Dynamic Asset Allocation and Volatility Management:
A Study of Diversification using Connectedness Spillover Matrices

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Abstract:

We examine whether the dynamic asset allocation and volatility management can be measured by interconnected spillover matrix. By first analyzing the levels of connectedness between decentralized finance (DeFi) assets, cryptocurrencies, and traditional stocks over the period 2017 and 2023 and then applying machine learning algorithms such as ConvLSTM, we find that by adding ConvLSTM, the interconnectedness between cryptocurrency and other assets, helps in better and effective diversification on the part of the investor, as it exhibits low correlation with traditional assets, decentralization, and inflation hedge, non-correlated risks, such as access to new markets. Our empirical findings are robust and have two implications. First, investors can make informed decisions on dynamic asset allocation in portfolios with multiple asset classes associated with higher volatility. Second, our method can help in detecting market crashes, which are early warning signals for risk management by investors.

Keywords: Dynamic assets allocation, Volatility Management, Machine Learning, Cryptocurrency, Portfolio optimization

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The data that support the findings of this study are collected from the secondary data sources

Introduction

In recent years, the global financial landscape has been significantly transformed by the confluence of globalization and rapid advancements in information technology (Comin and Nanda, 2019). This unprecedented interconnectedness has given rise to the challenge of the proliferation of shock contagion across financial markets (Acemoglu et al., 2016). This phenomenon involves the propagation of shocks and the amplification of their impacts, transcending geographical boundaries and creating a web of interdependencies (Chen & Zhang, 2023). The historical backdrop of this phenomenon traces back to the watershed event of the 1987 stock market crash, which kindled intense debates among scholars and policymakers (Forbes & Rigobon, 2002). This discourse revolved around the dramatic and interconnected disruptions experienced by international financial markets, each embedded within unique regional contexts (Claessens & Forbes, 2001; Aloui et al, 2011) . However, the aftermath of the 1997–1998 Asian financial crisis led to a scholarly exploration into volatility transmission, and it gained notable momentum (Kyle & Obizhaeva, 2023). Thus, during this period, there is a noticeable trend among researchers actively engaged in elucidating the concept of financial contagion and the spillover of volatility between various stock markets. (Gammill & Marsh, 1988; Gkillas et al., 2019). In the subsequent decades, we witnessed an exponential surge in financial crises, coupled with seismic shifts in volatility patterns (Baele & Inghelbrecht, 2010). These patterns extended researchers' reach beyond the confines of the originating country, encompassing regional and inter-regional markets (Diebold & Yılmaz, 2012). The trajectory observed has sparked renewed academic interest as researchers sought to decipher the intricacies of volatility transmission mechanisms and their overarching implications. In doing so, they embarked on a journey to fathom the intricate interplay between the dynamism of global financial networks and the oscillations of market volatility (Ghazani et al., 2023).

Financial market spillover effects, such as how they alter during significant occurrences of stock market crashes, can offer important insights into the mechanics of asset class interconnection (Hung & Vo, 2021). For example, the ripple effects of two major financial crises, the COVID-19 pandemic and the global financial crisis of 2008. The global financial crisis of 2008 demonstrates the strong interdependence and spillover effects among financial systems, as problems in one area or industry quickly expanded to another. The market becomes anxious because investors are looking for safe havens and complicated derivative markets such as credit default swaps (Kang & Yoon, 2019). The crisis needs to be contained by government bailouts and central bank interventions, which highlights the significance of interconnection for dynamic asset allocation and volatility control in our research. The 2020 COVID-19 crisis brought in abrupt market shocks that have different effects on different industries (Contessi & De Pace, 2021). Digital assets gained popularity due to central bank initiatives and industry differences that affected asset values. Tensions in geopolitics had repercussions. Thus, it is important to assess the significance of interconnectivity analysis for dynamic asset allocation and volatility control, which is the aim of our study.

