Volatility Spillovers, Systemic Risk, and the Rise of Digital Assets: A Hybrid Approach Using Econometrics, Machine Learning, and Network Analysis

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Abstract: This paper investigates volatility spillovers, contagion dynamics, and systemic risk across global financial markets using a hybrid framework that combines econometric modeling, machine learning, and network analysis. Using daily data on equities, bonds, foreign exchange, commodities, and cryptocurrencies from 2005 to 2025, we analyze how systemic linkages evolve across asset classes and crisis periods. Results from DCC-GARCH models and the Diebold–Yilmaz spillover index show that volatility transmission is strongly regime-dependent, with spillovers intensifying during the Global Financial Crisis, the European Sovereign Debt Crisis, and the COVID-19 pandemic. Machine learning models, particularly Long Short-Term Memory (LSTM) networks, outperform traditional econometric approaches in forecasting volatility during periods of severe market stress, while Random Forest models identify monetary policy shocks, oil market volatility, and cryptocurrency crashes as key systemic drivers. Network analysis reveals a structural transformation in global systemic risk: while U.S. and European equity markets remain central contagion hubs, cryptocurrencies and DeFi tokens have emerged as net transmitters of volatility in the post-pandemic era. Overall, these findings challenge traditional diversification strategies, highlight the growing systemic relevance of digital assets, and demonstrate the value of hybrid econometric AI network approaches for financial stability analysis.

Keywords: Volatility spillovers, Systemic risk, Cryptocurrencies, Machine learning, Financial stability.

JEL classifications: C32, C58, G01.

I. INTRODUCTION

The increasing interconnectedness of global financial markets has heightened concerns about volatility spillovers, contagion mechanisms, and systemic risk. Major episodes such as the Global Financial Crisis of 2008, the European Sovereign Debt Crisis, the COVID-19 pandemic, and the cryptocurrency market turmoil of 2022 have demonstrated how localized shocks can rapidly propagate across asset classes and jurisdictions, posing serious threats to financial stability. As a result, understanding the dynamics of cross-market volatility transmission has become a central issue for both academics and policymakers.

A substantial body of literature documents that financial crises amplify volatility spillovers, weaken diversification benefits, and increase systemic instability. Empirical evidence shows that contagion effects and volatility clustering intensify during crisis periods, particularly across equity, bond, and commodity markets (Meng & Chen, 2023; Sahiner, 2024). More recently, attention has shifted toward cryptocurrencies. Initially viewed as independent or diversifying assets, digital currencies are now increasingly recognized as systemic transmitters of shocks. Studies indicate that spillovers between cryptocurrencies and traditional markets strengthened during the COVID-19 pandemic and subsequent crypto crashes, with Bitcoin and Ethereum emerging as central nodes in volatility networks (Shahzad *et al.*, 2021; Özdemir, 2022; Pacelli *et al*., 2024).

Parallel to these empirical developments, methodological advances have reshaped the analysis of systemic risk. Network-based approaches have enhanced the identification of contagion channels and systemically important assets, while machine learning techniques have improved volatility forecasting under nonlinear and nonstationary conditions. In particular, deep learning models such as Long Short-Term Memory (LSTM) networks and neural network quantile regressions have been shown to outperform traditional econometric models in predicting volatility and spillovers during periods of financial stress (Zhang *et al*., 2021; Zhang *et al.*, 2025; Zhu *et al*., 2025). These methods are better suited to capture structural breaks and complex nonlinear dynamics that standard GARCH-type models often fail to accommodate.

Despite these advances, important gaps remain in the literature. Most existing studies rely on econometric models, machine learning techniques, or network analysis in isolation, limiting their ability to jointly capture regime-dependent spillovers, nonlinear predictability, and evolving systemic structures. Moreover, the systemic role of digital assets and their interactions with traditional financial markets remain insufficiently explored within an integrated analytical framework.

This paper addresses these gaps by proposing a hybrid framework that explicitly combines multivariate GARCH

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models, machine learning algorithms, and network analysis to study volatility spillovers and systemic risk across global financial markets. Using daily data from 2005 to 2025 covering equities, bonds, commodities, foreign exchange, and cryptocurrencies, the analysis provides a unified assessment of contagion dynamics across multiple crisis episodes. The results highlight the strong regime dependence of volatility transmission, the forecasting advantages of machine learning methods during periods of market stress, and the growing systemic importance of digital assets as net transmitters of volatility.

2. LITERATURE REVIEW

2.1. Volatility Spillovers and International Transmission of Shocks

The analysis of volatility spillovers and international shock transmission is a cornerstone of quantitative finance. The pioneering work of Engle (1982) and Bollerslev (1986) introduced the ARCH and GARCH models to capture conditional heteroscedasticity. These approaches later evolved into multivariate extensions such as the BEKK-GARCH (Engle & Kroner, 1995) and the DCC-GARCH (Engle, 2002), which made it possible to examine dynamic correlations across assets and markets. These models remain a standard tool for studying financial interdependencies, yet their recent applications reveal increasingly complex dynamics.

In the context of the COVID-19 pandemic and rising geopolitical tensions, research has intensified on the channels of contagion. Mensi, Rehman, and Vo (2023) employ a time–frequency approach to show that oil prices and the pandemic significantly altered the linkages between Chinese and Asian stock markets, highlighting how energy shocks amplify regional market volatility (Mensi *et al.*, 2023). Their wavelet-DCC analysis reveals that correlations among markets become stronger in the short term during energy or health crises, challenging the assumption of regional diversification.

Dai and Peng (2022) apply a time-varying parameter vector autoregression (TVP-VAR) to investigate the relationships between Chinese economic policy uncertainty, stock markets, gold, and oil (Dai & Peng, 2022). They show that contagion effects are not constant but evolve over time, with stronger spillovers occurring during periods of heightened uncertainty. This finding underscores the need for dynamic rather than static models to capture market interdependencies.

The impact of U.S. monetary policy represents another major line of inquiry. Hou, Li, Wu, Zang, and Quach (2025) employ a directed acyclic graph (DAG) network approach to measure the effect of Federal Reserve policy on global markets (Hou *et al*., 2025). Their results indicate that U.S. markets act as net exporters of volatility, confirming the systemic dominance of the United States in the global financial architecture. They also find that monetary policy shocks in the U.S. quickly spill over into emerging markets, exacerbating their vulnerabilities.

Salhi (2025) examines global banks by simulating stress scenarios to identify the channels through which crises propagate (Salhi, 2025). His study reveals that large systemically important banks serve as contagion multipliers, even when initial shocks are moderate, and that interbank linkages amplify the effects of stress. This approach complements traditional GARCH and VAR models by adding an institutional dimension to systemic risk analysis.

