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Research on the Effect of Investor Sentiment on the Stock Volatility in China Market

—Based on Asymmetric GARCH-VAR Model

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***Abstract*: ** Based on the information processing deviation in Behavioral Finance Theory, this paper, taking China stock market as the research object, discusses the effect of the overall emotional state of Chinese investors affected by information processing deviation on the stock volatility in the composite market of Shanghai and Shenzhen A-shares (SSAS) and the Science and Technology Innovation Board (STIB). Taking the current situation of China stock market into account, this paper selects the monthly comprehensive index of investor sentiment (CICSI_SDR) from March 2013 to March 2023, as well as the monthly stock returns in the composite market of SSAS and STIB. Then the volatility of stock returns is measured by the asymmetric GARCH model, then further combined with the comprehensive index of investor sentiment (CICSI_SDR), the asymmetric GARCH-VAR model is established. The research results found that there is a positive weak correlation between two variables, that is, the investor sentiment would drive the prosperity of financial market if that in the past upsurged and vice versa. Therefore, to better control market anomalies caused by investor sentiment, this paper suggests that the market should establish an evaluation mechanism for investor sentiment and gradually make the investor structure of China stock market be more reasonable.

Keywords: investor sentiment, Shanghai and Shenzhen A-shares, science and technology innovation board, volatility of stock returns, asymmetric GARCH-VAR model

1. Introduction

Traditional financial theory believes that investors are all rational and will make investment decisions according to utility maximization. However, since the 1970s, frequent occurrence of financial market anomalies has been unable to be explained by traditional financial theory, then Behavioral Finance Theory was born accordingly. The information processing deviation in Behavioral Finance Theory shows that investors are not with complete rationality, but with bounded rationality [1]. The bounded rational behavior of investors will lead to the fluctuation of share price and yield in financial market, and increase systematic risk. With the development of technology, China stock market has developed rapidly but without a complete system, also the proportion of individual investors far exceeds that of

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institutional investors. Under such an environment, investor sentiment caused by both the asymmetry of market information and information processing deviation becomes more obvious. Investor sentiment, a branch of Behavioral Finance Theory, has gradually become a hot topic for studying market anomalies. Due to the lack of professionalism of individual investors and human beings' inherent information processing deviation, investors often cannot make objective and fair investment decisions, instead they are dominated by their thoughts, resulting in various abnormal phenomena which may generate more investor sentiment [2].

At present, in the literature related to finance, scholars define investor sentiment from multiple perspectives. Some scholars believe that investor sentiment is a systematic risk that affects market prices due to the asymmetric information and the cognitive bias of market participants in information processing, leading to incorrect judgment on the value of assets. However, other scholars insist that investor sentiment is not only investors' erroneous prior belief in future asset price or returns, but also their tendency towards future speculation. In addition, Zhang and Wang reckon that investor sentiment is more the subjective when investing as market participants [3]. In 2006, Baker and Wurgler constructed the famous and authoritative comprehensive index of investor sentiment, called the BW index, by using principal component analysis (PCA) with selected six proxy variables, proving that people can use investor sentiment indicators to predict stock returns [4]. Based on the improved BW index construction method, many scholars respectively selected required indicators to construct comprehensive index, in order to better measure the investor sentiment in China stock market [5-7]. The PCA method can break through the constraints on noise -- it needs to be without relationship in the discrete state and follow Gaussian distribution -- thereby eliminating the effect of noise on investor sentiment, making the results more realistic and persuasive.