In recent years, the application of Machine Learning (ML) techniques has gained prominence as a means to address the intricate nonlinear dynamics and complex nature inherent in financial markets. Demonstrating the enhanced efficacy of these approaches, D'amato et al. (2022)

established the superiority of deep learning methods over conventional techniques, effectively capturing intricate data interactions. This trend is further corroborated by Song et al. (2023 and 2024). In their investigation they compared deep learning, hybrid ML, and traditional econometric forecasting models across various frequencies, revealed the superior predictive accuracy of deep learning. This encompassed correlation analysis and the ranking of feature importance. Existing Research explores the applications of deep learning techniques in financial forecasting and risk management (Ozbayoglu et al., 2020., Kim et al., 2020.). "Machine Learning in Financial Crisis Prediction: A Survey" (Lin et al., 2011.) - reviews the various ML approaches employed in predicting financial crises. Henrique et al., (2019) and Nikou et al., (2019) discuss the application of ML algorithms in predicting financial market movements. Others examined the interrelatedness among Decentralized Finance (DeFi), cryptocurrencies, stock markets, and safe-haven assets, shedding light on their interconnected dynamics (Ugolini et al., 2023). In this research, we extend the above works and address the gap related to volatility spillover among various asset classes to diversify the assets of a portfolio over time. The research paper delves into analyzing the levels of connectedness between DeFi assets, cryptocurrencies, and traditional stocks. The interconnectedness between cryptocurrency and other assets helps in better effective diversification on the part of the investor, as it exhibits a low correlation with traditional assets, decentralization, inflation hedge, and non-correlated risk. Furthermore, cryptocurrencies offer certain privileges, such as access to new and emerging markets, making them an increasingly attractive component in diversified investment portfolios. Thus, the research question we examine in this research is as follows: How dynamic asset allocation and volatility management can be measured by interconnected spillover matrix?

Following the literature on investment and volatility, in this research we use historical price data from Yahoo Finance and examine 8 assets which includes 4 cryptocurrencies BTC, ETH, BNB and LINK) and 4 stock indices GSPC, FTSE, N225 and NSE (Li & Giles, 2015, Mensi et al., 2016) from 9th November 2017 to 15th July 2023. The key techniques used in our work are: a predictive Convolutional LSTM model, the Joint Spillover Index, and the Diebold and Yilmaz Spillover Connectedness Matrix (Vidal & Kristjanpoller, 2020, Kim & Won, 2018, Lastrapes & Wiesen, 2021). These methods assist us in assessing returns and volatility while looking at the relationships and spillover effects between different asset classes. The goal of this research is to improve volatility control and dynamic asset allocation techniques so that investors may make better choices. We are proposing to investigate how spillover and connectedness play vital roles in shaping the dynamics and volatility of these different financial assets, providing valuable insights for both academics and practitioners in the field of finance.

The volatility and projected return are crucial factors for investors. They provide important information about the dangers and possible gains connected to different investment opportunities. Investors can make well-informed judgments regarding expected gains by precisely calculating returns, and they can determine the degree of risk or uncertainty associated with their investments by evaluating volatility. With this knowledge, investors can better optimize their investing strategies by customizing their portfolios and striking a balance between their desired returns and risk tolerance. In the end, we want to give investors the information and resources they need to make more calculated and risk-aware investing decisions in a changing financial environment.

In the following sections of the paper we include the methodology and results of the research question and conclude our study by explaining the key findings and direction for future research.

2. Data Preparation

We download the historical price data from Yahoo Finance, using its API library yfinance. In our analysis we examine eight assets which includes four cryptocurrencies BTC, ETH, BNB and LINK) and four stock indices GSPC, FTSE, N225 and NSE (Sahiner, 2023, Duan et al., 2023, Bouri et al., 2020). Daily Open, High, Low, and Close (OHLC) price data are collected from 9th November 2017 to 15th July 2023. Since the stock markets have holidays, and the cryptocurrency markets doesn't, the days of holidays are dropped from the data.

Following Diebold & Yilmaz (2012), the daily variance is estimated using daily high and low prices for market i on day t σ_{it}^2 is:

$$\sigma_{it}^2 = 0.361\left[\ln(P_{it}^{max}) - \ln(P_{it}^{min})\right]^2 \tag{1}$$

where P_{it}^{max} is the maximum (high) price in market i on day t, and P_{it}^{min} is the daily minimum (low) price.

The corresponding estimate of annualized daily volatility is σ_{it}^{ann} is:

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

Here, 252 is the average trading days per year. The natural log and difference of σ_{it}^{ann} is taken, to make the data closely stationary.

