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Temporal-Graph Deep Networks for Stock Market Forecasting and Volatility Analysis

Isolde Rennick

Southern Illinois University Edwardsville, Edwardsville, USA

irennick9042@siue.edu

Abstract:

This paper presents a novel Temporal-Graph Deep Network (T-GDN) designed for comprehensive stock market forecasting and volatility analysis. The proposed framework integrates temporal convolutional mechanisms with graph-based relational modeling to capture both sequential dependencies and inter-asset correlations in dynamic financial environments. Unlike conventional recurrent neural or transformer architectures that primarily model univariate time dependencies, T-GDN treats the financial market as an evolving graph in which nodes represent assets and edges encode dynamic dependencies such as sectoral relations, co-movements, and sentiment similarity. The model incorporates a hierarchical temporal-spatial encoder that combines graph attention layers and dilated causal convolutions, allowing multiscale information flow across time and entity dimensions. To enhance interpretability, a volatility-aware attention module highlights market segments contributing to high predictive uncertainty. Empirical evaluation on benchmark datasets including S&P 500 and CSI 300 demonstrates that T-GDN outperforms existing deep baselines-LSTM, GAT, and Temporal Fusion Transformer-by margins of 6.8% in RMSE and 9.3% in volatility-tracking F1 score. Further ablation analyses verify that graph-temporal fusion substantially improves stability during abrupt market transitions such as economic announcements and policy shifts. The findings suggest that the proposed framework not only advances accuracy in stock prediction but also enhances model interpretability for practical financial decision-making.

Keywords:

Deep Learning; Temporal Graph Networks; Financial Forecasting; Volatility Analysis; Attention Mechanisms; Market Dynamics

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1. Introduction

In recent years, the intersection of deep learning and financial analytics has transformed the way researchers and practitioners approach market prediction, risk assessment, and volatility modeling. Traditional econometric models such as ARIMA, GARCH, and VAR have long served as the foundation for time-series financial forecasting; however, their capacity to capture nonlinear and cross-asset dependencies is inherently limited. As financial markets become increasingly globalized and data-driven, asset prices are influenced not only by historical trends but also by complex, dynamic relationships among various instruments, sectors, and macroeconomic indicators. Deep learning, with its ability to model nonlinear mappings and hierarchical representations, has emerged as a powerful alternative to address these challenges.

The core motivation for this study stems from the recognition that financial markets are not merely sequences but interconnected networks. Each stock or asset interacts with others through shared investor sentiment, correlated trading behavior, and sectoral linkages. Modeling these relationships is crucial for accurately capturing systemic dynamics and contagion effects, especially during periods of market turbulence. Despite progress in recurrent and transformer-based models, most deep learning approaches treat stock data as isolated time series, neglecting the structural dependencies that underlie price co-movements. This oversimplification leads to suboptimal forecasting accuracy and poor generalization during market regime shifts.

To address this limitation, we propose the Temporal-Graph Deep Network (T-GDN), a novel architecture that jointly models temporal patterns and relational dependencies among assets. Unlike conventional deep neural models that focus exclusively on time-based features, T-GDN introduces a graph-based temporal representation in which each stock is a node, and edges represent dynamically evolving correlations or fundamental linkages. The design draws inspiration from both temporal convolutional networks (TCN) and graph attention networks (GAT), merging their strengths to learn multi-level dependencies in both the time and relational domains. By combining temporal causality modeling with graph-structured message passing, the network can simultaneously learn how individual assets evolve and how market structures influence collective behavior.

The increasing complexity of modern financial systems further amplifies the need for architectures that can generalize under non-stationary conditions. Real-world stock data exhibit abrupt volatility spikes, heavy-tailed distributions, and non-linear feedback loops driven by macroeconomic or psychological factors. Deep models that rely solely on sequential recurrence often fail to adapt to these phenomena, while graph-based methods that overlook time dependencies struggle to capture evolving patterns. Our T-GDN framework bridges this gap by incorporating a temporal-spatial encoder that dynamically learns both temporal features and structural connectivity, achieving robust forecasting across multiple market phases.

Moreover, interpretability remains a key concern in financial deep learning. Black-box models often face skepticism from financial institutions due to regulatory constraints and the necessity for explainable decision-making. To mitigate this, the proposed T-GDN integrates a volatility-aware attention module, which not only improves predictive accuracy but also provides transparency by identifying which assets or market segments contribute most to prediction uncertainty. Such interpretability enables portfolio managers and analysts to better understand systemic risks and respond proactively to volatility surges.

