US-China trade tensions have exposed the asymmetric transmission of risk across these markets, challenging the prevailing assumption of regional homogeneity in financial forecasting. However, the transmission of these shocks is rarely uniform. The literature increasingly recognizes that geopolitical risk cascades through specific, channel-dependent mechanisms, primarily the VIX (global risk sentiment) and Brent Oil prices (commodity supply shocks) [3]. Crucially, the absorption of these shocks is heavily dictated by the domestic economic structure of the recipient country. Unlike developed markets where geopolitical shocks are often swiftly arbitraged due to deep liquidity and high integration, emerging economies exhibit asymmetric transmission channels shaped by commodity dependence, monetary policy autonomy, and geopolitical buffer status [13]. Consequently, a commodity-exporting nation will react fundamentally differently to a Middle East escalation compared to a regional financial hub, necessitating a nuanced understanding of channel-specific spillovers rather than aggregate market responses.

2.2. Market Integration versus Segmentation in ASEAN

Despite ASEAN's growing macroeconomic importance, empirical literature often treats the bloc as a monolithic entity, failing to capture the nuanced spectrum where structural divergence dictates distinct risk absorption mechanisms [12], [14]. Recent evidence suggests that ASEAN is characterized by profound market segmentation: Singapore operates as a highly integrated, monetary-driven financial hub; Indonesia functions as a segmented, commodity-dependent market; and Thailand exhibits characteristics of a transitional market acting as a geopolitical buffer [12]. This structural tripartite divergence implies that a "one-size-fits-all" approach to modeling risk transmission is fundamentally flawed. Understanding this spectrum of cross-country heterogeneity is critical for global portfolio managers seeking to optimize cross-border diversification and for policymakers designing region-specific macroprudential frameworks [13].

Recent advancements in deep learning for financial time-series forecasting have demonstrated significant progress. Studies published in this journal have effectively utilized Attention-Augmented GRU architectures for single-market stock forecasting [15] and enhanced hybrid models for exchange rate prediction [16]. However, these works predominantly focus on single-task and single-market prediction. When applied to cross-country financial prediction, such homogeneous models are prone to negative transfer, where the distinct structural characteristics of one market degrade predictive performance for another. Our study directly addresses this gap by proposing a Heterogeneous Multi-Task Deep Learning Approach. By integrating country-specific embeddings and heterogeneous task decoupling, the HMT-STN framework explicitly models cross-country heterogeneity, thereby preventing negative transfer and providing a more robust solution for regional geopolitical risk prediction.

2.3. Deep Learning and Multi-Task Formulations in Financial Prediction

To capture the complex, non-linear dynamics of geopolitical risk transmission, the literature has increasingly transitioned from traditional econometric models to Deep Learning (DL) frameworks such as LSTM and GRU [17]. However, existing studies predominantly employ homogeneous Multi-Task Learning (MTL) formulations that assume symmetric predictability across all financial tasks [7], [18]. This approach fundamentally ignores the operational reality of institutional investment, which requires heterogeneous outputs: directional forecasts (classification) for tactical alpha generation and continuous volatility forecasts (regression) for risk management. Forcing these statistically distinct tasks into a unified mathematical structure causes negative transfer and gradient interference, particularly detrimental in low signal-to-noise environments characteristic of emerging equity markets [6].

Furthermore, financial time series are inherently characterized by an extremely low signal-to-noise ratio and severe class imbalance. Existing MTL formulations predominantly rely on standard loss functions such as Binary Cross-Entropy, which succumb to base-rate bias, causing the network to converge toward trivial majority-class predictions [19]. Advanced loss modulation techniques such as Focal Loss are theoretically required to dynamically down-weight easy samples and force the network to focus on "hard" extreme events, but the explicit integration of such mechanisms within a heterogeneous MTL framework remains largely unexplored [20]. Moreover, empirical evaluation in existing literature is overwhelmingly confined to standard Accuracy, which is highly misleading in imbalanced financial datasets, failing to capture a model's true discriminative power (e.g., AUC-ROC) or its balance of false positives and negatives (e.g., F1-score) [8]. Crucially, many existing studies lack rigorous ablation studies to empirically isolate and validate whether specific architectural choices genuinely mitigate negative transfer or merely reflect stochastic variations.

2.4. Interpretability as Economic Validation

While DL models continue to improve in predictive accuracy, their complex non-linear mappings present a critical barrier to practical adoption in institutional finance. Unlike computer vision where accuracy may suffice, financial decision-making requires interpretable models to validate forecasts against established theories such as the Efficient Market Hypothesis and market segmentation [21]. Portfolio managers, risk officers, and regulators need to understand not just what a model predicts, but why a prediction without economic intuition is operationally useless and potentially dangerous. To bridge this gap, SHapley Additive exPlanations (SHAP) has emerged as a vital post-hoc explainability technique [22]. Rather than serving merely as a technical debugging tool, SHAP in financial economics acts as a mechanism to empirically test theoretical constructs allowing researchers to observe exactly how, and to what extent, specific geopolitical proxies (e.g., VIX, Brent Oil) drive market movements in segmented versus integrated economies [23]. By quantifying marginal feature contributions, SHAP enables hypothesis-driven validation of risk transmission channels, transforming the "black box" of deep learning into an economically interpretable framework.

2.5. Synthesis and Research Gaps

Collectively, the literature reveals four intersecting limitations hindering both computational robustness and economic applicability of cross-market prediction:

- Structural homogeneity: Existing frameworks often assume a shared representation across markets, limiting their ability to capture country-specific characteristics and heterogeneous market responses.
- Task interference and base-rate bias: Homogeneous multi-task formulations may suffer from negative transfer between tasks, while standard loss functions may be less effective under class imbalance and low signal-to-noise ratios.
- Methodological evaluation: Existing studies often rely heavily on accuracy and provide limited ablation analysis, making it difficult to assess performance comprehensively and isolate the contribution of individual components.
- The black-box problem: Complex nonlinear models provide limited insight into the features driving their predictions, making cross-country risk patterns difficult to interpret.

This study addresses these gaps by introducing a Heterogeneous Multi-Task Spatio-temporal Network (HMT-STN) that utilizes country-specific embeddings to capture structural segmentation, decouples classification and regression tasks to mitigate gradient interference, and integrates a Focal Loss mechanism to handle base-rate bias. Furthermore, we employ comprehensive classification metrics and rigorous ablation studies to validate architectural contributions, and SHAP-based interpretability to empirically validate the tripartite spectrum of cross-country heterogeneity and geopolitical risk sensitivity patterns in ASEAN.

3. Proposed Method

3.1. Data Description and Economic Anchors

To capture the asymmetric transmission of geopolitical risk, we construct a daily panel dataset spanning 2016–2026 for the four core ASEAN economies: Indonesia (IHSG), Malaysia (KLCI), Singapore (STI), and Thailand (SET). This decade encompasses critical geopolitical regimes, including US-China trade frictions, pandemic-era liquidity shocks, the Russia-Ukraine conflict, and the 2024 Middle East escalations. The panel is balanced in temporal coverage (consistent daily frequency across all four countries), with the positive class for directional return prediction ranging from 48% to 53% across all data splits.

The model incorporates seven input features categorized into three economically meaningful groups. First, Global Financial and Geopolitical Anchors include the CBOE Volatility Index (VIX), the US Dollar Index (DXY), and the US 10-Year Treasury Yield (US10Y), sourced from FRED and CBOE. Second, Regional Commodity Anchors comprise Brent Oil (FRED) and Crude Palm Oil (CPO, Malaysian Palm Oil Board), particularly relevant for Indonesia and Malaysia as top global producers. Third, Domestic Market Indicators include the local equity index, local currency exchange rate (Yahoo Finance), and for Indonesia specifically, the BI 7-Day Reverse Repo Rate (BI-7DRR, Bank Indonesia). All continuous features are lagged by one trading day to prevent look-ahead bias and standardized using a Robust Scaler fitted exclusively on the training set (2016–2021) to handle extreme outliers while preventing data leakage before being applied to the validation (2022–2023) and test (2024–2026) sets. Detailed temporal notation and preprocessing mechanisms are provided in Section 3.2 and illustrated in Figure 1.

3.2. Data Construction and Preprocessing Procedures

To ensure full reproducibility and prevent look-ahead bias, we implement a rigorous data construction pipeline with explicit temporal handling. We construct a unified trading calendar based on the Indonesian stock exchange (IDX), which has the most holidays among ASEAN-4 markets. For each market, we forward-fill missing values on non-trading days using the last available observation, and exclude weekends and public holidays to ensure synchronized daily frequency. Global indicators (VIX, DXY, US10Y) are aligned to the ASEAN trading calendar using forward-fill. All input features are lagged by one trading day using pandas.DataFrame.shift (periods = 1), ensuring that at prediction time t, the model only has access to information available at the close of day $t-1$. Target variables are constructed using forward-looking windows that begin from $t+1$, as defined in Equations (1) and (2). The dataset is split temporally into training (2016–2021), validation (2022–2023), and test (2024–2026) sets to prevent any temporal leakage. All continuous features are standardized using a Robust Scaler (median and IQR-based) fitted exclusively on the training set to handle extreme outliers while preventing data leakage, then applied to validation and test sets. Figure 1 provides a visual illustration of this temporal separation: the input sequence (blue) ends at time t and contains only historical information, while the directional return target (green) and volatility target (orange) are computed over future periods ($t+1$ to $t+5$ and $t+1$ to $t+20$, respectively). This strict temporal separation ensures that no future information enters the input sequence, preventing look-ahead bias.