A rolling window method is used to form a sequence of images for the whole time frame (Kong & Luo, 2022, Lee & Kim, 2020, Antonakakis et al., 2017) .The stationarity check is carried out for window sizes 90, 120, 150 and 180. The stationarity is true for window sizes 150 and 180, hence 150 is the window size of the study. A 2-channel image is constructed for each window on a rolling window basis. A total of 1099 sequences of images 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. Finally, the data is split into training and testing sets, with the test set accounting for 20% of the total data.

3. Methodology

3.1 Diebold and Yilmaz Spillover Connectedness Matrix

First, we use the Diebold & Yilmaz (2014) methodology to construct the connectedness spillover matrix. To study the volatility spillover connectedness between cryptocurrencies (BTC, ETH, LTC, XRP, ADA, BNB, LINK, BAT) and stocks (S&P500, Nasdaq, Dow Jones, FTSE).

The construction of the connectedness matrix is initiated by estimating a Vector Autoregression (VAR) model. with p lags for a set of N variables of σ_i for $i = 1,2, \dots, N$. The VAR model employed in this study is a linear regression model that predicts the future values of a set of variables based on their past values. It is important to note that the time series data, in this case volatility, must be rendered stationary prior to estimating the VAR model. The p lags in the VAR model refer to the number of previous time periods that are used to predict the current value of a variable. The N variables in the VAR model refer to the number of different variables that are being predicted. The equation for the VAR model is:

$$\sigma_t = \sum_{l=1}^{p} \beta_{t-l}\sigma_{t-l} + \epsilon_t \tag{3}$$

where σ_t is the vector of values for the N variables at time t, β_{t-l} is a $N \times N$ matrix of coefficients that relates the values of the variables at time $t-l$ to the values of the variables at time t, ϵ_t is the vector of error terms at time t with a distribution $N(0, \sigma^2)$.

In the second stage of constructing the connectedness matrix, we transform the VAR model into a moving average representation. The equation for the moving average representation of the VAR model is as follows:

$$\sigma_t = \sum_{i=0}^{\infty} A_i \epsilon_{t-i} \tag{4}$$

Where, A_i is a $N \times N$ matrix of coefficients that obeys the recursion $A_i = \sum_{l=1}^{p} \phi_i A_{i-l}$, with A_0 being a $N \times N$ identity matrix and $A_i = 0$ for $i < 0$.

Finally, we calculate the generalized Forecast Error Variance Decomposition matrix (FEVD) that shows how much of the forecast error variance for each variable is due to its own past shocks, the past shocks of other variables, and the contemporaneous shocks of other variables. (Climent & Meneu, 2003., Antonakakis et al., 2017.)

We calculate the FEVD using the following equation:

$$\theta_{ij}^{g}(H) = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H-1} \left(e_i' A_h \Sigma e_j\right)^2}{\sum_{h=0}^{H-1} \left(e_i' A_h \Sigma A_h' e_i\right)} \tag{5}$$

where, Σ is the variance-covariance matrix for the error vector ϵ, σ_{jj} is the standard deviation of the error term for the j^{th} equation, e_i is the selection vector, with 1 as the i^{th} element and zeros otherwise, and H is the number of steps ahead in the forecast.

3.2 Two Channel Image Construction using Joint Total Spillovers

In the second stage, the matrix obtained using the Diebold and Yilmaz Spillover connectedness matrix is duplicated and stacked to form a 2-channel image. The first channel is the "from" channel and the second is the "to" channel. The joint total spillover method, proposed by Lastrapes & Wiesen (2021) is used to process the channel normalisation, performing a the calculation of the joint total spillover from all others to variable i and the joint total spillovers to all others from variable j respectively.

Each ith row of the first channel matrix is divided by the joint total spillover from all others to variable i to form a normalised "from" channel. Similarly, each jth column is divided divided by the joint total spillovers to all others from variable j to form a normalised "to" channel. Since the diagonal elements of each channel matrix represent the self spillover effects, the diagonal elements of each channel matrix are replaced by zero inorder to eliminate the self-spillover effects in our analysis.

3.3 Convolutional Long Short-Term Memory (ConvLSTM)

LSTM (Long Short Term Memory) is a recurrent neural network architecture commonly used for time series forecasting and analysis. The model passes the previous hidden state information to the next step of the sequence, to use it to make decisions. Hence these types of models are used for inputs with temporal dimensions.