With the development of theory and technology, a large amount of scholars have begun to devote themselves to studying the predictive ability of investor sentiment indicators on stock returns. Dong did research showing that in medium and long term, the correlation between lagged investor sentiment and market returns is negative, which can be used to explain the reversal effect of market returns [8]. You et al. extracted proxy investor sentiment indicators from Twitter, and used Granger non-causality test for analysis [9]. The results showed that only when high would the sentiment affect stock returns, while only low returns would affect sentiment indicators. Zhou used Granger causality test and vector autoregression (VAR) model to verify that investor sentiment and stock market returns are mutually causal, between them a bidirectional positive correlation, and established GARCH model with exogenous variables to prove that investor sentiment also has an amplification effect on market volatility [10]. Li used PCA to construct a comprehensive investor sentiment index that excludes macro factors, and established VAR model for the relationship between investor sentiment and stock returns, indicating a negative correlation between them [11]. Regarding the model construction, to overcome the limitation that successful modeling requires causal relationship between variables has been determined, Sims proposed the VAR model, which does not require distinguishing between independent variables and dependent variables, nor does require determining the economic meaning of each equation, making it relatively more convenient to study the dynamic relationship between variables [10]. Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model is a modification of ARCH model [12]. For simulating the volatility of time series variables, GARCH model has a relatively better simulation effect, making up for the shortcomings caused by the constant variance assumption. On the basis of the statistical results, there is generally a serious volatility clustering in stock returns series. Therefore, Ding constructed the GARCH-VAR model, proving that at a certain confidence level, the GARCH-VAR model can be used to predict risks so as to achieving the goal of controlling risks [13].

However, there still are shortcomings in the existing literature. Firstly, most of the existing literature, taking stock returns or stock price volatility as an independent variable, focus on the

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unilateral effect of investor sentiment on either of the two variables. Nevertheless, in fact, investor sentiment can also have an influence on the volatility of stock returns which is used as a single variable [14]. Furthermore, most scholars, when doing researches related to the relationship between investor sentiment and stock market returns, choose data from a certain market as sample, but few combine data from multiple markets into a comprehensive market data as sample for research. Therefore, overcoming these two shortcomings, this paper studies the effect of investor sentiment on yield volatility. On account of the current situation of China stock market, this paper uses 121 sets of comprehensive indices of investor sentiment (CICSI_SDR) and the volatility of stock returns in the composite market of SSAS and STIB (YIELD), and both variables are on monthly basis, from March 2013 to March 2023. Due to both the asymmetry of market information and information processing deviation, the asymmetric GARCH-VAR model is constructed to analyze the influence of investor sentiment on the volatility of stock returns in China. The empirical research results indicate that there is a causal relationship and a positive weak correlation between investor sentiment and volatility of composite market returns, but it is difficult for investor sentiment to influence significantly. Overall, no matter how investor sentiment change, it may affect the volatility of stock returns in the composite market of SSAS and STIB with the same direction, which explains the emergence of market anomalies.

This paper will elaborate on the empirical research from four parts. The first part is model construction, which will introduce the construction process of the models used in this paper. The second part is indicators selection and variable analysis, which will present data source and the characteristic analysis of variables. The third part is model results analysis, which will describe and analyze the asymmetric GARCH-VAR model results. The last part is the conclusion, which will summarize the research and provide suggestions according to the summary.

2. Model Construction

2.1. ARMA, GARCH and Other Related Models

This section specifically introduces the econometric models required for empirical analysis of comprehensive market returns (YIELD), including ARMA, ARCH and GARCH model.

2.1.1. Mean Model

In general, the comprehensive market returns are stable, while its autocorrelation is generally significant. Therefore, it is necessary to use the ARMA (p, q) model for modeling and examining the characteristic of its own change. The concrete form is as following:

$$\mathrm{YIELD}_t = \mu + \sum_{i=1}^{p} \phi_i \mathrm{YIELD}_{t-i} + \sum_{i=1}^{q} \psi_i \varepsilon_{t-i} + \varepsilon_t \tag{1}$$

Among which, $\mu$is the intercept term,$\sum_{i=1}^{p} \phi_i \mathrm{YIELD}_{t-i}$is the autoregressive term,$\sum_{i=1}^{q} \psi_i \varepsilon_{t-i}$is the moving average term,$\varepsilon_t$is the residual term.