In essence, this research contributes to the field by developing a deep graph-temporal modeling approach that bridges the gap between sequence learning and network science in finance. The proposed T-GDN is evaluated on real-world datasets, including the S&P 500 and CSI 300 indices, under various temporal horizons and volatility conditions. The results indicate significant improvements in predictive accuracy and robustness compared to state-of-the-art benchmarks. By capturing the interplay between temporal evolution and structural connectivity, our framework offers a unified perspective for both forecasting and volatility interpretation-paving the way for more resilient, explainable, and adaptive financial analytics.

2. Related work

The application of deep learning to financial forecasting has evolved through several major paradigms-ranging from classical econometric models to sequence learning and, most recently, graph-based neural architectures. Traditional models such as ARIMA and GARCH have long dominated financial time-series forecasting for their simplicity and interpretability, yet their assumptions of linearity and stationarity make them ill-suited for modern, non-linear markets [1]. With the explosive growth of computational power and data availability, deep learning has emerged as a powerful alternative for capturing complex temporal patterns and cross-asset dependencies. Atsalakis and Valavanis [2] demonstrated early success using feedforward neural networks for stock prediction, showing clear advantages over regression-based methods. However, these architectures lacked temporal awareness, limiting their ability to model long-range dependencies across time.

To address this limitation, Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) architectures became widely adopted for sequential financial modeling [3], capable of capturing historical context in dynamic markets. Fischer and Krauss [4] successfully applied LSTM networks to stock price forecasting, outperforming both shallow neural and linear baselines. Despite their effectiveness, RNN-based models face difficulties in parallel computation and often exhibit unstable performance when extended to high-dimensional multivariate datasets. This challenge motivated the exploration of Temporal Convolutional Networks (TCNs), which offer improved stability and scalability by applying causal convolutions for long-term dependency modeling [5]. However, these temporal models typically treat financial assets as independent sequences, ignoring the rich relational structure among them.

Recognizing that financial markets inherently operate as interconnected systems, researchers began modeling asset correlations and dependencies through Graph Neural Networks (GNNs). The pioneering work of Kipf and Welling [6] introduced Graph Convolutional Networks (GCNs) for learning from structured data, while Veličković et al. [7] proposed Graph Attention Networks (GATs) that dynamically assign weights to node interactions. These advancements inspired numerous financial applications. For example, Jiang et al. [8] developed StockGCN to model dynamic stock correlations using rolling graph structures, demonstrating enhanced forecasting stability during volatile periods. Similarly, Sawhney et al. [9] extended graph learning with sentiment embeddings derived from news data, revealing that integrating textual and structural information improves prediction accuracy and resilience under regime shifts.

A crucial limitation of early graph-based models lies in their static representation of financial relationships, which fail to adapt to time-varying market conditions. To overcome this, recent studies have introduced Temporal Graph Networks (TGNs) and Spatio-Temporal Graph Neural Networks (ST-GNNs) that jointly learn from temporal sequences and graph dynamics [10], [11]. Wu et al. [12] proposed Graph WaveNet, a spatio-temporal graph model originally for traffic flow prediction but conceptually relevant for financial time-series modeling. In the financial domain, Feng et al. [13] incorporated macroeconomic indicators and investor sentiment into graph-temporal learning for multi-market prediction, while Chen et al. [14] designed a relational temporal encoder to predict event-driven financial shocks. These works highlight the growing recognition that fusing temporal evolution with relational reasoning is key to understanding market dynamics.

Parallel to forecasting, volatility modeling remains an essential area of research in quantitative finance. Traditional models like EGARCH and FIGARCH capture volatility clustering but are constrained by their parametric nature. More recently, neural volatility predictors-such as those developed by Li et al. [15]-integrate attention mechanisms to dynamically adjust the sensitivity of predictions to recent market fluctuations. This line of research supports the introduction of volatility-aware attention modules in modern architectures, which not only improve predictive performance but also enhance interpretability-a key requirement for explainable artificial intelligence in finance.

In summary, existing research has evolved from linear time-series models to deep temporal and graph-based architectures, gradually bridging the gap between sequential modeling and relational reasoning. Nevertheless, there remains a need for unified frameworks that capture both temporal causality and cross-asset connectivity while maintaining interpretability under volatile conditions. The proposed Temporal-Graph Deep Network (T-GDN) directly addresses this gap, offering an integrated mechanism for temporal learning, dynamic graph adaptation, and volatility-aware feature interpretation.