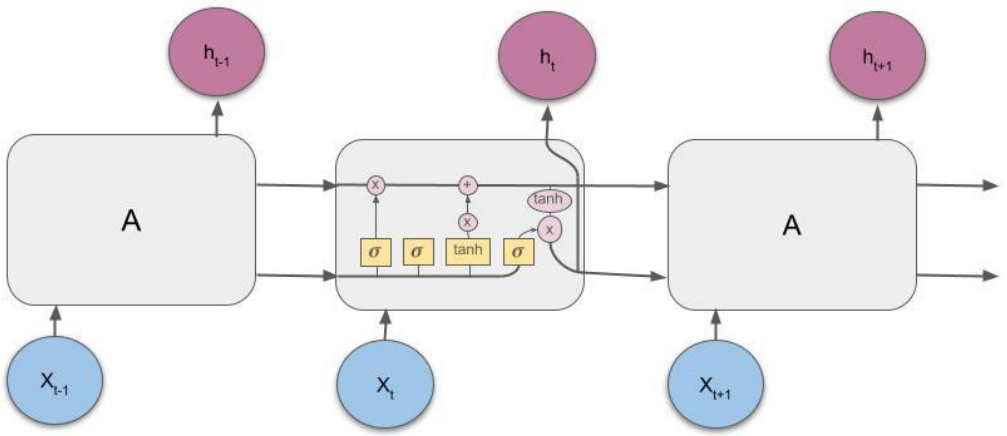

***Figure 1**: A LSTM Cell.*

When working with images the spatial positions also matter. Convolutional Neural Networks (CNN) architectures use convolutional layers that takes spatial positions into consideration while extracting important features from the images using several filters.

ConvLSTM layers, is a type of recurrent layer just like LSTM, but internal matrix multiplications are exchanged with convolutional operations (Zhou et al., 2017, Kelotra & Pandey., 2020). 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, cols).

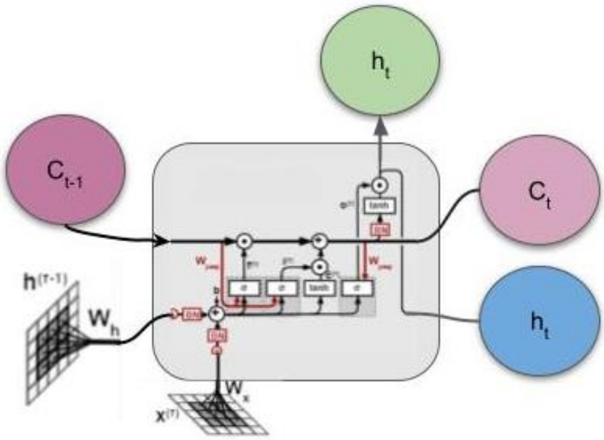

***Figure 2**: A ConvLSTM Cell,*

Finally, we propose a deep neural network architecture that has a ConvLSTM Encoder part followed by two LSTM layers and two dense layers. Finally, the model parameters are display in Table 1.

Sl. No.	Parameter	Value
1	Epochs	50
2	Loss Function	MSE
3	Optimizer	Adam
4	Batch size	32
5	Validation split	0.2

***Table 1**: Model Parameters*

3.4 Evaluation Metrics

The models are evaluated using the R-squared and Adjusted R-squared metrics. R-squared and Adjusted R-Squared metrics are commonly used to evaluate regression models. These metrics say how well the regression model explains observed data. The value of R-squared is between 0 and 1. The more the value is closer to 1, the better the model explains the observed data. R-squared tends to optimistically estimate the fit of the linear regression. It always increases as the number of effects are included in the model. Adjusted R-squared attempts to correct for this overestimation. Adjusted R-squared might decrease if a specific effect does not improve the model. Adjusted R-squared is always less than or equal to R-squared. (Leach & Henson, 2007, Ash & Shwartz, 1999)

The R-squared is calculated by:

$$R^2 = 1 - \frac{\sum_i^n (y_i - \hat{y})^2}{\sum_i^n \left(y_i - \underline{y}\right)^2} \tag{6}$$

Here, n represents the number of data points in our dataset. y represents the actual values, $\hat{y}$ is the predicted value and $\underline{y}$ is the mean of actual values.