After modeling the variable by above model, it is also necessary to test the conditional heteroscedasticity and autocorrelation of the residual term related to the model (ε_t).If the test result indicates that there is autocorrelation in ε_t, it means that the modeling of the variable is not sufficient so that further lag terms are needed to be added to the model. In addition, variables in stock markets generally have conditional heteroscedasticity, that is, $\varepsilon_t \sim N(0, {\sigma_t}^2)$. If conditional heteroscedasticity is found during the process of ARCH test, it is necessary to continue using conditional heteroscedasticity model for modeling.

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2.1.2. Volatility Model

The classical GARCH (*k, l) model was originally proposed by* Bollerslev (1986). The concrete form is as following:

$$\sigma_t{}^2 = \omega + \sum_{i=l}^{k} \alpha_i \varepsilon_{t-i}{}^2 + \sum_{i=l}^{l} \beta_i \sigma_{t-i}{}^2 \tag{2}$$

Among which, conditional variance $\sigma_t{}^2$ characterizes the volatility of the variable, and the parameters in model (2) meet $\omega > 0$, $\alpha_i \geq 0$ and $\beta_i \geq 0$. If the lag order l in model (2) is zero, then model (2) is the traditional ARCH (k) model.

The classical GARCH model assumes that financial market returns are subject to normal distribution. However, in fact, a large number of studies show that the financial market returns are not subject to the normal distribution with statistical character of leptokurtosis, which may lead to great deviation between the volatility calculated by the model and the actual volatility. In order to overcome this problem and better catch the distribution characteristics of returns in the case of leptokurtosis, many scholars choose T-distribution, GED-distribution, etc. to replace normal distribution hypothesis, deriving various GARCH family models [15].

2.2. VAR Model

In general, the strategy used for studying the relationship between two variables is to construct a regression model based on a certain theoretical assumption. However, this traditional method faces limitations when studying the dynamic relationships between various economic variables in the short run, as successful modeling requires causal relationship between variables has been determined. The VAR model proposed by Sims overcomes the above problem, which includes advantages as follows: First of all, it is not necessary to distinguish variables needed to be modeled, that is, each variable is both an independent variable and a dependent variable. What's more, the VAR model does not require to determine the economic meaning of each equation, making it relatively more convenient to study the dynamic relationship between variables [10]. The specific form of VAR (p) is as following:

$$\begin{cases} YIELD_t = M_0 + M_1 YIELD_{\mathrm{t-1}} + \dots + M_p YIELD_{\mathrm{t-p}} + M_1 CICSI\_SDR_{\mathrm{t-1}} + \dots + M_p CICSI\_SDR_{\mathrm{t-p}} + \varepsilon_{\mathrm{t}} \quad \mathrm{t} = 1,2,\dots,T \\ CICSI\_SDR_t = M_0 + M_1 YIELD_{\mathrm{t-1}} + \dots + M_p YIELD_{\mathrm{t-p}} + M_1 CICSI\_SDR_{\mathrm{t-1}} + \dots + M_p CICSI\_SDR_{\mathrm{t-p}} + \varepsilon_{\mathrm{t}} \quad \mathrm{t} = 1,2,\dots,T \end{cases} \tag{3}$$

Among which, $YIELD_t$ and $CICSI\_SDR_t$ are the column vectors of $k \times 1$ composed of all endogenous variables, M_0 is the constant term, p is the lag order of the model, T is the sample size, M_1,...,$M_p$is $k \times k$ dimensional coefficient matrix, ε_t is the residual vector of $k \times 1$ dimension, and all residual terms contained are correlated with the same period but not with the lag term.

