

Volatility Dynamics and Spillover Effects in Global Currencies: Evidence from Stochastic and BEKK GARCH Models

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Abstract

Currency prices are influenced not only by current information but also by past trends causing temporal dependencies. LSTM effectively captures the temporal dependencies, making the output compatible with forecasting stochastic volatility. It is a common nature of financial assets to exhibit shocks or irregular variations in the price movement. Combining the Attention mechanism with LSTM, we filter the irregular variations and retain only the refined data. To build the LSTM model pipeline, we standardise the input variables between 0 and 1 using a minimax scale. The processed data is transformed into a sequence of 60 days to build the LSTM model. The attention layer has been added to compute a weighted sum of the input sequence, allowing the model to pay greater attention to certain periods. The model is further optimised for reducing overfitting and underfitting by applying dropouts and batch normalisation. The performance of the LSTM model is tested using metrics such as MSE and RMSE. The estimates for the estimates of the LSTM Attention mechanism are taken as features for predicting stochastic volatility. Following (Diebold & Yilmaz, 2012), we predict the daily stochastic volatility of 11 pairs of foreign currencies. The stochastic volatility is estimated by assigning differential weights to OHLC. BEKK (Baba, Engle, Kraft, and Kroner) GARCH is applied to the forecasted stochastic volatility to estimate the spillover effect among foreign currencies. BEKK describes the dynamic relationships and volatilities spillover and persistence of shocks among multiple currencies. The BEKK (1,1,1) model is a popular specification due to its balance of flexibility and parsimony. The research provides a robust understanding on the patterns of currency volatility movements and spillover effects. The research study offers a profound methodology to the financial institutions, corporates and other stakeholders to forecast currency volatility and effectively manage foreign currency risk. The policymakers can scientifically estimate the transmission of shocks across various foreign currencies and develop measures to mitigate risk.

Keywords— *Stochastic Volatility, Volatility spillover, LSTM, Attention Mechanism, BEKK GARCH*

INTRODUCTION

Understanding foreign currencies' volatility patterns and spillover effect is paramount for businesses, traders, policymakers and financial institutions. Predicting the returns, volatility and spillover effects facilitates informed decision-making during hedging and trading in foreign currencies. Volatility in one currency pair can very well be

transmitted into other currency pairs and this may create a contagion effect, and therefore for getting a holistic understanding of currency risk, we need to analyze the volatility spillover observed in currency pairs. Incidences of volatility transmission were observed during the COVID-19 pandemic in the global foreign exchange market, as suggested in (Fasanya, Oyewole, et al., 2021). This study observed volatility spillovers in 6 most traded currency pairs in the world in the context of the pandemic.

Thus, an analysis of volatility and its transmission across multiple currency pairs is also important for predicting the future trends and transmissions of volatility and thereby supporting better and informed risk management frameworks. This could a long way in formulating appropriate portfolio diversification and hedging strategies before black swan events and thereby help prevent losses to a significant extent. Also, shocks or fluctuations in global currency markets do not remain restricted to one place and get transmitted to other markets as well. As suggested by (Fasanya, Adekoya, et al., 2021), there exists a high degree of connection between crude oil and currency, wherein oil is observed to be the net receivers of shocks. Thus, according to this study, fluctuations in the exchange rates affect oil prices as well. In addition, according to (Chen et al., 2018) fluctuations in exchange rates affect the integration and linkages between stock market indices like FTSE 100, S&P 500, and EURO STOXX 50 over time. Thus, through predicting the stochastic volatility and spillover involved in currency pairs we can obtain a better understanding of the risk of contagion across multiple markets.