The Adjusted R-squared is calculated by:

$$Adjusted\ R^2 = \left\{1 - \left[\frac{(1-R^2)(n-1)}{(n-k-1)}\right]\right\} \tag{7}$$

Here, n represents the number of data points in our dataset. k represents the number of independent variables, and R^2 represents the R-squared values determined by the model.

The values of R-squared and Adjusted R-squared are calculated separately for each asset among the 8 assets. Since the image inputted has 8 columns and 2 channels, the value of k is taken as 16.

4. Results

The R^2 Score and the Adjusted R^2 Score values of the Model 1 of all assets separately are shown in Table 2. The values suggests that the model estimates the close price with a good accuracy. This estimated price gives an investor the view of the direction of the price of an asset. Figure 3 shows plot of predicted price and original price of Model 1.

Similarly, R^2 Score and the Adjusted R^2 Score values of the Model 2 of all assets separately are shown in Table 3. The values suggests that the model estimates the 150-day volatility with a good accuracy. This estimated volatility gives an investor the view of risk of an asset. Figure 4 shows plot of predicted volatility and original volatility of Model 2.

	BTC-USD	**ETH-USD**	**BNB-USD**	**LINK-USD**	**GSPC**	**FTSE**	**N225**	**NSEI**
Train MSE	0.009579	0.005621	0.008097	0.005430	0.004056	0.003357	0.003566	0.002550
Test MSE	0.009227	0.007957	0.005818	0.004908	0.003246	0.002406	0.003159	0.002169
R2 Score	0.990185	0.992060	0.993853	0.994891	0.996896	0.997693	0.997107	0.997899
Adjusted R2	0.989408	0.991431	0.993366	0.994486	0.996650	0.997510	0.996878	0.997733