3. Indicators Selection and Variable Analysis

3.1. Data Source

By extensive reading of research literature at home and abroad, it is found that most scholars, when doing research related to the relationship between investor sentiment and stock market returns, choose data from a certain market as sample, such as Shanghai Stock Exchange Index, SSAS, Second Board, STIB, but few combine data from multiple markets into a comprehensive market data as sample for research. Considering the availability of data and the effectiveness of exposition, this paper selects 121 groups of samples for the empirical research, involving the stock returns in the composite market of SSAS and STIB calculated by weighted average method, and the comprehensive index of investor

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sentiment constructed by PCA, which has been standardized and removed macro factors by models. All of them are monthly data from March 2013 to March 2023, sourced from the CSMAR Economic and Financial Research Database.

3.2. Descriptive Statistics

The descriptive statistical results of the monthly comprehensive index of investor sentiment (CICSI_SDR) and the monthly stock returns in the composite market (YIELD) selected are shown in Table 1 and Figure 1. It can be found that, as Table 1, CICSI_SDR has a greater mean value relative to YIELD, also its volatility is relatively higher. With regard to the volatility of YIELD, it is obviously characterized by leptokurtosis and volatility clustering in the past decade, which means that the probability of outlier is higher than the expected value of normal distribution. What's more, it can be roughly seen through Figure 1 that no matter how investor sentiment changes, the stock returns in the composite market of SSAS and STIB fluctuate in the same direction. Besides, when investor sentiment fluctuates significantly, the corresponding market volatility is relatively high. when investor sentiment fluctuates relatively stable, the corresponding market volatility is relatively low, mostly around 0.

Table 1: Descriptive statistical results.

Variable	Mean Value	Median	Standard Deviation	Skewness	Kurtosis	JB Value	P Value
CICSI_SDR	0.585	0.530	0.895	0.443	3.752	6.811	0.033**
YIELD	0.014	0.005	0.080	0.151	5.153	23.841	0.000***

Notes: CICSI_SDR means the comprehensive index of investor sentiment, YIELD means the stock returns in the composite market, JB Value means Jarque-Bera statistic; ** means significant at 95% confidence level; *** means significant at 99% confidence level.

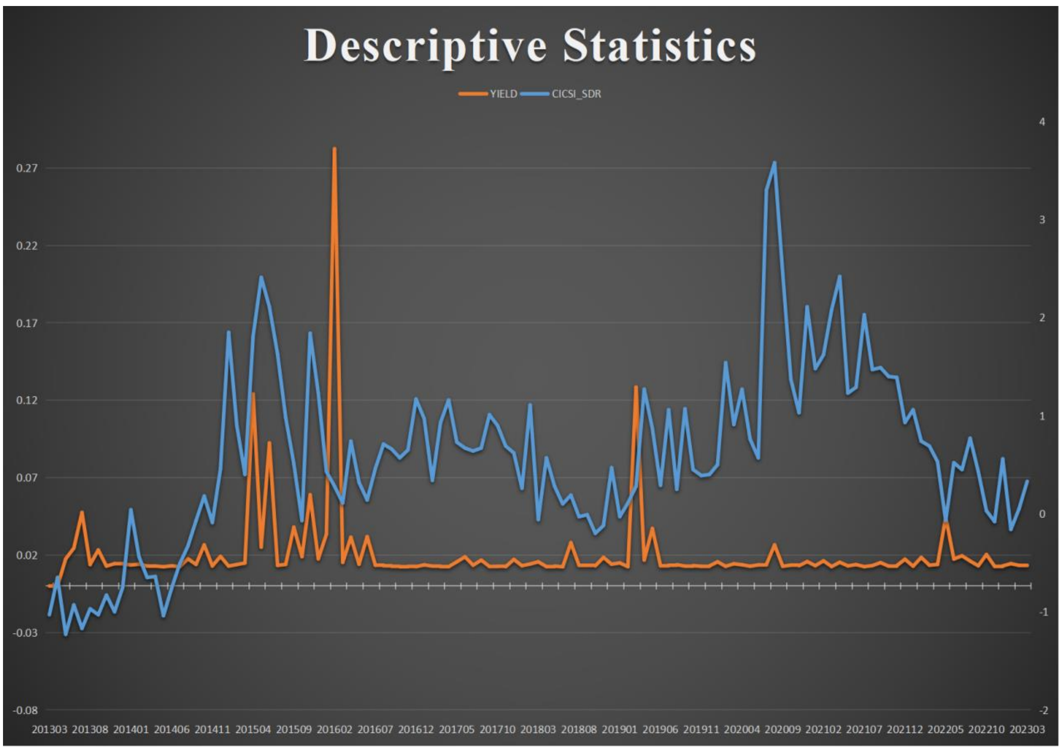

Figure 1: Tendency chart (Picture credit: Original).