Existing literature on volatility of currency pairs either presents an analysis of volatility spillover, as observed in (McMillan & Speight, 2010), (Andreou et al., 2013), (Inagaki, 2007) etc., or a prediction of volatility (Hemanth Kumar & Basavaraj Patil, 2018) or a prediction of exchange rates ((Nemavhola et al., 2021). What has possibly not been explored in the ambit of scholarly literature is a robust mechanism predicting stochastic volatility and volatility spillover across a significant number of currency pairs. Moreover, traditional econometrics models suffer from dealing with nonlinear patterns and improving the forecasting accuracy in the long run. In this paper, we try to bridge this gap by developing an innovative model integrating the BEKK (Baba, Engle, Kraft, and Kroner) GARCH with long short term memory (LSTM) enhanced by a self-attention mechanism. The integrated model provides forecasts of stochastic volatility and spillover of foreign currencies. The study is based on a sample of daily Open, High, Low and Closing (OHLC) prices of 11 pairs of foreign currencies between 2004 and 2024. The period from 2024 The methodology of this study involves 2 steps, i.e., Predicting stochastic volatility and estimating the spillover effect among the foreign currencies. In the first steps, using historical OHLC and applying LSTM with an attention mechanism, we predict the next four candles of every currency pair.

Currency prices are not often influenced only by current information but also by past trends causing temporal dependencies. LSTM effectively captures the temporal dependencies, making the output compatible with forecasting stochastic volatility. It is a common nature of financial assets to exhibit shocks or irregular variations in the price movement. Combining the Attention mechanism with LSTM, we filter the irregular variations and retain only the refined data. The integration of LSTM with the Attention Mechanism is apt for unravelling the non-linear patterns of currency prices, providing a deeper understanding of the price movements and improving forecasting accuracy.

The remaining 4 sections of the paper are as follows- Section II presents the literature review, Section III presents a detailed discussion of the methodology, Section IV highlights the results obtained and their interpretation, and finally, section V presents the conclusion.

LITERATURE REVIEW

Stochastic Volatility and Volatility spillover have been explored across myriad methodologies and themes in scholarly literature. Marking a significant deviation from the deterministic modelling of volatility, as suggested by (Engle, 1995) and (Bollerslev, 1995), the concept of stochastic volatility, given by (Taylor, 1982), proposed a different approach wherein the modelling of volatility was probabilistic and the log of squared volatilities (in the

latent state) followed an autoregressive process of order 1. In this context, (Chib et al., 2002) suggested the creation of a Markov Chain Monte Carlo (MCMC) algorithm for estimation in case of stochastic volatility models with heavy tailed student-t distributions, exogenous variables in the observation, volatility equations, and a jump component in the observation equation. (Kastner & Frühwirth-Schnatter, 2014) talked about the implementation of an Ancillarity Sufficiency Interweaving Strategy in order to improve the sampling efficiency of a stochastic volatility model that utilizes Markov Chain Monte Carlo (MCMC) estimation. (Kastner, 2016) introduces the stochvol functionality in R and to show that the predictive accuracy can be improved with this package through the utilization of the concept of stochastic volatility coupled with a Bayesian simulation-based approach.

Volatility spillover on the other hand, has been explored across many different markets as well as asset classes. (Kumar & Anandaram, 2019) presented an analysis of volatility spillover observed in the returns of some of the major crypto-currencies. (Yousaf et al., 2022) analyzes the volatility spillover between the crude oil-gold and oil-Bitcoin pairs during the COVID-19 pandemic. This paper analyzes the spillover effect in the pre COVID-19 as well the COVID-19 period, and it employs various multivariate GARCH models (one of which is BEKK GARCH) for the same. This paper highlighted the existence of volatility spillover across both the pairs taken into consideration both in pre COVID-19 and COVID-19 scenarios. (Baklaci & Yelkenci, 2022) examined the spillover effect across 11 currency pairs using the VAR-BEKK-GARCH with respect to different sampling frequencies, and depicted that the spillover effect was stronger in case of higher frequency data.

An analysis of dynamic spillover in the oil-natural gas markets is presented in (Gong et al., 2021) wherein time-varying volatility spillovers across for major energy commodities-crude oil, gasoline, heating oil, and natural gas. (Xie et al., 2021) presents an approach coupling BEKK-GARCH and adaptive Fourier decomposition (AFD), known as the BEKK-GARCH-AFD approach, using which the paper has analyzed the volatility spillover between the Chinese stock Market and the international crude oil market. This paper presents an analysis of volatility spillover from the perspective of the time-frequency domain. A comprehensive study of the transmission of volatility into the Indian commodity derivative market from the foreign exchange, stock, and gold markets is given by (Roy & Sinha Roy, 2017) wherein the time-varying nature of volatility is observed and stock and commodity markets are held as the net transmitters of volatility whereas bonds, foreign exchange, and gold markets are observed to be the net receivers of volatility. (Raavinuthala et al., 2024) presented an analysis of volatility spillover across the major stock markets of the world in the context of the Russia-Ukraine conflict and showed a significant volatility spillover across the global stock markets.

