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Connectedness spillover matrices : a tool for diversification

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Abstract
This research analyzes the performance and interconnectedness of major global stock market indices and decentralized finance assets, specifically cryptocurrencies, over the period from 2015 to 2025. The study includes indices such as the S&P 500 and Nasdaq Composite from the United States, the FTSE 100, DAX, and CAC 40 from Europe, and the Nikkei 225 from Japan, and two more indices from China and India representing different economic regions. Additionally, Bitcoin and Ethereum are included to assess the impact of decentralized finance on traditional financial indices and asset allocation strategies. By employing Artificial Intelligence algorithms like ConvLSTM, the research measures the dynamic asset allocation and volatility management through an interconnected spillover matrix. The findings reveal that integrating ConvLSTM enhances the understanding of the interconnectedness between cryptocurrencies and traditional assets, offering improved diversification opportunities due to their low correlation, decentralization, and inflation-hedge characteristics. The study's results suggest that investors can make more informed decisions regarding dynamic asset allocation in high-volatility portfolios, providing indicators of rising systemic risk and market stress.

Keywords Artificial Intelligence · Cryptocurrency · Risk Diversification · Volatility Spillover

1 Introduction

In recent years, global markets have undergone substantial changes, influenced by numerous factors, mainly driven by globalization and rapid advances in information technology (Comin

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and Nanda, 2019). However, this growing interconnection has led to the proliferation of contagion and shocks across various market sectors (Acemoglu et al., 2016; Hansen, 2021; Nguyen et al., 2023). Sudden movements in one stock market can significantly impact other markets worldwide, highlighting a high level of integration among financial assets (Box and Shang, 2021; Forbes, Forbes). This interconnectedness creates a web of interdependencies that propagates the shocks and amplifies their impact, transcending frontiers (Chen, Chen).

Additionally, in periods of high uncertainty in the stock market, risk propagation increases significantly, compromising the overall system's stability. Adverse events like economic crises and pandemics can trigger chain reactions and spread pessimistic expectations, affecting stock market stability, each within distinct regional contexts (Aloui et al., 2011). Historical crises such as the 1987 crash, the 1998 Asian financial crisis, the 2008 global financial crisis, the European debt crisis, and the COVID-19 pandemic have substantially affected financial stability (Abuzayed et al., 2021; Ghazani and Khosravi, Ghazani and Khosravi; Petrella et al., 2019).

Analyzing financial market spillover effects during significant events offers insights into the interconnections among asset classes (Hung, Hung; Kang and Yoon, S- M., 2019). To measure this interconnectedness and the propagation of shocks across financial markets, a notable method for estimating interdependence within a dynamic system of variables is introduced by Diebold and Yilmaz (2008). The authors created the spillover index based on Vector Autoregressive (VAR) models by analyzing financial returns and volatility spillovers. The index quantifies how shocks in one market can affect others, providing a comprehensive measure of systemic risk and interdependence.

Diebold (a) further developed their methodology with a generalized spillover index to capture more complex dynamics within financial systems. This index uses forecast error variance decompositions from generalized VAR frameworks to evaluate the direction and magnitude of spillovers across stocks, bonds, foreign exchange, and commodities markets. An additional extension to refine the methodology (Diebold, b) incorporates a time-varying parameter vector autoregressive model. This approach improves the ability to detect abrupt changes in connectedness and provides a more accurate analysis of systemic risk.

In recent years, numerous market crashes have occurred (Kyle and Obizhaeva, 2023), with the COVID-19 crisis bringing abrupt shocks that affected various industries and markets (Batten et al., 2023; Contessi, Contessi; Ftiti et al., 2023; Iqbal et al., 2023). Recent literature also indicates that the crisis must be addressed through coordinated fiscal and monetary policies, corporate governance, and advanced technologies such as Machine Learning (ML) and Artificial Intelligence (AI) (Zhang et al., 2024). In a joint effort, central banks and governments can take measures. However, the emergence of Decentralized Finance (DeFi) and cryptocurrency assets introduces new challenges for financial stability (Antonakakis et al., 2019; Matkovskyy and Jalan, 2019) due to exhibit significantly higher price volatility compared to traditional financial assets (Bouri et al., 2024). Nonetheless, despite being a relatively new concept, there are interconnected dynamics and spillovers between DeFi , cryptocurrencies, stock markets, and safe-haven assets (Ugolini and Reboredo, Ugolini and Reboredo).