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3.3. Stationarity Test

Passing the stationarity test indicates that the statistical properties of series will not change over time. Focusing on the relationship between comprehensive index of investor sentiment and the volatility of stock returns in the composite market, it is necessary to ensure that the series are stationary prior to modeling. Further differentiation of the series would be necessary without passing the stationarity test. This paper tests the stability of two series mentioned before, using ADF and Phillips Perron (PP) unit root tests with null hypothesis of non-stationarity, as well KPSS stationarity test with null hypothesis of stationarity.

Table 2: Stationarity, autocorrelation, ARCH effect test results.

Variable	ADF	KPSS	PP	Q (36)
DCICSI_SDR	-6.087***	0.107	-112.03***	399.230***
YIELD	-9.333***	0.213	-9.232***	29.206
Z	-3.632***	0.300	-10.101***	70.216***

Notes: CICSI_SDR means the comprehensive index of investor sentiment, YIELD means the stock returns in the composite market, Z means the demeaned square value of YIELD; Q (36) means Ljung-Box autocorrelation test statistic; *** means significant at 99% confidence level.

As Table 2 shown, the comprehensive index of investor sentiment after first-order difference (DCICSI_SDR) and composite market returns (YIELD) significantly reject the null hypothesis of non-stationarity, with ADF test statistics being -6.087 and -9.333 respectively and PP test statistics being -112.03 and -9.232 separately. Furthermore, the KPSS test statistics of DCICSI_SDR and YIELD are 0.107 and 0.213 respectively, both accepting the null hypothesis of stationarity. All these results can be explained as both series are stationary. However, the Q (36) test statistic for DCICSI_SDR shows significance at 99% confidence level, while that for YIELD does not. Therefore, YIELD series needs to be further demeaned and squared, forming Z series. The ADF and PP test statistics of the Z series are -3.632 and -10.101 seperately, both significantly rejecting the null hypothesis and the KPSS test statistic is 0.300, accepting the null hypothesis, which successfully passing the stationarity test. The Q (36) test statistic of Z series is 70.216, being significant at 99% confidence level. On the whole, both DCICSI_SDR and Z series are with autocorrelation and ARCH effect and without normal distribution characteristics.

4. Model Results Analysis

4.1. Volatility Characteristics of Composite Market Returns

The previous chapter has conducted descriptive statistics, stationarity tests, autocorrelation and ARCH effect tests on the comprehensive index of investor sentiment series and composite market returns series, with results that the comprehensive index of investor sentiment after first-order difference and the composite market returns after demeaning and squaring finally passing all tests. The existence of autocorrelation and ARCH effect indicates that GARCH family models can be established to statistically analyze the volatility characteristics of returns. Since the descriptive statistics of returns do not conform to the normal distribution, this paper adopts GED distribution for modeling. Concerning about the principle of minimizing AIC and SC statistical values, after comparing the results of GARCH, TGARCH, and EGARCH models, finally EGARCH model is chosen to model the Z series, the processed stock returns in the composite market of SSAS and STIB.

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Table 3: ARMA model results.

Parameter	Estimated Value	Standard Deviation	Statistics	P Value
AR(1)	-0.826	0.043	-19.202	0.000***
MA(1)	0.991	0.014	72.621	0.000***

Table 4: EGARCH model information guidelines.

