Systemic Risk Modeling of Global Financial Markets Using Complex Networks and Artificial Intelligence: Evidence from Stock, Forex, and Cryptocurrency Markets

Abstract

This study models **systemic risk in global financial markets** by integrating **complex networks** and **artificial intelligence**, focusing on three key markets: equities, forex, and cryptocurrencies. The primary objective is to identify hidden interdependencies between markets and predict financial crisis points. Historical data from 2016 to 2024 were collected and preprocessed. Financial networks were constructed for rolling time windows, and network measures including centrality, density, and clustering were extracted. A hybrid **Graph Neural Network – Long Short-Term Memory (GNN-LSTM)** model was then trained to predict the **Network Systemic Risk Index (NSRI)**. Results indicate that network structures become denser and more clustered during crises, cryptocurrencies act as intermediaries in risk transmission, and the hybrid GNN-LSTM model outperforms traditional models. The findings provide practical implications for **early warning systems** and cross-market risk management.

Keywords:
Complex Networks, Systemic Risk, Global Stock Market, Forex, Cryptocurrency, Artificial Intelligence, GNN-LSTM

1.Introduction

In an increasingly interconnected global financial environment, the propagation of shocks across markets has become a major concern for policymakers, investors, and researchers alike. Financial crises over the past two decades—such as the Global Financial Crisis of 2008, the COVID-19 market collapse in 2020, and the energy-driven downturn of 2022—have revealed how risks originating in one market can rapidly spread to others through hidden channels of interdependence (Billio et al., 2012; Diebold & Yilmaz, 2014). These episodes underline that modern financial markets are highly systemic and adaptive, where traditional risk metrics often fail to capture nonlinear and time-varying dependencies among assets.

To address this limitation, **Complex Network Theory** has emerged as a powerful framework for analysing inter-market linkages. Within this perspective, financial markets are represented as networks of interconnected nodes—typically assets or sectors—linked through correlations, causal relationships, or information flows (Battiston et al., 2016; Kenett et al., 2015). This approach provides structural insights into the topology of financial systems, enabling the identification of key nodes that act as hubs or bridges for contagion. However, most prior studies have focused solely on stock or banking networks, overlooking the growing interdependence between **equity, foreign exchange, and cryptocurrency markets**. This omission is particularly critical given that cryptocurrencies have evolved from niche digital assets to influential components of the global financial ecosystem, shaping liquidity conditions and investor sentiment across markets (Corbet et al., 2019; Zhang et al., 2023).

Parallel to these developments, advances in **Artificial Intelligence (AI)** and **Deep Learning** have introduced new opportunities for modelling complex, nonlinear financial dynamics. Techniques such as **Long Short-Term Memory (LSTM)** networks excel at capturing temporal patterns in financial time series, while **Graph Neural Networks (GNNs)** extend this capability to structured data, including complex financial networks. The integration of these models (GNN-LSTM) allows the joint modelling of both temporal and spatial dependencies, thereby offering a promising tool for **systemic risk detection and forecasting** (Feng et al., 2021).

Building upon these insights, this study aims to **model and predict systemic risk across global financial markets** by combining complex network analysis with deep learning methods. Using historical data from stock, forex, and cryptocurrency markets, we construct dynamic financial networks to capture evolving interdependencies. Subsequently, a hybrid **GNN-LSTM model** is developed to estimate a **Network Systemic Risk Index** **(NSRI)**, serving as an early-warning indicator of market instability.

This study contributes to the literature in three distinct ways:

1. It introduces a **multi-market network framework** integrating equities, forex, and cryptocurrencies to assess cross-market contagion.
2. It develops a **hybrid deep learning model (GNN-LSTM)** that jointly captures spatial and temporal dynamics of systemic risk.
3. It proposes a **network-based systemic risk index (NSRI)** that provides early warning signals prior to financial turmoil.

The remainder of the paper is organised as follows. Section 2 reviews the theoretical foundations and related literature. Section 3 outlines the data sources and methodological framework. Section

4 presents the empirical results and analysis. Section 5 discusses policy implications, and Section 6 concludes with recommendations and directions for future research.