The dynamics of cryptocurrencies are complex and highly volatile, driven by a combination of factors where traditional predictive models may not be fully effective. AI appears to be a suitable tool for addressing these challenges, offering advanced predictive capabilities. ML as a branch of AI models has gained popularity due to its ability to handle intricate non-linear dynamics and complex patterns in financial (De Prado, 2018; Henrique et al., 2019) and cryptocurrency (Akyildirim et al., 2023; Caliciotti et al., 2024) markets. Another subset of AI is Deep Learning (DL), which relies in the use of Artificial Neural Networks (ANN) and shows remarkable promise in financial applications (D'amato and Levantesi, D'amato and Levantesi; Kim et al., 2020; Nikou et al., 2019; Ozbayoglu and Gudelek, Ozbayoglu and Gudelek), establishing superiority over conventional techniques and effectively capturing intricate data interactions. This trend is further corroborated by Song et al. (2023, Song et al.); in their investigation, they compared DL , hybrid ML, and traditional econometric forecasting models across various frequencies, revealing the superior predictive accuracy of DL .

This research paper explores the levels of connectedness between cryptocurrencies and traditional stocks. Understanding the interconnectedness between these assets helps to achieve better diversification for investors, as cryptocurrencies exhibit a low correlation with traditional assets, offering decentralization and delivering an inflation hedge. Thus, this paper examines the research question: *How can dynamic asset allocation be enhanced using an interconnected spillover matrix and AI ?*

Following the literature, in this research, we use historical price data from different stock markets (Li and Giles, 2015; Mensi et al., 2016). We also include the two leading cryptocurrencies Bitcoin (BTC) and Ethereum (ETH) and six stock indices. The data ranges from 2 January 2015 to 30 May 2025. The techniques used in our work are a predictive model that combines a DL approach, together with the Joint Spillover Index, and the Diebold and Yilmaz Connectedness Spillover Matrix (CSM) (Kim and Won, 2018; Lastrapes and Wiesen, 2021; Vidal, Vidal). These methods help to evaluate returns and volatility while looking at the relationships and spillover effects between different asset classes. This research aims to improve volatility control and dynamic asset allocation techniques. We propose investigating how spillover and connectedness play key roles in shaping the dynamics and volatility of these different financial assets, providing valuable insights for academics and practitioners in finance.

The rest of the paper is organized as follows: Section 2 reviews the relevant literature on financial spillovers, systemic risk measurement, and the application of ML in finance. Section 3 describes the methodology, including the construction of the two-channel image, the architecture of the ANN used, and the training process. Section 4 presents the empirical results, demonstrating the effectiveness of our approach. Finally, Section 5 discusses our findings' implications and suggests future research directions.

2 Literature review

The construction of portfolios is arduous, and the search for significant factors and portfolio diversification is essential; however, optimizing portfolios due to growing financial market integration is becoming more challenging (Migliavacca and Goodell, Migliavacca and Goodell). The interconnectedness of global financial markets is a well-documented phenomenon, and its implications for portfolio construction are critical for ensuring market stability and effective risk management.

Increasing connectedness impacts portfolio diversification (Samitas and Kampouris, Samitas and Kampouris), making it more difficult to mitigate risks through traditional strategies. Therefore, it is possible to enhance portfolio performance by considering connectedness in building a portfolio, and covariance matrices can be adjusted to better reflect the actual interdependencies between assets, allowing for more accurate risk assessment and asset allocation. Some authors enhance portfolio selection by improving covariance matrix estimation in high-dimensional financial data (Agrawal et al., 2020; Moura and Santos, Moura and Santos; Zhao et al., 2021), while others use alternative methods.

In the attempt to build better portfolios using connectedness, de Carvalho and Gupta (2018) presents a methodology for analyzing the dynamic co-movement of asset prices through a network-based representation. The authors screen significant co-movement structures among large assets, integrating systematic and idiosyncratic factors. This method allows for analyzing hundreds of asset price variables and their complex interactions over time. The research reveals that a portfolio allocation strategy leveraging a network factor model outperforms a traditional factor model-based allocation. This approach, which considers the interconnectedness of assets within a network, provides superior results compared to the standard method that focuses on individual asset characteristics.

Similarly, Giudici and Sarlin (Giudici and Sarlin) analyzes systemic risk and interconnectedness in financial systems by measuring portfolio similarities through correlation network models using data obtained from international banking activity statistics. The results reveal that, before the financial crisis, funding increased via specific investments rather than a generalized increase, while post-crisis funding got concentrated rather than diversified. Additionally, indicating that the financial crisis acted as a tipping point for most of the countries in the study; however, they maintained stable risk profiles for offshore and high-quality flight countries. The authors conclude that combining their measures with Credit Default Swaps (CDS) spreads is relevant in predicting imbalances before crises, highlighting the significant role of common exposures in contagion.