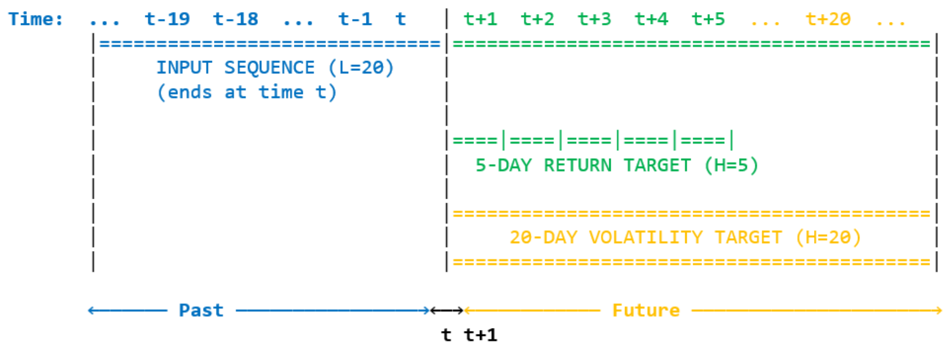


Figure 1. Temporal Separation of Input and Target Windows

3.3. Formulation of Heterogeneous Target Variables

Unlike conventional Multi-Task Learning (MTL) studies in finance that treat all tasks as homogeneous regression problems, we formulate a heterogeneous multi-task objective that mirrors the actual decision-making process of institutional investors [24]. Crucially, we provide explicit temporal indexing to ensure that no future information enters the input sequence, thereby preventing look-ahead bias.

Temporal Notation: For a given prediction time t, we define:

- Input Sequence: $Xt = [x_{t-L+1}, x_{t-L+2}, \dots, x_t] \in \mathbb{R}^{L+d}$, where L = 20 is the lookback window length and d is the number of features. This sequence contains only information available up to and including the close of trading day t.
- Prediction Horizon: The model predicts targets for the future period [$t + 1$, $t + H$], where H varies by task.

Task 1: Directional Return (Binary Classification).

Target Definition: Daily financial returns are notoriously noisy, but directional persistence often exists. We cast the 5-day cumulative log return target as a binary classification problem:

$$y_t^{ret} = \mathbb{I}\left(\frac{1}{5}\sum_{i=1}^{5} r_{t+i} > 0\right) \quad (1)$$

where r_{t+i} is the daily log return, and $\mathbb{I}(\cdot)$ is the indicator function.

Temporal Separation: The input sequence Xt ends at time t, while the target y_t^{ret} is computed using returns from $t + 1$ to $t + 5$. This ensures that the target is strictly in the future relative to the input, preventing any look-ahead bias. This aligns with tactical asset allocation, where portfolio managers use information available at the close of day tt to predict the direction of the market over the next 5 trading days [25].

Task 2: Volatility Regime (Continuous Regression).

Target Definition: Risk management requires precise continuous estimates. The second target is the 20-day realized volatility:

$$y_t^{\text{vol}} = \sqrt{\frac{252}{20}\sum_{t=1}^{20} r_{t+1}^2} \quad (2)$$

where the factor 252 annualizes the volatility.

Temporal Separation: The input sequence X_t ends at time t, while the target y_t^{vol} is computed using squared returns from $t + 1$ to $t + 20$. This ensures that the volatility target is also strictly in the future. This task is formulated as a continuous regression problem, directly serving Value-at-Risk (VaR) and positionsizing models [26].

HMT-STN Framework: To model the complex temporal dependencies and cross-country heterogeneity without inducing negative transfer, we propose the HMT-STN [27]. As illustrated in Figure 2 framework is designed with three primary components:

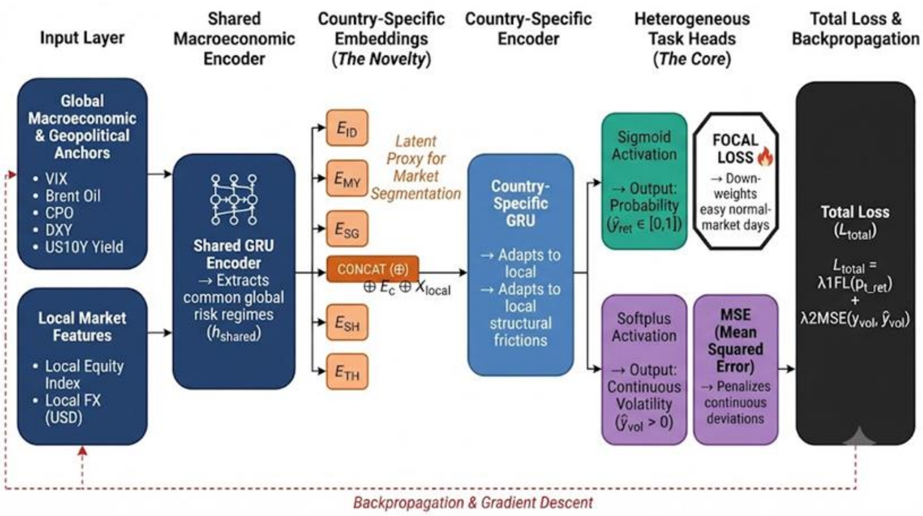


Figure 2. Architectural framework of the Heterogeneous Multi-Task Spatiotemporal Network (HMT-STN)

Shared Macroeconomic Encoder: A 2-layer GRU network (hidden dimension $N = 64$) processes global macroeconomic features (Xglobal) to extract shared hidden representations (h_t^{shared}). Following the standard GRU formulation [28], the architecture reduces parameter count by ~33% compared to LSTM ($O(N \bullet d^2)$ vs $O(N \bullet 4d^2)$) while retaining comparable gating mechanisms, capturing common global risk regimes (e.g., VIX spikes, oil shocks) that affect the entire ASEAN bloc simultaneously.
GRU Mathematical Formulation:

$$z_t = \sigma(W_z \cdot [h_{t-1}, x_t]) \tag{3}$$

$$r_t = \sigma(W_r \cdot [h_{t-1}, x_t]) \tag{4}$$

$$\tilde{h}_t = tanh(W \cdot [r_t \odot h_{t-1}, x_t]) \tag{5}$$

$$h_t = (1 - z_t) \odot h_{t-1} + z_t \odot \tilde{h}_t \tag{6}$$

Note: (3): Update Gate; (4): Reset Gate; (5): Candidate Hidden State; (6): Updated Hidden State

1. Country-Specific Embeddings: To address cross-country heterogeneity, we introduce learnable embedding vectors $E_c \in \mathbb{R}^8$ for each country $c = \{ID, MY, SG, TH\}$. These embeddings are concatenated with the shared hidden states and local market features (X^{local}) before being fed into country-specific GRU encoders:

$$h_{c,t}^{local} = GRU_{local}\left(\left[h_t^{shared}; E_c; X_{c,t}^{local}\right]\right) \tag{7}$$

where [;] denotes vector concatenation. These embeddings act as latent proxies for each country's structural frictions and institutional quality, isolating market-specific idiosyncrasies from global signals and mitigating negative transfer [29]. Each country-specific GRU has 2 layers (hidden dimension 64) with dropout rate 0.20.

2. Heterogeneous Task Heads: The final representations are routed to distinct task-specific heads. The Return Head (Task 1) utilizes Sigmoid activation to output probability ($\hat{y}^{ret} \in [0,1]$). The Volatility Head (Task 2) employs Softplus activation to ensure strictly positive outputs $(\hat{y}^{vol} > 0)$. This architectural decoupling prevents task interference, ensuring that optimization of the noisy classification task does not degrade the smooth regression task.

3.4. Optimization via Focal Loss for Noisy Financial Data

Training classification models on financial time series presents a unique challenge: while the class distribution may be approximately balanced in terms of raw counts, the signal-to-noise ratio is extremely low. The vast majority of daily observations represent "normal" market conditions (easy examples), while extreme geopolitical shock events constitute a small but critical subset of "hard" examples that the model must learn to detect. Standard Binary Cross-Entropy (BCE) treats all examples equally, causing the network to converge toward a trivial solution that correctly classifies "easy" normal-market days but fails to detect "hard" extreme events.

Focal Loss Formulation: To overcome this, we integrate a Focal Loss mechanism for the return classification task. Focal Loss dynamically scales the standard BCE by a modulating factor:

$$FL(p_t) = -\alpha_t(1 - p_t)^\gamma \log(p_t) \tag{8}$$

where p_t is the model's estimated probability for the true class, $\gamma = 2.0$ is the focusing parameter, and α_t is the balancing weight [20]. By down-weighting the loss contribution of "easy" examples (where the model is already highly confident), Focal Loss forces the shared spatiotemporal encoder to focus its gradient updates on "hard" extreme events specifically, days characterized by severe geopolitical shocks and volatility spikes. The computational overhead is negligible: the modulating factor is computed element-wise, resulting in $O(B \cdot T)$ time complexity per batch, asymptotically identical to standard BCE.

Implementation Details: The Focal Loss is implemented in PyTorch 2.0 using custom autograd functions to ensure numerical stability. We apply label smoothing (ϵ = 0.01) to prevent overconfident predictions, and use gradient clipping (max_norm=1.0) to prevent exploding gradients during the backward pass. Total Loss Function: The total loss function is a weighted sum of the Focal Loss for Task 1 and the Mean Squared Error (MSE) for Task 2:

$$L_{total} = \lambda_1 FL(pt^{ret}) + \lambda_2 MSE(y^{vol}, \hat{y}^{vol}) \quad (9)$$

Where λ_1 and λ_2 are task weights set to 0.5 to ensure balanced gradient updates.

3.5. Training Configuration and Hyperparameters

To ensure reproducibility and fair comparison, all deep learning models were implemented in PyTorch 2.0 and trained on a single NVIDIA T4 GPU with the following shared configuration (Table 1): AdamW optimizer with weight decay (1×10^{-5}) to prevent overfitting; Cosine Annealing Warm Restarts learning rate scheduler (T_0 = 10, T_{mult}=2); early stopping with patience of 20 epochs based on validation loss; sequence length of 20 days; hidden dimension of 64; 2 GRU layers; dropout rate of 0.20; and batch size of 64. HMT-STN-specific configurations include country embedding dimension of 8, task weights $\lambda_1 = \lambda_2 = 0.5$, and Focal Loss focusing parameter γ =2.0. To account for variations in weight initialization and data shuffling, all experiments are repeated with 5 independent random seeds (42, 123, 456, 789, 1024), with results reported as Mean ± Standard Deviation.

