Rend And Volatility Analysis Of Shanghai Composite Index Returns Based On ARMA And Long Short-Term Memory Model

Wenting Ma[1*]

[1] School of Finance and Economics, Zhengzhou University of Science and Technology, Zhengzhou 450064 China
[*] Corresponding author. E-mail: sarkozyteague@foxmail.com

Received: May 12, 2025; Accepted: Jun. 13, 2025

This paper takes the daily return rate of the Shanghai Composite Index as a sample to establish the ARMA-LSTM (Long Short-Term Memory) model for the Shanghai Composite Index. It compares the fitting effect of ARMA model on the volatility of the Shanghai Composite Index under different distribution assumptions, calculates and tests the coverage of the prediction results of the Value-at-Risk (VaR) value of the Shanghai Composite Index on the actual losses. The analysis results show that the ARMA model is more suitable for measuring the conditional variance of the Shanghai Composite Index. With the t -distribution, the model can better reflect the distribution characteristics of the perturbation term of the Shanghai Composite Index's return rate. Furthermore, in order to overcome the large errors that occur in the medium and long-term prediction of the ARMA model, the ARMA model combined with the LSTM model is used to predict the exponential volatility, effectively improving the prediction accuracy of the ARMA-LSTM model. Finally, through the ARMA model, the impact of the full implementation of the registration system in China's stock market on the volatility of the Shanghai Composite Index is preliminarily examined. It is found that the implementation of this policy significantly reduces the fluctuation range of the Shanghai Composite Index.

Keywords: Shanghai Composite Index, Value-at-Risk, ARMA-LSTM model, registration system

http://dx.doi.org/10.6180/jase.202603_29(3).0010

1. Introduction

Due to the continuous deepening of global financial and economic integration and the development of fintech, the global capital market has developed rapidly over the past few decades. Nowadays, the trading volume of the stock market and the financial derivatives market far exceeds that of the 1990s [1]. The daily trading volume of the Shanghai and Shenzhen stock markets in China has repeatedly exceeded the one trillion yuan level. The trading activities among financial markets of various countries are increasingly closely linked, which not only brings more investment opportunities, but also makes the risks of fluctuations in financial asset prices more threatening and prone to spread. In China's stock market, individual investors account for a relatively large proportion, and they are prone to irrational investment behaviors such as "buying high and selling low" [2, 3]. Therefore, effectively predicting and preventing risks in the financial market, especially those in the stock market, is of great significance for safeguarding the financial assets of Chinese investors. Among the methods for measuring financial market risks, Value-at-Risk (VaR) is one of the most commonly used tools in managing market risks. VaR refers to the maximum possible loss of a financial asset or portfolio of securities under normal market fluctuations. The calculation methods of VaR mainly include backtracking simulation method, Monte Carlo simulation method, and variance-covariance method, etc. The GARCHVaR model is based on historical data of assets [4]. Through the GARCH (Generalized Autoregressive Conditional Heteroskedasticity) model, the mean equation, variance equation and predicted standard deviation are obtained. At a certain confidence level, the risk value of assets on a specific trading day is predicted according to the VaR calculation method [5].

The Shanghai Composite Index, released by the Shanghai Stock Exchange of China, is one of the major indices of China's stock market [6]. This index comprehensively reflects the price changes of A-shares and B-shares on the Shanghai Stock Exchange and is widely used as one of the reference indices for measuring the overall performance and changing trends of China's stock market [7]. This paper uses the ARMA-VaR model to measure the volatility and daily value at risk of the return rate of the Shanghai Composite Index. Considering that the distribution of the financial yield series may have characteristics such as "asymmetry" and "sharp peaks and thick tails", this paper compares the calculation results of ARMA-type models under three different distribution assumptions (Normal, t , GED), and predicts the daily value at risk of the Shanghai Composite Index for subsequent tests [8]. Furthermore, the innovation of the research method in this paper is reflected in that the method of predicting value at risk by the traditional ARMA-VaR Model captures the linear relationship of time series data through the ARMA-LSTM to achieve the prediction. However, the ARMA model is difficult to effectively utilize the effective information provided by the nonlinear relationships and long-term dependencies of sequence data. Some studies have shown that this method will have large errors in medium and long-term predictions. Therefore, in this paper, ARMA-LSTM (Auto-Regressive and Moving Average Model-Long Short-Term Memory) is used Model. This hybrid model aims to improve the prediction accuracy of sequence data and is suitable for time series data that simultaneously have mixed characteristics of linear and nonlinear trends. On this basis, combined with the ARMA-type models to predict the volatility and VaR of the Shanghai Composite Index, it has been verified that the prediction accuracy of the ARMA-LSTM model has been effectively improved [9, 10].

