Exchange Rate, Investor Sentiment, and Fluctuation of China A-share Market

Xiaotong Zhu
eone@zhongxincc.com

Mathematics and Statistics, Minnan Normal University, Zhangzhou, China

Abstract—The development quality of China's stock market is related to the healthy development of the financial system and national economy, and it also affects the development speed of urbanization. Based on time series VAR model and EViews, this paper use the exchange rate of RMB and investor sentiment to conduct empirical analysis on the fluctuations of China's A-share market. Through computer simulation and calculation, the experimental results show that the change in investor sentiment and the fluctuation of the Chinese A-share market are Granger causes for each other. The impact of the changes in investor sentiment on the volatility of China's A-share market is stronger than that of changes in the RMB exchange rate, but the impacts are both limited. This paper illustrates the dynamic relationship between the volatility of China's A-share market, RMB exchange rate, and investor sentiment.

Keywords- A-share market; Investor sentiment; VAR model; Granger causality test

1 INTRODUCTION

At present, China's stock market has experienced many years of development. Since reform and liberalization, the Chinese economy has seen rapid growth. Also, China's stock market has gradually developed. However, there are huge market fluctuations in China's stock market. The greater the market fluctuation, the more likely it is to have a negative impact on the financial system and national economy. A large number of scholars have carried out a great deal of theoretical and applied research into the factors influencing market volatility and analysed the mode and degree of influence, to effectively reduce the market volatility and promote the healthy development of the stock market. Among them, Qi 'an Chen, Hui Zhang, and Shuyu Chen constructed GARCH-type model for empirical analysis and remarked that the introduction of forward trading on stock indices would alter the structure of investors and the behaviour of investors on the stock market, thus having an impact on the volatility of the stock market [1]. Bo Zhang, Wenxiu Hu, and Xi 'an Yang used the VAR model and Granger causality test to empirically analyze the actual effect of margin lending and short sales on the volatility of stock market due to the continuous expansion of margin lending and short sales in China [2]. By summarizing these research results, it can be concluded that the influencing factors of China's stock market volatility are very complex. Nowadays, the internationalization degree of China's financial market is constantly improving, and the correlation between the stock exchange and the currency exchange is increasingly obvious. At the same time, as one of the important transmission channels of monetary policy, exchange rate fluctuations have attracted extensive attention from the public and investors. When investor sentiment changes and the "herd effect"

FFIT 2022, October 28-30, Shenzhen, People's Republic of China

DOI 10.4108/eai.28-10-2022.2328400

is formed in the established market, the consensus expectation formed by market participants is bound to have an impact on the market.

Therefore, this paper will select appropriate indexes, starting from two aspects of RMB exchange rate and investor sentiment, and use EViews to construct VAR model to conduct empirical analysis of China's A-share market volatility, and further study the dynamic relationship between China's A-share market volatility, RMB exchange rate, and investor sentiment.

The first part of this paper is the introduction, the second part is the literature review, the third part includes data processing and research methods, the fourth part is empirical analysis and testing based on VAR model, and the fifth part is the summary.

2 LITERATURE REVIEW

2.1 Research on Investor Sentiment and Stock Market Fluctuation

At present, the literature on investor sentiment and stock market volatility is quite abundant. Yuan Yao, Qi Zhong, and Beibei Yao point out the existence of noise trading in the stock market. VAR model is used to prove that noise trading and stock market volatility have a one-way causative relationship. And the stock market is heavily influenced by noise trading. The more noise traders there are, the more intense the stock market volatility in China will be [3]. Fangzhao Zhou and Shaoqing Gu used the stepwise regression method, the between January 2010 and June 2018, the data is analyzed, and the results show that the uncertainty of economic policy under the different markets exists asymmetric volatility in the market, compared with institutional investors, the uncertainty of economic policies more easily through the retail sentiment on the stock market impact [4]. Wenqi Yang and Yan Wang selected the daily frequency time-series data of the KEChuang Board and constructed comprehensive indicators of investor sentiment, herd behavior, and market volatility based on a non-parametric HS model and other methods. The TVP-VAR model was established to prove that the influence of investor sentiment on market volatility does not have a time-varying effect and decreases with time. Herd behavior has a time-varying effect on market volatility and accumulates over time [5]. Xinyue Zhao empirically analyzed the causality and mechanism of policy and public opinion as the core influencing factors of investor sentiment against the background of China's non-tradable shares reform. Research conclusion: The interaction between the dominant and misleading social public opinion and the lag and discomfort of policies leads to the fluctuation of investor sentiment, and then leads to the irrational slump and surge before and after the reform of non-tradable shares [6].