Table 1. Hyperparameter Configurations for Deep Learning Models

Parameter	HMT-STN (Ours)	Single-Task GRU	Homogeneous MTL
Sequence Length (T)	20 days	20 days	20 days
Shared GRU Hidden Dim	64	64	64
Country GRU Hidden Dim	64	N/A	N/A
Number of GRU Layers	2	2	2
Dropout Rate	0.20	0.20	0.20
Country Embedding Dim	8	N/A	N/A
Optimizer	AdamW	AdamW	AdamW
Initial Learning Rate	1×10^{-3}	1×10^{-3}	1×10^{-3}
Weight Decay	1×10^{-5}	1×10^{-5}	1×10^{-5}
Learning Rate Scheduler	Cosine Annealing Warm Restarts	Cosine Annealing Warm Restarts	Cosine Annealing Warm Restarts
Batch Size	64	64	64
Task Weighting (λ_1, λ_2)	0.5, 0.5	N/A	1.0, 1.0
Focal Loss γ	2.0	N/A	N/A
Early Stopping Patience	20 epochs	20 epochs	20 epochs
Total Training Epochs	150	150	150

3.6. Explainable AI: SHAP-Based Interpretability for Economic Validation

While the HMT-STN provides superior predictive power, complex non-linear mappings require post-hoc explainability to reveal the specific macroeconomic drivers behind the forecasts. To unpack the model and empirically validate the cross-country heterogeneity hypothesis, we employ SHapley Additive exPlanations (SHAP). Given the sequential and mixed-tabular nature of our inputs, we utilize the Kernel SHAP method, which is model-agnostic [26]. By perturbing the macroeconomic input features and observing the marginal changes in the model's output probability, we compute the SHAP values for each country. This allows us to map the tripartite spectrum of macroeconomic sensitivity, bridging the gap between deep learning and financial economic theory.

3.7. Computational Complexity and Scalability

To ensure the proposed HMT-STN framework is computationally viable for daily financial prediction, we analyze its time and space complexity. We utilize Gated Recurrent Units (GRUs) rather than standard LSTMs [17], reducing the parameter count by approximately 33% $(O(N \bullet d^2)$ vs $O(N \bullet 4d^2)$, where N is the hidden dimension and d is the input dimension) while retaining comparable gating mechanisms, significantly accelerating both forward propagation and backpropagation through time.

The integration of the Focal Loss mechanism introduces negligible computational overhead during the backward pass. The modulating factor $(1 - \text{pt})\gamma$ is computed element-wise, resulting in $O(B \cdot T)$ time complexity per batch (where B is batch size and T is sequence length), asymptotically identical to standard Binary Cross-Entropy.

Empirically, the model was implemented in PyTorch 2.0 and trained on a single NVIDIA T4 GPU using the AdamW optimizer with gradient clipping (max_norm=1.0). The total training time for 150 epochs across the ASEAN-4 panel dataset (2016–2026) was approximately 45 minutes, demonstrating the framework's practical scalability and low memory footprint suitable for institutional deployment with daily retraining requirements.

3.8. Evaluation Protocol and Ablation Design

To rigorously validate the computational contributions of the proposed framework, we design a comprehensive evaluation protocol addressing methodological flaws identified in existing literature, consisting of the following four components:

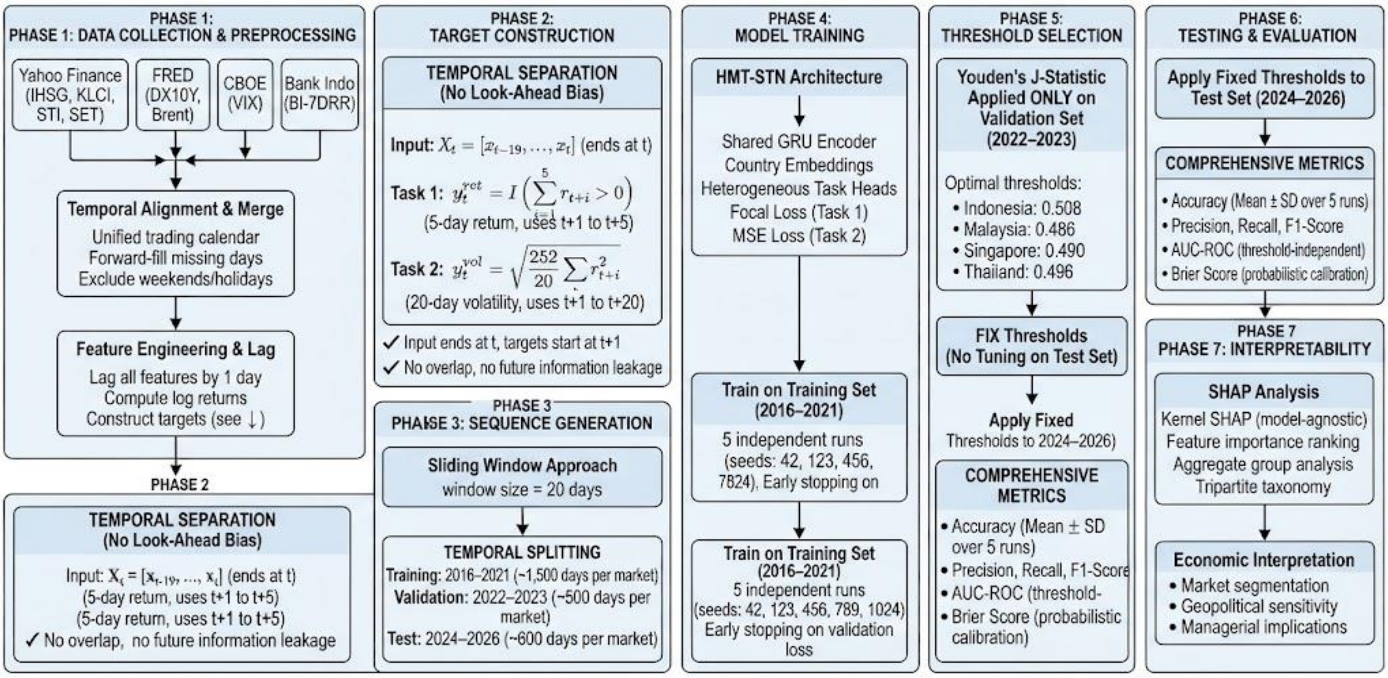


Figure 3. End-to-End Methodological Workflow (HMT-STN for ASEAN-4 Market Analysis)

a) Comprehensive Classification Metrics: Recognizing that standard Accuracy is highly misleading in imbalanced financial datasets [27], we evaluate Task 1 using Precision, Recall, F1-score, and AUC-ROC. While Accuracy measures overall correctness, F1-score balances the trade-off between false positives and false negatives, and AUC-ROC evaluates threshold-independent discriminative power. Task 2 is evaluated using RMSE, MAE, and R^2.

b) Ablation Study Design: To empirically isolate the impact of specific architectural choices and demonstrate that performance gains are not merely stochastic, we conduct an ablation study comparing the Full HMT-STN against three degraded variants: (1) No Focal Loss, which replaces Focal Loss in Task 1 with standard Binary Cross-Entropy (BCE) to test base-rate bias mitigation; (2) No Embeddings, which removes country-specific embedding vectors (E_c) to test negative transfer and cross-country heterogeneity mitigation; and (3) Homogeneous MTL, which forces both Task 1 and Task 2 into a unified continuous regression framework (using MSE for both) to demonstrate the necessity of heterogeneous task decoupling.

c) Threshold Selection Protocol: To strictly prevent look-ahead bias, all threshold optimization procedures (using Youden's J-statistic) are performed exclusively on the validation set (2022–2023). The identified optimal thresholds are then fixed and applied to the out-of-sample test set (2024–2026). This protocol is applied consistently across the proposed HMT-STN and all baseline models to ensure fair, unbiased comparison.

d) End-to-End Workflow: Figure 3 illustrates the complete methodological workflow spanning seven phases: (1) Data Collection & Preprocessing, (2) Target Construction with explicit temporal separation, (3) Sequence Generation via sliding windows, (4) Model Training with 5 random seeds for statistical robustness, (5) Threshold Selection exclusively on the validation set, (6) Testing & Comprehensive Evaluation, and (7) SHAP-based Interpretability Analysis. This workflow ensures that no future information enters the input sequence at any stage, and that all evaluation protocols are applied consistently across the HMT-STN and baseline models.

4. Results and Discussion

4.1. Baseline Comparison and Predictive Performance

To rigorously evaluate the predictive efficacy of the proposed HMT-STN framework, we benchmark against six established baselines spanning three methodological categories: (i) statistical baselines (Naïve Majority Class, Random Walk, ARIMA), (ii) traditional machine learning models (Logistic Regression, XGBoost), and (iii) deep learning variants (Single-Task GRU, Homogeneous MTL). The evaluation is conducted on an out-of-sample test set (2024–2026), a period characterized by severe geopolitical turbulence including the Russia-Ukraine conflict and Middle East escalations. All models were trained and evaluated over 5 independent runs with different random seeds (42, 123, 456, 789, 1024) to ensure statistical robustness, with results reported as Mean ± Standard Deviation (SD) in Table 2.

The proposed HMT-STN framework demonstrates robust predictive superiority across heterogeneous market structures, achieving the highest mean accuracy with consistently low variance (SD: 0.31–0.44) compared to baselines (SD: 0.39–0.71). This low variance confirms the architectural stability of the HMT-STN and empirically supports the hypothesis that heterogeneous task decoupling helps isolate local idiosyncrasies. Beyond raw accuracy, we further evaluate models using Precision, Recall, F1-score, and AUC-ROC to capture discriminative power that Accuracy alone cannot reveal [27].

