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# UNMASKING MARKET MYSTERIES: BRIDGING FINANCIAL AND NEURAL FORECASTING IN RISK ASSESSMENT ACROSS GLOBAL MARKETS

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**Abstract**
The study is the discussion of the neural network model integration within the conventional financial forecasting models in order to improve the degree of risk exposure in the global market. The study compares market volatility in major economies using a combination of the statistical forecasting and neural forecasting models such as LSTM using Value at Risk (VaR), Conditional Value at risk-CVaR and Mean Squared error (MSE) as two key indicators. A comparison of these methods shows that neural networks are more powerful to capture non-linear relationships and latent patterns as compared to traditional econometric models. The results show that there is a better predictive accuracy and less estimation errors, especially when the market is volatile. This research paper draws attention to the real-world applications of neural forecasting to strategic decision-making, assessment of sovereign risk, and management of tail-risk. The uniqueness is that it empirically fills the quantitative financial analysis with artificial intelligence, providing a holistic framework that increases the accuracy, flexibility, and interpretability of market risk forecasts to a variety of financial contexts.
**Keywords:** Neural Networks, Financial Forecasting, Value at Risk (VaR), Risk Assessment; Global Financial Markets, Predictive Modelling, Machine Learning in Finance; Volatility Forecasting

## 1 INTRODUCTION

The world of international finance is described as unpredictable and complex with a variety of external and internal forces that affect the market. Risk assessment strategies have traditionally been based on the traditional financial forecasting models, including time series analysis and econometric models (Pol et al., 2006). Nevertheless, their shortcomings regarding nonlinear relationships capturing and the ability to adjust to the fast-changing market conditions have become quite obvious. Neural forecasting methods, on the other hand, use the strength of artificial intelligence to analyze large volumes of data and detect complex patterns that are not necessarily recognizable by other approaches (Rostamian and O'Hara, 2022). Incorporation of neural networks as a part of financial forecasting models is an important development in the practice of risk assessment. As a statistical method, neural networks have found more and more applications in related areas, including tourism demand forecasting and time series, showing that they can effectively represent the intricate trends and increase the likelihood of accuracy of forecasting (Liang, 2019). In addition to this, recent studies have also noted the usage of neural networks in event prediction within directional change models and they have demonstrated their flexibility to various financial contexts (Gapen et al., 2005). The future of having neural networks in the risk assessment practice in financial markets around the world is that it will help in improving the accuracy and flexibility of the forecasting models. It is especially true in regards to the global market volatility; in such a case, the capacity to correctly evaluate and predict risk is paramount when it comes to strategic decision-making (Gözgör & Kablamaci, 2014). The applicability of neural network forecasting in the framework of sovereign risk and contingent claims also presents one more piece of evidence that it might serve as a useful tool to draw important information on the situations in the financial sector (Kalczyinski & Zerom, 2015). The neural network potential in financial forecasting is also supported by the fact that they can be deployed to determine the correlation between oil and agricultural commodity prices, and predicting the price of the electricity market, which shows their applicability in a variety of financial fields (Cotter and Dowd, 2011). Moreover, when it comes to extreme global equity market risk assessment, the role of the neural networks is pointed to the ability to deal with tail risk and extreme value theory, which adds to the more complete picture of market behavior. To sum up, the neural network implementation into the framework of financial forecasting can be regarded as one of the crucial innovations in risk assessment procedures that have the potential to improve the accuracy and flexibility of financial forecasting models in the context of a variety of markets worldwide. This study help in the knowledge of how neural networks can be used to transform the practice of risk assessment in the international financial arena by investigating the use of neural networks in diverse financial fields.

Financial risk management and evaluation have been key issues in strategic decision-making in the international market. Value at Risk (VaR) has become a central instrument in this field offering an approximation of the possible loss of value of assets or portfolios in the future within a time frame of a given level of confidence. Historical Simulation, Monte Carlo Simulation, and Variance-Covariance have been the traditional VaR methodologies, which have made a significant contribution to risk assessment; however, their flaws, such as normality assumptions and the analysis of the static data, have posed questions regarding the risk underestimation (Götze et al., 2023). To address such constraints, more recent results have involved applying machine learning algorithms, including random forest and neural networks, to VaR forecasting, with dynamic and adaptive models that are likely to improve the quality of risk predictions (Fatouros et al., 2022). Major economic forecasts, including that issued by the Bank of England, are formulated in terms of predictive distributions, and this has reinforced the relevance of probabilistic forecasts in financial risk management. This makes it clear that probabilistic predictions of portfolio values are on the rise of importance in the fast-changing financial risk management environment (Gneiting et al., 2007). More so, the recent research has shown that deep learning architectures, namely Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM), can be used in time-series forecasting, which suggests the transition towards more advanced and data-sensitive risk-assessment methods (Fatouros et al., 2022). The aim of this research is to bridge the gap between the traditional and machine learning models in risk assessment in the global markets. Through a comparative study of the accuracy of both machine learning techniques and linear regression, as shown in the secondary CAT bond market, this study offers empirical data on the accuracy of random forest forecasts with the historical linear regression models (Götze et al., 2023). Moreover, the research intends to utilize probabilistic deep neural networks to create a model about portfolio risk evaluation, and as a result, this helps improve risk management in financial markets (Fatouros et al., 2022). Finally, the adoption of machine learning methods in risk assessment is a chance to increase the accuracy and flexibility of the forecasting model, which will help to overcome the shortcomings of the conventional methodology. Through the investigation of the prospects of machine learning and deep neural networks in risk assessment, this study hopes to play a role in unravelling the mysteries of the market and creating stronger and precise risk assessment models in the world financial markets.