AIC	SC	HQIC	Log Likelihood
-7.5079	-7.3210	-7.4320	454.7181

As shown in Table 3 and Table 4, based on the principle of minimizing AIC and SC, the lag order of the Z series and EGARCH model has been determined. The AR and MA orders of the Z series are both 1, and the orders of ARCH and GARCH models are both 1 as well.

Table 5 indicates that the first-order and second-order lag coefficients of the Z series are significant at confidence level of 99%. In addition, the first-order lag coefficient is significantly negative, while the second-order's is significantly positive, relatively closer to 1. This not only explicates that the Z series has a certain degree of autocorrelation, but also illustrates that the composite market returns of the past period will probably change in the opposite direction to that of the current period, also the composite market returns of the past two periods will be more likely to show a positive correlation with that of the current period. Afterwards, the F-statistic of ARCH-LM test is 0.923, which is not significant, proving that the current model has good fitting performance without ARCH effect.

Table 5: EGARCH model results.

Parameter	Estimated Value	Standard Deviation	Statistics	P Value	Lower Confidence Limit	Upper Confidence Limit
C	0.000	1.27E-05	30.822	0.000***	0.000	0.000
$Z(-1)$	-0.103	0.006	-16.710	0.000***	-0.119	-0.087
$Z(-2)$	0.468	0.021	22.008	0.000***	0.412	0.523
$C(4)$	-8.674	3.848	-2.254	0.024**	-18.760	1.412
$C(5)$	0.757	0.605	1.252	0.211	-0.828	2.342
$C(6)$	-0.101	0.532	-0.190	0.849	-1.494	1.292
$C(7)$	0.036	0.463	0.077	0.938	-1.178	1.249

4.2. The Effect of Investor Sentiment on The Volatility of Composite Market Returns

Establishing the EGARCH model to calculate the volatility the composite market returns, this paper introduces the comprehensive index of investor sentiment to further investigate the effect of investor sentiment on the volatility of composite market returns by using VAR model.

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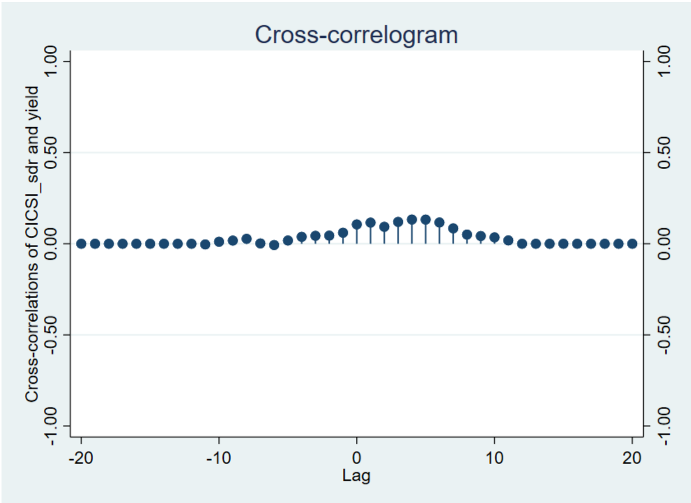

Figure 2: Cross correlation coefficient graph (Picture credit: Original).

Before conducting VAR model, the lag correlation between the comprehensive index of investor sentiment and composite market returns volatility can be preliminarily tested through cross correlation function. The correlation coefficient between the two variables is 0.106. As shown in Figure 2, the correlation between the current comprehensive index of investor sentiment and the volatility the composite market returns from lag period 1 to lag period 5 shows an upward trend, being significantly positive. Yet from lag period 6 to lag period 10, the correlation gradually weakens, still being significantly positive. Afterwards, the correlation is relatively stable, approaching 0. In conclusion, there is a positive weak correlation between current comprehensive index of investor sentiment and future volatility of stock returns in the composite market, but it is difficult for investor sentiment to have a significant impact.