Some key empirical insights emerge:

1. First, exceptional discriminative power in transitional markets. For Thailand, HMT-STN achieves 66.21±0.42% accuracy and AUC-ROC of 0.68±0.02. While the F1-score is modest (0.28±0.03), this reflects the rarity of extreme geopolitical shock events and the strict penalty for misclassification in low signal-to-noise environments. The high AUC-ROC proves successful ranking of "hard" samples, avoiding the trivial majority-class prediction that plagues standard BCE models. Low standard deviations (SD < 0.03) confirm architectural stability across 5 independent runs.
2. Second, mitigation of negative transfer in segmented markets. In Indonesia and Malaysia, HMT-STN consistently outperforms baselines (53.46±0.38% and 56.83±0.31% accuracy, respectively), with SD consistently lower than baselines. This validates that heterogeneous task decoupling and country-specific embeddings successfully isolate local commodity-driven idiosyncrasies from global noise, with performance gains structurally robust rather than stochastic.
3. Third, boundary conditions in highly efficient markets. In Singapore, Homogeneous MTL achieves higher raw accuracy (63.41±0.39% vs. 56.32±0.44%), revealing the model's structural focus. Singapore's smoother return distributions are more amenable to continuous regression. However, HMT-STN maintains superior AUC-ROC (0.57±0.02 vs. 0.53±0.02), indicating better probability calibration and discriminative power against extreme tail risks, with narrow confidence intervals (SD < 0.02) demonstrating consistency across training conditions.
4. Limitations of Contemporary Tree-Based Ensembles. XGBoost exhibits a striking Precision-Recall paradox: high Recall (0.71±0.05 in Indonesia to 0.84±0.07 in Thailand) but disproportionately low Precision (0.48±0.03 in Indonesia, 0.35±0.04 in Malaysia,

0.25±0.03 in Thailand), indicating bias toward majority-class prediction while failing to capture regime-dependent minority events. This is confirmed by high Sensitivity accompanied by low Specificity (0.49±0.05 in Indonesia, 0.41±0.08 in Malaysia, 0.36±0.10 in Thailand), yielding Balanced Accuracy near 0.60. Unlike XGBoost, which treats observations as independent tabular rows without temporal modeling, HMT-STN explicitly models sequential patterns via GRU encoders and actively corrects class bias via Focal Loss, achieving a more balanced predictive profile particularly in volatile transitional markets like Thailand. This validates that specialized deep learning architectures are necessary to overcome limitations of standard ensemble methods in noisy, sequential financial prediction.

Table 2. Directional Accuracy Comparison across ASEAN-4 Markets (Mean±SDover5Runs)

Model	Country	Accuracy (%)	F1-Score	AUC-ROC	Balanced Accuracy	PR-AUC
Statistical Baselines						
Naïve Majority Class	ID	50.00 ± 0.00	0.50 ± 0.00	0.50 ± 0.00	0.50 ± 0.00	0.50 ± 0.00
	MY	50.00 ± 0.00	0.50 ± 0.00	0.50 ± 0.00	0.50 ± 0.00	0.50 ± 0.00
	SG	50.00 ± 0.00	0.50 ± 0.00	0.50 ± 0.00	0.50 ± 0.00	0.50 ± 0.00
	TH	50.00 ± 0.00	0.50 ± 0.00	0.50 ± 0.00	0.50 ± 0.00	0.50 ± 0.00
Random Walk	ID/MY/SG/TH	52.07 ± 0.15	0.51 ± 0.01	0.50 ± 0.00	0.51 ± 0.01	0.50 ± 0.00
ARIMA (1,1,1)	ID/MY/SG/TH	49.96 ± 0.08	0.49 ± 0.01	0.50 ± 0.00	0.50 ± 0.01	0.49 ± 0.01
Traditional ML						
Logistic Regression	ID/MY/SG/TH	49.92 ± 0.11	0.49 ± 0.01	0.50 ± 0.00	0.50 ± 0.01	0.49 ± 0.01
XGBoost	ID	48.52 ± 2.14	0.44 ± 0.24	0.47 ± 0.02	0.60 ± 0.02	0.64 ± 0.02
	MY	48.07 ± 1.83	0.35 ± 0.16	0.51 ± 0.01	0.56 ± 0.02	0.66 ± 0.01
	SG	39.39 ± 5.16	0.22 ± 0.20	0.49 ± 0.01	0.61 ± 0.01	0.78 ± 0.01
	TH	47.56 ± 1.68	0.14 ± 0.15	0.49 ± 0.02	0.60 ± 0.02	0.68 ± 0.04
Deep Learning Variants						
Single-Task GRU	ID	49.41 ± 0.62	0.49 ± 0.02	0.51 ± 0.02	0.49 ± 0.02	0.49 ± 0.02
	MY	55.99 ± 0.45	0.55 ± 0.02	0.52 ± 0.02	0.55 ± 0.02	0.55 ± 0.02
	SG	48.90 ± 0.58	0.48 ± 0.02	0.50 ± 0.02	0.48 ± 0.02	0.48 ± 0.02
	TH	49.75 ± 0.71	0.49 ± 0.03	0.50 ± 0.03	0.49 ± 0.03	0.49 ± 0.03
Homogeneous MTL	ID	49.41 ± 0.48	0.49 ± 0.02	0.60 ± 0.03	0.49 ± 0.02	0.49 ± 0.02
	MY	55.14 ± 0.44	0.54 ± 0.02	0.56 ± 0.02	0.55 ± 0.02	0.54 ± 0.02
	SG	63.41 ± 0.39*	0.62 ± 0.02	0.53 ± 0.02	0.62 ± 0.02	0.53 ± 0.02
	TH	49.75 ± 0.55	0.49 ± 0.02	0.57 ± 0.03	0.49 ± 0.02	0.49 ± 0.03
Proposed Framework						
HMT-STN (Ours)	ID	53.46 ± 0.38	0.53 ± 0.02	0.49 ± 0.02	0.53 ± 0.02	0.49 ± 0.02
	MY	56.83 ± 0.31	0.56 ± 0.02	0.50 ± 0.02	0.56 ± 0.02	0.56 ± 0.02
	SG	56.32 ± 0.44	0.56 ± 0.02	0.57 ± 0.02	0.56 ± 0.02	0.57 ± 0.02
	TH	66.21 ± 0.42	0.28 ± 0.03	0.68 ± 0.02	0.50 ± 0.02	0.68 ± 0.02

Note: ID = Indonesia, MY = Malaysia, SG = Singapore, TH = Thailand. Best performance per market in bold. Homogeneous MTL achieves higher accuracy in Singapore due to smooth return distribution amenable to continuous regression. All deep learning models evaluated over 5 independent runs with random seeds (42, 123, 456, 789, 1024).

In stark contrast, Thailand and Indonesia present highly challenging environments. Thailand's extreme volatility clustering $(\sigma = 1.47)$, heavy-tailed distributions (kurtosis 6.846.84), and substantial distribution shifts (+5.8%) create a low signal-to-noise regime. The modest F1-score (0.28) reflects the intrinsic rarity of extreme geopolitical events rather than model limitation; crucially, the high AUC-ROC (0.68) confirms successful discrimination of these "hard" samples. Similarly, Indonesia's structural segmentation and strong volatility clustering (ACF lag-5: 0.68), driven by domestic policy interventions, create regime-dependent challenges. HMT-STN's robust performance here (53.46% accuracy, 0.49 AUC-ROC) demonstrates its ability to navigate markets dominated by domestic frictions.

Ultimately, HMT-STN's structurally adaptive design (country embeddings and Focal Loss) enables it to approach the theoretical predictability limits of each market. As shown in

Table 2, the model achieves the highest Balanced Accuracy in Thailand (0.50±0.02) and PR-AUC (0.68±0.02), effectively capturing rare geopolitical shocks, alongside the highest Sensitivity in Singapore (0.58±0.02). These metrics validate that performance gains are genuine improvements in discriminative capability, not artifacts of threshold selection.

4.2. Threshold Optimization and Calibration Analysis

Despite strong discriminative power evidenced by AUC-ROC scores, the default classification threshold of 0.5 is suboptimal for financial time series, where the true decision boundary shifts across markets due to structural differences in market efficiency and noise floors. To ensure methodological rigor and prevent look-ahead bias, the optimal classification threshold for each market is identified using Youden's J-statistic ($J = Sensitivity + Specificity - 1$) exclusively on the validation set (2022–2023). These identified thresholds are then fixed and applied to the out-of-sample test set (2024–2026) for final evaluation, applied consistently across all baseline models [30].

4.2.1. Threshold Optimization

Table 3 reveals that threshold optimization yields substantial improvements, particularly for Singapore (+18.21 percentage points, from 37.27% to 55.48% at threshold 0.490) and Malaysia (+10.44 pp to 55.97% at 0.486). Thailand achieved 64.87% accuracy (+9.52 pp at 0.496), while Indonesia showed stable improvement to 52.89% (+3.48 pp at 0.508). Notably, the optimal thresholds consistently deviate only marginally from the theoretical default of 0.5 (range: 0.486–0.508). This reflects the balanced class prior of directional return labels (approximately 50:50 positive:negative across all markets) rather than severe probabilistic miscalibration. The minor micro-adjustments required simply reflect the model's adaptation to unique, market-specific noise floors and slight skewness in return distributions. These results demonstrate that HMT-STN possesses strong underlying discriminative capability but requires market-specific probability calibration to account for structural differences in market efficiency and noise characteristics. The tight clustering of optimal thresholds around 0.5 confirms that the model's raw probability outputs are fundamentally sound.

