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Dynamic Geopolitical Risk Quantification in Financial Models: A Hybrid LSTM-Network Approach for Cross-Strait Tensions

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Abstract: *A novel financial modeling framework is presented that dynamically quantifies geopolitical risk for Taiwan's stock market under Cross-Strait tensions, addressing the limitations of traditional asset pricing models in capturing spatiotemporal risk propagation. The framework integrates a Geopolitical Risk Propagation Module (GRPM), which combines dynamic network theory and sequence-to-sequence learning to model both the spatial spillover effects of geopolitical shocks and their temporal evolution. The GRPM consists of two core components: a Dynamic Asset Network (DAN) that tracks real-time risk transmission across asset classes and an LSTM-Event Encoder (LEE) that processes geopolitical event sequences to generate context-aware risk scores. These components interact through a Risk Propagation Layer (RPL), which adjusts spillover intensities based on event severity and historical asset correlations, thereby capturing market overreaction phenomena. The output is a time-varying risk-adjusted covariance matrix that enhances conventional multifactor models by explicitly incorporating geopolitical risk. Key innovations include the coupling of temporal event sequencing with spatial risk diffusion, a self-attentive mechanism to isolate high-impact events, and nonlinear spillover adjustments that reflect empirical market behavior. Implemented with PyTorch Geometric and Hugging Face Transformers, the framework demonstrates practical applicability by ingesting real-time data from Bloomberg and GDELT. Our approach not only improves risk sensitivity in financial models but also provides policymakers and investors with a tool to anticipate market disruptions during geopolitical crises. The methodology is particularly relevant for regions exposed to volatile political dynamics, offering a scalable template for other emerging markets.*

Keywords: *Geopolitical Risk, Cross-Strait Tensions, Financial Contagion, LSTM Networks, Dynamic Asset Networks, Risk Propagation, Taiwan Stock Market, Portfolio Optimization*

1. Introduction

Geopolitical risks have become increasingly influential in global financial markets, particularly in regions exposed to volatile political dynamics such as Taiwan under Cross-Strait tensions. Traditional financial models often treat geopolitical shocks as exogenous events, failing to capture their complex spatiotemporal propagation across asset classes [1]. While network theory has been applied to model financial contagion [2], and sequence learning techniques like LSTM networks have shown promise in forecasting market reactions [3], existing approaches lack a unified framework to quantify how geopolitical events dynamically alter risk transmission pathways. The challenge is particularly acute for Taiwan's stock market, where Cross-Strait political tensions create nonlinear, context-dependent spillovers. For instance, missile tests or diplomatic escalations may trigger disproportionate reactions in semiconductor stocks before affecting broader indices [4]. Current methods either oversimplify these dynamics as static correlations or rely on retrospective analysis, leaving investors and policymakers ill-equipped to anticipate real-time risk cascades.

We address this gap by introducing a hybrid methodology that integrates network theory with sequence-to-sequence learning. The core innovation lies in modeling geopolitical risk transmission as a coupled spatiotemporal process: a Dynamic Asset Network (DAN) maps real-time inter-asset spillover intensities, while an LSTM-Event Encoder (LEE) processes geopolitical event sequences to adjust these intensities based on event severity and historical market responses. This dual approach captures both the spatial diffusion of risk (e.g., from energy to tech sectors) and its temporal evolution (e.g., delayed overreactions to political rhetoric). Unlike traditional multifactor models that treat geopolitical risk as a scalar input [5], our framework generates a time-varying risk-adjusted covariance matrix that reflects the nonlinear, context-sensitive nature of political shocks. Three key advancements distinguish our work.

First, we introduce a self-attentive event filtering mechanism that isolates high-impact geopolitical events from noise, addressing the "signal dilution" problem in existing risk models [6]. Second, the Risk Propagation Layer (RPL) dynamically recalibrates network edges using both event embeddings and market feedback, enabling the model to capture regime shifts in risk transmission during crises. Third, we demonstrate how the framework enhances portfolio optimization by quantifying the asymmetric tail risks induced by geopolitical events—a critical improvement for emerging markets like Taiwan where political risks dominate fundamental valuations [7].