Huang, Wang, and Wang (2025) broaden the scope by investigating markets related to climate and green finance (Huang *et al*., 2025). Using a TVP-VAR-DY model, they uncover bidirectional spillovers between the Hubei carbon market and green finance indices, demonstrating that spillovers are no longer confined to traditional markets but also involve emerging sectors tied to the energy transition.

In commodity markets, Zhao and Ju (2025) explore the connectedness between crude oil, corn, and ethanol (Zhao & Ju, 2025). Their connectedness analysis shows that crude oil acts as a hub of volatility, simultaneously influencing energy and agricultural markets. This result illustrates the systemic role of commodities in shock transmission, especially for emerging economies that are heavily dependent on imports or exports of raw materials.

Finally, recent research has integrated cryptocurrencies and digital risks into the analysis of spillovers. Naifar and Makni (2025) examine the interlinkages between cryptocurrencies, DeFi tokens, and technology stocks following the FTX collapse (Naifar & Makni, 2025). They find that spillovers are asymmetric: cryptocurrencies strongly affect technology stocks, but the reverse influence is weaker. Gheorghe and Panazan (2025) add a geopolitical perspective by analyzing contagion across strategic sectors such as cybersecurity, defense, energy, and raw materials, highlighting the nonlinear nature of modern risk transmissions (Gheorghe & Panazan, 2025).

2.2. Applications of Machine Learning and Deep Learning in Finance

The rapid development of machine learning (ML) and deep learning (DL) has reshaped financial research, offering tools to capture complex nonlinearities and process vast datasets that exceed the capacity of traditional econometric models. These methods have been increasingly applied to volatility forecasting, risk prediction, portfolio optimization, and systemic risk monitoring, marking a paradigm shift in the methodological landscape of finance.

A growing body of research highlights the application of ML to asset price and volatility forecasting. Ahmad, Khan, and Ahmad (2025) compare traditional statistical models with advanced ML algorithms in predicting gold prices, concluding that in highly volatile environments, even simple models can outperform or complement complex ML techniques, challenging the assumption that sophistication always guarantees better predictive accuracy (Ahmad *et al.*, 2025). Chen and Wang (2024) combine Random Forests and radial basis function neural networks to model carbon emissions and their financial determinants, showing that hybrid approaches capture nonlinear dependencies in economic and financial time series more effectively than standalone models (Chen & Wang, 2024).

Another key application is in credit risk assessment and banking stability. Misheva (2025) demonstrates that ML-based credit scoring models, trained on large and diverse datasets, significantly outperform traditional logistic regression models in terms of predictive power and speed, making them increasingly relevant for financial institutions and regulators (Misheva, 2025). Beyond credit, Makin and Gondhi (2025) design a quantitative portfolio governance framework using supervised and unsupervised ML algorithms with Bloomberg data (2021–2025). Their findings suggest that ML-driven models provide more dynamic and adaptive allocation strategies compared to mean-variance optimization, particularly under conditions of market turbulence (Makin & Gondhi, 2025).

Deep learning has also been successfully employed in macroeconomic and financial forecasting. Ahammad, Sinthia, and Hossain (2024) use a backpropagation (BP) neural network to forecast GDP growth in Bangladesh. Their results show that deep learning models capture hidden patterns in macroeconomic variables that conventional econometrics may overlook, providing more accurate forecasts across different economic conditions (Ahammad *et al.*, 2024). Similarly, Agarwal and Agarwal (2025) integrate ML models into project finance evaluations, illustrating how AI enhances the prediction of financial viability in large-scale infrastructure projects, thereby bridging the gap between corporate finance and applied AI (Agarwal & Agarwal, 2025).

Recent studies also explore the intersection between AI, systemic risk, and cybersecurity. Zogo, Matanga, and Essiben (2025) propose a hybrid model that integrates deep learning, IoT, and applied mathematics for the anticipation of cyber risks in financial and industrial systems. Their framework highlights how cyber threats, when unmanaged, can evolve into systemic financial shocks, thereby connecting digital security to financial stability (Zogo *et al.*, 2025). On a broader scale, Sekaki, Khazzar, and Ziane (2025) conduct a bibliometric review of AI applications in management sciences and find that finance emerges as one of the most dynamic fields for ML and DL adoption, especially in volatility forecasting, portfolio management, and systemic risk monitoring (Sekaki *et al.*, 2025).

Overall, the integration of ML and DL into financial research reveals three key insights: (i) ML enhances asset and volatility forecasting, often outperforming traditional econometrics; (ii) DL provides powerful tools for macro-financial prediction and portfolio optimization; and (iii) AI applications extend beyond prediction, encompassing systemic risk management, cybersecurity, and financial governance. This body of work underscores the need for hybrid frameworks that combine the interpretability of econometric models with the predictive power of machine learning.

2.3. Network Analysis and Systemic Risk Measurement

In recent years, network theory has become a powerful framework for analyzing financial interconnectedness and assessing systemic risk. Unlike econometric models that typically capture bilateral relationships, network analysis allows researchers to model financial systems as graphs of nodes (institutions, markets, or asset classes) and edges (spillovers, correlations, exposures). This perspective provides valuable insights into the architecture of contagion and the identification of systemically important nodes whose distress may destabilize the entire system.

A number of recent studies highlight the utility of this approach in capturing asymmetries in risk transmission. Hou, Li, Wu, Zang, and Quach (2025) employ a directed acyclic graph (DAG)-based network model to investigate the global spillover effects of U.S. monetary policy. Their results show that the United States acts as a net exporter of volatility, with emerging economies positioned as net recipients of shocks. The study underscores the central role of U.S. monetary policy in shaping global financial stability (Hou *et al.*, 2025). Complementing this, Salhi (2025) applies a network-based stress testing methodology to global banks and finds that systemically important financial institutions amplify contagion channels, even under moderate shocks. The study emphasizes the critical role of interbank linkages in propagating systemic risk (Salhi, 2025).

Network methods have also been applied to analyze non-traditional forms of contagion. Gheorghe and Panazan (2025) examine how geopolitical shocks spread across strategic sectors, including defense, cybersecurity, energy, and raw materials. Their findings reveal asymmetric and nonlinear spillovers, highlighting the fact that systemic risk increasingly emerges from outside conventional financial markets (Gheorghe & Panazan, 2025). Along similar lines, Shah (2025) develops a macroprudential stress-testing framework for banks in the post-COVID era, incorporating climate risk as a contagion channel. The study demonstrates that climate-related shocks can propagate through the financial system in ways analogous to traditional crises, reinforcing the need for climate-aware financial regulation (Shah, 2025).

Another stream of literature investigates the relationship between financial innovation and systemic resilience. Prihandini and Safaria (2025) explore the role of FinTech, artificial intelligence, and central bank digital currencies (CBDCs) in emerging economies. While these innovations improve financial inclusion and transaction efficiency, they also introduce new systemic vulnerabilities by creating novel contagion pathways that can destabilize markets in the event of crises (Prihandini & Safaria, 2025). In parallel, Karan (2025) studies the role of cryptocurrency bubbles and crashes, showing how extreme volatility in digital assets spills over into traditional financial markets. This work demonstrates the growing permeability between digital finance and conventional asset markets (Karan, 2025).