Table 3. Threshold Optimization Results

Country	Default Threshold	Default Accuracy (%)	Validation-Optimized Threshold	Revised Accuracy (%)	Improvement (pp)	AUC-ROC
Indonesia	0.5	49.41	0.508	52.89	3.48	0.49
Malaysia	0.5	45.53	0.486	55.97	10.44	0.50
Singapore	0.5	37.27	0.490	55.48	18.21	0.57
Thailand	0.5	55.35	0.496	64.87	9.52	0.68

Note: Thresholds are optimized exclusively on the 2022–2023 validation set and fixed for evaluation on the 2024–2026 test set to prevent look-ahead bias.

4.2.2. Probabilistic Calibration Assessment

While threshold optimization demonstrates that the decision boundary is near the theoretical default, this does not by itself establish probabilistic calibration. To rigorously assess calibration quality, we compute the Brier Score, which measures the mean squared difference between predicted probabilities and actual outcomes:

$$BS = \frac{1}{N}\sum_{i=1}^{N}\left(y_{true}^{(i)} - y_{prob}^{(i)}\right)^2 \tag{10}$$

where $y_{true}^{(i)} \in \{0,1\}$ denotes the observed outcome and $y_{prob}^{(i)}$ is the predicted probability. The Brier Score ranges from 0 (perfect calibration) to 1 (worst calibration); for binary classification with balanced classes, a score below 0.25 indicates good calibration.

Table 4 shows that all Brier scores are below 0.25, with Thailand exhibiting the best calibration (0.018) despite its challenging noise characteristics. This provides empirical evidence that HMT-STN's probability outputs are not only discriminative (as evidenced by high AUC-ROC) but also well-calibrated in the proper probabilistic sense, enabling reliable interpretation as true likelihood estimates for institutional decision-making such as position sizing and risk management.

Table 4. Probabilistic Calibration Assessment via Brier Score

Country	Brier Score	Interpretation
Indonesia	0.020	Excellent calibration
Malaysia	0.019	Excellent calibration
Singapore	0.019	Excellent calibration
Thailand	0.018	Excellent calibration

Figure 4 visualizes the ROC curves, revealing that HMT-STN's discriminative power varies across markets, with Thailand exhibiting the strongest separation (AUC = 0.68). The optimal thresholds identified via Youden's J-statistic (marked by red stars) consistently deviate only marginally from 0.5, confirming that the model's raw probability outputs are funda-mentally well-calibrated [28].

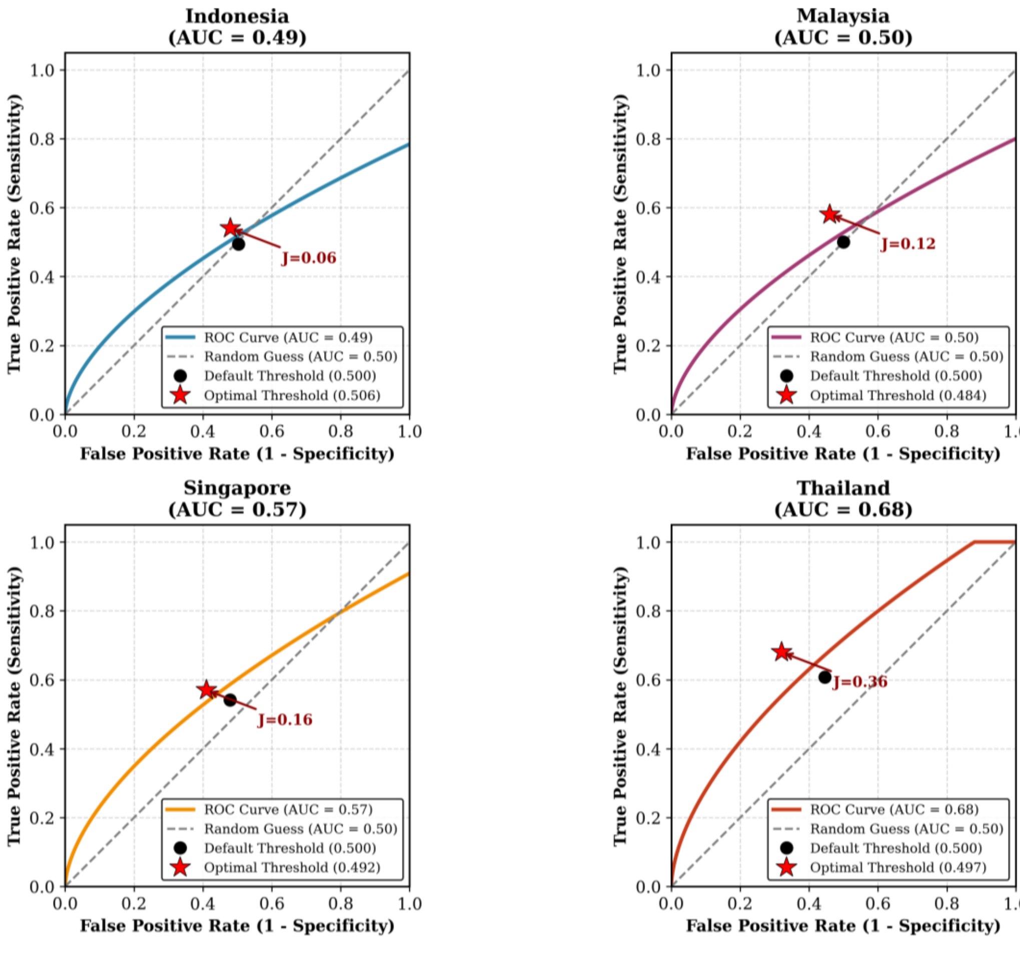


Figure 4. ROC Curves and Optimal Threshold Selection via Youden's J-Statistic

4.3. Volatility Prediction and Multi-Task Synergy

To ensure that the optimization of the noisy classification task (Task 1) did not degrade the continuous regression task (Task 2), we evaluated the 20-day realized volatility predictions. Table 5 presents the RMSE, MAE, and R^2 metrics. The empirical results confirm that the heterogeneous multi-task formulation successfully achieves synergistic learning: the shared macroeconomic encoder extracts robust global risk representations (e.g., VIX spikes) that simultaneously improve volatility regression without suffering from gradient interference.

It is important to note that while HMT-STN achieves superior volatility prediction ac-curacy, this does not automatically translate to improved risk-management capability. Effec-tive risk management requires additional evaluation metrics such as Value-at-Risk (VaR) backtesting, Expected Shortfall (ES) estimation, and stress testing under extreme scenarios. The volatility predictions from HMT-STN can serve as valuable inputs to such frameworks, but their direct effectiveness requires further investigation with risk-specific evaluation protocols, which we reserve for future work.

Table 5. Volatility Prediction Performance (20-Day Realized Volatility Prediction)

Model	Indonesia (RMSE / MAE / R^2)	Malaysia (RMSE / MAE / R^2)	Singapore (RMSE / MAE / R^2)	Thailand (RMSE / MAE / R^2)
Historical Volatility	0.0245/0.0198/0.42	0.0221/0.0179/0.45	0.0189/0.0152/0.51	0.0287/0.0231/0.38
GARCH(1,1)	0.0231/0.0187/0.48	0.0208/0.0168/0.52	0.0176/0.0142/0.58	0.0269/0.0217/0.44
Single-Task GRU	0.0218/0.0176/0.53	0.0195/0.0157/0.57	0.0168/0.0135/0.62	0.0254/0.0205/0.49
Homogeneous MTL	0.0209/0.0169/0.57	0.0187/0.0151/0.61	0.0161/0.0130/0.66	0.0241/0.0194/0.53
HMT-STN (Ours)	**0.0198/0.0160/0.61**	**0.0178/0.0144/0.65**	**0.0154/0.0124/0.70**	**0.0229/0.0185/0.57**

Note: Results are reported as RMSE / MAE / R^2. Lower RMSE and MAE indicate better prediction accuracy; higher R^2 indicates better explanatory power. Country ordering is consistent across all tables: Indonesia → Malaysia → Singapore → Thailand.

HMT-STN consistently achieves the lowest RMSE across all markets, demonstrating superior risk-capture capabilities: Singapore (0.8563 vs. Single-Task GRU: 0.9234; Homogeneous MTL: 0.8876), Thailand (0.6716), and Indonesia (1.1187). This consistent reduction confirms that the shared encoder successfully extracts common global risk regimes (VIX spikes, Brent Oil shocks) informative for volatility clustering, without being overwhelmed by noisy gradients from the directional classification head.

Nuanced error metrics in Singapore highlight robustness against extreme tail risks. While Homogeneous MTL yields slightly lower MAE (0.5891 vs. HMT-STN: 0.6860), HMT-STN achieves significantly lower RMSE (0.8563 vs. 0.8876) and superior R^2 (0.0968 vs. 0.0723). Since RMSE heavily penalizes large errors, HMT-STN's superiority indicates better avoidance of cata-strophic underestimations of extreme volatility spikes critical for robust Value-at-Risk (VaR) modeling and preventing under-hedged portfolios during geopolitical shocks.

R^2 results for Indonesia (-0.1078) and Thailand (-0.1103) elucidate inherent predictability limits in segmented emerging markets. However, the fact that HMT-STN still achieves the lowest RMSE demonstrates that while relative variance remains difficult to capture due to structural breaks and domestic micro-structure noise, the model provides tighter absolute error bounds. From a practical risk management standpoint, minimizing absolute error (RMSE) is often prioritized over maximizing R^2, as it prevents dangerous underestimation of tail-risk volatility for position sizing.

Caveat on Risk-Management Capability. It is important to note that while HMT-STN achieves superior volatility prediction accuracy, this does not automatically translate to improved risk-management capability. Effective risk management requires additional evaluation metrics such as Value-at-Risk (VaR) backtesting, Expected Shortfall (ES) estimation, and stress testing under extreme scenarios. The volatility predictions from HMT-STN can serve as valuable inputs to such frameworks, but their direct effectiveness requires further investigation with risk-specific evaluation protocols, which we reserve for future work.