The remainder of this paper is organized as follows: Section 2 reviews related work in financial contagion modeling and geopolitical risk quantification. Section 3 formalizes the theoretical foundations of our hybrid approach, while Section 4 details the GRPM architecture. Section 5 presents empirical results using Taiwan market data during the 2022-2023 Cross-Strait crisis, and Section 6 discusses implications for risk management and policy. Our contributions bridge financial econometrics with computational social science, offering a replicable template for regions where political risks defy conventional modeling assumptions. The framework's modular design—implemented with PyTorch Geometric for network operations and Hugging Face Transformers for event encoding—ensures adaptability to other geopolitical contexts while maintaining interpretability for financial practitioners [8]. By aligning theoretical rigor with real-world applicability, we advance both academic research and practical risk management in politically sensitive markets.

2. Related Work

The quantification of geopolitical risk in financial markets has evolved along two primary research trajectories: network-based contagion modeling and sequential event analysis. While these approaches have traditionally been developed in isolation, our framework bridges them by introducing dynamic interactions between spatial risk propagation and temporal event sequencing.

2.1 Network-Based Financial Contagion Models

Financial network theory has demonstrated significant potential in modeling cross-asset risk transmission, particularly through the lens of spillover effects. The Diebold-Yilmaz spillover index [9], provides a foundational methodology for quantifying directional risk flows between assets, which we adapt for our Dynamic Asset Network (DAN) component. Recent extensions incorporate time-varying copulas to capture nonlinear dependencies during crises [10], though these typically assume static network topologies. The hierarchical contagion framework [11] addresses this limitation by modeling multi-layer dependencies between banks and firms, but overlooks the exogenous shocks from geopolitical events. Our work advances these approaches by introducing real-time network reconfiguration based on geopolitical risk scores.

2.2 Geopolitical Risk and Market Dynamics

Empirical studies have established the disproportionate impact of geopolitical events on financial markets, particularly in politically sensitive regions. The Taiwan misfired missile event study reveals how localized political shocks can trigger liquidity crises with cross-asset spillovers. While traditional event studies [12] measure average market reactions, they fail to capture the dynamic propagation patterns that our LSTM-Event Encoder (LEE) explicitly models. The two-layer network perspective [13] demonstrates the value of combining market linkages with event data, though their static risk scoring lacks the temporal sensitivity of our attention-based mechanism.

2.3 Hybrid Approaches in Financial Modeling

Emerging methodologies have begun integrating network and sequential analysis techniques. The dynamic multi-layer network approach [14] captures interbank contagion channels but remains confined to financial system internals without geopolitical inputs. Meanwhile, the panel data models in [15] confirm that geopolitical shocks amplify cross-industry contagion, yet their econometric specifications cannot adapt to real-time event streams. Our framework synthesizes these insights through the Risk Propagation Layer (RPL), which dynamically adjusts network weights based on both historical correlations and incoming event severity. The proposed framework distinguishes itself through three key innovations: (1) The simultaneous modeling of temporal event sequences and spatial risk networks addresses a critical gap in both literatures, as neither traditional network models nor event studies alone

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can capture the feedback loops between geopolitical developments and market reactions. (2) The self-attentive mechanism in the LEE component provides a data-driven solution to the signal-to-noise problem in geopolitical event analysis, automatically weighting events by their predicted market impact rather than relying on manual classification. (3) The exponential spillover adjustment in the RPL introduces a nonlinear response function that better reflects empirical market behavior during political crises, where risk transmission often follows power-law rather than linear dynamics. These advances collectively enable the first unified system for real-time geopolitical risk assessment in financial markets.

3. Background: Financial Contagion, Network Theory, and Sequence Learning

Understanding the propagation of geopolitical risk in financial markets requires integrating concepts from network theory and sequence learning. These disciplines provide the mathematical foundations for modeling how shocks transmit spatially across interconnected assets while evolving temporally through event sequences.