The ARMA-VaR model is widely used in the related research on the risk measurement and prediction of financial assets. Numerous research results have also verified that the VaR method is applicable to the current financial market in China. In terms of the specific application fields of the model, Cao et al. [11], based on the description of the tail characteristics of the yield rate using the extreme value theory, combined the ARMA model with the extreme value theory to analyze the fluctuation trend of systemic risks in China's interbank lending rate market. Wang et al. [12] estimated the value at risk of the yield of the Shanghai and London gold spot markets under normal, student *t* and skewed *t* distributions respectively using ARMA models, and tested the results based on the failure frequency method and dynamic quantile method. It was pointed out that the t -distribution was more suitable for describing the risk characteristics of the Shanghai gold market, while the normal distribution was more suitable for the London gold market. Ardia et al. [13] constructed the SWARCH model and the MSGARCH (Markov-switching GARCH) model, combined with the extreme value theory, to calculate the dynamic VaR value to describe the systematic risk of the international carbon trading market. Chen et al. [14] used the GARCH-VaR model to measure the volatility of hedge funds and the Kupiec failure frequency method to compare the influence of observation data of different lengths on the estimation effect of VaR values. Lin et al. [15] used the historical trading data of the RMB and the US dollar in the foreign exchange market to establish the ARMA-VaR model to measure foreign exchange risks, and pointed out that under the t -distribution, this model could effectively measure the foreign exchange risk situation in a relatively long period in the future. Ratih et al. [16] established the ARMA-VaR model to measure the risks of fintech in China based on the daily return rate data of the Shanghai Composite Index and the CSI Shenwan Internet Finance Theme Index, and pointed out that emerging fintech innovations were more vulnerable to extreme loss risks than traditional finance. The above studies show that the ARMA-VaR model can effectively adapt to the risk characteristics of China's financial market, especially the stock market, and the Kupiec failure frequency method has been used as a test method to measure the model accuracy of VaR in many studies. This indicates that under the premise of long-term data observation, this method can meet the evaluation requirements for the prediction accuracy of the model. Based on this, this paper conducts risk prediction and analysis of the Shanghai Composite Index.

2. Materials and methods

2.1. VaR model

VaR refers to the maximum possible loss of a certain financial asset or portfolio under normal market fluctuations, or the maximum potential loss value of a certain financial asset within a certain period in the future at a certain confidence level [17, 18]. According to the definition, the VaR can be expressed by Eq. (1).

$$\text{prob}\{(\Delta V(t, \Delta x) \leq VaR)\} = 1 - \alpha \tag{1}$$

Where, ΔV represents the value loss of the underlying asset during period $t.x$ represents the risk factor in period $t.1-\alpha$ represents the confidence level. prob represents the probability that the actual loss of an asset does not exceed the upper limit of expected loss (VaR). The daily market risk of the Shanghai Composite Index is measured using the VaR model and expressed by Eq. (2).

$$\mathrm{VaR}_t = \sigma_t Z_\alpha P_{t-1} \tag{2}$$

Here, Z_α represents the quantile corresponding to the confidence level a under the hypothetical distribution. σ_t is the standard deviation of the rate of return of the exponential series in period $t.P_{t-1}$ corresponds to the closing price of the index of the previous period.