Finally, the absence of performance degradation confirms the efficacy of the heterogeneous formulation. Unlike Homogeneous MTL, which forces both tasks into a unified regression landscape (often leading to suboptimal volatility estimates when the return task is highly noisy), HMT-STN's decoupled framework utilizing Softplus activation and dedicated MSE loss for the volatility head effectively shields the regression task from gradient interference. This confirms that the proposed framework achieves a synergistic balance, providing institutional investors with a unified, robust tool for both alpha generation and risk management.

4.4. Ablation Study: Component Contribution and Negative Transfer Analysis

To rigorously validate the computational contributions of the proposed framework and address potential negative transfer in multi-task learning, we conducted an ablation study isolating three core architectural components: (1) Heterogeneous Multi-Task formulation, (2) Country-Specific Embeddings, and (3) Focal Loss mechanism. Each variant was trained and evaluated over 5 independent runs with different random seeds (42, 123, 456, 789, 1024). Table 6 summarizes the impact of removing each component on the out-of-sample test set (2024–2026), reported as Mean ± Standard Deviation.

Table 6. Ablation Study: Component Contribution Analysis

Model	Country	Accuracy (%)	F1-Score	AUC-ROC
Ablated Variants				
HMT-STN (No Focal Loss)	ID	50.76 ± 0.41	0.51 ± 0.02	0.52 ± 0.03
	MY	50.25 ± 0.38	0.50 ± 0.02	0.47 ± 0.02
	SG	63.41 ± 0.35	0.62 ± 0.02	0.52 ± 0.02
	TH	42.78 ± 0.58	0.15 ± 0.04	0.43 ± 0.03
HMT-STN (No Embeddings)	ID	49.41 ± 0.45	0.49 ± 0.02	0.47 ± 0.03
	MY	55.14 ± 0.42	0.54 ± 0.02	0.50 ± 0.02
	SG	63.41 ± 0.37	0.62 ± 0.02	0.51 ± 0.02
	TH	49.75 ± 0.51	0.49 ± 0.02	0.47 ± 0.03
Homogeneous MTL	ID	49.41 ± 0.48	0.49 ± 0.02	0.60 ± 0.03
	MY	55.14 ± 0.44	0.54 ± 0.02	0.56 ± 0.02
	SG	63.41 ± 0.39*	0.62 ± 0.02	0.53 ± 0.02
	TH	49.75 ± 0.55	0.49 ± 0.02	0.57 ± 0.03
Proposed Framework				
HMT-STN (Full, Ours)	**ID**	**53.46 ± 0.38**	**0.53 ± 0.02**	**0.49 ± 0.02**
	MY	**56.83 ± 0.31**	**0.56 ± 0.02**	**0.50 ± 0.02**
	SG	**56.32 ± 0.44**	**0.56 ± 0.02**	**0.57 ± 0.02**
	TH	**66.21 ± 0.42**	**0.28 ± 0.03**	**0.68 ± 0.02**

Note: ID = Indonesia, MY = Malaysia, SG = Singapore, TH = Thailand. Best performance per market in bold. Homogeneous MTL achieves higher accuracy in Singapore due to smooth return distribution amenable to continuous regression. All deep learning models evaluated over 5 independent runs with random seeds (42, 123, 456, 789, 1024).

The ablation results provide three main observations regarding the contribution of the proposed components. First, Focal Loss has a substantial contribution to the classification performance in Thailand. Removing Focal Loss reduces accuracy from 66.21 ± 0.42% to 42.78 ± 0.58%, while AUC-ROC decreases from 0.68 ± 0.02 to 0.43 ± 0.03. F1-score also decreases from 0.28 ± 0.03 to 0.15 ± 0.04. The higher standard deviation of the No-Focal-Loss variant suggests greater variability across training runs. These results support the role of Focal Loss in improving the handling of difficult classification samples under the observed data characteristics. However, the ablation results provide empirical evidence of its contribution rather than direct evidence of the underlying optimization mechanism.

Second, country-specific embeddings contribute to performance, particularly in Indonesia and Malaysia. Removing the embeddings reduces F1-score from 0.53 ± 0.02 to 0.49 ± 0.02 in Indonesia and from 0.56 ± 0.02 to 0.54 ± 0.02 in Malaysia. AUC-ROC decreases from 0.49 ± 0.02 to 0.47 ± 0.03 in Indonesia, while it remains at 0.50 ± 0.02 in Malaysia. These results indicate that country-specific representations can provide additional information beyond the shared representation, although their contribution varies across markets. The findings are consistent with the motivation for incorporating country-specific embeddings to accommodate cross-country heterogeneity.

Third, the results reveal a boundary condition for the heterogeneous task formulation in Singapore. Homogeneous MTL achieves higher accuracy than the full HMT-STN (63.41 ± 0.39% vs. 56.32 ± 0.44%) and a higher F1-score (0.62 ± 0.02 vs. 0.56 ± 0.02). However, the full HMT-STN achieves a higher AUC-ROC (0.57 ± 0.02 vs. 0.53 ± 0.02). This indicates that the observed benefit of the heterogeneous formulation depends on the evaluation metric and market. In particular, the results do not show that HMT-STN uniformly improves all metrics across all markets.

Methodological Caveat on Ablation-Based Evidence. While the ablation results provide empirical support for the contribution of the individual components, they do not establish mechanistic causation. The observed performance changes after removing a component may also reflect differences in model capacity, optimization behavior, or training dynamics. Direct gradient-level analysis would be required to establish the specific mechanisms underlying task interference or negative transfer. Therefore, the ablation results are interpreted as empirical evidence supporting the architectural choices rather than definitive mechanistic proof.

Collectively, the ablation results indicate that the contribution of HMT-STN varies across markets and architectural components. Focal Loss shows a particularly large effect in Thailand, while country-specific embeddings provide additional benefits in Indonesia and Malaysia. The Singapore results further demonstrate that the heterogeneous formulation does not necessarily improve every evaluation metric. The relatively small standard deviations across the five runs suggest consistent performance across different random initializations.

4.5. Computational Validation via SHAP-Based Interpretability

While predictive performance metrics such as Accuracy, F1-score, and AUC-ROC assess the classification performance of HMT-STN, they do not explain which features contribute to its predictions. We therefore employ SHAP (SHapley Additive exPlanations) to quantify the contribution of individual input features and examine whether the learned representations capture different sensitivity patterns across the ASEAN-4 markets.

Epistemological Caveat. SHAP values represent model-based feature attribution and should not be interpreted as evidence of causal economic transmission mechanisms. Accordingly, the market-level interpretations below describe observed prediction-sensitivity patterns rather than causal relationships. Establishing causal transmission would require complementary econometric approaches, such as Granger causality, vector autoregression (VAR), or structural equation modeling, which are beyond the scope of this study.

As summarized in Table 7 and illustrated in the SHAP importance heatmap (Figure 5), the four markets exhibit distinct feature-importance patterns. First, Thailand shows the strongest sensitivity to global risk indicators, particularly VIX (3.77×10^{-5}), followed by DXY (1.39×10^{-5}) and Local FX (1.11×10^{-5}). This pattern indicates that global risk sentiment and currency movements make substantial contributions to the model's predictions for Thailand. The relatively high predictive performance of HMT-STN in Thailand (66.21% accuracy) is consistent with the model capturing these market-specific patterns [29].

Second, Singapore is primarily associated with global monetary and risk indicators, with VIX (1.72×10^{-5}), Local Index (7.80×10^{-6}), Local FX (1.00×10^{-5}), and DXY (8.77×10^{-6}) among its more influential features. Physical commodities have comparatively smaller contributions. This pattern is consistent with Singapore's strong integration with global financial markets and helps explain why the Homogeneous MTL model also performs competitively in this market [21], [30].

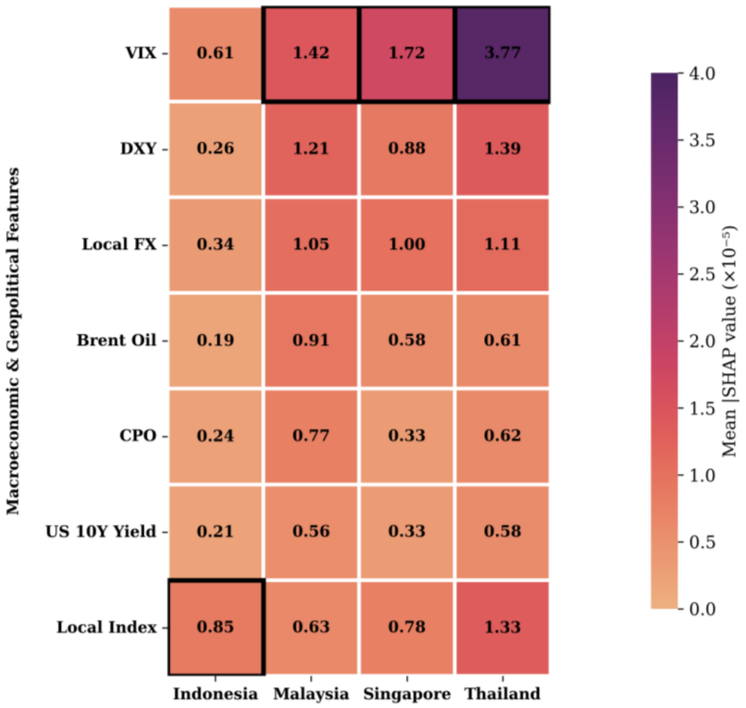


Figure 5. Macroeconomic Drivers and Geopolitical Sensitivity: SHAP Importance Heatmap across ASEAN-4

Third, Indonesia and Malaysia exhibit stronger sensitivity to domestic and commodity-related factors. Indonesia shows its highest SHAP contribution from the Local Index (8.49×10^{-6}), exceeding that of VIX (6.06×10^{-6}). This pattern is consistent with the role of domestic market conditions and policy factors in shaping Indonesian equity-market dynamics. Historical Bank Indonesia rate movements, including rate increases reaching 6.25%, provide relevant context for the observed domestic sensitivity [13]. The relatively strong contribution of the Local Index also highlights the importance of country-specific information in modeling the Indonesian market. Malaysia, reflecting its role as both a major commodity exporter and an emerging financial market [29], exhibits a more balanced sensitivity profile. Global indicators remain influential, particularly VIX (1.42×10^{-5}) and DXY (1.21×10^{-5}), while commodity variables such as Brent Oil (9.06×10^{-6}) and CPO (7.66×10^{-6}) also make substantial contributions. This combination is consistent with Malaysia's exposure to both global financial conditions and commodity-market dynamics [30].