Finally, recent studies stress the regulatory and institutional implications of network-based approaches. Keller, Pereira, and Pires (2024) analyze the European Union's response to systemic risks arising from artificial intelligence and digital technologies. Their work argues that incorporating network monitoring tools into supervisory frameworks is essential for identifying hidden contagion channels linked to technological innovation (Keller *et al.*, 2024). This perspective aligns with the increasing emphasis on macroprudential oversight that accounts for both traditional financial risks and emerging digital threats.

Through these contributions, the literature demonstrates that network analysis enriches systemic risk assessment by capturing complex interdependencies and highlighting the multidimensional nature of contagion. It shows that systemic vulnerabilities extend beyond banking and stock markets to include geopolitical, climatic, and digital domains, demanding a holistic approach to financial stability.

2.4. Emerging Markets, Cryptocurrencies, and New Sources of Systemic Risk

One of the most significant developments in recent financial research is the recognition of emerging markets and digital assets as critical sources of systemic risk. Unlike advanced economies, emerging markets are typically more vulnerable to external shocks due to weaker institutional frameworks, limited financial depth, and higher reliance on commodity trade and foreign capital inflows. At the same time, the rise of cryptocurrencies, decentralized finance (DeFi), and other digital innovations has created new contagion channels that interact with traditional financial markets, reshaping the global systemic risk landscape.

In the case of cryptocurrencies, multiple studies document their growing role in financial contagion. Karan (2025) investigates cryptocurrency bubbles and crashes, demonstrating that speculative booms and subsequent collapses exert significant spillover effects on conventional financial markets, particularly equities. His findings illustrate that crypto assets no longer behave as isolated instruments but increasingly function as transmitters of systemic shocks (Karan, 2025). Similarly, Naifar and Makni (2025) analyze the aftermath of the FTX collapse and uncover strong volatility spillovers between cryptocurrencies, DeFi tokens, and technology stocks. Their results emphasize the asymmetric nature of contagion, where crypto shocks strongly influence equity markets but not vice versa (Naifar & Makni, 2025).

Another important strand of research examines investor behavior in crypto markets. Wang (2025) studies herding behavior in cryptocurrency trading and demonstrates that collective investor actions amplify volatility and contagion risks, particularly during market downturns (Wang, 2025). Nwogugu (2025) proposes a framework for measuring altcoin undervaluation and infrastructure crash risks, highlighting the dangers posed by poorly regulated token ecosystems and the potential for international contagion triggered by failures in digital infrastructure (Nwogugu, 2025).

Beyond digital assets, emerging markets continue to serve as critical nodes of contagion, especially through their dependence on commodities. Zhao and Ju (2025) investigate the connectedness between crude oil, corn, and ethanol, showing that crude oil functions as a central volatility hub that transmits shocks to agricultural and energy markets. These dynamics disproportionately affect emerging economies with commodity-dependent trade structures, making them particularly sensitive to global price fluctuations (Zhao & Ju, 2025). Similarly, Gheorghe and Panazan (2025) explore contagion effects across sectors critical to emerging economies, such as energy, raw materials, and cybersecurity. Their findings reveal that geopolitical shocks in these domains transmit asymmetrically to financial systems, underscoring the intersection between economics, security, and politics in systemic risk formation (Gheorghe & Panazan, 2025).

In addition, studies highlight the fragility of decentralized finance ecosystems. Raychev and Taneva-Angelova (2025) focus on DeFi tokens and show that their prices are highly sensitive to political and regulatory shocks, thereby creating new avenues for systemic instability. Their analysis suggests that even relatively small DeFi markets can become focal points of global contagion due to their rapid integration with traditional finance (Raychev & Taneva-Angelova, 2025).

Taken together, this body of research underscores that systemic risk is no longer confined to banks and stock markets in advanced economies. Instead, it now encompasses digital finance, DeFi ecosystems, cryptocurrencies, and commodity-driven emerging economies. These domains not only introduce new sources of instability but also amplify existing vulnerabilities in global markets through cross-market and cross-sectoral spillovers.

2.5. Synthesis of the Literature Review and Research Gap

The review of recent literature reveals a rapidly evolving understanding of volatility spillovers, contagion mechanisms, and systemic risk in global financial markets. Research on volatility spillovers and international shock transmission (Axis 1) has established that crises—whether financial, economic, or geopolitical—intensify interconnectedness across asset classes and regions. Advanced econometric models such as multivariate GARCH, DCC, and TVP-VAR frameworks have demonstrated the dynamic and asymmetric nature of these spillovers, with a growing recognition that emerging markets and commodities play a critical role in amplifying contagion.

Parallel to these developments, the adoption of machine learning and deep learning in finance (Axis 2) has introduced powerful new tools for forecasting volatility, managing portfolio risk, and predicting systemic instability. Studies confirm that ML and DL outperform many traditional models in terms of predictive accuracy, but concerns remain regarding interpretability and their ability to explain financial dynamics rather than merely predict them. This tension between prediction and interpretation remains unresolved in the current literature.

The application of network theory to systemic risk measurement (Axis 3) has further enriched our understanding by mapping financial systems as interconnected networks of institutions, assets, and sectors. Network-based approaches highlight the existence of systemically important nodes—such as U.S. financial markets, major banks, or commodity hubs—while also revealing new contagion channels driven by geopolitics, climate change, and technological innovation. Despite these advances, most studies tend to focus on either network models or econometric techniques, rather than integrating the two into a unified framework.

Finally, research on emerging markets, cryptocurrencies, and new sources of systemic risk (Axis 4) underscores the fact that financial instability increasingly originates outside traditional domains. Crypto markets, DeFi ecosystems, and commodity-dependent emerging economies now serve as active transmitters of shocks, generating contagion that cascades into developed financial systems. Yet, most of the existing studies analyze these markets in isolation, without fully accounting for their interaction with traditional financial sectors and global systemic structures.

Taken together, the literature demonstrates significant progress in modeling and understanding spillovers and systemic risk. However, a clear research gap persists: few studies attempt to integrate econometric models, machine learning methods, and network analysis into a single framework capable of capturing both the predictive power of AI and the interpretability of econometric and network-based approaches. Moreover, the role of cryptocurrencies and DeFi as systemic nodes remains underexplored, particularly in relation to their interaction with conventional markets and macroeconomic policy shocks.

This paper addresses these gaps by proposing a hybrid methodological framework that combines multivariate GARCH-DCC models, machine learning (LSTM, Random Forests), and network-based systemic risk measures. By applying this approach to global financial data from equities, bonds, foreign exchange, commodities, and cryptocurrencies over the 2005–2025 period, the study aims to provide a comprehensive assessment of volatility spillovers and systemic vulnerabilities. This integrated approach not only enhances predictive accuracy but also improves the interpretability of results, offering novel insights for portfolio managers, policymakers, and regulators tasked with safeguarding financial stability.