Implementation of LSTM (Hochreiter & Schmidhuber, 1997) with an attention mechanism (Huang et al., 2023) can be observed in (Mu et al., 2024) wherein a bi-directional LSTM model has been incorporated with spatiotemporal attention mechanisms in order to achieve more accurate predictions of the closing prices of Hong Kong Hang Seng Index (HSI). In (Ouyang et al., 2021) also we observe the integration of LSTM with an Attention mechanism in order to achieve a greater prediction accuracy for systemic risk indicators. An exercise of prediction of carbon price returns in the European Union Emission Trading System (EU ETS) is observed in (Duan et al., 2023) where an Attention based long short term memory (AttLSTM) neural network is implemented for the same.

(Wang et al., 2024) implemented LSTM cells along with Deep Neural Networks (DNN) in order to effectively tackle the challenges associated with hedging illiquid assets and thereby provide for improved risk management through incisive examination of the long-term dependencies and complicated patterns in time series data.

Our domain of study presents a novel approach to forecasting stochastic volatility and spillover effects of currency pairs through the integration of LSTM Attention mechanism and BEKK GARCH and thus, contributes to the existing scholarly literature in terms of a methodology that has not been explored previously in studies on currency pairs.

METHODOLOGY

A. Stochastic Volatility

Stochastic volatility models depict the time-varying nature of volatility in asset price returns. We apply (Kastner & Frühwirth-Schnatter, 2014) Bayesian estimation of stochastic volatility using Monte Carlo Simulation. The estimation follows a non-centred parametrisation (NC), given through $y_t \sim N(0, \omega_e^2 \hat{h}_t)$, $\hat{h}_t = \phi \hat{h}_{t-1} + n_t$, $n_t \sim N(0,1)$, where $\omega = e^\mu$. The initial values of $\hat{h}_t | \phi$ is drawn from the stationary distribution of the latent process for a first-order autoregressive process where $\hat{h}_t | \phi \sim N(0,1)/(1 - \phi^2)$, ϕ is the auto-regressive parameter. The non-centred parametrisation improves the efficiency and estimation process of the stochastic volatility model using MCMC methods.

Bayesian estimation of Stochastic Volatility Model

The model is represented as:

$$y_t = \exp(2h_t) \epsilon_t$$

$$h_{t+1} = \mu + \phi(h_t - \mu) + \sigma \eta_t$$

where

y_t is the observed return at time t

h_t is the latent log volatility.

$\epsilon_t \sim \mathcal{N}(0,1)$ and $\eta_t \sim \mathcal{N}(0,1)$ are independent standard normal innovation

Estimation procedure for stochastic volatility

Step 1: Setting the Initial parameters μ , ϕ and σ_n

To run the MCMC simulation, we set the initial parameters of μ , ϕ and σ_n

We assume μ , the long-run mean volatility. under the stationary distribution is a mean reverting process where $\mu = 0$. It is a common practice to set the mean equal to 0 when there is no prior and the asset returns follow a stationary process. To set autoregressive parameter, we assume the current volatility of perishable by the past volatility in the short run. To start the initial estimation of stochastic volatility, we set $\phi = 0.9$, which reflects the high persistence. The parameter ϕ is finetuned later after running MCMC simulation. The standard deviation of log volatility σ_n is set equal to 0.1 which reflects moderate volatility and ensure stability in the initiating MCMC process.