2.2. ARMA model fitting analysis

A series of data output by inertial devices recorded in chronological order can be regarded as a time series. Due to the influence of various uncertain factors on the inertial device, the output time series contains various random errors. Meanwhile, as an actual existing physical system, the output of the inertial device at adjacent time points will have state continuity. It can be considered that the time series reflects the inherent laws of the system, and the further output of the system can be predicted through the method of fitting sequence modeling. In the absence of real-time requirements, the common approach is to establish an ARMA model, that is, to assume that the time series $y(n)$ of the inertial device contains the following decomposition terms.

$$y(n) = f(n) + s(n) + x(n) \tag{3}$$

In the Eq. (3), $f(n), s(n)$, and $x(n)$ represent the trend term, the period term, and the random term respectively. The trend term can be extracted by the difference method or the least square method, and the periodic term can also be removed by power spectral density analysis and difference. The ARMA model is mainly aimed at the random term $x(n)$, and considers that the measurement value at the current moment is compared with the previous p measurement values, the white noise $w(n)$, and the previous q time translation white noise $w(n-1), w(n-2), \dots, w(n-q)$ is related, that is,

$$x(n) = a_1 x(n-1) + \cdots + a_p x(n-p) + w(n) + b_1 w(n-1) + \cdots + b_q w(n-q) \tag{4}$$

However, in engineering applications, the most prominent feature of the error output of inertial devices is the poor repeatability of performance, that is, there are primary power-on errors and successive power-on errors. Therefore, a sufficiently long time sample must be obtained to truly reflect the characteristics of inertial devices. Suppose the time series samples follow the AR(1) model and the length of the time series is N, $N-1$ equations can be constructed according to Eq. (4), that is,

$$\begin{cases} x(2) = a_1 x(1) + w(2) \\ x(3) = a_2 x(2) + w(3) \\ \cdots \\ x(N) = a_1 x(N-1) + w(N) \end{cases} \tag{5}$$

In the Eq. (5), a_1 is the parameter of the AR(1) model. $w(N)$ is white noise.

When a_1 is solved by unitary linear regression, its estimated value $\bar{a}_1$ should follow a normal distribution, that is,

$$\bar{a}_1 \sim N\left(a_1, \frac{\sigma^2}{l_{xx}}\right) = N\left(a_1, \frac{\sigma^2\left(1-a_1^2\right)}{(N-1)\sigma^2}\right) = N\left(a_1, \frac{1-a_1^2}{N-1}\right) \tag{6}$$

Where $l_{xx} = \frac{(N-1)\sigma^2}{1-a_1^2}$, σ^2 is the variance of the white noise distribution. Approximating some parameters in Eq. (6), computing the following formula,

$$\begin{cases} \bar{a}_1 \approx e^{-1/\bar{\tau}} \approx 1 - 1/\bar{\tau} \\ N-1 = m\tau \end{cases} \tag{7}$$

Then the normal distribution that $\bar{a}_1$ follows can be expressed as:

$$1/\bar{\tau} \sim M\left(1/\tau, \frac{2}{m}/\tau^2\right) \tag{8}$$

According to the 3σ criterion of normal distribution, the probability that the distribution is within the interval $[u-3\sigma, u+3\sigma]$ is 99.74%, that is, $1/\bar{\tau}$ has a very high probability of being within the range of the interval $\left[\frac{1-3\sqrt{2/\mathrm{m}}}{\tau}, \frac{1+3\sqrt{2/\mathrm{m}}}{\tau}\right]$, which is approximately a deterministic event, that is,

$$\bar{\tau} \in \left[\frac{\tau}{1+3\sqrt{2/\mathrm{m}}}, \frac{\tau}{1-3\sqrt{2/\mathrm{m}}}\right] \tag{9}$$

For Eq. (9) it is necessary to ensure that $1-3\sqrt{2/m} > 0$, that is, $m > 18$. Meanwhile, combined with Eq. (7), the minimum value of the time series length N can be obtained as $18\tau + 1$, so $\bar{\tau} \in [0.5067\tau, 37.7358\tau]$. That is, the estimation made using the time series N of the current length still has an error of more than 50%.