2.2 Currency market and stock market research

In addition, there are also literature studies of the relation between the stock exchange and the currency exchange. Baicheng Zhou, He Zhang, and Qiguojian Can's VAR-GARCH (1,1) -bekk model demonstrated a strong correlation between the fluctuation in the exchange rate of the RMB and the fluctuation in the rate of return of the stock market industry, but there was no obvious asymmetry in the spillover effect of the fluctuation [7]. Dengkui Si et al. used TVP-SV-BVAR model to conduct an empirical study, and the results showed that investor sentiment had a significant impact on stock price in a short term but had a lag effect on the exchange rate, and stock price changes would not only have a direct impact on exchange rate [8]. Yun Chen, Langnan Chen, and Ludong Lin adopted the BVGarCH-BekK model, combined with the LR likelihood ratio test and Wald test, to experientially study the volatility spillover effect between the RMB exchange rate and the stock market. The findings suggest that the RMB exchange rate and the stock market have volatility spillover effects, with performance differing before and after the exchange rate reform [9].

In view of the above literature, this paper uses the RMB exchange rate and investor sentiment to construct VAR model to conduct an empirical analysis of China's A-share market volatility and studies its dynamic changes through impulse response and variance analysis.

2.3 Investor sentiment index

Due to the inherent complexity and dynamic variation of investor sentiment, it is particularly difficult to accurately measure it. Baker and Wurgler use principal component analysis to select multiple implicit indicators to construct a comprehensive index of investor sentiment [10]. Using the method of Baker and Wurgler for reference and combining China's national conditions, Xiaokui Ma and Jie Sun selected six indicators, such as discount rate of closed-end fund, IPO number, IPO first-day return rate, market trading volume, turnover rate, and consumer confidence index as proxy indicators to measure changes in investor sentiment. This study creates an ISI index that better reflects the variability in Chinese investor sentiment while excluding probable macroeconomic influences. The findings suggest that ISI is capable of explaining the fluctuations in China's stock market [11]. Xingji Wei, Weili Xia, and Tongtong Sun systematically analyzed the theoretical method of sentiment measurement, combined with the specific situation of China's securities market, selected six sentiment indicators such as market turnover rate based on the BW model and constructed the monthly investor sentiment index of China's securities market with principal component analysis method. Adjust and improve the calculation formula of some emotional indicators, and eliminate non-emotional factors of indicators through orthogonal regression with macro data [12].

Therefore, according to the literature, the StdExMacroISI index, namely the standardized investor sentiment index after excluding macroeconomic factors, is selected as the investor sentiment index, and its calculation formula is as follows:

$$ISI = 0.634NA + 0.536TURN + 0.391CCI + 0.272DCEF + 0.079NIPO + 0.552RIPO \tag{1}$$

Where NA is the number of newly opened accounts, TURN is the market turnover rate, i.e. (monthly market turnover/average value of the total market value of the last two months) * (average trading days of each month/accumulated trading days of each month), CCI is consumer confidence, DCEF is the average discount rate of closed-end funds, NIPO is the number of IPOs, RIPO is the average first-day return rate of IPO stocks.

3 RESEARCH DESIGN

3.1 Data source and variable selection

This paper conducts empirical analysis based on monthly data from January 2003 to February 2020 from the Bank for International Settlements and WIND database. Each variable contains 230 sample data and 690 sample data in total.

EViews, short for Econometrics Views, is a time series software package developed specifically for large organizations to process time series data. Therefore, the empirical analysis part of this paper uses EViews to conduct a series of data processing and model construction.