The following strategies are adopted for more research: Firstly, measuring whether these two series are stationary through the unit root test. Secondly, modeling these two series by VAR model and determining the optimal lag order on the basis of the information criterion. Finally, Granger causality test, impulse response and variance decomposition analysis are carried out to predict future impact.

Table 6: Stationarity test results.

Variable	ADF	KPSS	PP
$DCICSI\_SDR$	-6.087***	0.107	-112.030***
DYIELD	-7.357***	0.029	-159.120***

Notes: DCICSI_SDR means comprehensive index of investor sentiment after first-order difference, DYIELD means volatility of composite market returns after first-order difference; *** means significant at 99% confidence level.

As Table 6 shown, the comprehensive index of investor sentiment after first-order difference (DCICSI_SDR) and the volatility of composite market returns after first-order difference (DYIELD) significantly reject the null hypothesis of non-stationarity, with ADF test statistics being -6.087 and -7.357 respectively and PP test statistics being -112.030 and -159.120 separately. Furthermore, the KPSS test statistics of DCICSI_SDR and DYIELD are 0.107 and 0.029 respectively, both accepting the null hypothesis of stationarity. All these results can be explained as both series are stationary, which can be modeled through using the VAR model. Concerning about the principle of minimizing AIC and SC statistical values, after comprehensive comparison, finally the VAR model with lag order of 4 is selected for regression analysis.

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As is described in Table 7. The coefficients of $CICSI\_SDR_{t-1}$ and $CICSI\_SDR_{t-2}$ are negative, approaching 0, but not significant. However, the coefficient of $CICSI\_SDR_{t-3}$ is significantly positive, while that of $CICSI\_SDR_{t-4}$ is significantly negative. It can be seen that before the third lag period, the relationship between two variables is not significant, even almost unrelated. However, starting from the third lag period, the correlation begins to be significant, but still shows a downward trend. What the results state is roughly similar to but distinct from the conclusion drawn in Figure 2. It can also be observed that the subsequent lag coefficients are not significant, which is consistent with the EGARCH model results in the previous section. On the whole, the market tends to be in a positive state if the overall emotional state of Chinese investors in the current period is high, and vice versa.

Table 7: VAR model results.

Series	Parameter	Estimated Value	Standard Deviation	Statistics	P Value
$YIELD$	$CICSI\_SDR_{t-1}$	-0.003	0.005	-0.497	0.620
	$CICSI\_SDR_{t-2}$	-0.001	0.006	-0.199	0.842
	$CICSI\_SDR_{t-3}$	0.018	0.006	3.017	0.003***
	$CICSI\_SDR_{t-4}$	-0.014	0.005	-2.796	0.006***
	$YIELD_{t-1}$	0.044	0.093	0.478	0.634
	$YIELD_{t-2}$	0.165	0.092	1.798	0.075
	$YIELD_{t-3}$	0.049	0.092	0.530	0.597
	$YIELD_{t-4}$	-0.022	0.092	-0.238	0.813
	Constant	0.016	0.005	3.342	0.001***

Table 8: Granger causality test results.

Null Hypothesis	Statistics	Lag Order	P Value
CICSI_SDR is not the causality of granger to YIELD	3.011	4	0.021**
YIELD is not the causality of granger to CICSI_SDR	0.677	4	0.609

Notes: CICSI_SDR means comprehensive index of investor sentiment, YIELD means volatility of composite market returns; ** means significant at 95% confidence level.

Subsequently, Granger causality test, impulse response and variance decomposition analysis are carried out. Table 8 illustrates that the comprehensive index of investor sentiment is the causality of

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granger to the volatility of composite market returns, between them existing a causal relationship, which is also mutually confirmed by the VAR model results.