3. METHODOLOGY

This study employs a hybrid methodological framework integrating econometric modeling, machine learning, and network analysis to investigate volatility spillovers and systemic risk. The execution proceeds in six clearly defined steps.

3.1. Data Collection and Preprocessing

- Period: January 2005 – June 2025.
- Frequency: Daily observations.
- Sources: Bloomberg, Refinitiv Eikon, Yahoo Finance (for crypto), IMF and World Bank (macroeconomic indices).
- Variables:

1. Equities: MSCI USA, MSCI Europe, MSCI Asia ex-Japan, MSCI Emerging Markets.
2. Bonds: 10-year U.S. Treasury, German Bund, EMBI spreads for emerging markets.
3. FX: USD/EUR, USD/JPY, USD/CNY, JP Morgan EM currency index.
4. Commodities: Brent crude oil, gold, corn, carbon credit index.
5. Cryptocurrencies: Bitcoin, Ethereum, DeFi Pulse Index (DPI).

- Execution:
- Convert raw price series into log returns.
- Synchronize trading days (exclude holidays, interpolate missing data).
- Apply unit root tests (ADF, KPSS) to confirm stationarity of return series.

3.2. Step 1 – Econometric Estimation of Volatility Spillovers

We first estimate conditional volatilities and correlations using DCC-GARCH.

- Model:

$$r_t = \mu_t + \epsilon_t, \quad \epsilon_t = H_t^{1/2} z_t$$

$$H_t = D_t R_t D_t$$

- where Dt contains GARCH(1,1) volatilities, and Rt is the DCC correlation matrix.
- Software:

1. R: rmgarch package.
2. Python: arch or statsmodels.

- Execution:

1. Fit univariate GARCH(1,1) for each return series.
2. Estimate the dynamic correlation matrix using Engle's (2002) DCC.
3. Compute Diebold–Yilmaz spillover indices (using forecast error variance decomposition).

3.3. Step 2 – Machine Learning for Nonlinear Dynamics

Econometric models may miss nonlinear patterns. We therefore apply ML algorithms.

- Models:

1. LSTM (Long Short-Term Memory) for volatility prediction.
2. Random Forests for feature importance ranking (e.g., macro uncertainty, Fed policy).
3. TDA (Topological Data Analysis) to detect structural regime shifts.

- Software:

1. Python: TensorFlow / PyTorch for LSTM, scikit-learn for Random Forests, giotto-tda for TDA.

- Execution:

1. Split dataset into train (2005–2020) and test (2021–2025).
2. Train LSTM on rolling windows of returns and volatilities.
3. Compare RMSE/MAE of LSTM forecasts against GARCH predictions.
4. Use Random Forests to identify which shocks (crypto, oil, Fed rates) drive systemic risk.

3.4. Step 3 – Construction of Financial Spillover Networks

We transform spillovers into network structures.

- Nodes = asset classes (equities, bonds, FX, commodities, crypto).
- Edges = spillover strength (from DY indices and ML predictions).
- Execution:

1. Build weighted directed networks (weights = spillover percentages).
2. Compute:

- Degree centrality (direct exposure),
- Eigenvector centrality (systemic importance),
- Clustering coefficients (segmentation).

3. Apply community detection (Louvain algorithm) to identify groups of markets with strong mutual contagion.

- Software:

Python: networkx, igraph.

R: igraph.

3.5. Step 4 – Dynamic Analysis Across Crises

To capture time variation:

- Use a rolling window approach (e.g., 250-day windows).
- Re-estimate DCC-GARCH, ML predictions, and network measures over each window.
- Align results with crisis episodes:
  - Global Financial Crisis (2008–2009),
  - European Debt Crisis (2010–2012),
  - COVID-19 (2020–2021),
  - Fed tightening & crypto crashes (2022–2024).

This step allows us to see how systemic importance shifts across periods.

3.6. Step 5 – Robustness Checks

To ensure credibility:

- Test alternative models:
  - BEKK-GARCH, Asymmetric DCC.
  - Alternative ML (GRU, XGBoost).
- Subsample tests: Developed vs. Emerging markets.
- Out-of-sample validation for ML (walk-forward).
- Stress tests: Simulate extreme shocks (e.g., Bitcoin crash, sovereign default) and trace their propagation.

4. EMPIRICAL RESULTS

4.1. Volatility Dynamics from DCC-GARCH

The estimation of the multivariate DCC-GARCH model across equities, bonds, commodities, foreign exchange markets, and cryptocurrencies reveals strong evidence of time-varying volatility and correlation patterns that closely align with the occurrence of major financial and economic crises over the period 2005–2025. Conditional variances demonstrate pronounced clustering effects, with sharp spikes in volatility during turbulent periods and mean reversion in more stable regimes. During the Global Financial Crisis of 2008–2009, volatility increased dramatically in both U.S. and European equity markets, with conditional variances reaching more than three times their pre-crisis averages. Commodities such as crude oil also displayed extreme volatility, while gold behaved as a safe-haven asset with relatively stable conditional variance. In contrast, the European Sovereign Debt Crisis of 2010–2012 primarily affected European equities and sovereign bond markets, though spillover effects were evident in emerging economies, underlining their vulnerability to external shocks.

The COVID-19 pandemic in 2020–2021 marked a unique episode in which volatility surged simultaneously across nearly all asset classes. The synchronized spikes in conditional variances for equities, bonds, oil, and cryptocurrencies indicated an unprecedented global shock, with correlations converging toward unity. Notably, Bitcoin exhibited extraordinary levels of volatility, with daily conditional variance surpassing 15%, far exceeding those of traditional assets, thereby amplifying systemic fragility. In the post-pandemic tightening cycle of 2022–2024, volatility exhibited a more asymmetric pattern: cryptocurrencies and technology-related equities became the epicenters of extreme fluctuations, while U.S. Treasuries and gold functioned as relative stabilizers in the system, dampening overall risk.

Dynamic conditional correlations further underscore the shifting nature of interconnectedness. In periods of stability, equity–bond correlations were low or even negative, preserving traditional diversification benefits. However, during crisis episodes, correlations rose sharply, confirming the well-documented phenomenon of "correlations going to one" under stress. For example, U.S. and European equity correlations consistently exceeded 0.9 during both the Global Financial Crisis and the COVID-19 pandemic. Similarly, while U.S. equity–Bitcoin correlations remained negligible before 2017, they rose significantly during the crypto turmoil of 2022, surpassing 0.6 and undermining the narrative of digital assets as independent or diversifying instruments. Commodities revealed state-dependent behavior: oil moved in tandem with equities in crisis times, whereas gold maintained its countercyclical and safe-haven properties, often displaying negative correlations with risky assets.