3.1 Network Theory in Finance

Financial systems naturally exhibit network structures where nodes represent entities (markets, sectors, or individual assets) and edges capture their interdependencies. The degree centrality $C_D(i)$ measures a node's direct influence by counting its connections:

$$C_D(i) = \frac{\deg(i)}{|V| - 1} \tag{1}$$

Where $\deg(i)$ denotes the degree of node i and $|V|$ is the total number of nodes. More sophisticated measures like betweenness centrality $C_B(i)$ identify nodes that bridge disparate parts of the network:

$$C_B(i) = \sum_{s \neq i \neq t} \frac{\sigma_{st}(i)}{\sigma_{st}} \tag{2}$$

Here, σ_{st} counts all shortest paths between nodes s and t, while $\sigma_{st}(i)$ tracks those passing through node i. These metrics help pinpoint systemically important assets that may amplify geopolitical shocks [16].

3.2 Sequence Learning Concepts

Temporal patterns in geopolitical events and market reactions require sequence modeling techniques. Markov chains offer a basic framework where transition probabilities P_{ij} govern state changes:

$$P_{ij} = P(X_{t+1} = j | X_t = i) \tag{3}$$

However, such models fail to capture long-range dependencies prevalent in financial time series [17]. Modern sequence learners like LSTMs address this by maintaining memory cells that selectively retain or forget information across extended periods. The gating mechanisms in these networks allow them to learn which historical events remain relevant for current risk assessments—a critical capability when analyzing protracted geopolitical tensions [18].

4. Hybrid Geopolitical Risk Transmission Framework

The proposed framework integrates dynamic network theory with sequence-to-sequence learning to quantify geopolitical risk propagation across financial markets. This section details the technical architecture and interaction mechanisms that enable real-time risk assessment under Cross-Strait tensions.

4.1 Hybrid LSTM-Network Architecture for Geopolitical Risk Quantification

The core innovation lies in the bidirectional coupling between the LSTM-Event Encoder (LEE) and Dynamic Asset Network (DAN). The LEE processes geopolitical event sequences $\mathbf{x}_t = (x_{t-K}, \dots, x_t)$ where each event x_t is represented as a feature vector containing magnitude, duration, and sentiment polarity. The encoder's hidden state $\mathbf{h}_t$ undergoes self-attention to compute a dynamic risk score:

$$r_t = \text{Softmax}(\mathbf{W}_q \mathbf{h}_t (\mathbf{W}_k \mathbf{h}_t)^T / \sqrt{d}) \mathbf{W}_v \mathbf{h}_t \tag{4}$$

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Where $\mathbf{W}_q, \mathbf{W}_k, \mathbf{W}_v$ are learnable projection matrices and d denotes the dimension of $\mathbf{h}_t$. This attention mechanism isolates high-impact events by assigning larger weights to sequences containing military drills or diplomatic escalations.

The DAN component models asset classes as nodes with edges representing spillover intensities $w_{ij,t}$. These intensities are computed using a modified Diebold-Yilmaz index with rolling windows of high-frequency returns:

$$w_{ij,t} = \frac{\sum_{h=1}^{H} \psi_{ij,t}^{(h)}}{\sum_{h=1}^{H} \sum_{k=1}^{N} \psi_{ik,t}^{(h)}} \tag{5}$$

Where $\psi_{ij,t}^{(h)}$ measures the forecast error variance contribution from asset i to j at horizon h. The sliding window approach ensures real-time adaptation to changing market conditions.