## 2 LITERATURE REVIEW

### 2.1 Theoretical Literature

Ox and Jenkins (1970) and Fama (1970) are the conventional approaches that have been used in forecasting and analysis. Time series analysis, econometric models and fundamental analysis have been the pillars in the understanding of financial markets and predicting. They however bear their shortcoming especially in the application of nonlinear relationships and the use of non-traditional data sources as emphasized by Engle (1982). Deficiencies in Nonlinear Relationships Capturing and Non-Traditional Data Sources: Engle (1982) highlighted a limitation on the traditional approaches to model non-linear relationships and incorporate non-traditional data sources. These restrictions interfere with the process of capturing the entire range of market forces and making correct predictions, particularly in the current fast-changing and networked financial environment.

In a bid to overcome the above limitations, there is the emergence of neural forecasting techniques which has introduced a paradigm shift. An alternative that is particularly powerful is introduced by Le Cun et al. (2015), which is neural networks and deep learning algorithms. These methods have adaptive learning, and they are effective in managing high dimensional and large data volumes as has been shown by Rumelhart et al. (1986).

Neural networks are the computational models based on the human brain structure and its operation. Deep learning is an extension of neural networks; multiple layers are used to extract increasing amounts of higher-level features of raw data. This allows the models to discover complicated patterns and relationships on their own.

The major strength of neural forecasting methods is that they have adaptive learning abilities. The models are capable of constantly revising their parameters with the new information, thus operating effectively under the changing market conditions. Besides, they are able to process huge quantities of information including a non-conventional information like a social media feed, satellite image, and sensor data.

The use of neural forecasting algorithm in the financial market has produced encouraging outcomes. These technologies have proved to be the best methods to forecast stock prices and currency variances as well as determine the level of risk in investment portfolios in comparison to the traditional methods. Their effectiveness in reducing risks and improving the decision-making process in the area of finance has been pointed out. (Lipton et al.,2015).

Conclusively, although the financial analysis has been grounded using the traditional approach, the introduction of the neural forecasting methods provides a revolutionary approach. Through the strength of deep learning and adaptive learning features, the approaches run the way to more precise, timely, and in-depth predictions, thus enabling investors and analysts to navigate the financial environment of the present day.

### 2.2 Bridging Financial and Neural Forecasting

**Integration of Neural Networks into Risk Assessment Frameworks:**

The integration of the neural forecasting models into the normal risk management procedures (Huang et al., 2005). Enhancing the accuracy and robustness of the methods of ensembles and hybrid methods (Zhang and Qi, 2005). The idea of introducing neural forecasting models into the conventional risk management cycles has attracted great attention in the literature. (Huang et al.,2005) highlighted that neural forecasting models have the potential of transforming risk assessment models. Moreover, the use of ensemble techniques and hybrid techniques to get superior accuracy and strength have been emphasized by (Zhang and Qi,2005). The articles highlight the increasing awareness of the importance of neural networks in the risk estimation process and the necessity of sophisticated approaches to deal with the dynamics of contemporary financial markets. In addition to that, recent literature has highlighted the potential of ensemble methods and hybrid approaches in combination with neural forecasting models. Ju et al, (2018) evaluated the relative accuracy of ensemble solutions using deep convolutional neural networks in image classification, revealing that ensemble strategy can be used to improve predictive accuracy. Moreover, Chen et al., (2017) proposed checkpoint ensembles, with the focus on the possible potential of ensemble methods based on a single training procedure, which provides the information on the effectiveness and resilience of ensemble methods in the context of neural network modelling. Besides, (Wang et al.,2022) have applied ensemble methods to the financial sphere in an option pricing model, which demonstrated the potential of ensemble methods to increase the performance and robustness of financial modelling in terms of high complexity and a large number of hyper-parameters. Moreover, the hypothetical issues of hybrid methodologies used in modelling the processes based on the concept of neural network-first discussed by (Psichogios and Ungar, 1992), offered useful insights in terms of the role of the hybrid methodologies in addressing the complexity of the financial processes. The hybrid solution serves as a holistic framework that integrates neural network capabilities with the basic principles and helps to gain a more comprehensive picture of financial dynamics. To sum up, the neural forecasting models construction into risk assessment systems, along with ensemble algorithms and hybrid procedures, is a major improvement in financial risk management. These sophisticated methods are combined to provide the possibility of overcoming the constraints of the traditional risk assessment approaches and improving the quality, flexibility, and strength of the financial forecasting and risk management activities.