Step 2: Kalman Filter to estimate the hidden state h_t (log volatility)

We apply the Kalman Filter to estimate the hidden state h_t applying the state space model. It provides a recursive solution to estimate h_t for every observed return y_t . The log volatility estimates h_t are used for the Bayesian estimation of stochastic volatility under MCMC sampling. To begin the estimation process, we set the initial state $h_0 = \mu$. By using state space equation we predict h_t based on h_{t-1}

The equation of estimating h_t

$$h_t = \mu + \phi(h_{t-1} - \mu) + \eta_t, \quad \eta_t \sim N(0, \sigma_\eta^2)$$

This equation models the evolution of the log-volatility h_t as an Auto Regressive process of order 1 with innovations η_t

Assume initial log-volatility $h_0 = \mu$ where $u = 0$

$$h_1 = \mu + \phi(h_0 - \mu) + \eta_t, \quad \eta_t \sim N(0, \sigma_\eta^2)$$

$$h_1 = \eta_t, \quad \eta_t \sim N(0, \sigma_\eta^2)$$

Subsequently

$$h_2 = \mu + \phi(h_1 - \mu) + \eta_t, \quad \eta_t \sim N(0, \sigma_\eta^2)$$

The mean and variance is updated at every time step t. We repeat the estimation process for every time step t, to estimate the latent log volatility recursively,

Step 3: MCMC (Markov Chain Monte Carlo) sampling

MCMC method explores the parameter space through a sequence of iteration to estimate distribution properties. The samples are drawn from the posterior distribution based on the Metropolis-Hastings sampling methodology. The sample represents the possible values of h_t for every observed return. The Bayesian inference updates the initial belief about the unknown parameters based on the observed data. The efficiency is achieved by combining the prior information about the prior distribution with the likelihood of the observed data to form a posterior distribution.

Mathematically, the posterior distribution is given by Bayes' theorem:

$$p(\theta | y) \propto p(y | \theta)p(\theta)$$

Where

θ indicates the parameters

y represents the observed data

$p(\theta | y)$ is the posterior distribution

$p(y | \theta)$ is the likelihood of the data given the parameters.

$p(\theta)$ is the prior distribution.

We update the parameters of μ , ϕ , σ_η and h_t from its conditional posterior distribution given the current values of μ , ϕ , σ_η and h_t for each iteration. We run multiple MCMC chains to obtain the optimal parameter with maximum log-likelihood values. After obtaining the parameters, we use the remaining samples to make inferences about the parameters and log latent volatility.

B. BEKK GARCH

The BEKK (Baba, Engle, Kraft, and Kroner) GARCH is a multivariate model used to examine the relationships and volatility spillover among multiple time series. The model follows the first-order autoregressive process for the parameters C, A and G and is termed as BEKK(1,1,1)

BEKK model specification

The symmetric BEKK(1,1,1) model is defined as:

$$H_t = CC' + A'r_{t-1}r_{t-1}'A + G'H_{t-1}G$$

where:

H_t is the conditional covariance matrix of the returns at time t.

C is a lower triangular matrix that ensures H_t is positive definite.

r_{t-1} is the vector of returns at time t-1

A and G are coefficient matrices that capture the impact of past returns and past conditional covariances, respectively.

Description of the components C, A and G

Component C

The term C is a lower triangular matrix of $k \times k$ where k is the number of assets in the portfolio and C' is the transpose of C. The product CC' ensures positive definite values of the conditional variance H_t and ensures the stability of the covariance matrix.

Component A

A refers to ARCH term that captures the effects of past shocks on current volatility. It captures the immediate impact of past returns r_{t-1} on the current volatility. Here, r_{t-1} is a $k \times 1$ vector of past returns, and A is a $K \times k$ matrix. The product $A'r_{t-1}r_{t-1}'A$ represents the effect of past shocks on current volatility.

Component G

GARCH Term ($G'H_{t-1}G$):

G refers to the GARCH term that captures the persistence of long-term volatility. The matrix G shows the effect of past conditional variance H_{t-1} on the current variance. In the equation $G'H_{t-1}G$, H_{t-1} is the $k \times k$ conditional covariance matrix from the previous period, and G is a $k \times k$ matrix.

Estimation procedure

The parameters of BEKK(1,1,1) are estimated using the quasi-maximum likelihood estimation (QMLE) method. The method attempts to maximise the likelihood function for multivariate variables.