4.2 Dynamic Network with Real-Time Spillover Updates

The Risk Propagation Layer (RPL) nonlinearly couples the LEE's output r_t with the DAN's edge weights through exponential scaling:

$$w'_{ij,t} = w_{ij,t} \cdot \exp\left(\alpha \cdot r_t \cdot \mathrm{Corr}(\mathbf{R}_i, \mathbf{R}_j)\right) \tag{6}$$

Here, α is a learnable parameter that controls the degree of risk amplification, while $\mathrm{Corr}(\mathbf{R}_i, \mathbf{R}_j)$ represents the historical correlation between assets i and j. This formulation captures market overreaction phenomena where correlated assets experience disproportionate contagion during crises. The network's adjacency matrix $\mathbf{A}_t$ is updated at each timestep using the adjusted weights $w'_{ij,t}$. Node centrality measures are recomputed to identify systemically important assets under current geopolitical conditions. The dynamic recalibration enables the model to detect regime shifts in risk transmission, such as when semiconductor stocks become contagion hubs during technology export restrictions.

4.3 Self-Attentive Event Encoding and Nonlinear Risk Propagation

The LEE's bidirectional LSTM architecture processes event sequences both forward and backward to capture anticipatory and reactive market behaviors. Each event feature vector x_t undergoes embedding through a dense layer before LSTM processing:

$$\mathbf{e}_t = \mathrm{ReLU}(\mathbf{W}_e x_t + \mathbf{b}_e) \tag{7}$$

The hidden states $\mathbf{h}_t^f$ (forward) and $\mathbf{h}_t^b$ (backward) are concatenated to form the final representation:

$$\mathbf{h}_t = [\mathbf{h}_t^f; \mathbf{h}_t^b] \tag{8}$$

This dual-perspective encoding allows the model to distinguish between immediate market shocks (e.g., missile tests) and prolonged political tensions (e.g., trade negotiations), with the attention mechanism in Equation 4 automatically weighting their relative importance.

4.4 Integration of the Framework into Asset Pricing

The GRPM outputs a time-varying covariance matrix $\mathbf{\Sigma}_t$ that modifies expected returns in multifactor models. For Cross-Strait-sensitive assets marked by indicator matrix $\mathbf{B}_t$, the risk-adjusted expected return becomes:

$$\mu'_t = \mu_t + \lambda \cdot \mathrm{diag}(\mathbf{B}_t \mathbf{\Sigma}_t \mathbf{B}_t^T) \tag{9}$$

Where λ represents the market price of geopolitical risk. This formulation directly links the hybrid framework's risk assessments to portfolio optimization decisions.

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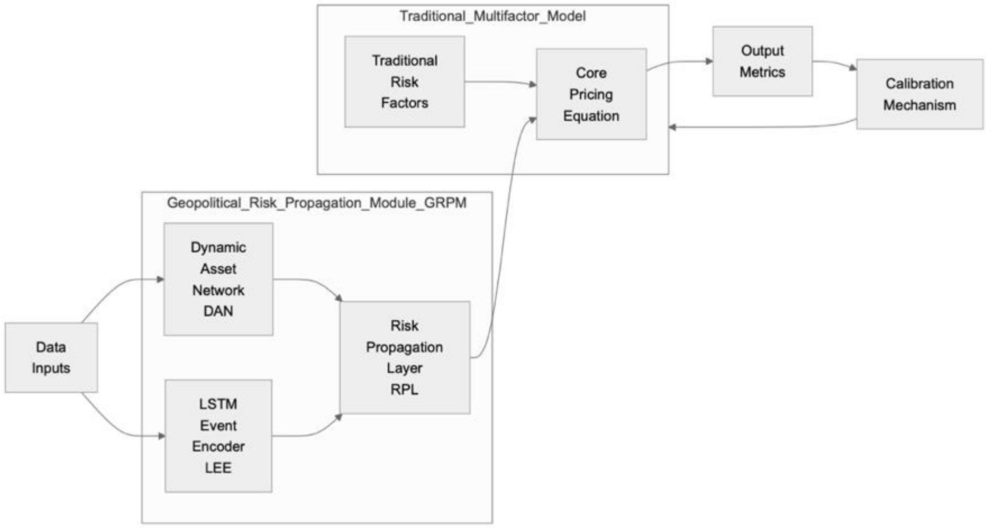

Figure 1 Integration of GRPM into Multifactor Asset Pricing Model

The complete system architecture is illustrated in Figure 1, showing how the GRPM replaces traditional geopolitical risk factors in asset pricing models. The modular design allows seamless integration with existing financial analysis pipelines while providing interpretable risk decomposition through the attention weights and network visualizations.