2.3. Construction of LSTM network

Through analysis, it can be seen that due to the successive energization error inherent in the inertial device itself, the time series samples are equivalent to extracting a fragment in a random process, and the robustness and ergodicity of this random process cannot be determined. High-precision ARMA modeling of "fragment data" is very likely to lead to overfitting, reducing the generalization ability of the model. However, improving the prediction accuracy requires a huge time cost, which is mainly reflected in the acquisition length of time series samples. Therefore, it is difficult to be applied in occasions with high real-time requirements. However, drawing on its idea, if the establishment of specific prediction models can be replaced by the establishment of deep learning networks, and they can be trained in advance with a large amount of labeled data, not only can the problem of insufficient generalization ability of the ARMA model be solved, but also the well-trained network has high real-time performance in practical use.

As an actual physical system, the output of an inertial device at the current moment must have a certain correlation with that at adjacent moments. The variation law does not involve infinite squares participating in the game like the passenger flow data in public places, resulting in random jumps. Therefore, the prediction of the output sequence of inertial devices using the LSTM network is a suitable construction form, and its basic constituent units are shown in Fig. 1.

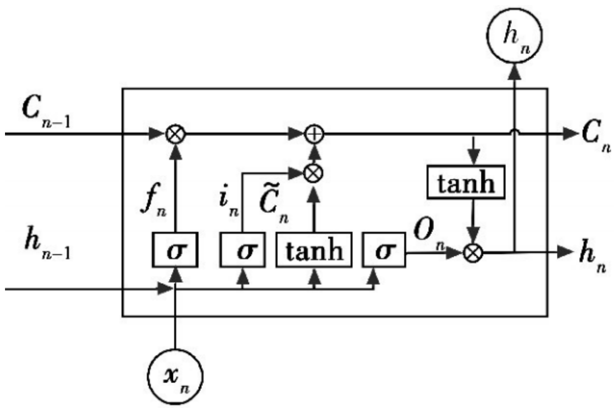

Fig. 1. LSTM network

The LSTM network is a type of recurrent neural network (RNN) [19, 20]. Each basic unit input x_n is connected to the output h_{n-1} of the previous unit and then transformed into a coefficient f_n within the interval $[0, 1]$ through a linear unit σ (Sigmoid function operation). Similarly, the tanh element represents mapping values to the interval $[-1, 1]$, and the feature mapping expression for this part is,

$$\begin{cases} f_n = \sigma\left(W_f \cdot [h_{n-1}, x_n] + b_f\right) \\ i_n = \sigma\left(W_i \cdot [h_{n-1}, x_n] + b_i\right) \\ \tilde{C}_n = \tanh\left(W_c \cdot [h_{n-1}, x_n] + b_c\right) \end{cases} \tag{10}$$

Where W_f, b_f, W_i, b_i, W_c and b_c represent the weight to be trained. Meanwhile, the transfer coefficient C_{n-1} of the previous basic unit is linearly superimposed with the calculation result $\tilde{C}_n$ of Eq. (10), that is,

$$C_n = f_n \cdot C_{n-1} + i_n \cdot \tilde{C}_n \tag{11}$$

Eq. (11) actually incorporates the design of the "forgetting Gate". The weight of the current input information and the forgetting ratio of the previous information are determined through linear superposition [21]. The design of the forgetting gating unit is mainly used to control the flow of long-term dependent information of data, similar to the idea of moving average, it can make $\alpha h_{n-1} + (1-\alpha) h_n \rightarrow h_n$. If α is close to 1 , information can be transmitted over a long period of time, while if α is close to 0 , it will be completely forgotten, preventing the disappearance of gradients caused by long-term dependencies during training.