QMLE is estimated as follows:

$$L(\theta) = -\frac{1}{2} \sum_{t=1}^T (k \log(2\pi) + \log \det(H_t) + r_t' H_t^{-1} r_t)$$

where θ represents the vector of parameters (C, A, G), T is the number of observations, and k is the number of assets. The output parameter θ is optimised for maximum likelihood using Berndt–Hall–Hall–Hausman (BHHH) optimisation technique. Finally, we check the model's fitness using [Akaike Information Criterion \(AIC\)](#) and the [Bayesian Information Criterion \(BIC\)](#) to ensure the adequacy of the model.

The symmetric BEKK(1,1,1) model assumes there is no significant difference between positive and negative shocks. Therefore we check the model fitness of Asymmetric BEKK(1,1,1) and finally select the model with minimum AIC or BIC values.

The Asymmetric BEKK(1,1,1) model is defined as:

$$H_t = CC' + A'r_{t-1}r_{t-1}'A + G'H_{t-1}G + B'\eta_{t-1}\eta_{t-1}'B$$

η_{t-1} is a vector of asymmetric shocks, typically defined as $\eta_{t-1} = \max(0, -r_{t-1})$ which captures the negative return.

B is a parameter matrix that captures the effect of these asymmetric shocks.

The BEKK model captures the spillover effect among multiple assets. The matrices of A and G reveal how shocks and past volatilities in one market influence another. The off-diagonal values of the A and G matrices indicate the spillover effect of past shocks and past volatility, respectively.

C. LSTM

LSTM model has the capability to capture the long-term dependencies in sequential data. Integrating attention mechanism with LSTM allow the model to perform sequence to sequence tasks focusing on the specific sections of the data. Combining the Attention mechanism with LSTM, we filter the irregular variations and retain only the refined data. To build the LSTM model pipeline, we standardize the input variables between 0 and 1 using a minimax scale. The processed data is transformed into a sequence of 60 days to build the LSTM model. The attention layer has been added to compute a weighted sum of the input sequence, allowing the model to pay greater attention to certain periods.

The LSTM model process the sequence data i.e., the historical price series of foreign currencies and generates hidden states

$$h = \{h_1, h_2, \dots, h_{60}\}$$

The hidden state captures the information from day 1 to day 60 in the sequence. The attention mechanism integrated with LSTM estimates attention score a_t for every hidden state h . Finally, a conduct vector is created by taking the weighted sum of attention score and hidden state.

The equation of attention score is as follows

Finally, using attention mechanism, we create the context vector c_t based on the hidden states of input sequence.

$$c_t = \sum_{i=1}^{60} \alpha_{t,i} h_i$$

where

c_t is the context vector

$\alpha_{t,i}$ is the attention weight

h_i is the hidden state

The model is further optimised for reducing overfitting and underfitting by applying dropouts and batch normalisation. The performance of the LSTM model is tested using metrics such as MSE and RMSE. The estimates for the estimates of the LSTM Attention mechanism are taken as features for predicting stochastic volatility and volatility spillover.

RESULTS

TABLE 1: DESCRIPTIVE STATISTICS OF ALL THE CURRENCY PAIRS

	EUR_USD	JPY_USD	GBP_USD	AUD_USD	CHF_USD	CAD_USD	EUR_JPY	EUR_GBP	EUR_CAD	EUR_CHF	EUR_AUD
count	5215	5215	5215	5215	5215	5215	5215	5215	5215	5215	5215
mean	-0.000026	-0.000074	-0.000072	-0.000013	0.00006	-0.000006	0.00005	0.000046	-0.00002	-0.000085	-0.000013
std	0.005574	0.006089	0.005864	0.007768	0.006562	0.005559	0.006907	0.004909	0.005567	0.004887	0.006425
min	-0.024339	-0.054743	-0.083955	-0.072937	-0.090912	-0.032518	-0.061509	-0.031325	-0.034392	-0.207877	-0.069619
25%	-0.003183	-0.003301	-0.003221	-0.003928	-0.003242	-0.003008	-0.003182	-0.002619	-0.003282	-0.001589	-0.00339
50%	0.000064	-0.000114	0	0.000253	-0.0001	0	0.000252	-0.000069	-0.000027	-0.000058	-0.000288
75%	0.003046	0.002939	0.003202	0.004181	0.003182	0.003056	0.003617	0.002605	0.003078	0.001522	0.00315
max	0.034506	0.038541	0.031033	0.082766	0.194959	0.039808	0.070039	0.060117	0.035339	0.083915	0.065549