Additionally, by analyzing CDS, Huang (Huang) investigates cross-market risk spillovers, employing the Diebold (b) Connectedness methodology, analyzing data from 2009 to 2022, the study indicates that sovereign CDS are closely interconnected with other financial markets, particularly stock markets. Recent evidence from Asia-Pacific markets confirms the time-varying nature of sovereign risk transmission, noticing the co-movement patterns across CDS markets (Lee, Lee). Also, their research shows that sovereign risk spillovers are sensitive to significant events such as wars or pandemics. In foreign exchange markets have shown to intensify in response to policy-related uncertainty, underscoring the role of macroeconomic shocks (Huynh et al., 2023). Similarly, Feng et al. (2023) demonstrates how different assets are interconnected through significant cross-border spillover effects, such as net spillover effects on foreign exchange markets and sovereign CDS. However, Jareño (Jareño) examines the interconnectedness between AI -based tokens and AI -based stocks, using a quantile connectedness approach, seeing that these assets exhibit a lower degree of spillover from the returns of other, serving as a good diversifier for, especially under extreme market conditions. Additionally, cryptocurrencies, particularly BTC and ETH , have potential as diversification tools due to their distinct and variable responses to macroeconomic news and monetary policy decisions, which differ from traditional assets (Ben Omrane et al., Ben Omrane et al.; Ben Omrane and Qi, Ben Omrane and Qi; Bouri, Bouri). Additionally, recent evidence further supports this view by examining the effects of green bonds, equities, cryptocurrencies, and commodities, highlighting their interconnectedness and its implications for portfolio diversification (Kamal and Bouri, 2025).

Additionally, Bouri et al. (Bouri et al.) make a valuable contribution by showing that technology-related US stocks, particularly the semiconductor sector and Nvidia, exhibit notable return predictability with major cryptocurrencies, suggesting meaningful cross-market linkages. However, a key limitation of the study is that the documented relationships may primarily capture broader market dynamics, such as shifts in liquidity conditions or changes in overall risk sentiment, rather than reflecting genuine information spillovers between technology stocks and cryptocurrencies.

However, the COVID-19 crisis triggered increased volatility spillover in cryptocurrencies, primarily due to contagion effects. Price movements during this period suggest limited diversification benefits within the market during times of high uncertainty (Ben Ameur and Ftiti, Ben Ameur and Ftiti). Similarly by analysing periods of extreme volatility Iqbal et al. (2023) find that agricultural futures generally provide diversification benefits except during extreme crises like the COVID-19 pandemic. Also, the authors find that energy futures like light crude oil act as main transmitters of volatility, and metal futures, particularly gold, show high connectedness, acting as safe havens during high volatility periods and crisis periods, reinforcing their role in portfolio protection (Kinateder and Gurrib, Kinateder and Gurrib).

Naeem et al. (Naeem et al.) investigates the transmission mechanisms across G20 stock market returns using a connectedness framework by integrating two approaches, the network approach of Dror et al. (2015) with the connectedness of Diebold (b). The study covers data from January 2000 to June 2022, showing that dynamic total connectedness is heterogeneous and dependent on economic events. The findings highlight dynamics in terms of risk diversification, showing that specific markets, such as those of France, Germany, and Great Britain, exhibit significant interconnectedness.

Likewise, using thirty years of daily data Raza et al. (Raza et al.) analyzes asymmetric spillover of returns between monetary policy uncertainty and sectoral stock returns to create dynamic connectedness and portfolio management strategies. The authors find that negative market sentiment and policy uncertainty have a more substantial impact on stock markets than positive news and that different sectors respond to these shocks differently.

Even though classic econometric models are effective in evaluating market connectedness, spillover effects, and integrating them into portfolio creation, there is a growing trend of using AI models. Lin and Hu (Lin and Hu) provides an early review on the use of ML applied to financial crisis prediction. The research accentuates the advantages of ML models compared to traditional statistical methods, proposing a combined approach using clustering techniques alongside multiple classifiers to achieve better results. Additionally, it remarks that feature selection is important in improving prediction accuracy by reducing the number of features and removing irrelevant or misleading information.

Additionally, Henrique et al. (2019) provides an exhaustive review of the application of ML models in financial market prediction, examining different models and hybrid approaches. The paper highlights the superiority of ML and ANN models over traditional ones in capturing financial time series data complexities. Similarly, Gu et al. (2020) shows equivalent results, where ML models outperformed traditional models in empirical asset pricing. The authors demonstrate that using ML models can lead to economic gains, with key predictive variables including deviations in momentum, liquidity, and volatility.

Similarly, Ozbayoglu and Gudelek (Ozbayoglu and Gudelek) gives a comprehensive review of the application of DL for financial applications, examining various architectures of ANN employed in diverse financial applications. The authors highlight the popularity of ANN and other ML models in predicting North American market indices, suggesting that future research should compare new models to established benchmarks and explore the predictions in developing markets like BRICS. Likewise, other authors in their respective reviews show that AI models can successfully study and analyze stock market activity, reaching similar conclusions (Chopra and Sharma, 2021; Thakkar, Thakkar).