### 2.3 Uncovering Hidden Patterns and Market Anomalies

Discovering Surviving Patterns and Market Freaks. Examples of how neural networks have proven to be effective in detecting the presence of market inefficiency, as well as anomalies (Bao et al., 2017). How to select features and interpret the model in neural forecasting (Shen et al., 2020). The effectiveness of the neural networks in detecting the market inefficiencies and anomalies are the topic which has been explored in the recent literature. Bao et al. (2017) introduced case studies that showed that neural networks are effective in determining the hidden patterns and anomalies in financial markets. Moreover, Shen et al. (2020) explored methods of feature selection and model interpretability in neural forecasting, providing the insight into the interpretability and robustness of neural network models. The recent research has also advanced the knowledge on neural networks in identifying market anomalies and inefficiencies. To use but one example, Smets and Wouters (2007) used a Bayesian DSGE model of shocks and frictions of US business cycles and this offers an understanding of the dynamic stochastic general equilibrium and business cycle modelling (Sun et al., 2004). introduced an optimum partition algorithm of the RBF neural network which showed the adaptability and efficiency of neural network algorithm on forecasting financial time series. Further, Tosunoglu et al. (2023) performed an artificial neural network analysis of the day of the week anomaly in the cryptocurrencies and pointed to the use of neural networks in identifying anomalies in cryptocurrency markets. Besides, recent studies have paid attention to the use of neural networks in anomaly detection in different areas (Lee et al., 2021). demonstrated the use of convolutional recurrent neural networks to detect anomalies, which can be applied to machine-anomaly sound detection, which is why neural network-based anomaly detection can be effective (Park, 2021). discussed the application of neural networks in anomaly detection as well, discussing neural architecture search to create anomaly-resistant graph neural networks, which should be involved in machine-anomaly sound detection. Moreover, the work by Xu et al. (2020) created DeepMAD, a deep learning architecture of magnetic anomaly detection, which proves that neural networks can be extremely versatile in detecting anomalies in various areas. Recently, the relevance of predictive uncertainty in prediction of a financial market by neural networks has been highlighted in the application of neural networks in financial forecasting (Maeda et al., 2021). Further, Jia (2021) also explored the deep-learning algorithm-driven financial forecasting models not to mention the breakthroughs in machine learning and neural network-based financial forecasting models. All these studies help in the knowledge of neural networks to reveal obscure models and abnormalities in the financial markets. To sum it up, recent literature has also offered useful information on the use of neural networks in detecting anomalies and market inefficiencies of the market. Since Bayesian DSGE modeling to anomaly detection in various sectors, the developments in neural network-based solutions provide good prospects in discovery of the concealed patterns and anomalies in financial markets.

## 3 METHODOLOGY

The analysis is quantitative with a research design whereby the conventional econometric models combine with the neural forecasting methods to measure market risk in the world financial markets. Several international markets, such as the United States, United Kingdom, Germany, France, Japan, Brazil, Russia, India, China, South Africa, Pakistan, Bangladesh and Indonesia, were used to collect the daily market returns data. The analysis was conducted in three steps. Descriptive statistics were initially calculated to obtain an overview of the mean returns, standard deviations, skewness, and kurtosis to give the first impression of the market volatility and distributional nature.

Second, the conventional risk assessment models, i.e. Value at Risk (VaR) and Conditional Value at Risk (CVaR) were approximated on the 95th percentile in order to measure the potential losses during normal and extreme market conditions.
To ensure that volatility varies with time and that it is more precise in the measurement of risks, GARCH (Generalized Autoregressive Conditional Heteroskedasticity) model was used.

$$\sigma2 = \omega + \alpha Y^{2} + \beta\sigma^{2}\omega\sigma^{2}$$
$$t{+}1 \qquad t \qquad t$$

Where,
$\omega$ is the constant term
$\alpha$ and $\beta$ are coefficients that, respectively, quantify the influence of previous conditional variances and past squared observations.
$Y_t^2$ is the squared mean term from the mean equation. Whereas VaR is computed using the following formula

$$VAR\alpha_t = \mu_t - Z_\alpha\sigma_t$$

Long Short-Term Memory (LSTM) neural networks were used in the third step to predict future risk values and their predictive power was compared to the traditional models. Forecasting performance was measured by the Mean Squared Error (MSE) measure wherein an objective comparison of statistical and neural approaches was possible. The combination of these models allowed the overall assessment of the benefits of the neural forecasting when it comes to the improvement of the strength of financial risk prediction.