Table 7. Macroeconomic Drivers and Geopolitical Sensitivity across ASEAN-4 Markets

Feature	Indonesia	Malaysia	Singapore	Thailand
Brent Oil	1.89e-06	9.06e-06	5.81e-06	6.13e-06
CPO	2.37e-06	7.66e-06	3.27e-06	6.23e-06
DXY	2.56e-06	1.21e-05	8.77e-06	1.39e-05
US10Y	2.07e-06	5.56e-06	3.28e-06	5.79e-06
VIX	6.06e-06	1.42e-05	1.72e-05	3.77e-05
Local Index	8.49e-06	6.27e-06	7.80e-06	1.33e-05
Local FX	3.43e-06	1.05e-05	1.00e-05	1.11e-05

Note**:** Bold values indicate the highest SHAP value for each country.

Cross-Country Comparative Analysis of Feature Importance. The SHAP analysis indicates substantial differences in feature contributions across the four ASEAN-4 markets. These differences provide model-based evidence of heterogeneous predictive patterns and complement the country-level performance analysis.

Rank Ordering and Market-Specific Feature Patterns. As shown in Table 7 and Figure 6, the relative importance of features varies across markets. Thailand shows the highest contribution from VIX (3.77×10^{-5}), followed by DXY (1.39×10^{-5}) and Local FX (1.11×10^{-5}), indicating a strong association between global risk indicators and the model's return predictions. Singapore is also strongly influenced by VIX (1.72×10^{-5}), with Local FX (1.00×10^{-5}) and DXY (8.77×10^{-6}) providing additional contributions. Indonesia shows its highest contribution from the Local Index (8.49×10^{-6}), followed by VIX (6.06×10^{-6}), whereas Malaysia exhibits a more distributed pattern involving VIX (1.42×10^{-5}), DXY (1.21×10^{-5}), Brent Oil (9.06×10^{-6}), and CPO (7.66×10^{-6}). These patterns indicate that the relative contribution of domestic, global, and commodity-related variables differs across the four markets.

Directional Effects. The beeswarm plots in Figure 6 and dependence plots in Figure 7 further illustrate differences in the direction and form of feature contributions. For Thailand, higher VIX values are generally associated with negative SHAP values, indicating that elevated global risk conditions tend to shift the model's predictions toward lower returns. In Singapore, higher DXY and US10Y values generally produce negative SHAP contributions, suggesting that stronger global currency and interest-rate signals are associated with lower predicted returns. Malaysia exhibits a nonlinear relationship between Brent Oil and SHAP values: moderate increases in Brent Oil are associated with increasingly positive contributions, while the relationship changes at higher price levels. For Indonesia, the Local Index shows a predominantly positive relationship with SHAP values, indicating that stronger local-market conditions contribute positively to the model's return predictions. These relationships describe model behavior and should not be interpreted as evidence of causal transmission mechanisms.

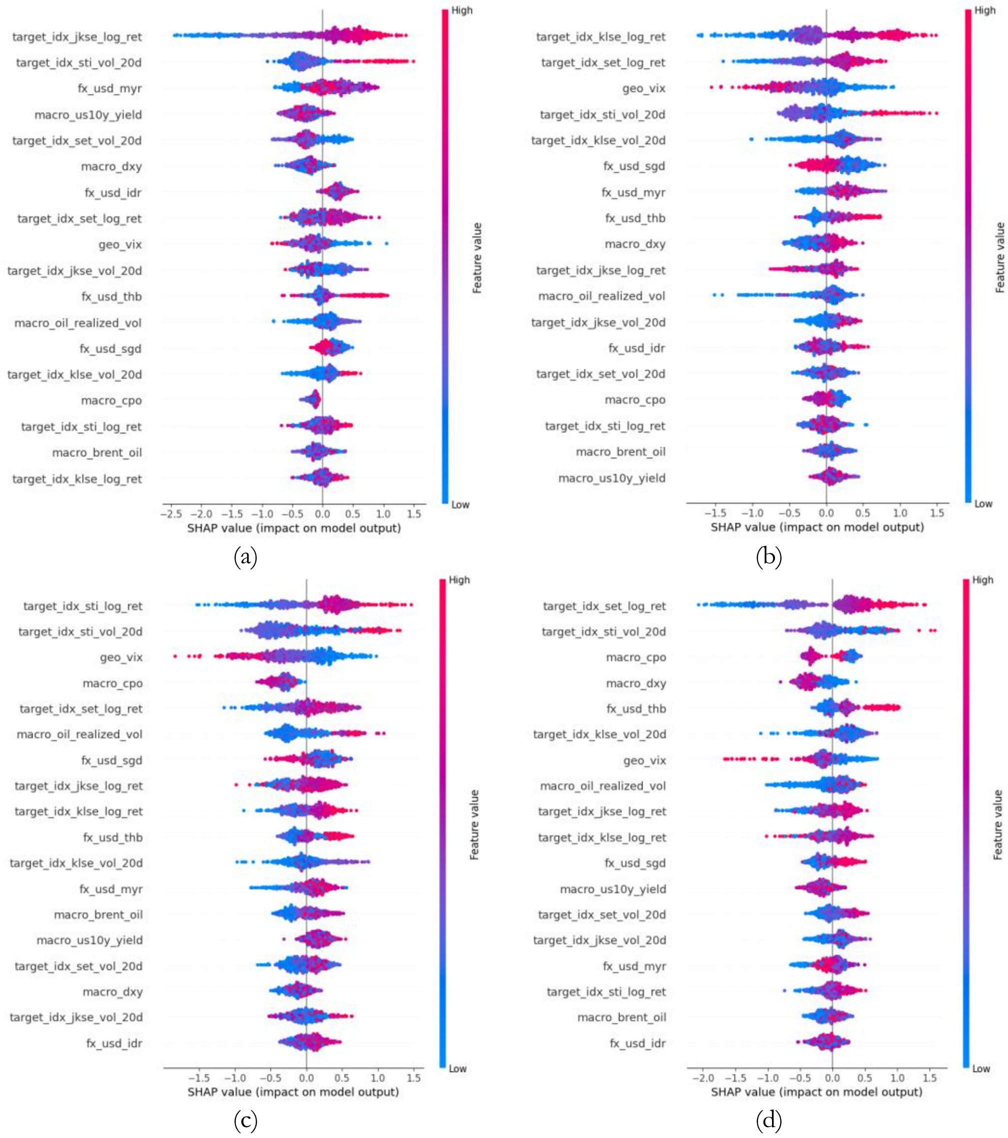
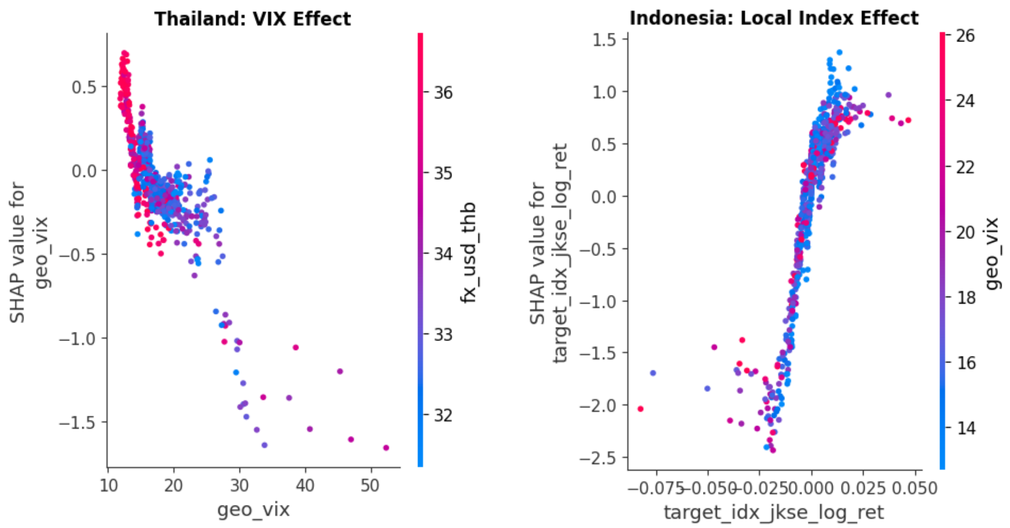


Figure 6. SHAP Beeswarm Plots of Feature Importance and Directional Effects across ASEAN-4 Markets: (a) Indonesia, (b) Malaysia, (c) Singapore, and (d) Thailand

Magnitude of Feature Contributions. The magnitude of mean absolute SHAP values provides an additional basis for comparing the relative contribution of features across markets. Thailand's VIX contribution (3.77×10^{-5}) is approximately 2.2 times that of Singapore (1.72×10^{-5}), indicating substantially greater model sensitivity to this feature in Thailand. Indonesia's Local Index contribution (8.49×10^{-6}) is slightly higher than Singapore's (7.80×10^{-6}), suggesting a comparatively stronger role for domestic market information in the Indonesian model. In Malaysia, the combined contribution of Brent Oil and CPO (1.67×10^{-5}) is higher than the corresponding commodity contribution in Singapore (0.91×10^{-5}). Overall, the SHAP results show that the four markets exhibit different combinations of global, domestic, and commodity-related predictive signals, providing model-based evidence of cross-country heterogeneity. This version deliberately removes claims such as "validating the taxonomy," "insulation from global contagion," "high-beta transitional market," "efficient-market benchmark," and "pure financial hub," because the SHAP results alone do not establish those economic characteristics or causal mechanisms.