Among the common DL architectures to predict the stock markets are the Recurrent Neural Networks (RNN), including the Long Short-Term Memory (LSTM) networks, which are extensively used due to their ability to process data sequences and capture temporal dependencies. The LSTM, introduced by Hochreiter and Schmidhuber (1997), is a RNN that has been specifically designed to improve common pitfalls of this ANN architecture, such as the vanishing gradient that stops standard RNNs from effectively learning long-range dependencies within sequence data. Another standard DL architecture is the Convolutional Neural Network (CNN), introduced by Lecun et al. (1998) for image processing tasks. Then the Convolutional Long Short-Term Memory (ConvLSTM) combines CNN with LSTM, improving the ability to capture both spatial and temporal correlations effectively and improving the prediction performance in the financial markets Kong and Luo (2022). Hence the ConvLSTM cells keep the temporal and spatial dimensions into consideration. The input of a ConvLSTM is a set of images over time as a 5D tensor with shape (samples, time steps, channels, rows, columns).

By considering the connectedness of the markets, spillover, and contagions, Sahiner (2023) creates an early warning approach to predict crises accurately based on a DL model, using an LSTM. The authors use an assemblage of advanced econometric models, including the Diebold-Yilmaz spillover index, for the level of volatility contagion to analyze the transmission channels of volatility across international stock markets. The authors observe that during crises, due to contagion, the impacts of external shocks on domestic markets are persistent on time with a long-lasting effect.

In this paper, we initially use the CSM as outlined by (Diebold, b) to then construct a two-channel image using joint total spillovers, which is used as input for an ANN. By having a two-channel image representation of the connectedness matrix, we can effectively leverage different ANN architectures to analyze risk propagation in the financial network. This approach enables a more detailed analysis of how shocks propagate within the network, as AI can detect patterns and anomalies in the data more effectively than classical econometric models alone. By adding advanced ANN architectures such as ConvLSTM , we are improving the existing model to capture market interconnectedness during extreme events like the COVID-19 pandemic. The ConvLSTM helps capture the data's temporal dependencies and spatial correlations, providing a robust tool to enhance predictions considering how extreme events affect financial markets globally.

3 Methodology

To construct the connectedness matrix, we start by estimating a VAR model for the set of variables X_t represented as:

$$X_t = \sum_{i=1}^{p} A_i X_{t-i} + \epsilon_t \tag{1}$$

where A_i are coefficient matrices and ϵ_t is the vector of error terms. We then compute the variance decomposition of the H-step ahead forecast error variance,

$$\theta_{ij}(H) = \frac{\sigma_{ij}(H)}{\sum_{j=1}^{N} \sigma_{ij}(H)} \tag{2}$$

where $\theta_{ij}(H)$ denotes the contribution of shocks to variable j to the forecast error variance of variable i.

The CSM $\mathbf{C}$ is constructed with entries:

$$C_{ij} = \theta_{ij}(H) \tag{3}$$

where each entry C_{ij} represents the contribution of variable j to the forecast error variance of variable i. The diagonal elements, C_{ii}, represent the own-variable spillovers, while the off-diagonal elements, C_{ij} for $i \neq j$, represent the cross-variable spillovers.

The structure of this matrix allows us to identify not only the direct spillovers between variables but also the indirect effects that propagate through the network of variables.

The total spillover index is calculated as:

$$\frac{\sum_{i \neq j} \theta_{ij}(H)}{N^2} \tag{4}$$

providing a measure of overall system interconnectedness. This methodology allows for the quantification of interdependencies and systemic risk within the network of variables, facilitating a comprehensive understanding of shock propagation and the identification of key sources of systemic risk.

Finally, we calculate the Forecast Error Variance Decomposition matrix (FEVD) which provides a detailed breakdown of the forecast error variances attributable to each shock, allowing for a more nuanced understanding of the transmission mechanisms within the system.

The generalized FEVD for an H-step ahead forecast is represented by:

$$\psi_{ij}(H) = \frac{\sum_{h=0}^{H-1} \left(e_i' \Phi_h \Sigma e_j\right)^2}{\sum_{h=0}^{H-1} \left(e_i' \Phi_h \Sigma \Phi_h' e_i\right)} \tag{5}$$

where: - Φ_h is the h-step ahead forecast error impulse response matrix, - Σ is the variance-covariance matrix of the error terms, - e_i and e_j are selection vectors with 1 in the i-th and j-th positions, respectively, and 0 elsewhere.

Each element $\psi_{ij}(H)$ of the matrix quantifies the proportion of the H-step ahead forecast error variance of variable i that is attributable to shocks to variable j. This decomposition accounts for both direct and indirect effects, offering a more detailed view of the spillover dynamics.