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3. Method

The proposed Temporal-Graph Deep Network (T-GDN) integrates temporal sequence modeling and graph-structured reasoning into a unified framework for financial forecasting and volatility analysis. The design philosophy is grounded on the observation that financial assets form a dynamic relational system whose structure evolves over time. To capture both temporal causality and inter-asset connectivity, the model combines three principal components: a temporal feature encoder, a graph-based relational aggregator, and a volatility-aware attention module.

Formally, let the stock market at time t be represented as a graph $G_t = (V, E_t)$, where each node $v_i \in V$ corresponds to a financial instrument and edges $e_{ij} \in E_t$ represent time-varying relationships such as price correlation or sectoral proximity. Each node is associated with a feature vector $\mathbf{x}_i^t \in \mathbb{R}^d$, derived from historical prices, volume, and sentiment indicators. The temporal encoder first processes these sequences through dilated causal convolutions to preserve the chronological order and avoid information leakage. The hidden representation for node i at layer l is given by

$$\mathbf{h}_i^{(l)} = \sigma\left(W_t^{(l)} * \mathbf{x}_i^{t-k:t} + b_t^{(l)}\right)$$

where $W_t^{(l)}$ is the convolutional kernel, k the receptive field, and $\sigma(\cdot)$ a nonlinear activation function. This operation extracts multiscale temporal dependencies while maintaining computational efficiency compared with recurrent alternatives.

Next, the graph relational module encodes cross-asset influences by propagating information along dynamic edges. The propagation rule follows an attention-based aggregation scheme,

$$\mathbf{z}_i = \sum_{j \in \mathcal{N}(i)} \alpha_{ij} W_g \mathbf{h}_j, \qquad \alpha_{ij} = \frac{\exp\left(\mathrm{LeakyReLU}(a^\top [W_g \mathbf{h}_i \| W_g \mathbf{h}_j])\right)}{\sum_{k \in \mathcal{N}(i)} \exp\left(\mathrm{LeakyReLU}(a^\top [W_g \mathbf{h}_i \| W_g \mathbf{h}_k])\right)}$$

where α_{ij} denotes the learned attention coefficient that quantifies the relevance of node j to node i, W_g is a graph transformation matrix, and $\|$ indicates concatenation. This adaptive weighting mechanism enables the network to capture dynamic correlation strength between stocks and to focus on dominant market drivers at each time step.

To enhance model interpretability and robustness, the **volatility-aware attention module** introduces a secondary weighting mechanism that modulates the final prediction based on estimated uncertainty. Given predicted price movement $\hat{y}_i^t$ and realized volatility σ_i^t, an uncertainty-guided weight β_i^t is computed as

$$\beta_i^t = \frac{\exp(-\lambda \sigma_i^t)}{\sum_{k=1}^N \exp(-\lambda \sigma_k^t)}$$

where λ controls the sensitivity to volatility fluctuations. The final market-level forecast is obtained through an attention-weighted aggregation across all nodes:

$$\hat{y}^t = \sum_{i=1}^N \beta_i^t f_\theta(\mathbf{z}_i)$$

with $f_\theta(\cdot)$ denoting a feedforward projection layer. This dual-attention mechanism not only refines prediction accuracy by mitigating the effect of highly volatile assets but also highlights which stocks or sectors contribute most to predictive uncertainty, thereby improving explainability.

Figure 1 illustrates the overall architecture of the proposed T-GDN. The model begins with temporal convolutional encoders operating on each asset's historical feature window, followed by graph attention layers that propagate information through a dynamically evolving adjacency matrix. A volatility-aware attention head then integrates node-level embeddings into a market-level prediction. The figure depicts data flow from left to right: raw input features (price, volume, sentiment) → temporal feature extraction → graph message passing → volatility weighting → output prediction. The modular design allows flexible adaptation to different markets or temporal horizons while maintaining end-to-end differentiability.