Table 1 shows the descriptive statistics of the selected foreign currencies. On the daily return, EUR_AUD has given the maximum daily return and EUR_CAD has given the lowest mean return (-0.000012). On volatility, EUR_AUD has the highest volatility (0.010861) and the lowest is shown by EUR_JPY (0.006526).

TABLE 2: LSTM PERFORMANCE METRICS

Currency pairs	Mean Absolute Error	Root Mean Square Error
AUD/USD	0.001605971	0.002015182
CAD/USD	0.013171761	0.015421094
CHF/USD	0.031123019	0.032965571
EUR/AUD	0.016984076	0.019332351
EUR/CAD	0.014129557	0.017891834
EUR/CHF	0.009887368	0.012663135
EUR/GBP	0.016207391	0.022910101
EUR/JPY	0.016220717	0.020002018
EUR/USD	0.008911037	0.011439014
GBP/USD	0.053252338	0.056260258
JPY/USD	0.049436043	0.062579035

Table 2 shows the forecasting accuracy of LSTM attention mechanism. The accuracy is tested using RSME. The RMSE values are significantly lower (>5%) for all currencies except GBP/USD and JPY/USD, where the error is more than 5 %. The highest predicting accuracy is observed for EUR/USD pair.

TABLE 3: LSTM: PREDICTED EXCHANGE RATES FOR THE NEXT 30 DAYS

AUD/USD	CAD/USD	CHF/USD	EUR/AUD	EUR/CAD	EUR/CHF	EUR/GBP	EUR/JPY	EUR/USD	GBP/USD	JPY/USD
1.27762	0.73643	1.31301	1.62685	1.49001	0.92421	0.84533	165.60507	1.10265	1.29521	0.00633
1.28071	0.73240	1.30687	1.61839	1.49052	0.91288	0.84598	168.32285	1.09838	1.28745	0.00620
1.28467	0.72810	1.29991	1.60732	1.49199	0.89356	0.84675	169.07521	1.09361	1.27812	0.00606
1.28811	0.72433	1.29352	1.59260	1.49420	0.85399	0.84748	168.34663	1.08934	1.26766	0.00595
1.29145	0.72087	1.28844	1.57279	1.49655	0.73481	0.84783	166.71603	1.08433	1.25848	0.00597
1.29359	0.71847	1.28321	1.56076	1.49990	0.02240	0.84801	163.80336	1.07917	1.25814	0.00614
1.29448	0.71817	1.27816	1.60116	1.50092	2.49065	0.84814	161.23232	1.07455	1.28281	0.00646
1.29487	0.72246	1.27481	1.60574	1.50084	3.25614	0.84761	158.26952	1.07101	1.33632	0.00669
1.29485	0.73053	1.27114	1.58792	1.50119	1.90101	0.84774	156.19023	1.06912	1.37865	0.00699
1.29505	0.73728	1.26727	1.57502	1.50071	0.58338	0.84728	156.28722	1.06833	1.38711	0.00716
1.29600	0.73988	1.26402	1.58047	1.49988	0.65743	0.84624	158.67091	1.06871	1.38710	0.00717
1.29652	0.73953	1.26195	1.59782	1.50021	0.54104	0.84502	163.66489	1.07423	1.39557	0.00720
1.29544	0.73742	1.26022	1.60236	1.50002	3.39107	0.84409	164.94278	1.08560	1.40455	0.00731
1.29544	0.73349	1.25723	1.58892	1.50032	13.89470	0.84336	162.87039	1.09802	1.40338	0.00759
1.29496	0.73001	1.25283	1.56447	1.49958	10.24095	0.84284	159.91945	1.10894	1.39373	0.00790
1.29388	0.72735	1.24700	1.56582	1.49813	7.53589	0.84213	156.45236	1.11634	1.37587	0.00838
1.29229	0.72627	1.24213	1.59392	1.49580	5.47511	0.84097	152.01747	1.11911	1.35111	0.00910
1.29179	0.72719	1.23988	1.59697	1.49393	10.44147	0.83967	146.97142	1.11988	1.32178	0.01001
1.29092	0.72985	1.24162	1.56703	1.49185	19.64562	0.83893	162.50955	1.12123	1.29493	0.01086
1.28981	0.73277	1.24406	1.55009	1.49083	16.90245	0.83831	209.50276	1.12043	1.27838	0.01152
1.29012	0.73472	1.24522	1.57858	1.48932	19.00049	0.83793	223.03673	1.11768	1.30164	0.01239
1.28999	0.73466	1.24736	1.61474	1.48830	19.83123	0.83771	207.39838	1.11399	1.38134	0.01342
1.28977	0.73357	1.25182	1.59701	1.48866	21.43916	0.83769	181.38152	1.10867	1.44508	0.01475
1.29047	0.73245	1.25805	1.53124	1.48929	20.77527	0.83741	157.00220	1.10238	1.41884	0.01612
1.29188	0.73163	1.26932	1.52309	1.49046	20.54534	0.83680	139.28648	1.09700	1.37271	0.01718
1.29367	0.73037	1.28411	1.63447	1.49228	15.79279	0.83633	83.23217	1.09285	1.35232	0.01775
1.29626	0.72893	1.30065	1.65238	1.49404	7.00180	0.83653	156.57175	1.09002	1.34781	0.01812
1.29929	0.72887	1.31996	1.58067	1.49469	5.40473	0.83742	4116.77300	1.08858	1.33897	0.01811
1.30191	0.72935	1.33943	1.44087	1.49557	3.10657	0.83863	3275.73200	1.08880	1.32903	0.01764
1.30239	0.72892	1.35667	1.56401	1.49737	5.98585	0.83997	2978.44750	1.08807	1.31371	0.01757