The outward transfer coefficient C_n of the output of the basic unit passes through a forget gate again and is transferred to the same layer and other layers, that is,

$$\begin{cases} O_n = \sigma\left(W_o \cdot [h_{n-1}, x_n] + b_o\right) \\ h_n = O_n \cdot \tanh C_n \end{cases} \tag{12}$$

The main part of the network can be built by connecting the basic units into a topological structure according to the scale of the problem and the length of the predicted output. The implementation of the LSTM network adopts the Keras sequential model, adding multiple LSTM network layers to receive input information and train them as hidden layers. For real-time estimation of random errors, the design purpose of deep learning networks is to be able to detect inertial devices of the same model based on the data they are sensitive to online. The trained neural network is relied on to estimate the upcoming random errors in real time. Therefore, when the LSTM network outputs, a fully connected layer (Dense) should be designed according to the scale of the length of the random error sequence to be estimated to connect the hidden layer and the output layer [22].

3. Results and discussion

3.1. Data selection and data feature description

The daily trading data of the Shanghai Composite Index from January 1, 2020 to May 30, 2024 are selected for analysis, with a total of 1550 pieces of data in the sample. During the construction process of the ARMA-LSTM model, the first 1450 pieces of data are used as the training set, and the following 100 pieces of data are used as the test set to compare the coverage effect of the daily VaR values predicted by the model on the actual incurred gains and losses. First, the outliers and missing values of the data set are detected and processed. The return rate of the Shanghai Composite Index is calculated by logarithmic method, that is $r_t = \ln(p_t/p_{t-1})$. The time trend chart of the daily return rate of the Shanghai Composite Index is shown in Fig. 2. The daily yield rate shows a distinct "volatility aggregation" effect.

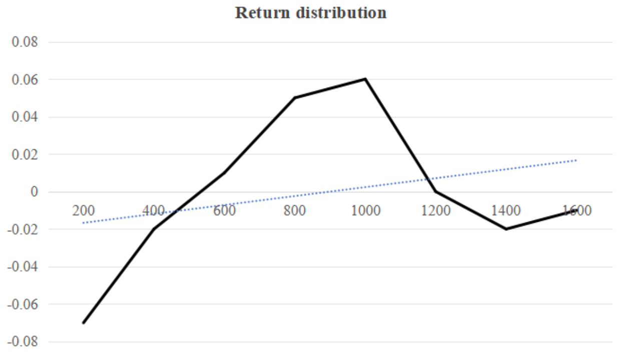

Fig. 2. The time trend chart of the daily return rate of the Shanghai Composite Index

Under the assumption that the perturbation term follows the standard normal distribution, the skew of the sequence data should be 0 and the kurtosis should be 3 . As can be seen from Table 1, the skew of the return rate of the Shanghai Composite Index is -0.61728 , and the kurtosis is 7.9223 , presenting the characteristics of "sharp peak and thick tail", and the Jacobella statistic significantly rejects the assumption that "the perturbation term follows a normal distribution". The graph of the kernel density function of the return rate and the standard normal distribution also reflects the above differences (as shown in Fig. 3).

Therefore, for the fitting of the conditional variance of the return rate of this Shanghai Composite Index, the t -distribution and the generalized error distribution still need to be introduced.

The ARMA model is only applicable to stationary sequences, and in order to avoid the pseudo-regression problem of time series, it is necessary to test the stationarity of the yield sequence first. The DF, PP, and ADF unit root tests are conducted. Here, the PP test can be regarded as the optimized DF test statistic. The DF statistic is corrected through non-parametric methods to have the function of lag period estimation. The results are shown in Table 2. All the above tests reject the null hypothesis that "the rate of return is a non-stationary sequence" at the 1% significance level.

The ARMA model is required only when there is conditional heteroscedasticity in the perturbation term. Therefore, the ARCH-LM test is conducted on the return series of the Shanghai Composite Index, and the results show that there is a significant ARCH effect as shown in Table 3.