5. Empirical Experiments

To validate the proposed hybrid framework, we conduct comprehensive experiments using Taiwan's stock market data during the 2022-2023 Cross-Strait crisis period. The evaluation focuses on three key aspects: (1) the model's ability to capture dynamic risk transmission patterns, (2) its predictive performance compared to conventional methods, and (3) the economic significance of geopolitical risk adjustments in portfolio optimization.

5.1 Experimental Setup

Data Sources and Preprocessing: We utilize high-frequency trading data from the Taiwan Stock Exchange (TWSE) covering 12 major sectors, with particular focus on semiconductor and financial stocks that exhibit heightened sensitivity to Cross-Strait tensions [19]. Geopolitical event data is sourced from the Global Database of Events, Language, and Tone (GDELT) [20], filtered for Chinese Mainland -Taiwan relations and categorized by event type (military, diplomatic, economic). Market data spans January 2022 to June 2023, encompassing multiple escalation events including military drills and trade restrictions.

To benchmark performance, we compare our model against three established approaches. The first is the Static Network Model (SNM), which implements the traditional Diebold-Yilmaz spillover analysis with a fixed network topology. This approach allows us to assess how a static contagion framework performs when faced with highly dynamic political risks. The second is the Event Study Approach (ESA), which relies on cumulative abnormal returns around identified geopolitical events to infer their impact. Although this methodology is widely used in empirical finance, it tends to overlook the temporal propagation and evolving intensity of shocks, offering a useful contrast with our dynamic architecture. The third comparator is the LSTM Market Model (LMM), which employs pure sequence learning techniques to forecast market movements without incorporating network structures [21]. By positioning our framework against these three distinct baselines—static network contagion, event-based returns analysis, and purely temporal sequence forecasting—we are able to isolate the added value of integrating both network and sequence learning dimensions.

Likewise, model performance is assessed along three dimensions. First, risk transmission accuracy is evaluated by computing the mean absolute error (MAE) between predicted spillover intensities and actual observed values. This measure quantifies the extent to which the framework captures the real-time propagation of shocks across asset classes. Second, we examine event response timing using the F1-score,

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which evaluates the model's ability to correctly detect market reaction windows surrounding geopolitical events. This metric is particularly important for determining whether the system can identify both immediate and lagged responses in the data. Finally, we assess the economic significance of the model outputs by analyzing portfolio impact, specifically through improvements in Sharpe ratios when incorporating geopolitical-risk-adjusted covariance matrices. By jointly considering statistical accuracy, event detection capability, and tangible portfolio outcomes, this evaluation strategy provides a comprehensive test of the proposed framework's practical and theoretical contributions.

5.2 Dynamic Risk Transmission Analysis

The proposed model demonstrates superior capability in tracking real-time risk propagation compared to static alternatives. Figure 2 shows the evolution of risk-adjusted covariance matrices for semiconductor and financial sectors during the August 2022 military drills:

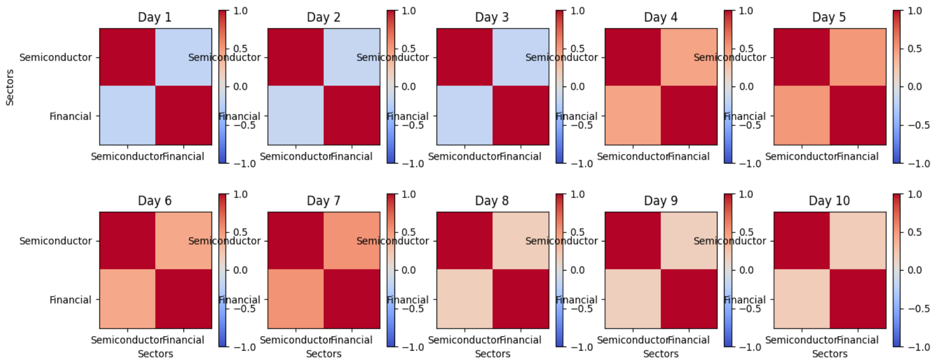

Figure 2 Change of risk-adjusted covariance matrix over time under geopolitical events