The FEVD matrix $\Psi(H)$ can be expressed as:

$$\Psi(H) = \begin{pmatrix} \psi_{11}(H) & \psi_{12}(H) & \cdots & \psi_{1N}(H) \\ \psi_{21}(H) & \psi_{22}(H) & \cdots & \psi_{2N}(H) \\ \vdots & \vdots & \ddots & \vdots \\ \psi_{N1}(H) & \psi_{N2}(H) & \cdots & \psi_{NN}(H) \end{pmatrix}$$

To interpret the FEVD matrix, the diagonal elements $\psi_{ii}(H)$ represent the own contributions, indicating the proportion of the forecast error variance of variable i due to its own shocks. The off-diagonal elements $\psi_{ij}(H)$ for $i \neq j$ capture the cross-variable contributions, highlighting how shocks to variable j impact the forecast error variance of variable i.

By analyzing the FEVD matrix alongside the CSM, we gain deeper insights into the structure and dynamics of the system. This combined approach enhances our understanding of how shocks propagate through the network and enables the identification of critical nodes that contribute significantly to systemic risk, extending the current literature (Ben Ameur and Ftiti, Ben Ameur and Ftiti; Kong and Luo, 2022; Sahiner, 2023).

In summary, the use of the CSM and the generalized FEVD matrix provides a robust framework for analyzing the interdependencies and systemic risk within a network of variables. This methodology not only quantifies the degree of interconnectedness but also uncovers the pathways through which shocks are transmitted, offering valuable information for risk management and policy-making.

In the second stage, the matrix derived from the CSM is duplicated and stacked to create a 2-channel image. The first channel represents the "from" effects, while the second channel represents the "to" effects. The joint total spillover method, as proposed by Lastrapes and Wiesen (2021), is employed to normalize the channels. This involves calculating the joint total spillover from all other variables to variable ii and the joint total spillovers to all other variables from variable jj.

The joint total spillovers are defined as follows:

$$\text{Total Spillover to } i = \sum_{k \neq i} C_{ik}, \quad \text{Total Spillover from } j = \sum_{k \neq j} C_{kj} \tag{6}$$

To form the normalized "from" channel, each ii-th row of the first channel matrix is divided by the joint total spillover from all others to variable ii:

$$F_{ij} = \frac{C_{ij}}{\sum_{k \neq i} C_{ik}} \quad \text{for } i \neq j \tag{7}$$

Similarly, the normalized "to" channel is formed by dividing each jj-th column by the joint total spillovers to all others from variable jj:

$$T_{ij} = \frac{C_{ij}}{\sum_{k \neq j} C_{kj}} \quad \text{for } i \neq j \tag{8}$$

Since the diagonal elements of each channel matrix represent self-spillover effects, these diagonal elements are set to zero to eliminate self-spillover effects from our analysis. Therefore, for both channels, we set:

$$F_{ii} = 0 \quad \text{and} \quad T_{jj} = 0 \tag{9}$$

where ii and jj are the indices of the variables.

The resulting two-channel image representation effectively separates the directional flow of risk, providing a clearer picture of the interconnectedness in the system. This approach allows us to identify the main sources and receivers of systemic risk more precisely.

Then, this two-channel image representation goes to a ConvLSTM ANN. In this research we propose a DL architecture that has a ConvLSTM Encoder part followed by two LSTM layers and two dense layers, the model parameters are display in Appendix B.

By employing this two-channel normalization, we enhance our ability to detect and analyze the propagation of shocks within the network. This method provides a robust framework for understanding the directional spillover effects and their implications for risk management and policy-making.

To clarify the integration of connectedness into the proposed framework, the Diebold–Yilmaz spillover matrix is not treated as a standalone descriptive measure but is directly embedded into the forecasting model. Specifically, the normalized “from” and “to” spillover matrices are stacked to form a two-channel network representation that encodes the directional transmission of shocks across assets at each point in time. These two-channel connectedness images serve as the direct inputs to the ConvLSTM architecture, allowing the model to learn how the evolving topology and intensity of spillovers predict future asset prices and volatilities.

4 Empirical results

In this research, the empirical analysis evaluates how forecasts generated from spillover-informed ConvLSTM inputs translate into improved covariance estimation and portfolio allocation decisions. We utilized a selection of major global stock market indices to analyze and compare market performance across different regions. The indices included in the study were the S&P 500 Index (GSPC) and the Nasdaq Composite (IXIC) IXIC representing the United States markets. For the European markets, the indices included were the FTSE 100 (FTSE) from the United Kingdom, the DAX (GDAXI) from Germany, and the CAC 40 (FCHI) from France. Additionally, the research incorporated the Nikkei 225 (N225) representing the Japanese market, as well as the iShares China Large-Cap ETF (FXI) and iShares MSCI India ETF (INDA) to capture the Chinese and Indian equity markets, respectively.