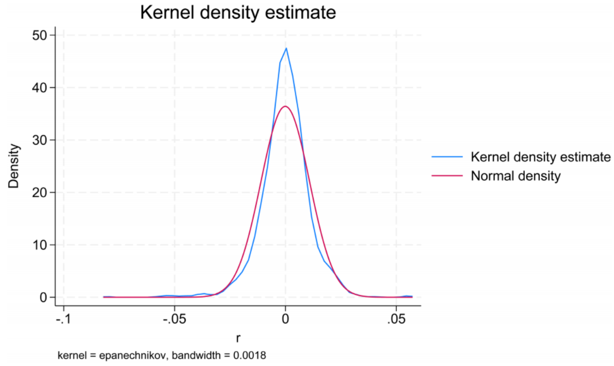

Fig. 3. Comparison chart of yield kernel density function and standard normal

3.2. The determination and prediction results of the model

To construct the generalized autoregressive conditional heteroscedasticity model, it is necessary to establish the ARMA (p,q) model for the yield series to obtain the mean equation.

Considering the AIC Criterion and the SBIC criterion comprehensively, the lag order of the yield autoregressive model is determined to be the six-order. Furthermore, considering the impact of the amount of funds in the stock market on stock returns, the change rate of stock market transaction volume x_t in period t and its first-order lag term x_{t-1} are added as explanatory variables. The change rate of stock market transaction volume is calculated using a logarithmic method, that is, $x_t = \ln(l_t/l_{t-1})$, which is the transaction volume in period t. This AR(6) model is represented by Eq. (13), and the OLS estimation results are shown in Table 4.

$$r_t = \alpha_0 + \sum_{i=1}^{6} \alpha_i r_{t-i} + \beta_1 x_t + \beta_2 x_{t-1} + \delta\sigma_t + \varepsilon_t \qquad (13)$$

According to the AIC and SBIC criteria, referring to the results of autocorrelation, partial autocorrelation and Q tests, the GARCH-type models and their lag orders are screened. The TARCH(1,1), EGARCH(1,1)-M and EGARCH(2,2)-M models are selected, and they are reported respectively in the standard normal distribution and t distribution. The coefficient regression estimation results under the GED distribution assumption are presented in Tables 5 to 7respectively.

Table 1. Statistical characteristics of data

	Jarque-Bera test	Skewness test	Kurtosis test
Test statistics	none	-0.6173	7.9223
P value	0.0000	0.0000	0.0000

Table 2. Stability test of yield

r_t	DF test	PP test	ADF test (trend)
$Z(t)$	-38.100	-8.148	-8.147
P value	0.000	0.000	0.000

Table 3. ARCH-LM test results

Lags(P)	Chi ^{2}
1	11.426
2	15.389
3	25.003
4	25.936
5	27.701

Table 4. Regression results of the AR(6) model for the Shanghai Composite Index return rate

Lags(P)	Chi ^{2}
1	11.426
2	15.389
3	25.003
4	25.936
5	27.701

Table 5. TARCH (1,1)-M coefficient regression results

TARCH (1,1)-M	α_1	β_1	M-term coefficient	φ	α_0
Standard normal	0.2492	0.6974	6.4686	-0.1458	0.0001
t distribution	0.1553	0.7435	13.6871	-0.1023	0.0001
GED	0.1859	0.7387	14.8963	-0.1361	0.0001

Table 6. EARCH $(1,1)$-M coefficient regression results

EARCH (1,1)-M	α_1	γ_1	M-term coefficient	β_1
Standard normal	-0.1301	0.3017	10.8454	0.8457
t distribution	-0.1378	0.1894	24.3203	0.8349
GED	-0.1178	0.2287	19.4278	0.8348

Table 7. EARCH (2,2)-M coefficient regression results

EARCH (2,2)-M	$\alpha_1;\alpha_2$	$\gamma_1;\gamma_2$	M-term coefficient	$\beta_1;\beta_2$
Standard normal	-0.2111;0.2276	0.2152;-0.1653	3.5311	1.7268;-0.7365
t distribution	-0.2117;0.2221	0.0992;-0.0473	10.6956	1.6794;-0.6932
GED	-0.2121;0.2147	0.1512;-0.1071	11.1573	1.7022;-0.7121