Table 3 shows the forecasted exchange rates for the selected currency pairs.

TABLE 4: SYMMETRIC BEKK GARCH OUTPUT

Symmetric BEKK using default starting values				Symmetric diagonal BEKK				Symmetric Scalar BEKK			
Estimated parameter matrices:											
C	[.1]	[.2]	[.3]	C	[.1]	[.2]	[.3]	C	[.1]	[.2]	[.3]
[1,]	0.001356	0	0	[1,]	0.003409	0	0	[1,]	0.001219	0	0
[2,]	0.002369	0.001698	0	[2,]	0.000186	0.001627	0	[2,]	-0.00031	0.00216	0
[3,]	-0.00529	0.00862	0.001903064	[3,]	0.002664	0.000933	0.008244	[3,]	0.000346	-0.00162	0.009975
A	[.1]	[.2]	[.3]	A	[.1]	[.2]	[.3]	a			
[1,]	2.50E-01	-0.01641	-0.03087835	[1,]	0.73123	0	0	[1]	0.593203		
[2,]	0.0299	0.294556	0.15726735	[2,]	0	0.613157	0				
[3,]	0.021876	0.030393	0.30666935	[3,]	0	0	0.363767	g			
								[1]	0.406794		
G	[.1]	[.2]	[.3]	G	[.1]	[.2]	[.3]				
[1,]	0.905293	0.000282	0.03773756	[1,]	0.09812	0	0				
[2,]	-0.01669	0.880266	-0.08915608	[2,]	0	0.789961	0				
[3,]	0.046116	0.011155	0.91366865	[3,]	0	0	0.887053				
Standard errors of parameter indices:											
C	[.1]	[.2]	[.3]	C	[.1]	[.2]	[.3]	C	[.1]	[.2]	[.3]
[1,]	0.101638	0	0	[1,]	0.001192	0	0	[1,]	0.000566	0	0
[2,]	0.421141	0.393292	0	[2,]	0.002502	0.002477	0	[2,]	0.001078	0.000793	0
[3,]	1.968448	5.564871	32.65851	[3,]	0.0143	0.005193	0.030672	[3,]	0.006378	0.003897	0.002849
A	[.1]	[.2]	[.3]	A	[.1]	[.2]	[.3]	a			
[1,]	4.226419	7.855939	19.97749	[1,]	0.384284	0	0	[1]	0.29258		
[2,]	16.5135	8.612265	31.03503	[2,]	0	0.341203	0				
[3,]	3.671532	2.391022	10.31702	[3,]	0	0	0.308599	g			
								[1]	0.11266		
G	[.1]	[.2]	[.3]	G	[.1]	[.2]	[.3]				
[1,]	3.160106	3.356954	16.934688	[1,]	1.981703	0	0				
[2,]	17.36878	13.79038	45.393828	[2,]	0	0.319916	0				
[3,]	2.376463	3.692579	5.357113	[3,]	0	0	0.613478				