These indices were selected due to their broad representation of the economic sectors within their respective regions, allowing for a comprehensive analysis of market trends and performance on a global scale. Additionally, we include BTC and ETH in the research to consider the impact of DeFi with traditional financial indices in asset allocation strategies.

We used daily Open, High, Low, and Close prices for each index from January 2, 2015, to May 30, 2025, covering a 10-year period. To ensure synchronous timing, cryptocurrency data are aligned to equity trading days by excluding weekend observations. This time frame provides a substantial period for analyzing long-term trends and capturing various market cycles, including periods of volatility and stability. Following the daily variance from Diebold (a) the daily variance is estimated using daily high and low prices for market i on day t is

$$\sigma_{it}^{2} = 0.361 \left[ln \left(P_{it}^{max} \right) - ln \left(P_{it}^{min} \right) \right]^{2} \tag{10}$$

Where P_{it}^{max}, and P_{it}^{min} is the highest and the lowest price in market i on day t respectively.

The corresponding estimate of annualized daily volatility is:

$$\sigma_{it}^{ann} = \sqrt{\sigma_{it}^{2} \cdot 252} \tag{11}$$

A rolling window method is employed to create a sequence of images over the entire time frame. Stationarity checks are performed for window sizes of 90, 120, 150, and 180. Stationarity holds true for window sizes of 150 and 180; therefore, the study adopts a window size of 150. For each window, a 2-channel image is generated on a rolling basis. In total, 1581 image sequences are constructed.

Since the sequence of images must be inputted into a ConvLSTM layer, a batch of six consecutive images are used as a sample input (i.e. time-steps = 6). Model 1 outputs an array of the 7th day's closing prices of all assets, while Model 2 outputs the 7th day's annualized volatility of all assets. Price prediction is used only as an auxiliary step, with returns and volatility remaining the economically meaningful targets. Finally, the data is split into training and testing sets, with the test set accounting for 20 % of the total data. To ensure robustness and mitigate overfitting, the ConvLSTM is trained using a rolling window framework with strict out-of-sample evaluation, incorporating regularization and early stopping.

The models in a first stage are evaluated using the R^2, Adjusted R^2, and MSE metrics. These metrics assess the explanatory power of the regression models and their ability to accurately fit the observed data, and are discussed in detail in Appendix A. The results for all assets, evaluated separately, are reported in Table 1. Overall, the high values of R^2 and Adjusted R^2, together with the consistently low MSE across assets, indicate that the models estimate returns with a very high degree of accuracy. In particular, most assets exhibit R^2

Table 1 R-squared, Adjusted R-squared, and Mean Squared Error (MSE) Values for returns and volatility of ten assets.

	Returns (Ret)			Volatility (Vol)		
Asset	R^2	Adjusted R^2	MSE	R^2	Adjusted R^2	MSE
GSPC	0.9965	0.9963	0.0032	0.9988	0.9987	0.0013
IXIC	0.9952	0.9949	0.0043	0.9977	0.9976	0.0023
FTSE	0.9678	0.9656	0.0321	0.9979	0.9977	0.0022
N225	0.9936	0.9932	0.0063	0.9980	0.9978	0.0022
GDAXI	0.9917	0.9911	0.0091	0.9983	0.9981	0.0018
FCHI	0.9899	0.9892	0.0102	0.9975	0.9973	0.0026
FXI	0.9900	0.9894	0.0096	0.9952	0.9949	0.0050
INDA	0.9944	0.9940	0.0054	0.9977	0.9975	0.0024
BTC	0.9939	0.9935	0.0061	0.9399	0.9358	0.0603
ETH	0.9895	0.9888	0.0109	0.9811	0.9798	0.0181

values above 0.99, suggesting an excellent in-sample fit. Moreover, the volatility estimates display similarly strong performance, with even higher goodness-of-fit measures for most assets, highlighting the model's effectiveness in capturing volatility dynamics. This comparative evidence across assets confirms that Model 2 provides reliable and robust estimates for both returns and volatility.

In the second stage, four Global Minimum Variance (GMV) portfolios were constructed using different covariance estimation methods. Before constructing the GMV portfolios, an Equal Weight portfolio (EW) portfolio is used as a benchmark. The EW portfolio assigns identical weights to all assets and does not rely on an estimation of the expected returns or covariance between the assets. In this way, the portfolio acts as a baseline to validate that performance gains occurs by model improvements rather than a naive diversification.

The first portfolio estimated covariance using the traditional approach based on past returns and volatilities from daily closing prices. The second portfolio utilized predicted closing prices from Model 1 for covariance estimation. The third portfolio employed predicted volatilities, while the fourth portfolio combined both predicted closing prices and predicted volatilities for covariance estimation.