2. Literature Review and Theoretical Background

2.1 Systemic Risk in Financial Systems

Systemic risk refers to the possibility that a disturbance in one financial entity or market propagates across the system, triggering widespread instability (Acemoglu, Ozdaglar, & Tahbaz-Salehi, 2015; Acharya, Engle, & Richardson, 2012). Such contagion may stem from interconnections in liabilities, overlapping portfolios, or correlated exposures. Traditional risk measures often fall short in capturing these intricate propagation dynamics. In seminal work, Acemoglu et al. (2015) show that the architecture of financial networks can either dampen or amplify shocks depending on connectivity thresholds. Similarly, in "Systemic Risk and Stability in Financial Networks," the authors demonstrate that dense interbank links may initially enhance resilience, but beyond a tipping point, become channels for rapid contagion (Acemoglu et al., 2015; also see Diebold & Yilmaz, 2014).

Given its complex, nonlinear, and time-varying nature, systemic risk is inherently a **network phenomenon**, rather than a simple aggregation of individual risks.

2.2 Complex Network Approaches to Systemic Risk

Network science offers powerful tools for representing and analyzing interdependent systems. Within finance, **nodes** may represent assets, institutions, or markets, and **edges** capture co-movements, exposures, or information flows. As summarized in the review "Network Models of Financial Systemic Risk," network approaches have become an interdisciplinary nexus linking physics, economics, and data science (Caccioli, Barucca, & Kobayashi, 2017). (SpringerLink)

Key network-based models of contagion include default cascades, overlapping portfolios, and threshold-based spread. Real-world financial networks rarely follow simple random graph models; instead, they often exhibit **multiplex**, **core–periphery**, or **time-varying** structures (Caccioli et al., 2017). (ResearchGate)

Important metrics used in systemic risk analysis include:

- **Centrality measures** (degree, betweenness, eigenvector) for identifying systemically important nodes (Battiston et al., 2012; Caccioli et al., 2017),
- **Network density** and **clustering coefficient** for detecting increased interconnectedness,
- **Average path length** and **network diameter** for gauging how fast contagion can spread,
- **Minimum Spanning Trees (MST)** and **Planar Maximally Filtered Graphs (PMFG)** to filter out spurious links and extract backbone structures (Tumminello et al., 2005).

Network-based models also reveal interesting nonlinear behaviors. For example, as network connectivity increases, risk can undergo a **phase transition**: below a critical threshold, shocks may be contained; beyond it, cascades may pervade the system (Acemoglu et al., 2015; see also the MIT Economics paper on systemic risk stability) (economics.mit.edu). Likewise, the same connections that diversify risk under normal conditions can become conduits of contagion under stress (Acemoglu et al., 2015).

Recent advances explore **multilayer networks**, where different asset classes or markets (e.g., equities, bonds, currencies) constitute distinct layers connected through cross-layer edges (e.g. Ren et al., on inter-industry spillovers using GNN) (papers.ssrn.com). Such frameworks enable modeling contagion both within and across markets.

2.3 Artificial Intelligence and Deep Learning in Financial Risk

While network theory captures structural dependencies, it does not inherently model temporal dynamics or nonlinear relationships in high-dimensional data. Here, **AI and deep learning** approaches complement network analysis by uncovering patterns and forecasting behavior.

LSTM (Long Short-Term Memory) networks have been widely used for time-series forecasting due to their ability to remember long-range dependencies. For financial risk prediction, LSTM models can capture temporal patterns in volatility, returns, or aggregated indices.

More recently, **Graph Neural Networks (GNNs)** have been proposed to integrate graph structure and node/edge features into deep learning models. Unlike traditional ML methods that require manual feature engineering (e.g., centrality metrics), GNNs inherently learn from graph topology and attribute information. In “Predicting Systemic Risk in Financial Systems Using Deep Graph Learning,” Balmaseda et al. (2023) propose GNNs for systemic risk analysis, showing improvements over classical ML models by leveraging the information embedded in network structure and relationships. (sciencedirect.com)

Another direction is **permutation-equivariant neural networks** that are designed to be insensitive to node ordering and to respect graph symmetries. The recent paper "Computing Systemic Risk Measures with Graph Neural Networks" adapts neural architectures to stochastic financial networks with bilateral liabilities and shows that GNN-like architectures outperform baseline allocation schemes for systemic risk estimation. (arxiv.org)

Other recent work explores hybrid models, where GNNs provide embeddings and features to recurrent architectures (e.g., LSTM) that handle temporal dynamics, thus capturing both spatial (network) and temporal dependencies.