In this paper, the standardized investor sentiment index ISI after excluding macroeconomic factors is selected as the index of investor sentiment. Regarding the selection of indicators of the RMB exchange rate, the nominal effective exchange rate and the real effective exchange rate are the most common divisions of the effective exchange rate. The nominal effective exchange rate of a country is the weighted average of the bilateral nominal exchange rate of its currency and the currencies of all trade partners. It is also feasible to determine the real effective exchange rate by subtracting the impact of inflation on the buying power of each country's currency. The real effective exchange rate considers not only the relative changes in all bilateral nominal exchange rates, but also the influence of inflation on changes in the currency's value, allowing it to correctly represent the domestic currency's external worth and relative buying power. Therefore, the real effective exchange rate of RMB is used as the index of the exchange rate of RMB in this article.

As for the index selection of A-share market volatility, the CSI 300 index is a weighted average of the 300 equities in the Shanghai and Shenzhen stock exchanges with the highest market value and greatest liquidity. In addition, its weighted industry distribution is relatively more balanced and it is more consistent with the industry distribution of the real economy. It has a good market representation and is known as the "barometer" of China's economy. The compilation method of the CSI 300 Index is reasonable and effective with wide and balanced coverage, which is highly representative of the overall performance of the A-share market. Therefore, this paper selects the closing price of the CSI 300 index as the index of a-share market volatility.

3.2 Data analysis

The closing price of the CSI 300 index is set as the dependent variable, and the real effective exchange rate of RMB and the investor sentiment index are set as the independent variables. The Cobb-Douglas production function is selected to establish the relationship model between variables, and the model is empirically analyzed through EViews7.2 software. The basic form of the function is as follows:

$$V = \alpha R + \beta S + \mu \qquad (2)$$

Where V is the closing price of the CSI 300 index, R is the real effective exchange rate of RMB, S is the investor sentiment index,α and β are the elastic coefficients of factors, and μ is the influence of random interference ($\mu \leq 1$).

Correlation analysis of variables to get correlations between variables.

Table 1 Correlation analysis

	V	R	S
V	1	0.6522	0.8106
R	0.6522	1	0.4237
S	0.8106	0.4237	1

As can be seen from Table 1, the correlation coefficient between V and R is 0.6522, indicating an obvious positive correlation. the correlation coefficient between V and S is 0.8106, indicating a significant positive correlation. the correlation coefficient between R and S is 0.4237, indicating a moderate positive correlation.

After a simple regression analysis of Formula (2), get

$$V = -147.5905 + 28.5407R + 520.6701S$$
$$P = \quad (0.6094) \quad (0.0000) \quad (0.0000) \tag{3}$$
$$\overline{R^2} = 0.7713$$

The decidable coefficient in the regression analysis results can be used to measure the goodness of fit of the equation, and the decidable coefficient can be obtained by regression sum of squares (ESS) and the total sum of squares (TSS). Where determination coefficient$R^2 = SSR/SST$, and modified determination coefficient$\overline{R^2} = 1 - [RSS/(n-k)]/[TSS/(n-1)]$. The goodness of fit of this regression equation is 77.33%, indicating that there is a certain linear regression relationship between the closing price of the CSI 300 index, investor sentiment, and the RMB exchange rate. However, the goodness of fit of this equation is not particularly high, so the model needs to be adjusted progressively.

3.3 VAR model specification

This paper mainly analyzes the samples by constructing a VAR model. VAR model usually selects stationary data to establish, which takes each variable as the explained variable and each explained variable regresses several lag values of itself and other explained variables. The general form of this model is

$$Z_t = \alpha_0 + \sum_{i=1}^{k} A_i Z_{t-i} + \varepsilon_t \tag{4}$$

Where Z_t is the vector composed of the corresponding values of variables at the t-time, α_0 is the vector composed of intercept terms, k represents lag order, t is the year, and ε_t is the vector composed of random error terms.

The VAR model is typically composed of multiple variables and multiple periods of latency, and it is probable that there is a high level of multicollinearity between the variables, leading to non-significant variables. Consequently, the importance of the variables is generally not verified, but the impulsive response and variance decomposition of the VAR model are used in the audit analysis.