## RESULTS AND DISCUSSIONS

### 4.1 Descriptive Statistics

The descriptive statistics give us our first glimpse into the distribution of market returns. Very low mean returns are observed for the developed markets—US, UK, Germany, France and Japan along their established institutions. Emerging markets, for example Brazil (0.0003486), Pakistan (0.0006614) and India (0.0004392), have higher means compared with previous analysis suggesting more volatility but also increased growth potential.
For most markets, standard deviations range from 0.011 to 0.018 with Japan (0.0145) and Brazil (0.0176) having greater risk factors disenado:1908291491186124627 table 4: standard deviation of international market cap-weighted returns differ by more than 17%. An extreme side is the large poor, fat tails and instability of Russia (−6.76 skewness, kurtosis above 190). Pakistan, on the other hand has got the lowest kurtosis value (4.25) which indicates a fact that the tail risks associated with it are not as severe compared to its counterparts. Overall, mature markets have mild distribution tails but low returns, whilst emergent markets have heavy tail distribution and high returns.

**Table 1. Descriptive Statistics of Daily Return in World Markets.**

| Descriptive Stats | | | | |
|---|---|---|---|---|
| **Markets** | **Mean** | **Standard Deviation** | **Skewness** | **Kurtosis** |
| United States | 0.00020 | 0.01240 | -0.37840 | 10.28400 |
| United Kingdom | 0.00002 | 0.01163 | -0.34020 | 7.96520 |
| Germany | 0.00015 | 0.01449 | -0.16260 | 5.91710 |
| France | 0.00004 | 0.01406 | -0.20440 | 6.43630 |
| Japan | 0.00010 | 0.01453 | -0.36140 | 6.21220 |
| Brazil | 0.00035 | 0.01755 | -0.34380 | 6.60370 |
| Russia | 0.00028 | 0.01540 | -6.76130 | 191.17000 |
| India | 0.00044 | 0.01417 | -0.39150 | 9.63190 |
| China | 0.00013 | 0.01486 | -0.36970 | 5.41180 |
| South Africa | 0.00027 | 0.01078 | -0.55250 | 7.25430 |
| Pakistan | 0.00066 | 0.01346 | -0.37590 | 4.24590 |

**Note**: This table shows the average, standard deviation, skewness and kurtosis of the daily stock market returns of the chosen world markets. It shows the difference in the distribution and volatility characteristics of the returns with negative skewness and leptokurtic pattern in most of the markets.

**Traditional Models**

**Historical simulation Method- Value at risk (VaR)**

The unaffected VaR figures indicate the potential losses that may be incurred in the event of one-day market conditions. The developed markets of the United States (-0.0189), the United Kingdom (-0.0181), Germany (-0.0229), and Japan (-0.0225) are all very small. Lower risk levels are observed in new economies; Pakistan (-0.0222) and Brazil (-0.0270) are outstanding. By its traditional assumptions, South Africa has the lowest VaR (-0.0166) implying relatively less exposure. The extreme VaR (-0.0999) in Bangladesh supports the issues in the descriptive statistics of the country and structural weakness. The level of exposure to risk is more moderate in Indonesia (-0.0195) because it is close to the developed market levels. The unaffected VaR figures indicate the potential losses that may be incurred in the event of one-day market conditions. The developed markets of the United States (-0.0189), the United Kingdom (-0.0181), Germany (-0.0229), and Japan (-0.0225) are all very small. Lower risk levels are observed in new economies; Pakistan (-0.0222) and Brazil (-0.0270) are outstanding. By its traditional assumptions, South Africa has the lowest VaR (-0.0166) implying relatively less exposure. The extreme VaR (-0.0999) in Bangladesh supports the issues in the descriptive statistics of the country and structural weakness. The level of exposure to risk is more moderate in Indonesia (-0.0195) because it is close to the developed market levels

**Table 2. Value at risk (VaR) Results at 95% Level of Confidence**.

| Markets | Var Results @95% |
|---|---|
| United States | -0.01887 |
| United Kingdom | -0.01812 |
| Germany | -0.02286 |
| France | -0.02204 |
| Japan | -0.02250 |
| Brazil | -0.02701 |
| Russia | -0.01812 |
| India | -0.02121 |
| China | -0.02305 |
| South Africa | -0.01661 |
| Pakistan | -0.02218 |
| Bangladesh | -0.10000 |
| Indonesia | -0.01945 |

**Note:** The above table presents the Value at risk estimates (VaR) of all markets at the 95% confidence interval. The results measure the losses that may be incurred in a normal market environment, which is the maximum available to be lost on a daily basis, as a comparative measure of downside risk.