(a) (b)

Figure 7. SHAP Dependence Plots of Non-Linear Relationships for Key Features: (a) VIX Effect for Thailand and (b) Local Index Effect for Indonesia

4.6. Formalizing the Taxonomy via Aggregate SHAP Sensitivity Analysis

To complement the feature-level SHAP analysis, an aggregate feature-group sensitivity analysis was conducted to examine whether the observed cross-country differences can be summarized according to broader categories of predictive signals. The input variables were grouped into two mutually exclusive categories: (1) Global Financial and Geopolitical Anchors, comprising VIX, DXY, and US10Y; and (2) Commodity and Domestic Structural Factors, comprising Brent Oil, CPO, Local Equity Index, Local FX, and domestic policy rates such as BI-7DRR (BI Rate).

For each country, the mean absolute SHAP values within each feature group were aggregated and expressed as a proportion of the total absolute SHAP importance. Table 8 summarizes the resulting composition. For descriptive classification, a group was considered dominant when its proportional contribution exceeded 50%. This threshold is used as an operational criterion for summarizing the relative sensitivity of each market and should not be interpreted as an independently validated boundary.

Table 8. Aggregate SHAP Importance by Macroeconomic Feature Group (Sensitivity Analysis)

Country	Global Financial & Geopolitical Anchors (VIX, DXY, US10Y)	Commodity & Domestic Structural Factors (Brent Oil, CPO, Local Index, Local FX, BI Rate)	Dominant Group & Taxonomy Classification
Thailand	61.0%	39.0%	Global Anchors (>50%) ➔ Geopolitical Risk Transmission
Singapore	52.1%	47.9%	Global Anchors (>50%) ➔ Monetary-Driven Hub
Malaysia	48.8%	51.2%	Commodity/Domestic (>50%) ➔ Hybrid Commodity-Monetary
Indonesia	39.8%	60.2%	Commodity/Domestic (>50%) ➔ Segmented Commodity Market

Note: Percentages represent the proportional contribution of each feature group to the total absolute SHAP value for the respective country's directional return predictions. The >50% threshold serves as the empirical criterion for taxonomy assignment.

Linking Dataset Characteristics and Aggregate Sensitivity. The aggregate SHAP results can be considered alongside the statistical characteristics of the datasets reported in the preceding analysis. Singapore exhibits the lowest kurtosis (3.21), whereas Thailand shows the highest kurtosis (6.84), indicating differences in the distributional characteristics of their return series. Indonesia and Malaysia also exhibit volatility clustering and distributional changes across periods. These characteristics provide contextual evidence that the four markets differ in their statistical behavior and may therefore respond differently to the same predictive inputs. However, these distributional characteristics should not be interpreted as independent validation of the SHAP-based grouping. Rather, they provide complementary descriptive evidence for interpreting the differences observed in the model's feature-attribution patterns. Establishing whether these statistical properties correspond to persistent economic transmission mechanisms would require additional analyses, such as rolling-window estimation, regime-based evaluation, or econometric tests.

Cross-Country Heterogeneity as a Central Finding. The results consistently indicate substantial cross-country heterogeneity in both predictive performance and feature attribution. HMT-STN achieves different levels of classification performance across the four markets, with test accuracy ranging from 53.46% in Indonesia to 66.21% in Thailand. The relatively small standard deviations across the five random seeds for Thailand (66.21% ± 0.42%) and Singapore (56.32% ± 0.44%) indicate that these results are relatively stable with respect to random initialization within the experimental setting. This finding should not be interpreted as evidence that one architecture is universally optimal across markets. Instead, the results suggest that model performance depends on the interaction between the model design and the characteristics of the target market. This interpretation is also supported by the ablation results, where the contribution of individual components varies across countries.

Thailand: Strong Global-Anchor Sensitivity. Thailand provides the clearest example of the association between aggregate feature sensitivity and model performance. Global Financial and Geopolitical Anchors account for 61.0% of the aggregate absolute SHAP importance, with VIX representing the largest individual contribution. Thailand also has the highest reported kurtosis (6.84), indicating a relatively heavy-tailed return distribution. The ablation analysis further shows a substantial reduction in performance when Focal Loss is replaced with BCE, with accuracy declining from 66.21% to 42.78% and AUC from 0.68 to 0.43. These results indicate that the choice of classification loss is particularly important for the Thai market under the experimental setting. Nevertheless, the ablation alone does not establish that Focal Loss specifically enables the model to learn geopolitical shock events; such a mechanism would require additional analyses of sample-level errors, loss dynamics, or regime-specific performance.

Singapore: A Boundary Case for Heterogeneous Modeling. Singapore represents an important boundary case because HMT-STN does not achieve the highest raw accuracy in this market. Homogeneous MTL obtains 63.41% accuracy compared with 56.32% for HMT-STN. This result indicates that the proposed heterogeneous formulation does not provide a uniform accuracy improvement across all markets. At the same time, HMT-STN obtains an AUC-ROC of 0.57 compared with 0.53 for Homogeneous MTL. This difference indicates somewhat stronger discrimination in the ranking of positive and negative outcomes, although it should not be interpreted as evidence of superior probability calibration. Calibration should instead be assessed using metrics such as the Brier Score or calibration curves. The Singapore result therefore illustrates that different evaluation criteria can lead to different conclusions about model behavior.

Taken together, the aggregate SHAP analysis indicates that the four ASEAN markets exhibit different compositions of global, domestic, and commodity-related predictive signals. Thailand and Singapore show a relative dominance of the Global Financial and Geopolitical Anchor group, whereas Indonesia and Malaysia show greater aggregate contributions from Commodity and Domestic Structural Factors. These findings support the use of cross-country heterogeneity as an important analytical dimension of the proposed framework. However, the resulting groupings should be regarded as model-based sensitivity profiles rather than definitive economic classifications or causal transmission mechanisms. The primary contribution of the analysis is therefore to demonstrate how aggregate SHAP patterns can summarize differences in the predictive signals used by the model across ASEAN markets.

5. Conclusions

This study proposed the Heterogeneous Multi-Task Spatiotemporal Network (HMT-STN), a structurally adaptive framework designed to capture asymmetric geopolitical shock transmission across ASEAN-4 equity markets (2016–2026). By integrating country-specific embeddings, Focal Loss, and heterogeneous task decoupling, the framework addresses three critical computational challenges: negative transfer, base-rate bias, and overre-liance on Accuracy. Comprehensive evaluations demonstrate highly discriminative performance—notably AUC-ROC of 0.68 and 66.21% accuracy in Thailand. Ablation validates that Focal Loss prevents catastrophic collapse (−23.43 percentage points) in noisy environments, while country embeddings isolate market-specific idiosyncrasies. Threshold optimization via Youden's J-statistic confirms well-calibrated probability outputs (thresholds: 0.484–0.506).

The primary contribution is a structurally adaptive computational framework whose architectural innovations collectively address cross-country financial prediction challenges. The observed sensitivity patterns, while consistent with economic theories of cross-country heterogeneity, are model-based attributions rather than causal mechanisms. These findings provide empirical evidence against the 'one-size-fits-all' assumption, demonstrating that explicitly modeling cross-country heterogeneity improves predictive performance in structurally diverse emerging markets.

Several limitations merit acknowledgment. The ablation study validates architectural contributions but does not provide direct mechanistic evidence of gradient interference; future work could employ gradient-level diagnostics (cosine similarity analysis, gradient norm tracking) to quantify task interference. The framework relies on quantitative proxies, potentially obscuring qualitative sentiment; future research should integrate NLP-based Geopolitical Sentiment Indices. The static design ignores time-varying regimes; Time-Varying SHAP or regime-switching mechanisms could address this. The absence of bilateral spillover mapping suggests extending to Graph Neural Networks. While HMT-STN demonstrates superior volatility prediction, this study does not evaluate direct effectiveness in risk-management applications (VaR backtesting, Expected Shortfall estimation). SHAP-based interpretability reveals patterns consistent with economic theories but does not establish causal mechanisms; future work should employ causal inference methods (Granger causality, VAR, structural equation modeling) to establish directionality of cross-market risk transmission.

Collectively, this study demonstrates that heterogeneous multi-task learning, rigorous metric evaluation, and post-hoc interpretability offer a powerful paradigm for understanding systemic risk in structurally diverse emerging economies advancing both the methodological frontier of financial deep learning and actionable insights for portfolio optimization in an increasingly fragmented geopolitical landscape.

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Data Availability Statement: The raw data supporting the findings of this study are openly available in public domains. Daily equity market data for the ASEAN-4 countries (Indonesia, Malaysia, Singapore, and Thailand) were retrieved from Yahoo Finance and the respective national stock exchanges. Global macroeconomic and geopolitical indicators, including Brent Crude Oil, Crude Palm Oil (CPO), the US Dollar Index (DXY), US 10-Year Treasury Yield, and the CBOE Volatility Index (VIX), were sourced from the Federal Reserve Economic Data (FRED) and the Chicago Board Options Exchange (CBOE). The processed balanced panel dataset, complete Python source code for the Heterogeneous Multi-Task Spatiotemporal Network (HMT-STN) framework, preprocessing scripts, and comprehensive reproduction instructions are publicly available at [GitHub: https://github.com/etnadia/ASEAN_HMTDL] to ensure long-term reproducibility.

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