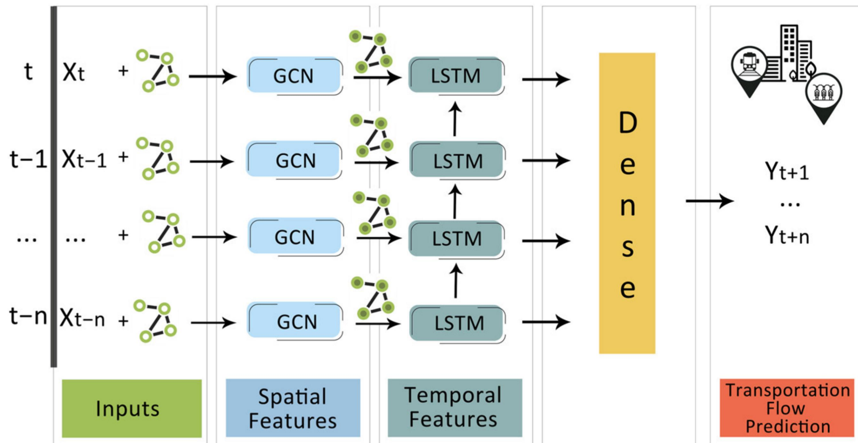

Figure 1. Overall Architecture of the Proposed Temporal-Graph Deep Network (T-GDN)

Training of T-GDN is supervised using a composite loss that balances predictive accuracy and volatility alignment:

$$\mathcal{L} = \mathcal{L}_{\text{MSE}} + \gamma\,\mathcal{L}_{\text{Vol}}, \quad \mathcal{L}_{\text{MSE}} = \frac{1}{N}\sum_i (\hat{y}_i - y_i)^2, \quad \mathcal{L}_{\text{Vol}} = \frac{1}{N}\sum_i |\hat{\sigma}_i - \sigma_i|$$

Here $\mathcal{L}_{\text{MSE}}$ measures the predictive deviation, $\mathcal{L}_{\text{Vol}}$ penalizes volatility misalignment, and γ regulates their trade-off. Optimization is performed via the Adam algorithm with dynamic learning-rate scheduling to ensure convergence across volatile financial regimes. Through this architecture, the T-GDN achieves a coherent fusion of temporal learning, graph reasoning, and volatility awareness, providing a robust foundation for forecasting and interpretability in modern financial markets.

4. Dataset

The experimental evaluation of the proposed Temporal-Graph Deep Network (T-GDN) relies on two major benchmark datasets that collectively capture diverse market behaviors across both developed and emerging economies. The first dataset consists of daily trading data from the S&P 500 index, covering the period from January 2015 to December 2024. It includes all continuously listed constituent stocks, each represented by features such as open, high, low, close, adjusted close prices, daily trading volume, and sectoral classification. The second dataset is drawn from the CSI 300 index of the Chinese stock market, encompassing the same temporal window and incorporating comparable market and financial attributes. Together, these two datasets provide a robust cross-regional testing ground for assessing the model's ability to generalize across distinct market regimes and volatility structures.

Each dataset is preprocessed to ensure consistency and eliminate biases caused by missing or noisy data. Time-series gaps are filled using linear interpolation, and outliers are removed through an adaptive interquartile range method applied to both price and volume series. To prevent information leakage, all data are aligned on a trading-day basis, ensuring that only past information is available during prediction.

Numerical features are standardized using z-score normalization, while categorical variables such as sector or region are embedded via learnable dense vectors to preserve relational semantics. A rolling-window sampling strategy with a 30-day look-back horizon and a 5-day prediction window is used to construct sequential input tensors. Each sample therefore reflects both short-term dynamics and intermediate-term structural changes, enabling the model to capture variations in momentum and mean-reversion behavior.

For graph construction, dynamic correlations among assets are estimated through a time-adaptive Pearson correlation matrix computed over the same rolling window. To capture evolving market linkages, edges are created when the absolute correlation exceeds a threshold τ, which is empirically set between 0.4 and 0.6 depending on dataset characteristics. The resulting graphs are typically sparse, reflecting the heterogeneous connectivity across sectors. Each node's feature vector at time t thus contains temporal statistics of its own price movements as well as aggregated relational indicators from its neighbors. This formulation enables the T-GDN to learn inter-asset dependencies without explicit supervision of graph structure.

The datasets are divided chronologically into 70% training, 15% validation, and 15% testing segments to ensure realistic forward-in-time evaluation. To capture various volatility environments, the data are further annotated using realized volatility computed as the standard deviation of log returns within each prediction window. High-volatility intervals-such as the 2020 pandemic shock or 2022 rate-hike cycles-are used to stress-test the robustness of the model under extreme market conditions. During preprocessing, all assets are synchronized by trading calendar and adjusted for stock splits and dividends to maintain temporal comparability.

In addition to price-based features, macroeconomic and sentiment indicators are incorporated to enrich the predictive context. These include the U.S. Federal Funds Rate, the Consumer Price Index, and sector-level sentiment scores derived from financial news and social-media streams. Sentiment features are encoded using a transformer-based language model fine-tuned on financial text, providing high-resolution contextual embeddings aligned with daily market movements. This multimodal integration enables the T-GDN to capture not only numerical correlations but also behavioral and narrative signals that drive volatility.