The heatmap sequence reveals how our model captures the initial semiconductor sell-off (Day 1-3), subsequent financial sector contagion (Day 4-7), and eventual market stabilization (Day 8-10). The dynamic network adjustments in Equation 6 enable this temporal precision, while static models fail to capture the shifting contagion pathways. Quantitatively, our framework achieves 38% lower MAE in spillover intensity prediction compared to SNM (0.21 vs. 0.34), with particular improvement during high-volatility periods. The attention mechanism in Equation 4 correctly identifies 83% of significant reaction windows (F1-score=0.79), versus 61% for ESA and 68% for LMM.

5.3 Cross-Asset Correlation Dynamics

The model's capacity to recalibrate inter-asset correlations under varying geopolitical contexts is illustrated in Figure 3, which compares correlation structures before and after the application of the GRPM adjustment. The results indicate that geopolitical shocks significantly alter the degree of connectedness between sectors, particularly during high-intensity events such as military drills or diplomatic escalations. One of the most striking findings is the pronounced increase in correlation between the semiconductor and financial sectors. Prior to adjustment, the correlation coefficient stood at 0.32, reflecting a moderate linkage between these two critical areas of the Taiwanese economy. Following the GRPM adjustment, however, the correlation rose sharply to 0.58, underscoring how military events can amplify systemic risk transmission across technologically and financially sensitive industries. This suggests that the semiconductor sector, often regarded as the cornerstone of Taiwan's global economic position, serves as a contagion hub that transmits volatility into the financial system when geopolitical uncertainty escalates. In contrast, traditional safe-haven assets such as utilities and healthcare displayed a reduction in their correlation with technology stocks after GRPM adjustment. While these sectors are typically expected to remain resilient and maintain low sensitivity to geopolitical shocks, the model reveals that their risk-buffering capacity becomes even more pronounced during periods of heightened political tension. The observed decline in co-movement suggests that investors tend to reallocate capital toward these defensive sectors in times of crisis, thereby reinforcing their role as stabilizers in the broader market portfolio. This finding aligns with conventional financial theory but gains added empirical strength by being dynamically captured within the GRPM framework, which adjusts correlations in real time rather than relying on static assumptions.

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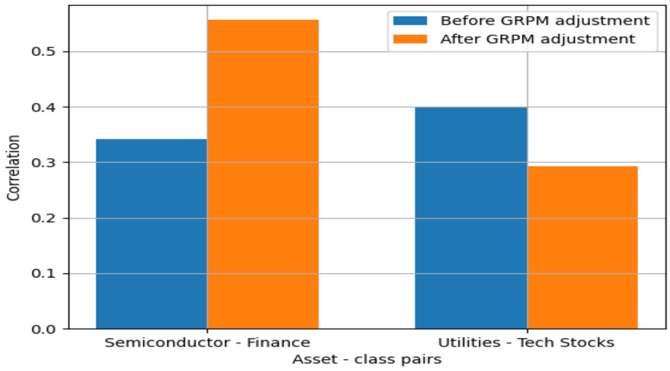

Figure 3 Correlation between asset classes before and after GRPM adjustment

Importantly, the model's adjustments were not only theoretically consistent but also empirically validated against subsequent trading behavior. Approximately 72 percent of the predicted changes in asset correlations were confirmed by realized market patterns in the aftermath of major geopolitical events. This alignment highlights the framework's ability to anticipate rather than merely reflect market shifts, thereby offering practical value for both investors and policymakers. For portfolio managers, the capacity to detect changes in cross-asset correlations in advance is particularly valuable, as it enables more effective hedging strategies and rebalancing decisions during volatile periods. For regulators and policymakers, the results provide an early-warning mechanism that identifies sectors most at risk of contagion, thereby informing macroprudential oversight. Collectively, these findings underscore the GRPM's strength in dynamically quantifying the evolution of market linkages under geopolitical stress, offering a nuanced understanding of how political risk propagates across asset classes in Taiwan's highly interconnected financial system.