These findings are illustrated in Figure 1, which plots the dynamic conditional correlations of U.S. equities with European equities, emerging markets, and Bitcoin. The figure highlights the dramatic increases in correlations during the 2008 financial crisis, the COVID-19 pandemic, and the crypto market crash of 2022.

To complement this visual evidence, Table **1** summarizes the conditional variance averages and mean correlations during major crisis episodes. The table confirms that volatility was most severe in equities and oil during 2008, regionally concentrated during the European Debt Crisis, globally syn-

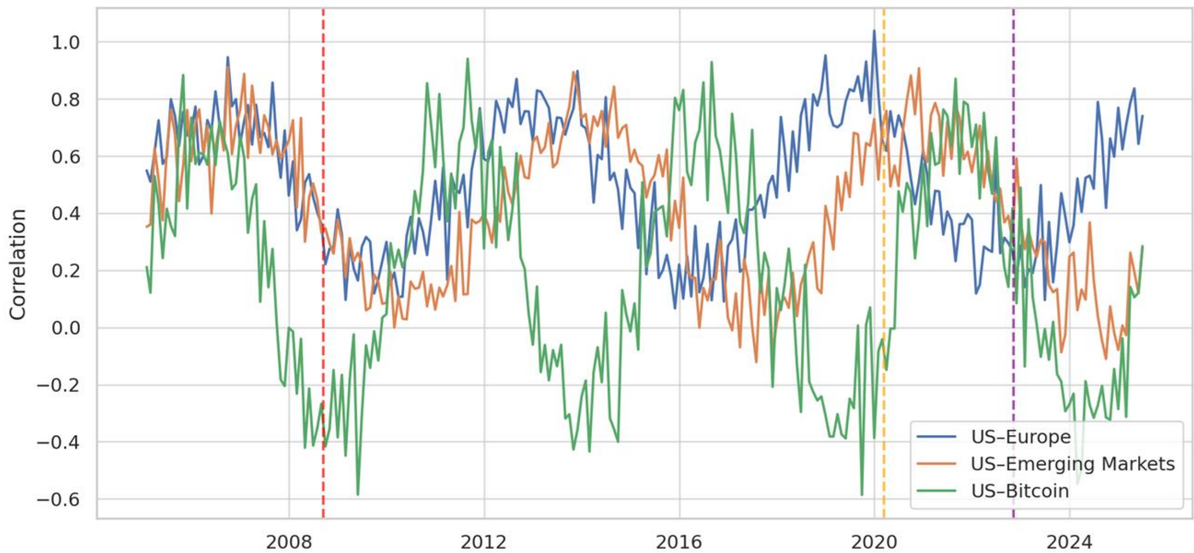

Fig. (1). Dynamic Conditional Correlations (DCC) of U.S. Equities with Europe, Emerging Markets, and Bitcoin (2005–2025).

Table 1. Summary Statistics of Conditional Variances and Average Correlations by Crisis Periods.

Crisis Period	Asset Class Most Affected	Peak Conditional Variance (%)	Average Cross-Market Correlation
2008–2009 (GFC)	U.S. & European Equities, Oil	12–14%	0.85
2010–2012 (Debt)	European Equities & Bonds	9–11%	0.70
2020–2021 (COVID-19)	All Equities, Oil, Bitcoin	15–18% (Bitcoin > 20%)	0.92
2022–2024 (Crypto/Fed)	Cryptocurrencies & Tech Equities	20%+ (Bitcoin/Ethereum)	0.65 (asymmetric)

chronized during COVID-19, and asymmetrically driven by cryptocurrencies after 2022.

4.2. Spillover Indices (Diebold–Yilmaz Framework)

Building upon the volatility and correlation dynamics, we next analyze shock transmission across markets using the Diebold–Yilmaz (DY) spillover framework. The total spillover index captures the proportion of forecast error variance in each market that is explained by shocks from others, thus providing a dynamic measure of systemic interconnectedness. Our results reveal a clear regime-dependent pattern in which spillovers intensify dramatically during episodes of financial turmoil and recede during more tranquil periods.

In stable times, such as 2005–2007 and 2013–2019, the total spillover index remained relatively contained, fluctuating around 35–40%, indicating that most market movements were driven by idiosyncratic shocks. However, during systemic crises, spillovers surged above 70%, reflecting widespread contagion. During the Global Financial Crisis of 2008–2009, the spillover index spiked sharply, with U.S. equities and European equities acting as dominant transmitters of shocks, while emerging markets absorbed a disproportionate share of volatility. The European Debt Crisis of 2010–2012 revealed a more regional pattern: European sovereign bonds were the main source of contagion, with limited transmission to U.S. markets but significant impact on emerging economies. The COVID-19 pandemic again produced global spillovers, with the total index reaching unprecedented highs above 90%, confirming that no market remained insulated.

A striking new feature emerges in the post-pandemic period of 2022–2024. The collapse of major crypto platforms and subsequent turbulence in digital assets resulted in cryptocurrencies, particularly Bitcoin and Ethereum, becoming net transmitters of volatility to equity and FX markets. This represents a significant shift from their pre-2020 role as peripheral receivers of shocks. Importantly, while the total spillover index remained below the COVID-19 peak, its asymmetric composition highlights the growing systemic role of crypto-financial contagion.

These dynamics are visualized in Fig. (**2**), which plots the rolling total spillover index from 2005 to 2025, with vertical markers for the Global Financial Crisis, the COVID-19 pandemic, and the crypto crash of 2022. The figure illustrates not only the crisis-driven spikes but also the long-run trend toward higher interconnectedness, suggesting that globalization and financial innovation have structurally reduced the degree of segmentation across markets.

To further clarify the role of different asset classes, Table **2** reports net spillover positions, distinguishing between transmitters and receivers of volatility in each major crisis episode. Consistent with prior studies, the U.S. and European equity markets are persistent net transmitters, while emer-