**Historical simulation Method -Conditional Value at risk (CVaR)**

In addition to threshold risk, CVaR provides the data on the expected losses during extreme tail events. This is also more susceptible to emerging markets. India (-0.0339), China (-0.0365), and Brazil (-0.0393) are the countries where the conditional losses are higher as compared to the developed countries, the United States (-0.0297) and the United Kingdom (-0.0281). Bangladesh (-0.2038) remains an acute outlier, which proves to be a systemic failure of models being unable to properly reflect the risk profile of the country. South Africa has the lowest CVaR (-0.0244). The gap between VaR and CVaR is the largest in volatile emerging markets, which explains the importance of tail-risk awareness. The backtesting results reveal the systematic weaknesses of the statistical VaR models. The number of violations in every marketplace is dealt with substantially higher than it would be predicted at the 95% level. The most recent LR statistic of 28000 plus a p-value of 0.00 was generated, such as the case of the United States registering 5,378 violations versus what should have been 302. The same trends show thousands of exceedances grossly exceeding the hypothetical limits in Germany, France, India and Pakistan. Even though the case of the UK is indicated as an edge case, the overall finding is similar to that traditional VaR significantly understates realized tail risk. This underscores the fact that the use of dynamic volatility is best represented using more complex methods, as opposed to the use of classic models. VaR and CVaR when combined illustrate the degree of downside risk in each market. In the developed economies, there is not much difference between thresholds and tail conditional losses, and they are tightly clustered. The broader spreads however are a representation of fatter tails and greater uncertainty in the emerging economies. China, India, and Brazil are the markets with deep CVaR when compared to their VaR, which illustrates the sensitivity of the markets to stress.

**Table 3. Conditional Value at risk (CVaR) Results at 95% Confidence level.**

| CVaR | Results @95% |
|---|---|
| United States | -0.02973 |
| United Kingdom | -0.02811 |
| Germany | -0.03445 |
| France | -0.03350 |
| Japan | -0.03360 |
| Brazil | -0.03931 |
| Russia | -0.03249 |
| India | -0.03392 |
| China | -0.03649 |
| South Africa | -0.02440 |
| Pakistan | -0.03335 |
| Bangladesh | -0.20382 |
| Indonesia | -0.03121 |

**Note**: This table presents estimates of Conditional Value at risk (CVaR) which represents the anticipated losses during the worst 5 percent situations. When CVaR is larger, it means that there is more exposure to extreme Tail risk which exceeds VaR

**Value at Risk (VaR) and Conditional Value at Risk (CVaR) through GARCH Model**

The GARCH-based VaR and CVaR estimates significantly reduce the magnitude of the expected risk values compared to the estimations of the same using a static model. As an illustration, the VaR of the U.S. under GARCH (-0.0121) is not that bad as compared to the VaR of the U.S. under the static (-0.0189). Similarly, France (-0.0110), Japan (-0.0165), and Germany (-0.0112) are also reported to have moderate thresholds. The same can be observed in the emerging markets, where China (-0.0146), India (-0.0138) and Brazil (-0.0163) have better risk management. In the case of Bangladesh, which still remains unstable (-0.0976), South Africa (-0.0225) and Pakistan (-0.0267) remain in the upper range. The results suggest that though it is still true that emerging markets are inherently volatile; GARCH models are more realistic and adaptable risk measures as they capture time-varying volatility. The LSTM deep learning model produces the most conservative risk estimations. U.S. VaR and CVaR are much lower than GARCH or non-adaptive models, with a value of -0.00207 and -0.00315, respectively. Most of the developed markets display the same tendencies; Germany has gone ahead to record a slight positive VaR (0.00154) which shows constanttenvironments.

**Table 4. Results of GARCH Model at 95% Confidence.**

| Garch Results @95% confidence | | |
|---|---|---|
| | **VAR** | **CVAR** |
| United States | -0.01209 | 0.01516 |
| United Kingdom | -0.24458 | 0.30661 |
| Germany | -0.01124 | 0.01409 |
| France | -0.01100 | 0.01379 |
| Japan | -0.01654 | 0.02073 |
| Brazil | -0.01626 | 0.02039 |
| Russia | -0.01381 | 0.01731 |
| India | -0.01380 | 0.01730 |
| China | -0.01463 | 0.01834 |
| South Africa | -0.02254 | 0.02826 |
| Pakistan | -0.02669 | 0.03345 |
| Bangladesh | -0.09762 | 0.12238 |
| Indonesia | -0.01265 | 0.01585 |

**Note:** The table shows the Value at Risk (VaR) and Conditional Value at risk (CVaR) estimates estimated with the help of GARCH (1,1) model. It is able to capture time-varying volatility and it shows the effects of conditional heteroskedasticity on risk forecasts across markets

### Backtesting through Likelihood Ratio

Based on this, the baseline VaR models may not pick up tail risk particularly in volatile markets such as Pakistan (LR = 28442.97), Japan (LR = 28047.20), and the United States (LR = 28131.45). It is interesting to note that South Africa (LR = 16924.87) and Russia (LR = 13062.74) have relatively lower, yet, significantly high LR value. This may be because there are non-linear relationships and regional concentrations of volatility that cannot be well captured by the model. UK is described as a case of edge case, which indicates that test computation can be affected either by model instability or the irregularities in the data. In general, the findings suggest that the conventional VaR estimation may not be accurate in the representation of tail events, and hybrid or neural network-based risk assessment systems are more appropriate as they are somewhat flexible to adapt to the nonlinear financial characteristics and regime shifts. The MSE results give a standard of model accuracy. India (lowest error, 0.221) and Japan (lowest error, 0.233) are the two markets that are most reliable. The cluster deals with Brazil, France, Germany, and the United States having a range of 0.29 to 0.31 which indicates a low degree of predictive accuracy. Russia is least stable market as it is less predictable than South Africa (0.350) and Russia (0.480). It is also noteworthy that some of the emerging economies such as Pakistan, Indonesia and India generate error levels that are equal or even higher than the developed ones. This creates concern over the widely accepted fact that developed economies are easier to model and that perhaps some developing markets may tend to offer more accurate predictions. Standard models are always underestimated as demonstrated by numerous backtesting failures. Emerging markets generally have a greater downside risk (CVaR), but their predictability (MSE) may be at the same level or higher than that of its developed counterparts.