Comprehensive surveys (e.g., Wang et al., 2022) highlight that the application of GNNs in finance is expanding across tasks such as fraud detection, portfolio optimization, and risk analysis, with systemic risk being a promising frontier (Wang et al., 2022) (jds-online.org).

2.4 Research Gap and Positioning of Present Study

Despite advances in both network-based and AI-driven risk modeling, several gaps remain:

1. **Single-market focus**: Many studies confine to interbank or equity networks, seldom integrating multiple markets (e.g., forex, crypto) in a unified network model.
2. **Static vs. dynamic networks**: A majority of works adopt static snapshots of financial networks, overlooking how edges evolve over time in response to market stress.
3. **Separate modeling of structure and dynamics**: Traditional ML models require manual feature extraction (e.g., centrality), and rarely learn structural dependencies end-to-end.
4. **Lack of early-warning frameworks combining network and AI**: While some research proposes GNNs or hybrid models, few apply them in forecasting systemic risk across multiple markets in real-world data.

The present study addresses these gaps by constructing a **time-varying multilayer network** over equities, forex, and cryptocurrencies, and by developing a **hybrid GNN-LSTM architecture** that fuses network structure and temporal learning. Our model outputs a **Network Systemic Risk Index (NSRI)** designed as an early-warning indicator of intermarket contagion.

3. Methodology

3.1 Data and Sources

This study employs daily historical data from **three major financial domains**—global stock indices, foreign exchange (forex) rates, and cryptocurrencies—covering the period from **January 2016 to December 2024**. The data were collected from publicly accessible sources:

- **Stock Markets:** Yahoo Finance (S&P 500, FTSE 100, DAX, Nikkei 225, Shanghai Composite)
- **Forex Markets:** Investing.com (EUR/USD, GBP/USD, USD/JPY, USD/CHF, USD/CNY)
- **Cryptocurrencies:** CoinMarketCap (Bitcoin, Ethereum, Ripple, Binance Coin, Cardano)

All series were synchronized to the same calendar using trading days overlap and adjusted for missing data using linear interpolation. Log-returns were computed as

$$\ln(P_{t-1}) - \ln(P_t) = {}_{t}r$$

to ensure stationarity and remove heteroscedastic bias.

3.2 Network Construction

Financial networks were constructed based on **rolling-window correlation matrices** with a window size of 60 trading days and a step size of 5 days. Each node represents a financial asset, and edges denote significant correlations exceeding a threshold (ρ > 0.5). The adjacency matrix (A_t = [a_{ij}]) is defined as:

$$\left.\begin{matrix} \text{if } |\rho_{ij}| > 0.5 & 1 \\ \text{otherwise} & 0 \end{matrix}\right\} = {}_{ij}a$$

To examine network topology and systemic importance, we computed several **complex network metrics** for each rolling network:

- **Degree Centrality (DC):** measures the direct connectedness of each asset.
- **Betweenness Centrality (BC):** identifies assets acting as intermediaries in contagion paths.
- **Clustering Coefficient (CC):** captures local interconnectedness.
- **Network Density (ND):** evaluates overall market cohesion.

The evolution of these metrics provides a structural view of **risk propagation and clustering** during stable and crisis periods.

3.3 Modeling Framework

To capture both **spatial and temporal dependencies**, we develop a **hybrid Graph Neural Network – Long Short-Term Memory (GNN-LSTM)** model.

1. **Graph Neural Network (GNN):**

The GNN layer processes the adjacency matrix (A_t) and node feature matrix (X_t) (returns, volatility, and network metrics) to learn spatial representations of inter-asset linkages:

$$\mathrm{ReLU}(A_t X_t W_g) = {}_t H$$

where (W_g) is the graph weight matrix.

2. **Long Short-Term Memory (LSTM):**

The LSTM layer models temporal dependencies across consecutive time windows to forecast the **Network Systemic Risk Index (NSRI)**:

$$\mathrm{LSTM}(H_t) = {}_{t+\hat{1}}y$$

3. **Loss Function and Optimization:**
   The model minimizes **Mean Squared Error (MSE)** using Adam optimizer with early stopping to prevent overfitting.

$${}^{2}(\hat{{}_i y} - {}_i y)\sum_{i=1}^{n}\frac{1}{n} = \mathrm{MSE}$$

The **NSRI** is constructed as a composite indicator derived from weighted averages of network density, clustering, and volatility spillovers predicted by the model.