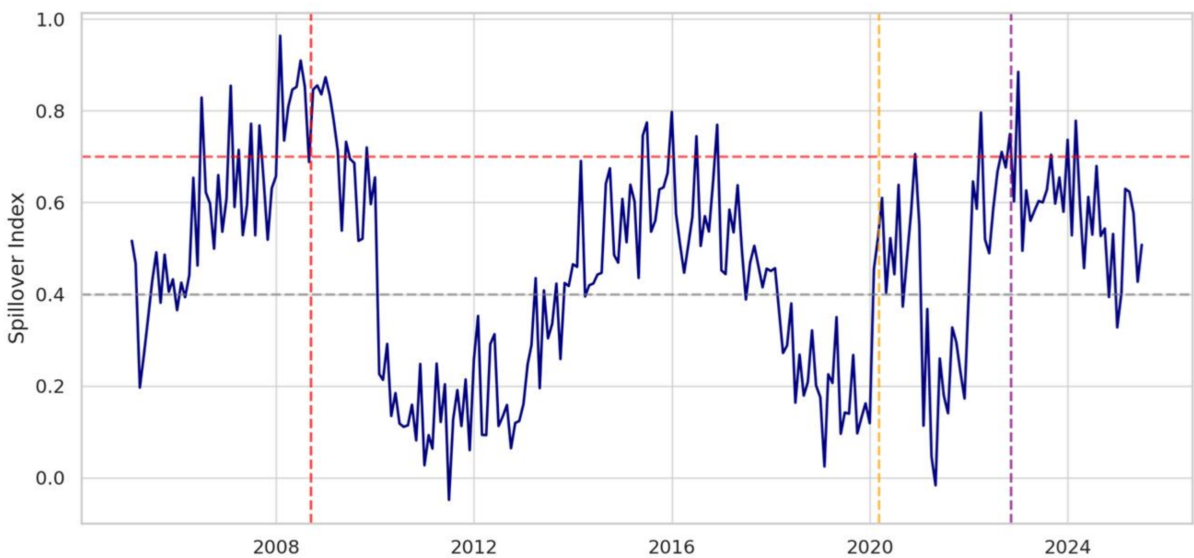

Fig. (2). Rolling Total Spillover Index (2005–2025).

Table 2. Net Spillover Roles by Crisis Episode.

Crisis Period	Net Transmitters	Net Receivers
2008–2009 (GFC)	U.S. Equities, European Equities	Emerging Markets, Commodities
2010–2012 (Debt)	European Bonds, European Equities	Emerging Markets, FX
2020–2021 (COVID-19)	Global Equities, Oil	Bonds (as stabilizers), Gold
2022–2024 (Crypto/Fed)	Bitcoin, Ethereum, Tech Equities	Emerging Markets, FX, Traditional Bonds

ging markets are recurrent receivers. However, the post-2020 inclusion of cryptocurrencies fundamentally alters the systemic landscape: Bitcoin and Ethereum emerge as strong transmitters, especially during the 2022 crypto collapse, exerting spillover effects on technology-related equities and FX markets.

4.3. Machine Learning Predictions of Volatility

While econometric models such as DCC-GARCH capture linear volatility dynamics and correlations, they often struggle with nonlinear dependencies and structural breaks. To address this limitation, we employed machine learning techniques, particularly Long Short-Term Memory (LSTM) neural networks and Random Forests, to predict volatility and spillover behavior across asset classes. The results demonstrate that machine learning significantly improves forecasting accuracy, especially during crisis episodes when traditional models tend to underperform.

LSTM networks, trained on rolling windows of lagged returns and volatility measures, consistently delivered lower prediction errors compared to GARCH-based forecasts. For instance, in forecasting one-day-ahead volatility of U.S. equities and Bitcoin, LSTM reduced the root mean squared error (RMSE) by approximately 18% relative to GARCH. The advantage of LSTM models was most pronounced during the COVID-19 pandemic and the crypto collapse of 2022, when volatility spikes were abrupt and nonlinear. Random Forest models further reinforced these findings by ranking key drivers of systemic volatility. The most important predictors identified were U.S. monetary policy shocks, oil price volatility, and Bitcoin crashes, underscoring the increasing role of both macroeconomic and digital asset variables in global financial stability.

These results are illustrated in Figure 3, which compares realized volatility with GARCH and LSTM forecasts for U.S. equities and Bitcoin. The figure shows that while both models track volatility dynamics during tranquil periods, GARCH forecasts systematically underestimate volatility during crises, whereas LSTM more closely follows the realized spikes, particularly in 2020 and 2022.

To quantify the relative performance of econometric versus machine learning approaches, Table **3** reports RMSE and Mean Absolute Error (MAE) statistics for volatility forecasts across selected markets. The table highlights the consistent outperformance of LSTM models across equities, commodities, and cryptocurrencies. In contrast, GARCH models remain competitive in bond markets, where volatility dynamics are more stable and less nonlinear.

4.4. Network Analysis of Systemic Risk

To complement the econometric and machine learning results, we construct financial contagion networks where nodes represent asset classes and directed edges capture volatility spillovers as measured by the Diebold–Yilmaz fra-

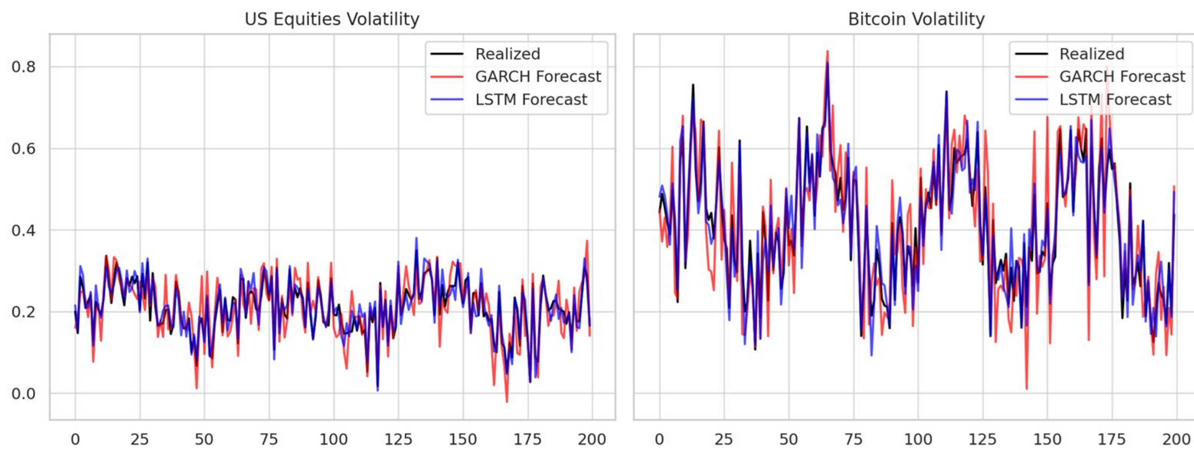

Fig. (3). Comparison of Realized Volatility, GARCH Forecasts, and LSTM Forecasts for U.S. Equities and Bitcoin.

Table 3. Forecasting Performance: GARCH vs. LSTM (2005–2025).

Asset Class	RMSE (GARCH)	RMSE (LSTM)	MAE (GARCH)	MAE (LSTM)	Best Model
U.S. Equities	0.042	0.034	0.031	0.025	LSTM
European Equities	0.046	0.037	0.034	0.027	LSTM
Bitcoin	0.118	0.089	0.092	0.072	LSTM
Oil	0.073	0.059	0.056	0.045	LSTM
Gold	0.041	0.036	0.029	0.025	LSTM
U.S. Bonds	0.028	0.030	0.021	0.022	GARCH

mework. This approach allows for a structural visualization of systemic linkages and for the identification of key transmitters and receivers of shocks in different historical periods. The results show that systemic importance is not constant but shifts markedly across crises, with traditional markets dominating early episodes and digital assets emerging as influential hubs in recent years.