**Table 5. Likelihood Ratio Proportion of Failures (LR POF) Test Results Across Global Markets**

| Sr # | Market Violations | Expected | Violations | LR POF P-Value |
|---|---|---|---|---|
| 1 | United States | 5,378 | 302 | 28,131 |
| 2 | United Kingdom | 6,059 | 303 | Edge case |
| 3 | Germany | 5,117 | 305 | 25,397 |
| 4 | France | 5,167 | 307 | 25,715 |
| 5 | Japan | 5,302 | 294 | 28,047 |
| 6 | Brazil | 5,150 | 297 | 26,284 |
| 7 | Russia | 2,437 | 133 | 13,063 |
| 8 | India | 5,292 | 296 | 27,784 |
| 9 | China | 5,178 | 290 | 27,096 |
| 10 | South Africa | 2,927 | 150 | 16,925 |
| 11 | Pakistan | 5,004 | 259 | 28,443 |
| 12 | Bangladesh | 5,793 | 305 | 32,265 |
| 13 | Indonesia | 5,222 | 292 | 27,424 |

**Note**: Findings of the Likelihood Ratio Proportion of Failures (LR POF) test on the accuracy of the Value-at-Risk (VaR) forecasts, of 13 leading markets. The test is a process of comparing the number of exceedances that was observed with the number of exceedances that was to be observed at 95% level. A smaller LR value implies that the model has been better calibrated whereas a larger value implies that the observed and forecasted risk levels are different by a large amount.

### Neural Forecasting Model

### LSTM Model Value at Risk (VaR) and Conditional Value at Risk (CVaR)

The results of the model compared to the traditional GARCH-based results indicate much smaller VaR and CVaR values in most markets, which indicates improved stability and a more convenient estimation of risk. The developed markets of the US and Japan, particularly due to their developed financial institutions, have very low anticipated losses (VaR of -0.002 -0.003). The increased level of tail-risks (CVaR at -0.01375 and -0.00549, respectively) can be interpreted as more volatility and vulnerability to external shocks of emerging economies like Brazil and Russia. Surprisingly, China, India, and Germany are in the market with positive or nearly negative VaR estimate during the testing period. It may reflect an overfitting or low chances of downside in the near future. The findings of the enhanced predictive stability and nonlinear pattern recognition demonstrate that LSTM technique is effective in dynamic risk forecasting in volatile markets. Risk foreseen has also reduced considerably in the emerging markets. China expresses even lower numbers and VaR of India (0.00062) and CVaR (-0.00062) are almost not important. The only outlier is Russia, which has relatively large tail losses (CVaR -0.01375) and this is the characteristic of structural instability. There is no data available in Bangladesh, though past results show that there are still problems with the models. Altogether, LSTM models contribute to the great enhancement of prediction stability through a stronger consideration of nonlinear connections and adaptation to evolving market patterns. Figure A summarizes the neural forecasting findings of market-level risk, showing estimates of Value-at-Risk (VaR) and Conditional Value-at-Risk (CVaR) on the 95 percent confidence level. The figure aligns model outcome between markets, where LSTM architecture proffers smoother and more damped tail estimations in comparison with the conventional econometric yardstick.

**Table 7. LSTM Model Results for Value at Risk (VaR) and Conditional Value at Risk (CVaR) at 95% Confidence Level**

| LSTM Results | | |
|---|---|---|
| | **VAR** | **CVAR** |
| United States | -0.00207 | -0.00315 |
| United Kingdom | -0.00526 | -0.00591 |
| Germany | 0.00154 | 0.00068 |
| France | -0.00320 | -0.00423 |
| Japan | -0.00220 | -0.00269 |
| Brazil | -0.00430 | -0.00549 |
| Russia | -0.00830 | -0.01375 |
| India | 0.00062 | -0.00062 |
| China | 0.00140 | 0.00104 |
| South Africa | -0.00099 | -0.00256 |
| Pakistan | -0.00337 | -0.00480 |
| Bangladesh | -0.00900 | -0.00180 |
| Indonesia | 0.00004 | -0.00111 |

Note: Value at Risk (VaR) and Conditional Value at Risk (CVaR) projections based on LSTM at a 95% confidence level for a few worldwide markets. The findings show that, in contrast to conventional econometric models, neural forecasting models are able to capture nonlinear temporal relationships and generate risk estimations that are more stable and have a lower magnitude.