The Table 2 presents the performance metrics of different portfolios based on real data and covariance estimates from models 1 and 2 and the the combined model. The benchmark equal-weight EW portfolio, using real data achieved an annualized return of 10.60% with an annualized volatility of 14.56%.

It exhibited a negative skewness of -0.6001 and a kurtosis of 17.4337, indicating a distribution with a fat tail. The Cornish-Fisher VaR (5%) for this portfolio is 0.0134, and it achieved a Sharpe ratio of 0.5277 with a maximum drawdown of -0.3324.

The portfolio with covariance estimated by Model 1 had a slightly higher annualized return of 10.69% and a higher annualized volatility of 15.46% than the standard model. Its skewness was negative at -0.7034, and the kurtosis was 15.4169. This portfolio's Cornish-Fisher VaR (5%) was 0.0149, indicating , and it had a Sharpe ratio of 0.5028 with a maximum drawdown of -0.2926.

The portfolio with covariance estimated by Model 2 performed better, with an annualized return of 10.65% and a similar annualized volatility to the real data portfolio at 14.48%. Its skewness was negative at -0.5492, and it had a kurtosis of 17.1867. The Cornish-Fisher VaR

Table 2 Portfolio performance of four GMV portfolios.

Indicator	Covariance estimated Model 1	Model 2	Combined	Standard
Annualized Return	0.1069	0.1065	0.1241	0.1060
Annualized Volatility	0.1546	0.1448	0.1485	0.1456
Skewness	-0.7034	-0.5492	-0.1668	-0.6001
Kurtosis	15.4169	17.1867	13.8215	17.4337
Cornish-Fisher VaR (5%)	0.0149	0.0133	0.0132	0.0134
Sharpe Ratio	0.5028	0.5335	0.6363	0.5277
Maximum Drawdown	-0.2926	-0.3282	-0.3017	-0.3324

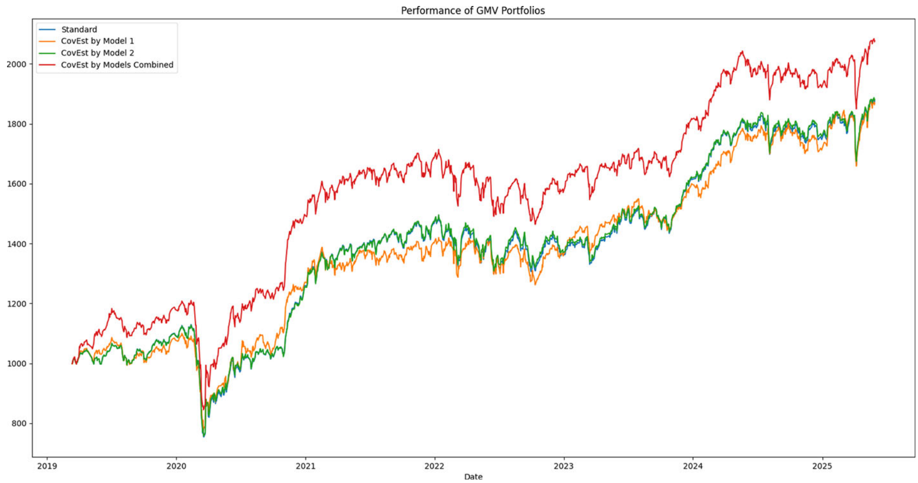

Fig. 1 Out-of-Sample Testing Performance of Four GMV Portfolio Strategies (2019–2025).

(5%) was 0.0133, and it achieved a Sharpe ratio of 0.5335 with a maximum drawdown of -0.3282.

The combined model estimates resulted in the highest annualized return of 12.41% and an annualized volatility of 14.85% as Fig. 1 shows. This portfolio had the least negative skewness at -0.1668 and a kurtosis of 13.8215. The Cornish-Fisher VaR (5%) was 0.0132, and it achieved the highest Sharpe ratio of 0.6363, with maximum drawdown of -0.3017.

In summary, combining models for covariance estimation provided the best performance in terms of annualized return and Sharpe ratio, despite slightly higher volatility, suggesting a more optimized risk-return profile compared to using individual models or real data alone. Also, showing a risk-adjusted returns metric through the Sharpe ratio provides a more meaningful comparison across portfolio strategies, showing that spillover-based covariance estimation improves the portfolio efficiency.

5 Conclusion

In this paper, we examine an effective method of measuring the interconnection of dynamic asset allocation and volatility management with a spillover matrix. In doing so, we employ a three-stage approach - the Diebold (b) method to construct the CSM, Lastrapes and Wiesen (2021) algorithm to process the channel normalization and a AI approach using a ConvLSTM network to address a research gap related to volatility spillover among various asset classes to diversify assets of a portfolio over time.