Table 4 shows the output of BEKK GARCH model with the parameters C, A and G and the standard errors. The metric C refers to the constant term, A indicates the ARCH effect and G represents GARCH effects. In matrix A that shows the ARCH effect, the diagonal element shows the effect of past shocks on the current volatility. The diagonal elements are statistically significant, which indicates a strong association between the past shocks and current volatility. The elements above the diagonal shows the spillover effects from one currency to other. The estimated above diagonal values indicate significant spillover among the foreign currency markets.

Matrix G shows the GARCH effect. The diagonal elements are close to one, highlighting strong persistence in volatility within each market. The elements above the diagonal are small, indicating minimal long-term volatility spillover from one market to another. The elements below the diagonal show some spillover effects, with positive values suggesting volatility transmission from lower to higher-indexed markets.

CONCLUSION

Forecasting exchange rate across a wide spectrum of currencies has always been a challenging task. Information coming such as economic, political, geopolitical issues, global commodity prices etc will bring irregular variations in the price movement. In this research, we build a robust framework using LSTM model with attention mechanism to predict the exchange rate of 15 foreign currencies. The LSTM models are a special kind of Recurrent Neural Network, has the capability to capture the temporal dependencies in sequence data. The LSTM model is able to predict the exchange rates with minimum RMSE i.e less than 6 % for all currencies. The low error in forecasting underscores the forecasting accuracy of LSTM model. The model framework applying LSTM attention mechanism facilitates volatility forecasts and spillover effects using an appropriate econometric model

In this study, we apply BEKK GARCH model to examine the spillover effects of all selected foreign currencies. The integration of LSTM and BEKK GARCH advances the theoretical understanding of volatility dynamics and spillover effects. On the practical implication, the model is robust in examining the return dynamics and volatility spillover effects. The LSTM effectively filters the irregular variations and captures the temporal dependencies, while BEKK GARCH examines the effect of past shocks on own market and spillover from one currency to the other currency market. The BEKK GARCH model's results highlight the persistence of volatility within markets and the presence of spillover effects providing a nuanced understanding of inter-market volatility transmission. Further integrating the LSTM and BEKK GARCH overcomes the limitations of traditional forecasting models.

The ability to forecast return and volatility is pertinent in making business decision impacted by exchange rate movement. The methodological framework of the study aids the policy makers, financial institutions, Central banks, Exporters and Importers to forecast the returns dynamics and spillover effects to make foreign exchange risk appropriately.

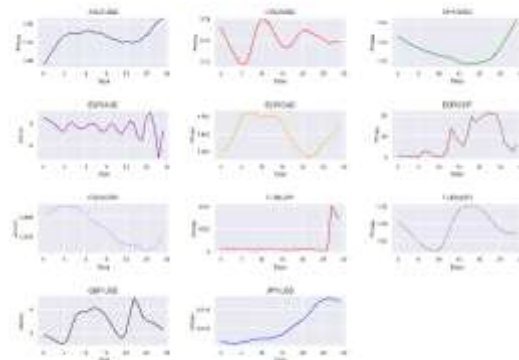


Figure 5: GRAPHS OF THE PREDICTED EXCHANGE RATES OF ALL THE CURRENCY PAIRS

Figure 5 shows the forecasted trend of exchange rate of all currency pairs. It is evident that the LSTM Attention mechanism is able to capture the dynamic patterns in the exchange rate movements.

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