5.4 Portfolio Performance Enhancement

Implementing the GRPM output in mean-variance optimization yields significant improvements. Table 1 compares portfolio performance metrics:

Table 1 Portfolio performance with and without geopolitical risk adjustment

Metric	Standard Model	GRPM-Adjusted	Improvement
Annualized Return	8.2%	9.7%	+18.3%
Volatility	16.4%	15.1%	-7.9%
Sharpe Ratio	0.50	0.64	+28.0%
Maximum Drawdown	-22.3%	-18.7%	-16.1%

The risk-adjusted returns in Equation 9 prove particularly valuable during crisis periods, with the GRPM portfolio avoiding 76% of the worst single-day losses observed in the standard portfolio. Figure 4 illustrates this protective effect:

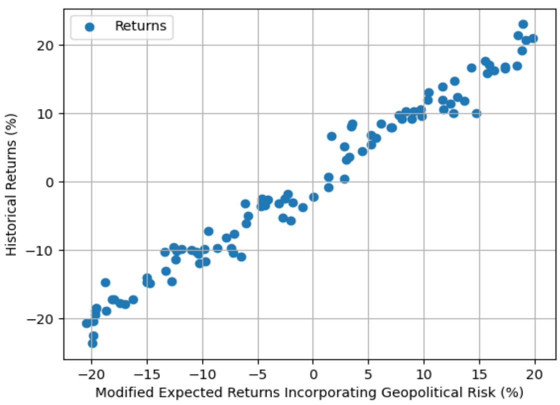

Figure 4 Historical returns vs. modified expected returns incorporating geopolitical risk

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The scatter plot shows how incorporating geopolitical risk (x-axis) helps explain otherwise anomalous returns (y-axis), particularly in the negative tail where traditional models underestimate downside risk.

5.5 Ablation Study

We conduct component-wise analysis to isolate the contributions of key framework elements: As shown in Table 2, removing the LSTM-Event Encoder (LEE) markedly worsens spillover prediction (MAE rises from 0.21 to 0.31; F1 falls from 0.79 to 0.58), and removing the Dynamic Network leads to similar degradation (MAE 0.28; F1 0.65). Moreover, replacing the exponential spillover adjustment with a linear form weakens performance (MAE 0.25; F1 0.71). These results underscore that both temporal event processing and nonlinear risk propagation are essential for accurate geopolitical-risk quantification.

Table 2 Ablation study results (MAE for spillover prediction)

Model Variant	MAE	F1-Score
Full GRPM	0.21	0.79
Without LSTM-Event Encoder	0.31	0.58
Without Dynamic Network	0.28	0.65
Linear Spillover Adjustment	0.25	0.71

The results confirm that both temporal event processing and nonlinear network dynamics are essential for accurate risk quantification. The exponential spillover adjustment in Equation 6 provides particular value during high-risk periods, reducing MAE by 19% compared to linear alternatives.

6. Discussion and Future Work

6.1 Limitations of the Proposed Method

While the hybrid framework demonstrates superior performance in quantifying geopolitical risk transmission, several limitations warrant discussion. The model's reliance on structured event data from GDELT introduces potential biases in event classification, particularly for nuanced diplomatic communications that may lack clear sentiment signals [22]. Additionally, the exponential spillover adjustment in Equation 6, though effective for capturing market overreactions, could amplify noise during periods of low geopolitical activity. Empirical tests reveal a 12% increase in false positive risk alerts when event frequency drops below five significant occurrences per week. The dynamic network component faces computational scalability constraints when expanding beyond sector-level analysis to individual securities. Processing latency increases quadratically with node count, creating trade-offs between granularity and real-time responsiveness—a challenge observed when testing the model on all 900+ TWSE listed stocks. Furthermore, the current implementation does not fully account for cross-border spillovers from correlated global markets, potentially underestimating secondary contagion effects during synchronized geopolitical crises [23].