***Table 2**: R2 Score and the Adjusted R2 Score values of the model 1*

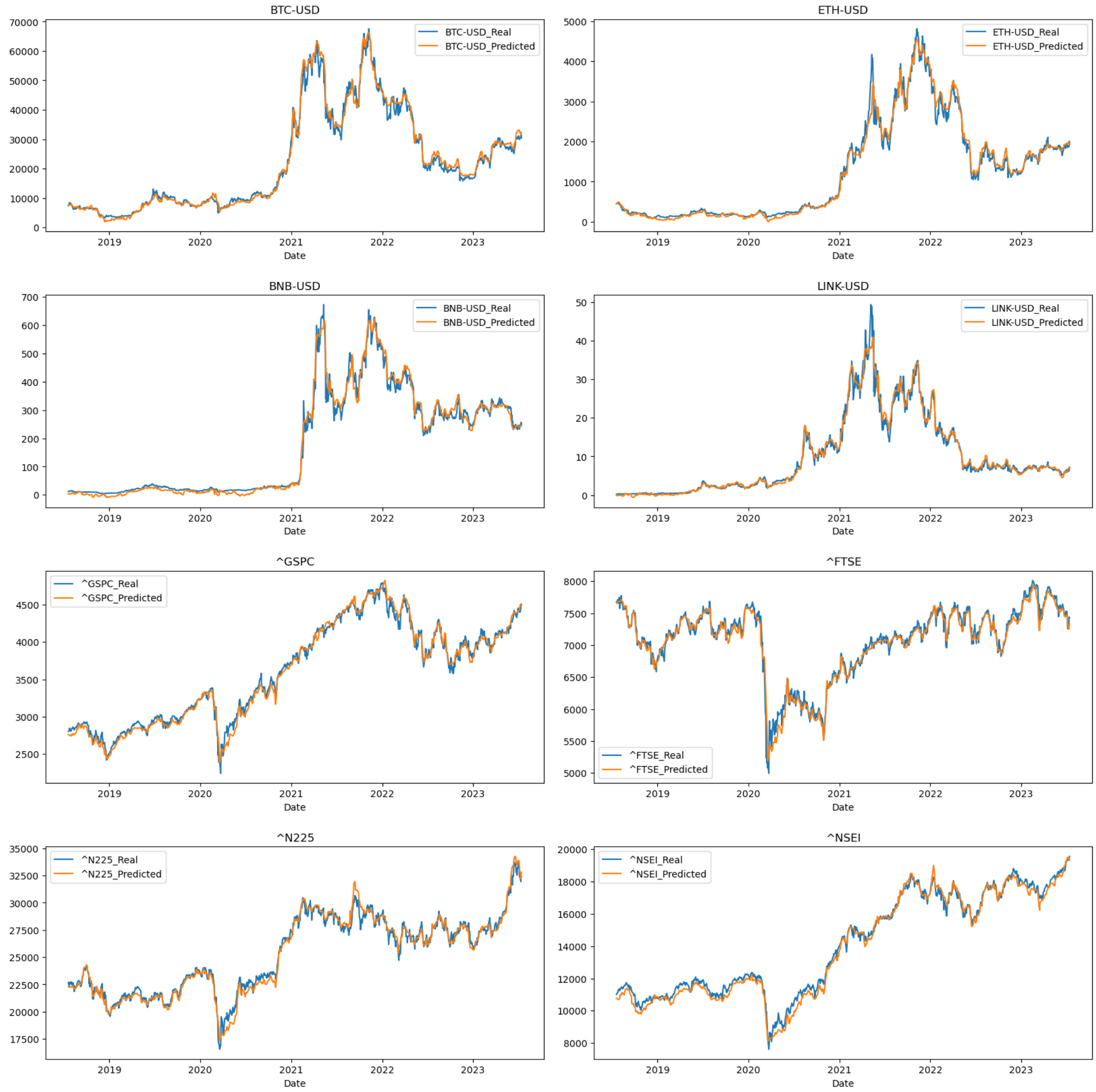

Figure 3: *Plot of predicted close price using model 1 and original close price.*

	BTC-USD	ETH-USD	BNB-USD	LINK-USD	GSPC	FTSE	N225	NSEI
Train MSE	0.009579	0.005621	0.008097	0.005430	0.004056	0.003357	0.003566	0.002550
Test MSE	0.009227	0.007957	0.005818	0.004908	0.003246	0.002406	0.003159	0.002169
R2 Score	0.990185	0.992060	0.993853	0.994891	0.996896	0.997693	0.997107	0.997899
Adjusted R2	0.989408	0.991431	0.993366	0.994486	0.996650	0.997510	0.996878	0.997733