We use historical price data to examine the impact of two significant cryptocurrencies and six major stock indexes. With an estimated higher R-squared and adjusted R-squared, as well as the covariance in our baseline analysis, we find that the model that predicts the volatility of an asset can predict a slight increase in annualized return and a decrease in annualized volatility, which eventually increases the Sharpe ratio and diminish the maximum drawdown.

Our study contributes to the investment and volatility literature by providing evidence that the covariance estimation using the trained models using spillover effects connectedness matrix to construct GMV portfolios shows an example of how investors can use predicted values. Extending the works of numerous scholars studying the influence of inter interconnectedness and spillovers (Ben Ameur and Ftiti, Ben Ameur and Ftiti; de Carvalho and Gupta, 2018; Giudici and Sarlin, Giudici and Sarlin; Huang, Huang; Jareño, Jareño) integrating a combination of econometrics and AI models (Sahiner, 2023).

While connectedness measures and DL models are individually well established in the literature, the principal contribution of this study lies in their endogenous integration within a unified, AI -driven forecasting and allocation framework. In contrast to existing Operations Research approaches, such as network and correlation-based portfolio allocation methods that rely on static or exogenously estimated dependence structures (Clemente et al., 2022), our methodology uses the dynamic Diebold–Yilmaz spillover matrix directly into a ConvLSTM architecture, allowing systemic interconnectedness to consider volatility forecasting. This integration captures nonlinear, time-varying shock transmission across asset classes that isolated approaches cannot display.

Prior studies in the literature of operation research, for instance, Clemente et al. (2022) introduces a network-based approach to portfolio allocation by incorporating correlation-network dependence structures and alternative covariance estimators and compares it with standard methods across several high-dimensional portfolios. On the other hand, Ricca and Scozzari (2024) present new mixed-integer linear formulations–based on an assortativity criterion and neighbourhood constraints–for the portfolio selection problem, aiming to maximize expected returns while simultaneously controlling the portfolio's worst-case loss. Furthermore, di Tollo et al. (2025) highlight the increasing need to detect and quantify contagion effects in asset allocation across markets, drawing on immunization concepts from network theory, which emphasise identifying highly connected nodes to monitor and mitigate the spread of shocks or risk. To the best of our knowledge, no prior research has integrated dynamic spillover networks with advanced deep learning architectures, such as ConvLSTM, to jointly model, forecast, and interpret systemic interconnectedness.

By considering robustness, there are several design choices in the proposed framework that are guided by the objective of preserving the network structure implied by the connectedness matrices. In particular, the ConvLSTM architecture is employed because its convolutional component allows the model to exploit the spatial topology of spillover networks, which a LSTM cannot handle. Regarding the connectedness estimation, the rolling window length is based on stationarity tests, and the sample period allows the model to be evaluated in a out of the sample period. While alternative specifications, such as different assets, lag structures, DL models, different window sizes, or using log returns instead of volatility may provide additional insights, a systematic comparison of all such variants is left for future research. Additionally, it is important to noticed that from a regulatory perspective, the framework may offer insights into evolving cross-asset interconnectedness that could be informative for discussions on market stability and risk transmission, without being designed as a regulatory monitoring tool.

We therefore, offer the following two conclusions. First, there is potential for the further development of efficient asset allocation in portfolios, especially when considering volatility and connectedness within global financial markets. Advanced models incorporating these factors and enhanced by AI can significantly improve risk management.

Second, our framework provides signals of increasing interconnectedness and heightened risk conditions that may precede periods of market stress, rather than a formal or validated early-warning system for market crashes. Since traditional mean-variance spanning tests ignore higher order moments, by using Diebold (b) model and DL such as ConvLSTM, one can extend our analyses to mean–variance-skewness spanning tests on the diversification benefits for multiple asset classes.

A Appendix metrics

The MSE is calculated as:

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

The R^2 is calculated as:

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2}$$

where n is the number of data points, y_i the actual values, $\hat{y}_i$ the predicted values, and $\bar{y}$ the mean of actual values.

The Adjusted R^2 is given by:

$$\text{Adjusted } R^2 = 1 - \left[\frac{(1 - R^2)(n - 1)}{n - k - 1}\right]$$

where k is the number of independent variables. R^2 and Adjusted R^2 are computed for each of the 8 assets. Given the input image with 8 columns and 2 channels, k is set to 16.

B Appendix neural networks

The details of the architecture of the ANN are the following Table. 3

Table 3 Model parameters.

Parameter	Value
Epochs	50
Loss Function	MSE
Optimizer	Adam
Batch size	32
Validation split	0.2

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Conflict of Interest The authors declare that they have no conflict of interest.

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