Each variable in the VAR model is interdependent, so the independent coefficient estimation can only reflect limited information. In order to better study the dynamic behavior of the model, impulse response (IR) is selected to judge whether the variables have a long-term equilibrium connection. The impulse response function is used to measure a standard deviation of the random disturbance caused by the impact of an endogenous variable. The function might represent the dynamic effect of other variables in the model once one variable in the VAR model is influenced. The impulse response graphs are created using dynamic changes in these variables over time after being subjected to this shock.

The influence of one endogenous variable on other endogenous variables can be represented by the impulse response function when it receives an impact in the VAR model. While variance decomposition can reflect the proportion of changes in the sequence due to the impact of its impact and other variables so as to evaluate the impact degree of different variables. Therefore, in the empirical analysis of the paper, the method of variance decomposition will be used to study the degree to which the first variable will be affected by the other two variables in the future changes, in addition to being affected by its impact.

4 EMPIRICAL RESULTS

4.1 Stationarity test

When establishing the VAR model, the stationarity of data needs to be considered first, so the ADF test is employed in the unit root test to determine if the sequence is stationary. If the ADF test is passed, that is, the sequence is stationary. Otherwise, the sequence is non-stationary, and the ADF test shall be carried out after differential processing of the original sequence. The results of the ADF test of the original sequence are shown in Table 2.

Table 2 ADF test

Variables	t-statistic	p-value
V	-3.7653	0.0202**
R	-3.0266	0.1273
S	-3.3718	0.0008***

From the ADF test results of the original sequence in Table 2, the P-value corresponding to R in the original sequence is greater than 0.05, which accepts the null hypothesis, that is, there is a unit root, and R is a non-stationary sequence. At a 5% significance level, the P-values for V and S in the original sequence are both less than 0.05, rejecting the null hypothesis. That is, there is no unit root, and V and S are both stationary sequences. Therefore, the unit root test should be performed after differential processing of the original sequence. The ADF test results of the above four original sequences after first-order difference processing are shown in Table 3.

Table 3 Revised ADF test

Variables	t-statistic	p-value
DV	-13.8072	0.0000***
DR	-10.6343	0.0000***
DS	-13.8479	0.0000***

According to the revised ADF test results in Table 5, the P values corresponding to ADF tests of DV, DS, and DR are all 0.0000, meaning that all sequences reject the null hypothesis at the significance level of 1%, that is, there is no unit root. The results show that sequences after first-order differential processing are stationary sequences, therefore, the differential data is used for the establishment of vector autoregression (VAR) models.

4.2 VAR order identification

Before the VAR model, the optimal lag order should be determined according to AIC and SBIC criteria. VAR model is established based on the serial data of Fujian's regional GDP, urban per capita disposable income, the number of employments, and total import and export trade. The lag structure test is conducted to determine the optimal lag order. The test results are shown in Table 4.

Table 4 VAR order identification

Lag	Log L	LR	FPE	AIC	SBIC	HQIC
0	-2218.4100	NA	82486.5700	19.8340	19.8797	19.8525
1	-2176.8530	81.6306	61679.7500	19.5433	19.7261*	19.6171*
2	-2165.5670	21.8671	60436.4600	19.5229	19.8428	19.6520
3	-2157.7820	14.8749	61102.8100	19.5338	19.9907	19.7182
4	-2140.9800	31.6531*	57003.5600*	19.4641*	20.0581	19.7039
5	-2137.0400	7.3172	59658.1900	19.5093	20.2404	19.8044

The VAR(m) model is constructed based on the results shown in Table 6, where M represents the selected lag order. According to the asterisk marked automatically by the software, it can be judged that the order that satisfies the greatest number of criteria to be met is 4th order. Therefore, the optimal lag order in the 4th order, that is, the 4th order is selected as the lag order to establish a VAR (4) model.

4.3 Stationarity test of VAR model

The AR root test is necessary prior to impulsive response and VAR-based variance decomposition. Only if the model passes this test can it proceed to the next step. If the model is unsteady, the pulse response chart will be emanative and it can not be confirmed. The AR root test criterion is that all the roots of the AR(P) characteristic polynomial are within the unit circle.