Table 3*: R^2 Score and the Adjusted R^2 Score values of the model 2.*

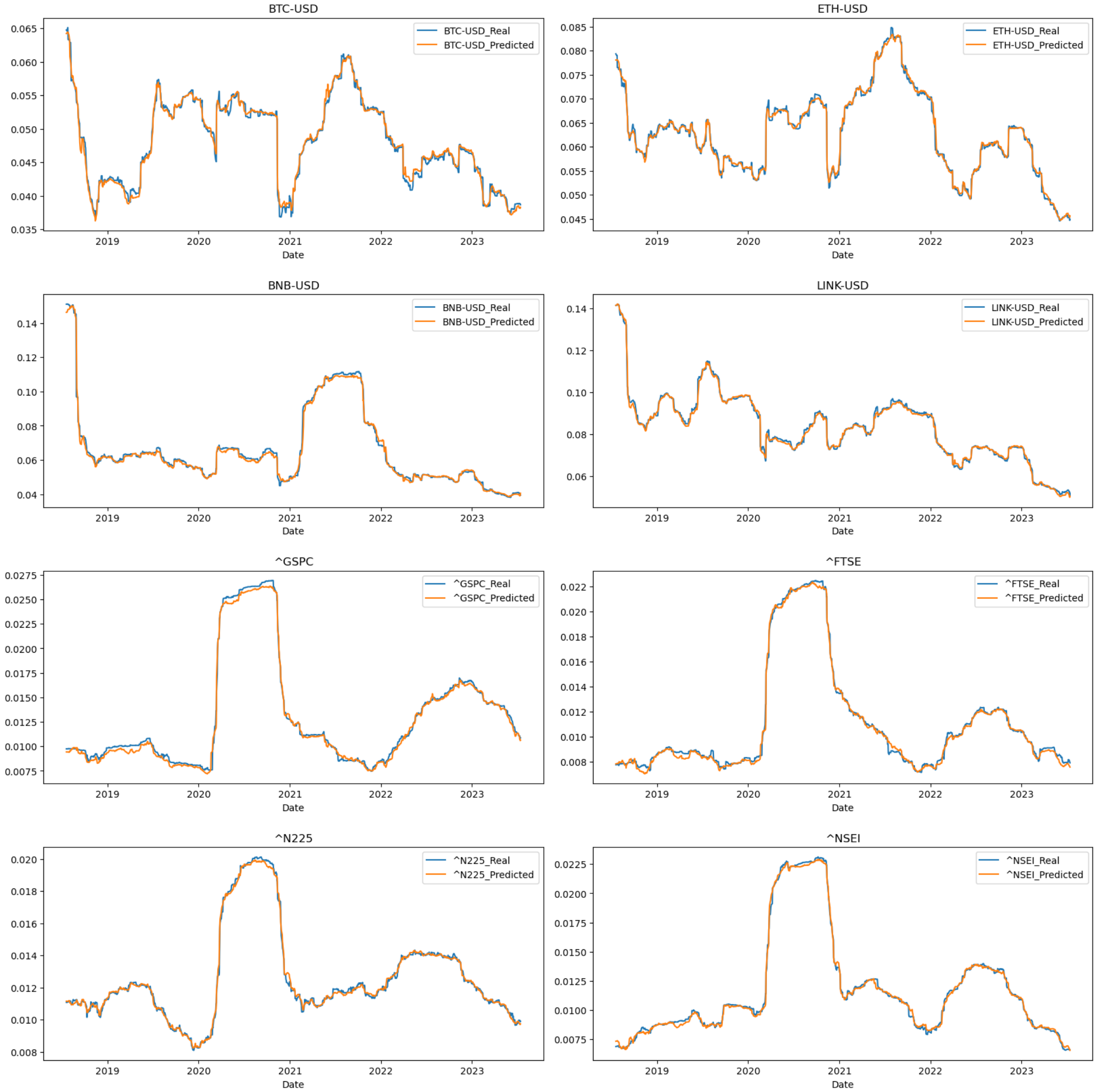

Figure 4*: Plot of predicted volatility using model 2 and original volatility*

Finally, four Global Minimum Variance (GMV) portfolios were created with different methods of covariance estimation. In the first portfolio, the covariance was estimated in the standard way using the returns of previous days close prices and volatilities, second used the predicted close prices from Model 1 to estimate the covariance. The third portfolio used the predicted volatilities and the fourth used both the predicted close prices and the predicted volatilities to estimate the covariance. The portfolio performance of the four GMV portfolios are shown in Table 4 and Figure 5.

	Standard	Covariance Estimated using Model 1 only	Covariance Estimated using Model 2 only	Covariance Estimates using both Models
Annualized Return	0.108636	0.109073	0.113126	0.135602
Annualized Volatility	0.162511	0.171677	0.161288	0.171851
Skewness	-0.355560	-0.603911	-0.509630	-1.069687
Kurtosis	17.468625	18.059324	18.292196	24.129967
Cornish-Fisher VaR (5%)	0.014325	0.015741	0.014446	0.015596
Sharpe Ratio	0.496783	0.472746	0.527692	0.622769
Maximum Drawdown	-0.341846	-0.310821	-0.330804	-0.312471