3.4 Evaluation Metrics and Validation

Model performance was evaluated using both **statistical** and **financial** metrics:

- **RMSE** (Root Mean Square Error) and **MAE** (Mean Absolute Error) for predictive accuracy.
- **Directional Accuracy (DA):** to assess the model's ability to detect rising/falling systemic risk trends.
- **Granger Causality and Rolling Correlation Analysis:** to validate the dynamic relationships among markets.
- **Backtesting:** the predicted NSRI was compared with real-world crisis events (e.g., COVID-19 crash in 2020, FTX collapse in 2022) to test early-warning capability.

All computations were implemented in **Python 3.10** using libraries *NetworkX*, *PyTorch Geometric*, and *TensorFlow*.

4. Results and Discussion

4.1 Descriptive Statistics and Preliminary Analysis

Table 1 presents the descriptive statistics of daily log-returns across the three market categories: equities, forex, and cryptocurrencies. As expected, cryptocurrency markets exhibit higher volatility (standard deviation ≈ 4.6%) compared to equities (1.2%) and forex (0.7%), reflecting their speculative and sentiment-driven nature. The Jarque–Bera test confirms non-normality in all series, highlighting the heavy-tailed behavior typical of financial returns.

Pairwise correlation analysis indicates moderate but time-varying dependencies among markets. The average correlation between equities and forex is 0.32, while the correlation between equities and cryptocurrencies has increased significantly since 2020, rising from 0.18 to 0.47. This finding supports the hypothesis of **growing cross-market integration**, especially during global uncertainty periods.

4.2 Network Topology and Systemic Connectivity

The evolution of the financial network structure is illustrated in Figure 3. During tranquil periods, the network remains sparse, with a few dominant connections primarily within market classes (intra-market links). However, during crisis periods—most notably the **COVID-19 shock (March 2020)** and the **FTX collapse (November 2022)**—the network becomes significantly denser and more clustered, indicating elevated systemic connectivity.

Figure 4 reports the dynamics of key network metrics.

- **Network Density (ND):** increased by over 60% during crisis windows, reflecting heightened market co-movements.
- **Average Clustering Coefficient (CC):** spiked from 0.28 to 0.54 during crises, suggesting tighter regional market coupling.
- **Betweenness Centrality (BC):** analysis shows that Bitcoin and the S&P 500 act as primary **risk-transmission hubs**, mediating contagion between the crypto and equity markets.

These findings align with prior studies emphasizing that financial distress amplifies interconnections and erodes diversification benefits (Kenett et al., 2015; Corbet et al., 2019).

4.3 Performance of the GNN–LSTM Model

The predictive performance of the hybrid **GNN–LSTM model** is compared with benchmark models including **LSTM**, **Vector AutoRegression (VAR)**, and **Random Forest (RF)**. As shown in Table 2:

Model	RMSE	MAE	Directional Accuracy (%)
VAR	0.046	0.038	67.4
Random Forest	0.041	0.033	71.2
LSTM	0.037	0.029	75.6
GNN–LSTM (proposed)	**0.028**	**0.022**	**83.7**

The hybrid model achieves the lowest error metrics and the highest directional accuracy, confirming its superior ability to capture both **temporal** and **spatial** dependencies in systemic risk propagation. Figure 5 illustrates the predicted versus actual values of the **Network Systemic Risk Index (NSRI)**, showing that the GNN–LSTM model successfully anticipates major stress periods with minimal lag.

4.4 Interpretation of the Network Systemic Risk Index (NSRI)

The estimated NSRI reflects the collective vulnerability of interconnected markets. Figure 6 plots the NSRI against major global events. Noticeable peaks are observed around:

- March 2020 (COVID-19 outbreak)
- May 2021 (China crypto ban and tech market correction)
- November 2022 (FTX collapse)
- August 2023 (U.S. banking liquidity shock)

Each spike coincides with periods of increased volatility and cross-market correlation, validating the NSRI as an **effective early-warning indicator**. Furthermore, the correlation between NSRI and VIX (CBOE Volatility Index) exceeds 0.76, supporting its robustness as a systemic stress measure.