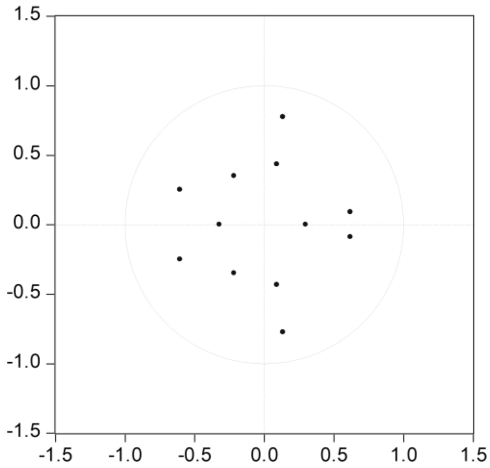

Figure 1. AR root test

The AR root test results from Figure 1 show that all points are in the unit circle, and all characteristic polynomial coefficients of AR are less than 1, that is, the VAR (4) model has passed the test and is stable. As a result, the model is ready for further testing and may be used to create impulse response graphs and a variance decomposition table.

4.4 Granger causality test

The purpose of the Granger causality test is to confirm the causal relationship among variables, that is, to see if one variable's combined lag impacts another variable. Table 5 presents the outcomes of the Granger causality test.

Table 5 Granger causality test

Dependent variable: DV				Dependent variable: DS			
Excluded	Chi-sq	df	Prob.	Excluded	Chi-sq	df	Prob.
DS	20.5449	4	0.0004	DV	54.3409	4	0.0000
DR	8.0395	4	0.0901	DR	0.9000	4	0.9246
All	27.9639	8	0.0005	All	58.1731	8	0.0000

The probability of P-value corresponding to the chi-square value is 0.0004 when assessing if DS seems to be the cause of DV change. Rejecting the null hypothesis at a significance level of 1%, DS is the Granger cause of the DV change. The probability of P-value corresponding to the chi-square value is 0.0000 when assessing if DV seems to be the cause of DS change. Rejecting the null hypothesis at a significance level of 1%, DV is the Granger cause of the DS change, and both cause the development and change of each other. Similarly, DR is the Granger cause of DV change at a 10% significance level, but DR is not the Granger cause of DS. In addition, the p-value corresponding to the joint significance is 0.0000, indicating that the VAR model is overall significant, that is, from the perspective of long-term development, all factors are endogenous variables, which can be analyzed in the next step.

4.5 Impulse response analysis of VAR model

The impulse response can response to the dynamic interaction among variables. The direction of brief fluctuations induced by fluctuations and fluctuations changes with time once a variable has each unit standard error impact on another variable. The diagram presented in figure 2 are respectively DV for DV, DR for DV, and DS for DV impulse response figure, take 10 period study period.