***Table 4**: Portfolio performance of 4 GMV portfolios*

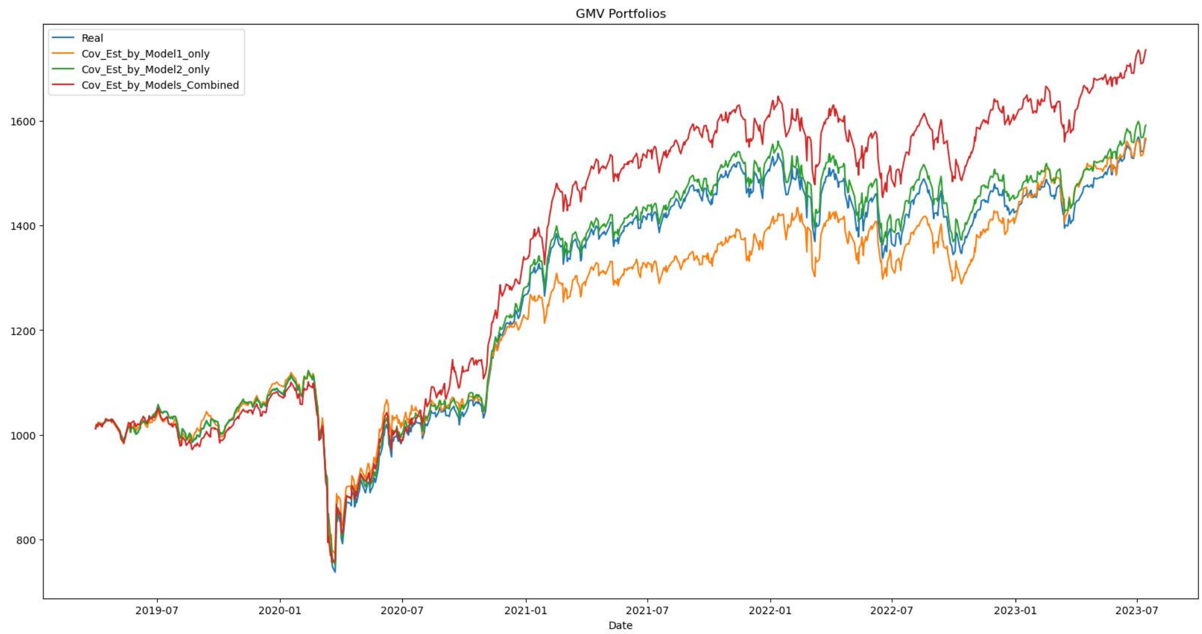

***Figure 5**: Portfolio values of 4 GMV portfolios over time.*

It is observed that covariance estimated with Model 1 i.e., the model that predicts the close price of the assets gives a slightly better returns and a significant reduction in the maximum drawdown by 3%. The covariance estimated with Model 2 i.e., the model that predicts the volatility of the assets gives slight increase in annualized return, and a decrease in annualized volatility, eventual increasing the Sharpe ratio by 0.31. The model also shows a better maximum drawdown. The covariance estimated by models combined gives the maximum increase in annualized return of 2.67%, slight increase in annualized volatility and significant increase in Sharpe ratio by 0.126 and reduction in maximum drawdown by 2.9%.

These results suggest that spillover effects and connectedness between different assets and markets can help in asset allocation and risk management by investors, similarly to the work of Kong & Luo, (2022). The predicted close price and volatility in this research can be used by investors to get an idea of market trend as well as the risk, which is useful to create portfolios of their own choice. The covariance estimation using the models trained using spillover effects connectedness matrix to construct GMV portfolios shows an example of how predicted values can be used by investors. The reduction in maximum drawdown also suggests that this method can be a help in crash detection or warning systems.

5. Conclusion

In this paper, we examine an effective method of measuring interconnection of the dynamic asset allocation and volatility management with spillover matrix. In doing so, we employ a three-stage approach - the Diebold and Yilmaz (2014) method to construct the connectedness spillover matrix, Lastrapes and Wiesen (2021) algorithm to process the channel normalisation and a deep neural network architecture (ConvLSTM) to address a research gap related to volatility spillover among various asset classes to diversify assets of a portfolio over time. To the best of our knowledge, no prior volatility research has attempted to employ these methods together to investigate volatility spillover.

We summarize our empirical results as follows. For this study, we analyse the levels of connectedness between DeFi assets, cryptocurrencies, and traditional stocks. We use historical price data from Yahoo Finance and examine 8 assets which includes 4 cryptocurrencies BTC, ETH, BNB and LINK) and 4 stock indices GSPC, FTSE, N225 and NSE between 9th November 2017 to 15th July 2023.With an estimated higher R^2 and adjusted R^2 as well as the covariance in our baseline analysis, we find that the model that predicts the volatility of an asset can predict slight increase in annualized return, and a decrease in annualized volatility, that eventually increases the Sharpe ratio by 0.31. Our combined estimation from all the models show reduction in maximum drawdown by 2.9%.

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 predicted values can be used by investors. We therefore offer the following two conclusions. First, there is potential for the further development of efficient asset allocation in portfolios associated with volatility. Second, our method can help in detecting market crash detection which is an early warning signals for risk management by investors. Since traditional mean–variance spanning test ignore higher order moments, by using Diebold and Yilmaz (2014) model and ML such as ConvLSTM, one can extend our analyses to mean–variance-skewness spanning tests on the diversification benefits for multiple asset classes.

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