4. Conclusions

In this paper, the ARMA-LSTM model is established to measure the value at risk of the Shanghai Composite Index and compare it with the actual loss of the index. The prediction effect is tested through the failure frequency method. Typically, ARMA models assume that the perturbation terms of time series data satisfy the normal distribution assumption. However, by combining the basic characteristics of the exponential rate of return with the kernel density function graph, $t(k)$ and GED are used as replacement distribution assumptions to fit the conditional variance equation. Referring to the results of information criteria, Q tests, etc., finally, three models (TARCH (1,1)-M, EGARCH (1,1)-M, and EGARCH (2,2)-M) are selected to estimate the conditional variance of the return rate of the Shanghai Composite Index and calculate the VaR value. Furthermore, although the fitting effect of the ARMA model under the training set is basically in line with expectations, in the test set, especially in the medium and long-term prediction, it shows the problem of poor linear prediction effect on the closing price series of the Shanghai Composite Index, and the coverage effect of the VaR value on the actual loss is relatively poor. Therefore, this paper introduces the ARMA-LSTM hybrid model to improve the prediction accuracy of the closing price series. Judging from the time trend chart, the prediction results of this model are basically consistent with the actual trend of the index closing price. The prediction results are used to estimate the daily VaR value, and the coverage effect of the obtained prediction results on the actual loss is significantly improved. Finally, after a preliminary analysis of the policy purpose of the registration system reform, this paper examines the impact of the implementation of this policy on the overall risk level of China's stock market through the TGARCH (1,1)-M model. The results show that the full implementation of the registration system has significantly reduced the volatility level of the overall market represented by the Shanghai Composite Index, providing some evidence that the registration system can curb speculative and manipulatory behaviors in China's stock market.

5. References

References

[1] M. B. Devereux and C. Yu, (2020) *"International financial integration and crisis contagion"* **The Review of Economic Studies** ***87***(3): 1174–1212. DOI: http://mcej.modares.ac.ir/article-16-7658-en.html.

[2] A. A. Syed, (2025) *"Assessing the role of global and regional economic integration on financial inclusion among BRICS economies"* **Journal of Financial Economic Policy**: DOI: 10.1108/JFEP-08-2024-0236.

[3] E. G. Mendoza, V. Quadrini, and J.-V. Rios-Rull, (2009) *"Financial integration, financial development, and global imbalances"* **Journal of Political economy** ***117***(3): 371–416. DOI: 10.1086/599706.

[4] I. Morkūnaitė, D. Celov, and R. Leipus, (2024) *"Evaluation of Value-at-Risk (VaR) using the Gaussian Mixture Models"* **Research in Statistics** ***2***(1): 2346075. DOI: 10.1080/27684520.2024.2346075.

[5] F. M. Müller and M. B. Righi, (2024) *"Comparison of value at risk (VaR) multivariate forecast models"* **Computational economics** ***63***(1): 75–110. DOI: 10.1007/s10614-022-10330-x.

[6] S. Yin, H. Li, A. A. Laghari, L. Teng, T. R. Gadekallu, and A. Almadhor, (2024) *"FLSN-MVO: Edge Computing and Privacy Protection Based on Federated Learning Siamese Network With Multi-Verse Optimization Algorithm for Industry 5.0"* **IEEE Open Journal of the Communications Society** ***6***: DOI: 10.1109/OJCOMS.2024.3520562.

[7] Y. He, C. Zhu, and C. Cao, (2024) *"A wind power ramp prediction method based on value-at-risk"* **Energy Conversion and Management** ***315***: 118767. DOI: 10.1016/j.enconman.2024.118767.

[8] K. Syuhada, R. Puspitasari, I. K. D. Arnawa, L. Mufaridho, E. Elonasari, M. Jannah, and A. Rohmawati, (2024) *"Enhancing Value-at-Risk with Credible Expected Risk Models"* **International Journal of Financial Studies** ***12***(3): 80. DOI: 10.3390/ijfs12030080.