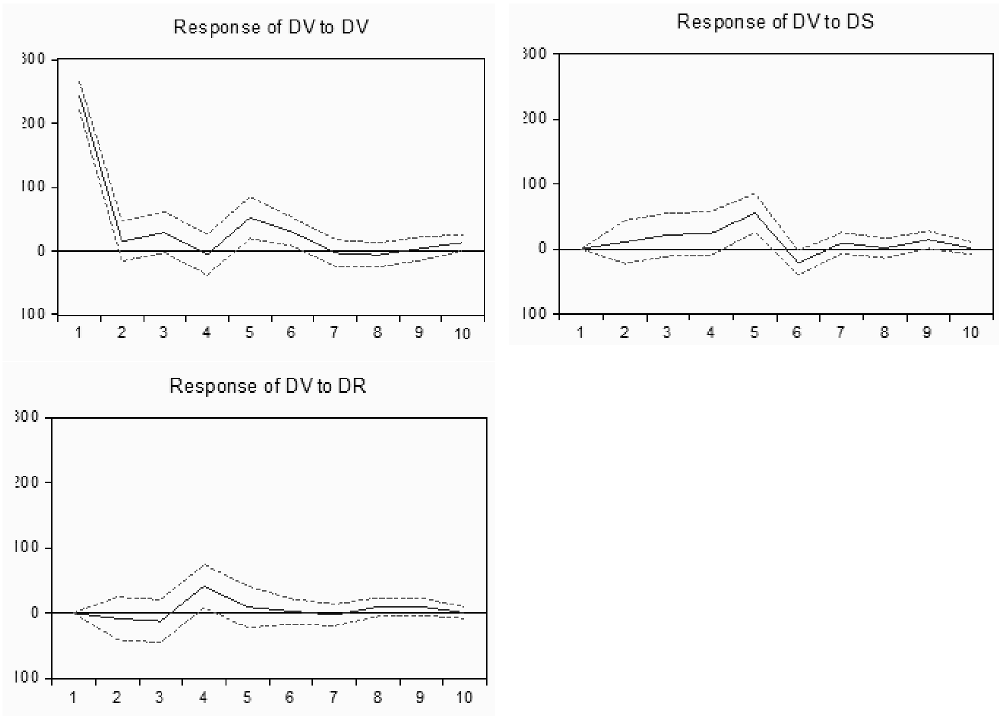

Figure 2. Impulse response

According to Figure 2, when the DV produces a unit of the standard deviation of positive impact on itself, DV at the first stage is the maximum of forwarding impact response, and then decreases rapidly. After a period of fluctuation, DV converges to 0 after the seventh stage. The impact intensity and duration of shock reaction indicate that the closing price of the CSI 300 index fluctuates greatly after being impacted, so we should pay close attention to the changes in China A-share market in real-time.

When DR produces a unit of the standard deviation of positive impact on DV, DV in the first phase of the response is 0. After then, there is a positive impact response. In the 5th step, the positive impact reaction reached its peak. Then, in the 6th period, it progressively declined and began to swing around zero.

When the DS produces a unit of the standard deviation of positive impact on DV, DV in the first phase of the response is 0, followed by a small negative shock reaction. As the period increases, the negative impact response decreases, and a positive shock reaction is gradually produced. The maximum value of the forward impact reaction is reached in the 4th period, followed by a decrease in the positive impact reaction and convergence at 0 in the 5th period.

The results show that, over time, changes in the exchange rate of the RMB and investor attitude will have a positivel influence on China's A-share market over time, with investor sentiment having a bigger impact than the RMB exchange rate, but the impact of both are limited.

4.6 Variance decomposition

After the positive and negative impacts of independent variables on dependent variables were obtained by impulse response, variance analysis was conducted on the model to further understand the impact proportion of shocks. The variance decomposition of VAR (4) model is carried out below, and the research period is set to 10 periods. The results are shown in Table 6.

Table 6 Variance decomposition

Period	S.E.	DV	DLNS	DLNR
1	243.7723	100	0	0
2	244.6195	99.7034	0.1852	0.1114
3	247.6001	98.6713	0.9735	0.3552
4	252.2355	95.1284	1.8494	3.0223
5	263.6391	91.0058	6.1127	2.8815
6	266.2026	90.5091	6.6553	2.8356
7	266.3948	90.3926	6.7626	2.8448
8	266.6359	90.2830	6.7527	2.9642
9	267.2019	89.9199	7.0024	3.0778
10	267.5205	89.9423	6.9871	3.0706

According to the results in Table 6, the proportion of DV's impact on self-disturbance gradually decreased from 100% in the 1st step to 89.94% in the 10th step, while the influence of DS on DV rose from 0% in the 1st step to 6.99% in the 10th step, indicating that DS has a certain short-term impact on DV. Similarly, the influence ratio of DLNR on DLNS increased from 0 liters in the first phase to 3.07% in the 10th phase, and DLNR also had a certain short-term influence on DLNS. Namely in the a-share market fluctuations, the change of investor sentiment on its probably at around 7%, and the impact of changes in the exchange rate of RMB on its effect will be around 3%. By contrast, investor sentiment on the impact of China's a-share market compared to the impact of the RMB exchange rate will become stronger. But the explanation is limited, it may be that the reasons for the formation of fluctuations in China's A-share market are quite complex.