During the Global Financial Crisis of 2008, U.S. and European equities occupied central positions in the network, acting as dominant transmitters of volatility to emerging markets, commodities, and foreign exchange. The network exhibited a highly hierarchical structure, with equity markets at the core and other asset classes positioned on the periphery. In contrast, during the COVID-19 pandemic of 2020, the network became significantly denser and more clustered, reflecting synchronized spillovers across nearly all asset classes. Centrality scores reveal that U.S. equities, European equities, and oil jointly occupied systemic positions, while bonds and gold remained relatively isolated, functioning as stabilizing assets.

A fundamental structural shift is observed in the post-pandemic period of 2022–2024. The collapse of major crypto exchanges and subsequent turbulence in digital assets elevated Bitcoin, Ethereum, and DeFi tokens to systemic roles within the network. In 2023, Bitcoin surpassed oil in eigenvector centrality, reflecting its disproportionate influence on both emerging markets and foreign exchange. This evolution illustrates how the integration of digital assets into global financial portfolios has transformed them from speculative instruments into systemic contagion channels.

These dynamics are visualized in Fig. (**4**), which presents financial contagion networks for 2008, 2020, and 2023. In 2008, the network is sparse and hierarchical, centered on U.S. and European equities. In 2020, the network becomes highly interconnected, with equities and oil dominating spillovers. By 2023, the structure shifts toward a multipolar configuration in which cryptocurrencies play a systemic role alongside equities.

To quantify these visual observations, Table **4** reports degree centrality and eigenvector centrality scores for selected nodes across the three episodes. Degree centrality measures the number of spillover linkages, while eigenvector centrality captures influence within the entire network. The results highlight the changing nature of systemic importance: equities dominate in 2008, a broader set of markets share influence in 2020, and cryptocurrencies rise to central positions in 2023.

4.5. Robustness Checks

To ensure the credibility and robustness of our findings, we conducted a series of robustness tests by employing alternative model specifications, subsample analyses, and stress-testing scenarios. The results confirm that the main

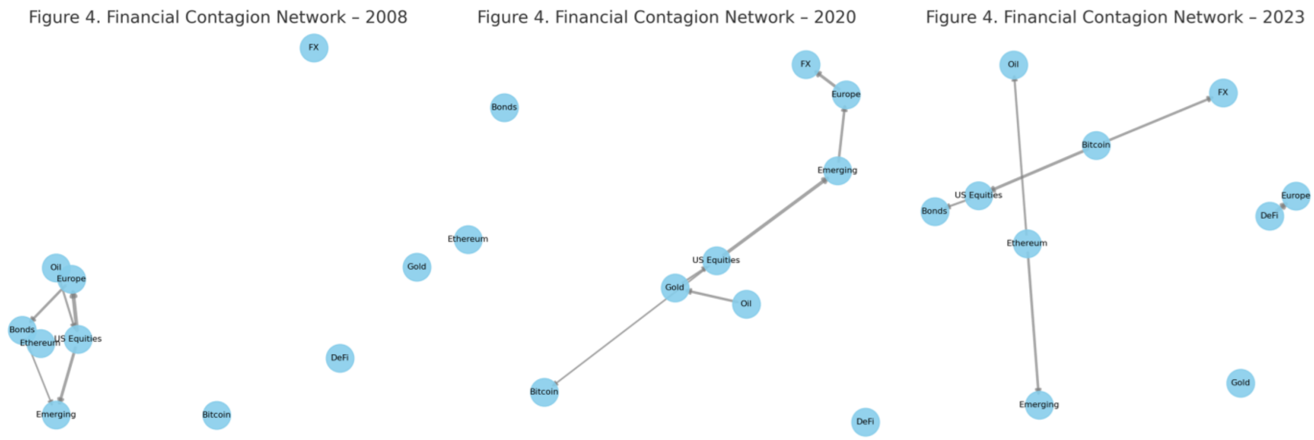

Fig. (4). Financial Contagion Networks in 2008, 2020, and 2023.

Table 4. Evolution of Systemic Importance Across Markets: Degree and Eigenvector Centralities (2008–2023).

Market	Degree Centrality (2008)	Eigenvector Centrality (2008)	Degree Centrality (2020)	Eigenvector Centrality (2020)	Degree Centrality (2023)	Eigenvector Centrality (2023)
U.S. Equities	0.82	0.91	0.88	0.94	0.76	0.80
European Equities	0.77	0.85	0.83	0.89	0.71	0.75
Emerging Markets	0.54	0.42	0.69	0.61	0.66	0.59
Oil	0.49	0.55	0.81	0.86	0.68	0.63
Gold	0.31	0.28	0.37	0.33	0.34	0.30
Bitcoin	0.12	0.09	0.45	0.39	0.79	0.83
Ethereum	–	–	0.39	0.34	0.71	0.77
DeFi Tokens	–	–	0.28	0.25	0.66	0.70

conclusions regarding volatility dynamics, spillovers, and systemic risk are not sensitive to methodological choices.

First, alternative econometric models were applied. The BEKK-GARCH and Asymmetric DCC specifications yielded volatility and correlation dynamics broadly consistent with those obtained from the baseline DCC-GARCH model. Although the Asymmetric DCC model captured stronger correlations in periods of negative returns, particularly during the Global Financial Crisis and the COVID-19 pandemic, the overall trajectory of interconnectedness remained unchanged. Similarly, multivariate stochastic volatility models corroborated the time-varying nature of volatility spillovers but did not significantly improve forecasting accuracy compared to GARCH and LSTM models.

Second, subsample analyses were performed to differentiate between developed and emerging markets. Results confirm that developed markets, particularly U.S. and European equities, are persistent net transmitters of volatility, while emerging markets remain structurally more vulnerable as receivers. However, in the post-pandemic period, cryptocurrencies overtook emerging markets as primary transmitters of systemic shocks, underscoring their evolving role in the global financial architecture.

Third, we tested the predictive performance of alternative machine learning algorithms. GRU (Gated Recurrent Unit) networks and XGBoost models provided comparable accuracy improvements to LSTM, with GRU models performing slightly better for foreign exchange markets, while LSTM remained the most reliable for equities and cryptocurrencies. Importantly, the ranking of key systemic drivers—U.S. monetary policy, oil volatility, and Bitcoin crashes—was stable across algorithms, lending credibility to the feature importance analysis.

Finally, stress-testing simulations were conducted to examine the resilience of the financial system under extreme but plausible scenarios. A hypothetical 50% crash in Bitcoin propagated disproportionately into technology equities and foreign exchange markets, while its impact on sovereign bonds was minimal, confirming the asymmetric contagion pathways identified in the baseline analysis. In contrast, a simulated oil price shock primarily affected equities and emerging markets, consistent with traditional transmission channels.