[9] S. M. Shariff, (2022) *"Autoregressive integrated moving average (ARIMA) and long short-term memory (LSTM) network models for forecasting energy consumptions"* **European Journal of Electrical Engineering and Computer Science** ***6***(3): 7–10. DOI: 10.24018/ejece.2022.6.3.435.

[10] Z. S. Khozani, F. B. Banadkooki, M. Ehteram, A. N. Ahmed, and A. El-Shafie, (2022) *"Combining autoregressive integrated moving average with Long Short-Term Memory neural network and optimisation algorithms for predicting ground water level"* **Journal of Cleaner Production** ***348***: 131224. DOI: 10.1016/j.jclepro.2022.131224.

[11] H. Cao, Y. Li, W. Chen, J. Chen, et al., (2017) *"Systemic risk in China's interbank lending market"* **Journal of Mathematical Finance** ***7***(01): 188. DOI: 10.4236/jmf.2017.71010.

[12] G.-J. Wang, C. Xie, Z.-Q. Jiang, and H. E. Stanley, (2016) *"Extreme risk spillover effects in world gold markets and the global financial crisis"* **International Review of Economics & Finance** ***46***: 55–77. DOI: 10.1016/j.iref.2016.08.004.

[13] D. Ardia, K. Bluteau, K. Boudt, L. Catania, and D.-A. Trottier, (2019) *"Markov-switching GARCH models in R: The MSGARCH package"* **Journal of Statistical Software** ***91***: 1–38. DOI: 10.18637/jss.v091.i04.

[14] S. Chen, B. Zhang, and J. Deng, (2018) *"Research on Risk Measurement in Financial Market Based on GARCH-VaR and FHS——An Example of Chinese Bond Market"* **Applied Economics and Finance** ***5***(4): 102–116. DOI: 10.11114/aef.v5i4.3307.

[15] S.-S. Lin, (2014) *"Investigation of forecasted risk inter-relationship: base on GARCH model, causality in China markets"* **Journal of Business Economics and Management** ***15***(5): 853–861. DOI: 10.3846/16111699.2013.839474.

[16] I. D. Ratih, B. S. S. Ulama, and M. Prastuti. "Value-at-Risk analysis using ARMAX GARCHX approach for estimating risk of banking subsector stock return's". In: *Journal of Physics: Conference Series*. ***974***. 1. IOP Publishing. 2018, 012029. DOI: 10.1088/1742-6596/974/1/012029.

[17] I. Yousaf, M. Youssef, and M. Gubareva. "Return and Volatility Spillovers Between Non-fungible Tokens and Conventional Currencies: Evidence from the TVP–VAR Model". In: *Blockchain, Crypto Assets, and Financial Innovation*. Springer, 2025, 326–351. DOI: 10.1007/978-981-96-6839-7_12.

[18] J. Anttonen, M. Lanne, and J. Luoto, (2024) *"Statistically identified structural VAR model with potentially skewed and fat-tailed errors"* **Journal of Applied Econometrics** ***39***(3): 422–437. DOI: 10.1002/jae.3019.

[19] J. Yu, L. Zhao, S. Yin, and M. Ivanović, (2024) *"News recommendation model based on encoder graph neural network and bat optimization in online social multimedia art education"* **Computer Science and Information Systems** ***21***(3): 989–1012. DOI: 10.2298/CSIS231225025Y.

[20] A. Jisi, S. Yin, et al., (2021) *"A new feature fusion network for student behavior recognition in education"* **Journal of Applied Science and Engineering** ***24***(2): 133–140. DOI: 10.6180/jase.202104_24(2).0002.

[21] W.-X. Ma and E. Fan, (2011) *"Linear superposition principle applying to Hirota bilinear equations"* **Computers & Mathematics with Applications** ***61***(4): 950–959. DOI: 10.1016/j.camwa.2010.12.043.

[22] S. Kim, J. Son, and B. Shim, (2021) *"Energy-efficient ultra-dense network using LSTM-based deep neural networks"* **IEEE Transactions on Wireless Communications** ***20***(7): 4702–4715. DOI: 10.1109/TWC.2021.3061577.