5 CONCLUSION

The oscillations of China's A-share market are studied empirically in this research from the exchange rate of RMB and investor sentiment based on monthly data from January 2003 to February 2020 from the Bank for International Settlements and the WIND database. The model selects CSI 300 index closing price as the measure of China's a-share market price, the SIS Investor Sentiment Index to measure investor sentiment, and the real effective exchange rate of RMB to measure the exchange rate of RMB. The VAR model is constructed by EViews to better study the dynamic relationship between variables. Through computer simulation and calculation, the experimental results show that:

Through correlation analysis and simple regression of variables, it is found that there is a regression relationship between the closing price of the CSI 300 index, RMB real effective exchange rate, and investor sentiment index. And there is an obvious positive correlation between explained variables and explanatory variables. It indicates that the rise of the RMB exchange rate and the optimism of investors can promote the price rise of China's A-share market.

The original sequence of each variable is non-stationary under the significance of 5%, but their first-order difference is stationary. The results show that the equilibrium and stability of the relationship between China's A-share market price, RMB exchange rate, and investor sentiment occasionally deviates. But the deviation does not always exist, and it will be restored to equilibrium and stability through the adjustment of the market economy.

Under the significance of 10%, the Granger cause of China's A-share market volatility is a change in the RMB exchange rate. Under the significance of 1%, the Granger cause of China's A-share market volatility is a change in investor sentiment. And the fluctuation of the Chinese A-share market is also the Granger cause of the change in investor sentiment, and the two cause the development and change of each other.

Through impulse analysis and variance decomposition of the VAR (4) model, it can be concluded that changes in the exchange rate of RMB and investor sentiment will have a certain effect on the fluctuations of China's A-share market. And investor sentiment will have a stronger impact on China's A-share market comparatively. But the impacts of both are limited, it may be that the reasons for the formation of fluctuations in China's A-share market are quite complex.

REFERENCES

[1] Q Chen, H Zhang and S Chen, “Does stock index futures trading increase the stock market volatility in China? ——theoretical and empirical research based on investor structure,”Chinese Journal of Management Science, vol. 28, pp. 1-13. April 15, 2020.

[2] B Zhang, W Hu and X Yang, “Empirical study of the impact of margin trading system on Chinese stock market volatility,” Journal of Industrial Engineering and Engineering Management, vol. 31, pp. 109-115, October 15, 2017.

[3] Y Yao, Q Zhong and B Yao, “Research on the relationship between investor emotion and stock market volatility——based on the analysis of the relationship between noise trading and the irrational fluctuation of stock market price,” Price:Theory & Practice, pp. 92-95, May 8, 2019.

[4] F Zhou and S Jia, “Economic policy uncertainty, investor sentiment and volatility of China's stock market,” Financial Regulation Research, pp. 101-114, August 25, 2019.

[5] W Yang and Y Wang, “Investor sentiment, herd behavior and market volatility——empirical research on TVP-VAR Model based on SSE STAR Market,” Journal of Industrial Technological Economics, vol. 40, pp. 72-81, March 1, 2021.

[6] X Zhao, “Analysis on Factors Affecting the Sentiment of Securities Investors and the Causality of Market Volatility,”Journal of Financial Development Research, pp. 81-85, June 11, 2018.

[7] B Zhou, H Zhang and Q Cao, “Industry Heterogeneity of Volatility Spillover Effects between RMB Exchange Rate and Stock Market,” Taxation and Economy, pp. 55-61, September 15, 2021.

[8] D Si, X Li, C Jiang and X Ge, “Investor sentiment, herd behavior and market volatility——empirical research on TVP-VAR Model based on SSE STAR Market,” Journal of Industrial Technological Economics, vol. 40, pp. 72-81, March 1, 2021.
[9] Y Chen, L Chen and L Lin , “Volatility spillover effects between RMB exchange rate and stock market,” Journal of Management Sciences, vol. 22, pp. 104-112, June 20, 2009.
[10] M Baker and J Wurgler, “Investor sentiment and the Cross-Section of stock returns,” The Journal of Finance, vol. 61, pp. 1645-1680, August 1, 2006.
[11] X Ma and J Sun, “A study on investor sentiment index building in China stock market,” Journal of Beijing Technology and Business University(Social Science), vol. 27, pp. 89-95, November 18, 2012.
[12] X Wei, W Xia and T Sun, “Research on investor sentiment measurement in A-share market based on BW model,” Management Observer, pp. 71-73, November 25, 2014.