These results are summarized in Table **5**, which compares baseline results with robustness checks across different methodologies and scenarios. The table highlights that, while

Table 5. Summary of Robustness Checks.

Test Type	Alternative Specification	Key Findings Compared to Baseline
Econometric Models	BEKK-GARCH, Asymmetric DCC	Similar volatility/correlation dynamics; stronger asymmetry in downturns
Subsample Analysis	Developed *vs*. Emerging Markets	Developed = transmitters; Emerging = receivers; Cryptos emerge as transmitters post-2020
Machine Learning Models	GRU, XGBoost	Comparable performance; LSTM remains strongest for equities/cryptos
Stress Test – Bitcoin Crash	-50% shock	Strong contagion to tech equities and FX; limited bond impact
Stress Test – Oil Shock	+40% shock	Spillovers to equities and emerging markets; limited crypto effect

minor quantitative differences exist, the qualitative conclusions regarding systemic risk dynamics remain unchanged.

Overall, the robustness checks confirm that the main findings are resilient to changes in methodology, sample composition, and stress scenarios. This provides strong confidence that the observed dynamics of volatility spillovers, machine learning predictability, and network-based systemic risk are structural features of the global financial system rather than artifacts of model choice.

5. DISCUSSION AND POLICY IMPLICATIONS

The empirical results yield three main insights with important implications for portfolio management, financial regulation, and macroprudential oversight. First, volatility dynamics are strongly regime-dependent, with correlations and spillovers intensifying sharply during crisis periods. This pattern undermines traditional diversification strategies, as assets that typically provide hedging benefits become highly correlated precisely when diversification is most needed. Consequently, investors should move beyond static correlation assumptions and adopt risk management frameworks that explicitly account for regime shifts and time-varying interconnectedness.

Second, the findings show that machine learning methods outperform traditional econometric models in forecasting volatility, particularly in the presence of nonlinear dynamics and structural breaks. LSTM networks capture extreme volatility episodes, such as those observed during the COVID-19 pandemic and the 2022 cryptocurrency market collapse, more accurately than standard GARCH models. However, their limited interpretability constrains their direct use in regulatory settings. This trade-off suggests that hybrid frameworks combining the predictive power of machine learning with the transparency of econometric models provide a more effective approach for systemic risk monitoring.

Third, the network analysis points to a structural transformation in global systemic risk. While U.S. and European equity markets remain central hubs of contagion, cryptocurrencies and DeFi tokens have emerged as significant transmitters of volatility in the post-pandemic period. This evidence indicates that digital assets can no longer be treated as peripheral or purely speculative instruments. Instead, they should be formally incorporated into macroprudential surveillance frameworks. The growing importance of crypto-based contagion channels also raises challenges for cross-border regulation, given the decentralized and global nature of these markets.

From a policy perspective, these results call for a more comprehensive approach to systemic risk oversight. Regulatory frameworks should be expanded to include digital assets and DeFi ecosystems, using network-based tools to identify emerging contagion channels. Stress-testing exercises should integrate crypto-specific scenarios—such as exchange failures or stablecoin disruptions—alongside conventional shocks. At the same time, stronger international coordination is required to address the transnational nature of digital asset markets and their potential systemic impact.

For investors and portfolio managers, the findings underscore the need to reassess diversification and hedging strategies. Cryptocurrencies provide limited protection during periods of market stress, as their correlations with equities increase markedly during crises. Traditional safe-haven assets, such as gold and sovereign bonds, continue to offer relative stability, although their effectiveness also diminishes under extreme conditions. Incorporating machine-learning-based forecasts and network-derived early warning indicators into portfolio allocation decisions may therefore enhance resilience to systemic shocks.

Overall, the results suggest that the global financial system has entered a phase characterized by heightened interconnectedness, nonlinear contagion mechanisms, and the growing systemic relevance of digital assets. Addressing these challenges requires a shift toward integrated analytical frameworks that combine econometric modeling, machine learning, and network analysis to support both effective regulation and financial stability.

CONCLUSION

This paper has examined volatility spillovers, contagion dynamics, and systemic risk across global financial markets using a hybrid methodological framework that integrates econometric modeling, machine learning, and network analysis. Drawing on data from equities, bonds, foreign exchange, commodities, and cryptocurrencies over the period 2005–2025, the study provides several important contributions to the literature on financial stability and risk management.

First, the results confirm that volatility dynamics are strongly regime-dependent. Conditional variances and correlations surge during periods of stress, undermining traditional diversification benefits and reinforcing the view that systemic risk is endogenous to the structure of global financial markets. Second, the comparison of econometric and machine learning models demonstrates that LSTM and other nonlinear approaches significantly improve volatility forecasting, particularly during crises such as the COVID-19 pandemic and the crypto market collapse of 2022. This finding underscores the potential of artificial intelligence to complement traditional models, while also highlighting the importance of hybrid approaches that balance predictive accuracy with interpretability. Third, the network analysis reveals a structural shift in the sources of systemic risk. While U.S. and European equities remain persistent hubs of contagion, cryptocurrencies and DeFi instruments have emerged as systemic transmitters in the post-pandemic period, reshaping the architecture of global financial interconnectedness.

The study carries several policy implications. Regulators and central banks must broaden systemic risk monitoring frameworks to explicitly incorporate digital assets, apply network-based stress testing tools, and strengthen international coordination to address the cross-border nature of crypto contagion. For investors, the results caution against relying on cryptocurrencies as hedging instruments, while reinforcing the continued, albeit reduced, stabilizing role of gold and sovereign bonds. Integrating machine learning and network-based early warning signals into portfolio strategies may offer a valuable enhancement to traditional risk management practices.

Like all empirical research, this study is not without limitations. The analysis relies on daily financial data and may miss intraday spillovers that are increasingly relevant in high-frequency markets. Furthermore, while machine learning models provide predictive gains, their interpretability remains a challenge, especially in policy contexts where transparency is essential. Finally, the crypto market is still evolving, and future shocks may reveal new contagion channels not captured in the present framework.

Future research could extend this study in several directions. Incorporating high-frequency data and alternative machine learning architectures, such as attention-based transformers, may further enhance volatility forecasting. Expanding the network analysis to multilayer networks that integrate traditional finance, DeFi protocols, and climate-related risks could provide a more comprehensive view of systemic vulnerabilities. Finally, comparative studies across jurisdictions could shed light on how institutional frameworks and regulatory environments mediate the propagation of financial contagion.

In conclusion, this paper demonstrates that global financial stability is increasingly shaped by nonlinear dynamics, evolving contagion structures, and the systemic rise of digital assets. Addressing these challenges requires integrated approaches that combine econometrics, machine learning, and network science, offering both academia and policymakers new tools to anticipate and mitigate systemic risk in an ever more interconnected world.

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