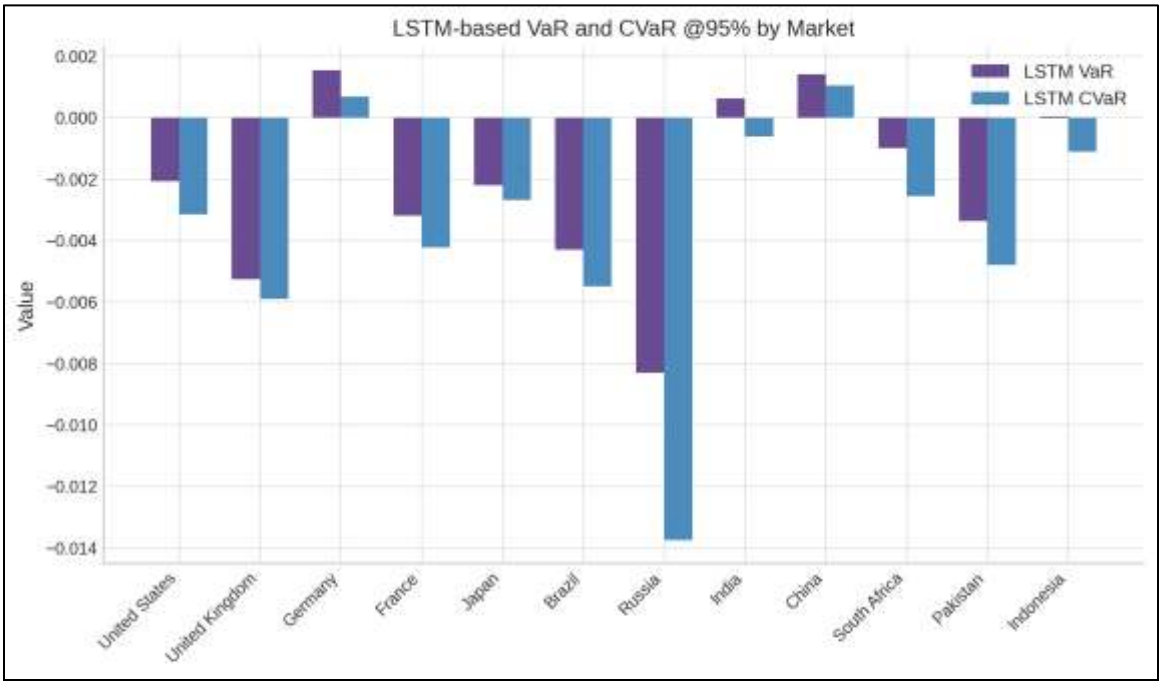


**Figure A. LSTM-based VaR and CVaR @95% by Market. Neural forecasting comparison showing smoothed/tempered tail estimates.**

**Mean Squared Error (MSE)**

The ability of the LSTM model to represent the nonlinear dynamics of the financial markets is justified by the fact that most of these markets show a low level of prediction errors. Japan (0.2331) and India (0.2206) are the lowest in MSE, and this indicates that they have good forecasting accuracy in markets that are highly liquid and stable. Russia (0.4804) on the other hand has the highest MSE probably due to the fact that data stationarity was affected by geopolitical unrest and unpredictable market behaviour. Mean MSE values (=0.29-0.31) are considered to be in the middle of predictability and volatility in advanced markets such as the US, UK, and

Germany. Mistakes are somewhat higher in such emerging markets as South Africa and Brazil in accordance with their higher volatility regimes. The results generally suggest that LSTM framework is more stable and flexible in most financial settings than traditional econometric models and decreases the errors in predictions. Figure B illustrates the relative forecasting performance of the markets showing the visual intensity as the relative Mean Squared Error (MSE). Markets that are light-shaded are associated with models that have a high predictive accuracy as illustrated.

**Table 8. Mean Squared Error (MSE) Results at 95% Confidence Level**

| **MSE** | **Results @95%** |
|---|---|
| United States | 0.29443 |
| United Kingdom | 0.31125 |
| Germany | 0.30064 |
| France | 0.31152 |
| Japan | 0.23314 |
| Brazil | 0.29828 |
| Russia | 0.48039 |
| India | 0.22064 |
| China | 0.24672 |
| South Africa | 0.34996 |
| Pakistan | 0.29124 |
| Bangladesh | 0.27000 |
| Indonesia | 0.29081 |

**Note:** Long Short-Term Memory (LSTM) model performance in terms of Mean Squared Error (MSE) on international financial markets with 95 percent confidence level. MSE metric which is a measure of averageness of squared distance between the projected and actual risk estimates depicts the forecasting accuracy and generalization capacity of the model.