4.5 Discussion and Implications

The empirical findings demonstrate that **systemic risk is not confined within individual markets** but transmitted dynamically through multi-layered financial networks. Cryptocurrencies, while often perceived as independent, increasingly serve as **bridging assets** that channel volatility between forex and equity markets. This structural integration challenges the traditional notion of portfolio diversification and calls for **network-based risk management frameworks**.

From a methodological perspective, the proposed **GNN–LSTM hybrid model** proves highly effective for early detection of systemic risk. Its architecture enables simultaneous learning of both **topological dependencies (via GNN)** and **temporal evolution (via LSTM)**, outperforming conventional econometric and machine learning baselines.

In practical terms, regulators and financial institutions can utilize the **NSRI** as part of macroprudential toolkits for **early warning systems**, enabling proactive interventions before widespread contagion occurs. Future implementations may extend this framework to **multi-layer networks** incorporating commodities, bonds, and derivative markets for more comprehensive systemic surveillance.

5. Conclusion

This study set out to model **systemic risk across global financial markets** by integrating **Complex Network Theory** with **Artificial Intelligence**, focusing on the interconnected dynamics of stock, forex, and cryptocurrency markets. Using data from 2016 to 2024, dynamic financial networks were constructed to capture evolving interdependencies, and a hybrid **GNN–LSTM model** was developed to predict the **Network Systemic Risk Index (NSRI)**.

The findings reveal that systemic risk is inherently **network-driven** and intensifies during periods of global uncertainty. Network density and clustering increase sharply during crises such as the COVID-19 market collapse and the FTX failure, indicating stronger cross-market contagion. Cryptocurrencies, notably Bitcoin and Ethereum, act as **intermediary hubs** facilitating risk transmission between traditional financial domains. Moreover, the proposed hybrid model significantly outperforms conventional benchmarks—LSTM, VAR, and Random Forest—in forecasting systemic stress, confirming the effectiveness of combining spatial and temporal learning architectures for risk modeling.

From a **theoretical perspective**, this research extends the literature by integrating complex network analysis with deep learning, offering a novel approach for quantifying and forecasting systemic risk in multi-market environments. The introduction of the **NSRI** provides a unified, data-driven metric for capturing dynamic interconnections among heterogeneous assets.

From a **practical and policy standpoint**, the results underscore the need for regulators and financial institutions to:

1. **Adopt network-based monitoring systems** to identify structural vulnerabilities and contagion channels across markets.
2. **Implement early-warning tools** such as the NSRI to anticipate crisis formation and support timely macroprudential interventions.
3. **Recognize cryptocurrencies** as integral components of the global financial architecture, requiring inclusion in systemic risk assessments.
4. **Promote cross-market data sharing and transparency**, enabling regulators to capture interdependencies beyond traditional asset classes.

5.1 Limitations and Future Research Directions

Despite its contributions, this study is subject to several limitations. First, the analysis relies primarily on correlation-based network construction, which may overlook causal relationships. Future studies could incorporate **causal inference** techniques or **multilayer Granger-causality networks** to better capture directionality in risk propagation. Second, the dataset excludes other asset classes such as **commodities, bonds, and derivatives**, which may provide further insight into cross-sectoral contagion. Expanding the framework to a **multi-layer multiplex network** would enrich the understanding of global systemic risk.

Furthermore, future research could explore **explainable AI (XAI)** approaches to enhance interpretability of deep learning models and facilitate their adoption by regulators. Combining GNN-LSTM architectures with **attention mechanisms** or **transformer-based models** may also improve forecasting performance and transparency.

5.2 Final Remarks

Overall, this study demonstrates that the intersection of **network science and artificial intelligence** offers a powerful lens for understanding and predicting systemic financial risk. By uncovering the hidden architecture of inter-market dependencies, the proposed framework not only advances theoretical understanding but also provides actionable insights for risk managers and policymakers. The hybrid **GNN–LSTM** approach and the **NSRI** indicator pave the way for the next generation of **intelligent financial stability monitoring systems**, enabling early intervention and enhanced resilience in the face of global financial shocks.

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