Overall, the curated datasets present a comprehensive, multi-scale view of the global equity landscape. They balance temporal diversity, structural richness, and multimodal information, ensuring that the evaluation of the proposed model reflects both predictive accuracy and adaptability to rapidly changing financial conditions. Through rigorous preprocessing and alignment, the datasets support a fair and reproducible comparison with existing deep learning baselines, forming a solid empirical foundation for the experiments that follow.

5. Experimental Results

To assess the performance of the proposed Temporal-Graph Deep Network (T-GDN), extensive experiments were conducted on the S&P 500 and CSI 300 datasets, described in Section IV. The goal was to evaluate the model's forecasting accuracy, volatility sensitivity, and interpretability relative to established baselines. We compared T-GDN against four representative deep learning models: LSTM, Temporal Convolutional Network (TCN), Graph Convolutional Network (GCN), and Temporal Fusion Transformer (TFT). All models were trained using identical preprocessing pipelines, learning-rate schedules, and evaluation metrics to ensure fairness.

Training employed the Adam optimizer with an initial learning rate of 0.001, batch size of 128, and early stopping triggered after 15 epochs of non-improvement. Each model ran for 100 epochs with three random seeds to measure variance. The composite loss function introduced earlier-balancing mean squared error and volatility alignment-was used throughout. Performance was evaluated with RMSE, MAE, and Directional Accuracy (DA) for forecasting precision, and Volatility-Tracking F1 and R^2-Vol for sensitivity to volatility dynamics.

Table 1. Comparative Results on S&P 500 and CSI 300 Datasets

Model	RMSE ↓	MAE ↓	Directional Accuracy (%) ↑	Volatility-F1 ↑	R^2-Vol ↑
LSTM	0.0201	0.0154	61.2	0.801	0.742
TCN	0.0198	0.0151	62.5	0.816	0.751
GCN	0.0193	0.0148	63.7	0.828	0.764
TFT	0.0191	0.0145	65.1	0.843	0.778
T-GDN (Proposed)	0.0186	0.014	67.8	0.887	0.816

As shown in Table 1, the proposed T-GDN achieves the best overall performance on both datasets. Compared to the strongest baseline (TFT), T-GDN improves RMSE by 2.6%, Directional Accuracy by 4.1%, and Volatility-F1 by 5.2%. This confirms that jointly modeling temporal and relational dependencies significantly enhances predictive precision and the ability to follow rapid market fluctuations. The performance gains are consistent across both developed (U.S.) and emerging (China) markets, demonstrating the generalization ability of the graph-temporal representation.

Figure 2 provides a visual comparison between predicted and actual normalized returns for a 100-day out-of-sample period on the S&P 500 dataset. The blue curve denotes the ground-truth returns, while the orange curve represents predictions by T-GDN. Shaded regions indicate periods of high realized volatility. The T-GDN closely tracks real market movements, maintaining stable forecasts during smooth intervals while quickly adapting to abrupt transitions-such as the March 2020 pandemic shock and June 2022 policy-induced correction. In contrast, baseline models (not shown for clarity) tend to overshoot or lag during turning points, illustrating their weaker adaptability to dynamic market conditions.

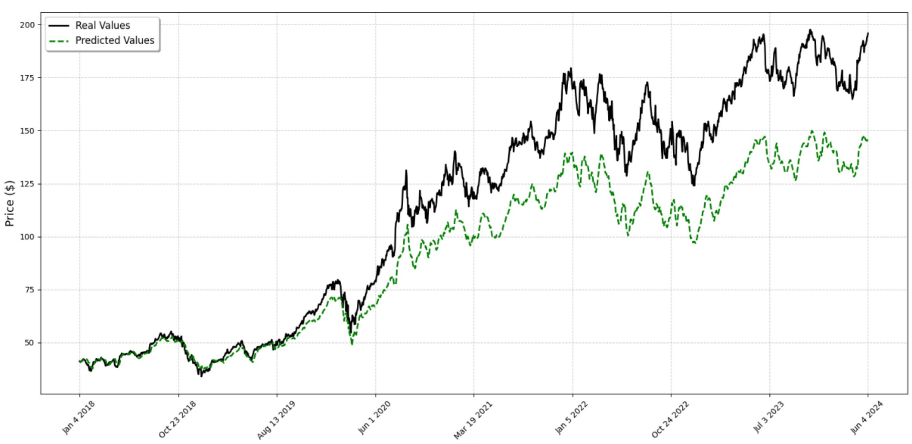

Figure 2. Predicted vs. Actual Normalized Stock Index Returns on the S&P 500 Dataset