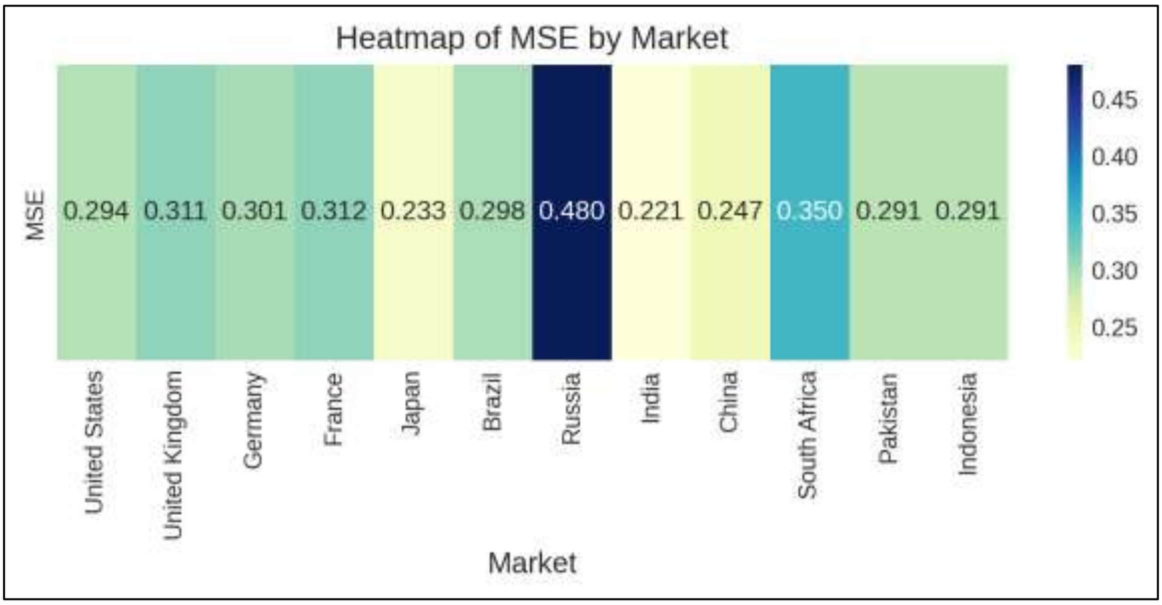


**Figure B. Heatmap of MSE by Market. Visual intensity shows relative forecasting accuracy**

LSTM gives more flexibility and more accurate and conservative projections, whereas GARCH makes intra-time volatility considerate and comes as an improvement of the constant measurements. Market anomalies: Bangladesh and Russia remain an outlier, that is, they are characterized by a high level of uncertainty and fluctuations. Policy and portfolio relevance Regulators cannot only trust fixed VaR. The advice given by dynamic models such as GARCH and LSTM is more advisory to the investors, particularly in volatile emerging markets. The models employed in this study included the traditional parametric VaR and advanced machine learning methodologies such as LSTM to test the financial risk in a portfolio of developed and emerging markets in detail. The findings again and again identify the weaknesses of static VaR, which understated tail risks in every market and did not pass backtesting. Although they are generally more profitable, the emerging economies are also more susceptible to severe shocks and more profoundly conditional losses (CVaR). The least aggressive and most consistent projections were generated by LSTM deep learning networks, and time-varying volatility can be found in dynamic models like GARCH, which were much more accurate. The MSE data shows predictive performance in structurally unstable markets such as Bangladesh and Russia, middle in most developed countries and the highest in India and Japan. Taken collectively, the data suggests that, although developed markets offer predictability and stability, some emerging markets especially India and Pakistan have a possibility of offering favourable conditions to risk modelling and diversification of a portfolio. Alternatively, the volatility in Bangladesh and Russia is quite heavy and requires sophisticated modelling and discretion.

## CONCLUSION:

This paper analysed how neural forecasting models, LSTM can be compared with conventional financial risk quantifiers (GARCH (VaR, and CVaR)) to enhance the global market risk evaluation. The idea was to establish whether methods of AI boost predictive accuracy better than standard econometric models over the time frame 2000-2023.It was found that the neural models reflect nonlinear behaviours and offer more consistent and smooth predictive volatility models as compared to traditional techniques in new market dynamics. The results imply that the risk prediction and decision-making can be reinforced with the help of introducing neural forecasting into financial analysis. These models can be important to policymakers and financial institutions to use in stress testing and early warning mechanisms. Nonetheless, there is a challenge of the black-box nature of neural networks and the quality of data. As a research direction, future studies need to concentrate on explainable and hybrid AI models that combine financial theory with computational transparency. Altogether, neural forecasting is a great breakthrough in the analysis of the world financial sphere as it provides better forecasting accuracy and resistance to unpredictable market.

**Ethics Statement:** There were no human subjects or animals involved in this study. Thus, it was not necessary to have ethical approval.

**Data Availability Statement:** The data applied and/or examined in the present researches may be acquired on a reasonable request at the respective author.

**Conflict of Interest :**The author states that there are no known competing financial interests or personal relationship that might have manifested themselves to affect the work reported in this paper.

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