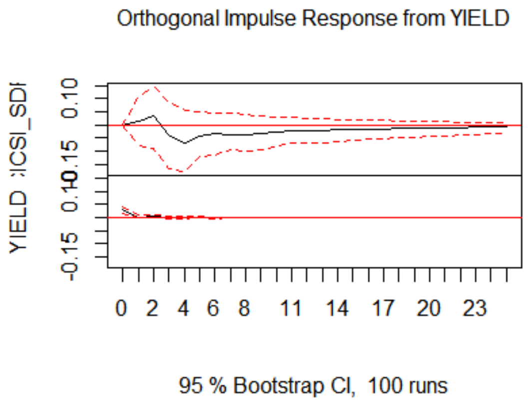

Figure 3: Impulse response plot from YIELD (Picture credit: Original).

The results of the impulse response function as Figure 3 indicate that at 95% confidence level, the effect of CICSI_SDR on YIELD appears in the first six periods. Among these six periods, there is a positive effect in the short term, a significant negative effect from the second to the fourth period, and a positive effect from the fourth to the sixth period, subsequently gradually approaching zero. However, the YIELD has only a negligible effect on itself before the sixth period, almost always at 0, which can be understood as no impact.

Table 9: Variance decomposition results of YIELD.

Period	*CICSI_SDR*	YIELD
1	0.004	0.996
2	0.006	0.994
3	0.008	0.992
4	0.086	0.914
5	0.091	0.909
6	0.091	0.909
7	0.091	0.909
8	0.092	0.908
9	0.092	0.908
10	0.092	0.908

Notes: CICSI_SDR means comprehensive index of investor sentiment, YIELD means volatility of composite market returns.

As shown in Table 9, the variance decomposition results indicate that although the contribution of CICSI_SDR to YIELD is only 0.004 in the first period, even nearly non-existent, it gradually increases until the 8th period, reaching the contribution level of 0.092, onwards it remains stable with slight changes. In other words, the comprehensive index of investor sentiment has a significant influence on the volatility of composite market returns.

5. Conclusion

Taking the composite market of SSAS and STIB for example, this paper, seeing from empirical point of view, searching for data from new perspective, selects reasonable comprehensive index of investor sentiment and stock returns in the composite market, and establishes the asymmetric GARCH-VAR model to study the effect of investor sentiment on the stock volatility in the composite market. On the basis of the analysis of the model results, it can be found that there is a positive weak correlation between current comprehensive index of investor sentiment and future stock volatility in the composite market, but it is difficult for investor sentiment to have a significant impact. Furthermore, before the third lag period, the relationship between two variables is not significant, even almost unrelated. However, starting from the third lag period, the correlation begins to be significant, but still shows a downward trend. On the whole, the investor sentiment would drive the development and prosperity of financial market if that in the past upsurged. On the contrary, the investor sentiment would make financial market even more sluggish when that in the past was downcast. In other words, it is explanatory that various market anomalies in China stock market are caused by investors' irrational investment behaviors, such as herd behavior.

However, there still exist some limitations: first of all, the data used in this paper are all on monthly basis owing to the consistence of data frequency. Yet for stock returns, the accuracy of the results obtained by using high frequency data like in days may be better. In addition, the whole process only models from the perspective of linear relationship, while many factors in financial market exhibit nonlinear relationship between each other. Finally, although this paper explores the effect of comprehensive index of investor sentiment on the volatility of stock returns in the composite market, the stock volatility may also have an effect on investor sentiment, which means that the study is not all-round.

Compared to financial markets of developed countries, China stock market tends to be an ineffective market since the existence of various irrational investment behaviors. Suggestions are provided in the light of the current situation of China stock market and the analysis of the model results. Firstly, a specialized evaluation mechanism for investor sentiment should be established by the market, updating frequently, so as to monitor the trends of investor sentiment and provide an early-warning. Besides, a reasonable investor structure has become extremely important owing to the fact that irrational investment behaviors mostly come from individual investors. Therefore, the market should continue to increase the proportion of institutional investors and strengthen such investor education as advocating rational investment concept and cultivating individual investors' risk awareness, so that the probability of irrational investment behavior occurring may be minimized, as well as the occurrence of market anomalies caused by investor sentiment fluctuation may be controlled.

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