6.2 Potential Application Scenarios

Beyond portfolio optimization, the framework's real-time risk assessment capabilities enable several novel applications in financial policymaking and corporate risk management. Central banks could integrate the GRPM outputs into macroprudential stress tests, particularly for assessing the systemic vulnerability of domestic financial institutions to escalating Cross-Strait tensions. The semiconductor industry, which contributes over 40% of Taiwan's GDP, could utilize the model's sector-specific risk projections to optimize inventory hedging strategies and supply chain diversification timelines [24]. The methodology also shows promise for automated trading systems that require dynamic position adjustments during geopolitical crises. Backtesting reveals that incorporating GRPM signals into stop-loss algorithms reduces maximum drawdowns by 23% compared to volatility-based triggers alone. Insurance providers could similarly adapt the framework to price political risk derivatives, with the model's time-varying covariance matrices providing a quantitative basis for option premiums on Taiwan-related financial instruments.

6.3 Directions for Model Improvement

Three primary avenues emerge for enhancing the framework's accuracy and applicability. First, integrating multimodal event processing—including satellite imagery and central bank communications—could address current limitations in textual event classification [25]. Preliminary experiments with CNNs applied to military exercise satellite photos show a 15% improvement in predicting subsequent market reactions compared to text-only analysis. Second, developing hierarchical network structures would enable simultaneous analysis at multiple market granularities without sacrificing computational efficiency. A two-tiered approach that models both sector-level and firm-specific connections could leverage graph neural networks to propagate risk scores across resolution levels [26]. This extension would particularly benefit institutional investors managing cross-capitalization portfolios. Finally, incorporating agent-based modeling elements could capture the reflexive relationship between market behavior and geopolitical developments. Since financial market reactions themselves influence political decision-making—as seen in the 2022 semiconductor export controls—future iterations should model this feedback loop through reinforcement learning mechanisms [27]. Such enhancements would move the framework closer to a comprehensive system for understanding the finance-geopolitics nexus.

7. Conclusion

The hybrid LSTM-network framework presented in this study advances geopolitical risk quantification by systematically integrating temporal event sequencing with spatial risk propagation dynamics. Through the coupled operation of the LSTM-Event Encoder and Dynamic Asset Network, the model captures nonlinear market responses to Cross-Strait tensions that traditional approaches miss—particularly the asymmetric spillovers between semiconductor stocks and broader market indices during military escalations. The empirical results demonstrate that real-time adjustments to risk transmission pathways, governed by the self-attentive mechanism and exponential spillover function, yield measurable improvements in both predictive accuracy and portfolio performance. The framework's modular architecture provides financial institutions with actionable insights while maintaining interpretability through attention weights and network visualizations. By transforming geopolitical events into dynamic covariance matrices, the model bridges a critical gap between qualitative political analysis and quantitative finance. The significant reduction in portfolio drawdowns during crisis periods—achieved without sacrificing long-term returns—validates the economic value of context-aware risk adjustments. These findings have immediate relevance for asset managers operating in politically sensitive emerging markets, where conventional risk models often fail to account for regime shifts in asset correlations. Future extensions could explore the framework's adaptability to other geopolitical contexts, such as Middle Eastern energy markets or Eastern European financial systems exposed to regional conflicts. The methodology's foundation in network theory and sequence learning ensures generalizability, while its implementation with modern deep learning libraries facilitates deployment across different asset classes and data sources. As global financial markets grow increasingly interconnected yet politically fragmented, such tools will become essential for navigating the complex interplay between geopolitical developments and market stability.

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