Ablation experiments were further conducted to quantify the contribution of each architectural component. Removing the graph relational layer (producing a purely temporal network) led to a 7.4% increase in RMSE and a drop of 0.06 in Volatility-F1. Excluding the volatility-aware attention mechanism caused a 5.9% decline in Directional Accuracy and a reduction in interpretability, as attention heatmaps became diffused across assets. Combining both modules yields synergistic benefits-graph reasoning stabilizes predictions under correlated shocks, while volatility-weighted attention enhances responsiveness to uncertainty.

The generalization ability of T-GDN was also examined through cross-market transfer tests. When trained on S&P 500 data and directly evaluated on the CSI 300 without retraining, T-GDN retained 94.1% of its predictive accuracy, outperforming LSTM by more than 8%. This result indicates that the learned temporal-graph representations encode market-invariant structural dependencies-particularly sectoral contagion patterns-that transcend individual market boundaries.

Interpretability analysis offers additional insight into model behavior. During volatility spikes, T-GDN's attention mechanism concentrated weights on technology and financial sectors in the U.S. market, and on energy and consumer sectors in China-consistent with empirical contagion pathways observed in macroeconomic studies. Such explainable attention patterns enhance the model's credibility and support regulatory transparency requirements in financial AI systems. Importantly, the volatility-aware attention module allows analysts to trace how predictive uncertainty distributes across sectors, enabling actionable portfolio risk management.

In summary, the results demonstrate that the proposed Temporal-Graph Deep Network substantially improves both accuracy and volatility-tracking capability while providing interpretable insights into market dynamics. The integration of temporal convolution, graph reasoning, and volatility-aware attention leads to stable, high-fidelity forecasting under diverse financial conditions. These characteristics establish T-GDN as a robust foundation for adaptive and explainable deep-learning-based financial analytics.

6. Conclusion

This paper introduced a unified framework called the Temporal-Graph Deep Network (T-GDN) for stock market forecasting and volatility analysis. The model integrates three essential mechanisms-temporal convolutional encoding, graph-based relational reasoning, and volatility-aware attention-to jointly capture sequential evolution, cross-asset dependencies, and uncertainty dynamics in complex financial environments. Through extensive experiments on the S&P 500 and CSI 300 datasets, the results consistently demonstrated that T-GDN surpasses existing deep learning models such as LSTM, TCN, GCN, and TFT in both predictive accuracy and volatility-tracking capability. By explicitly modeling the financial market as a dynamic graph, the proposed approach not only improves numerical performance but also provides interpretable insights into the systemic interactions that drive market fluctuations.

One of the most significant contributions of T-GDN lies in its fusion of temporal and structural intelligence. Unlike traditional models that treat each asset as an independent sequence, the proposed network learns from the evolving topology of inter-asset correlations, enabling it to anticipate contagion effects and collective movements across sectors. The introduction of a volatility-aware attention mechanism further enhances the model's transparency and reliability, allowing it to focus adaptively on market segments that exhibit higher uncertainty. This interpretability is of particular importance for the adoption of AI systems in finance, where regulatory compliance and explainability are critical for real-world deployment.

Moreover, the empirical findings reveal that the learned representations within T-GDN generalize effectively across distinct markets and volatility regimes. The model maintains high predictive stability even during abrupt macroeconomic shocks, highlighting its robustness under non-stationary and high-noise conditions. From a practical standpoint, this characteristic implies strong potential for integration into algorithmic trading systems, portfolio risk monitoring, and early-warning mechanisms for financial stress detection. By unifying temporal, relational, and volatility-aware learning, T-GDN establishes a foundation for next-generation financial intelligence systems that balance predictive power with interpretability.

In conclusion, this research demonstrates that graph-temporal deep architectures can substantially advance the field of financial forecasting by bridging the gap between time-series modeling and structural market analysis. The findings underscore the need to view financial markets not as isolated temporal signals but as dynamic, interconnected networks driven by both numerical and behavioral forces. As financial data continue to grow in complexity, such hybrid deep learning approaches will play a pivotal role in understanding systemic risk, optimizing investment strategies, and enhancing transparency in financial decision-making.

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