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The Relationship Between Investor Sentiment and Stock Market Price

Qi Guo

Business college, Nanjing Normal University, Nanjing, China

Abstract: With the birth of behavioral finance, more and more researchers have brought the individual psychology of investors and the behaviors that it fosters into the theoretical research scope of finance. From the perspective of micro individual behavior, they try to explain the causes of complex phenomena in the financial market with psychological factors such as behavioral motivation. This paper mainly analyzes the impact of investor sentiment on the price volatility of China's stock market. On the basis of combing the existing theoretical literature, based on the daily Chinese investor sentiment index published by the National Development Research Institute of Peking University and the return of the CSI 300 Index, the research hypothesis is put forward. First, the GARCH model is constructed to calculate the daily volatility of the return of the CSI 300 Index and the Granger causality is used to test the relationship between investor sentiment, stock price return and volatility. Secondly, the paper empirically analyzes the relationship between investor sentiment and stock price volatility by constructing VAR model, and finds that investor sentiment will indeed have the same impact on the price volatility of China's stock market, and the stock price volatility will react on investor sentiment and form an interactive impact, which will gradually weaken over time. Finally, from investors The government and other aspects put forward suggestions to further improve the operation of China's stock market.

Keywords: Investor sentiment, Stock price volatility, GARCH model, VAR model.

1. Introduction

In the early 1990s, the Shanghai Stock Exchange and Shenzhen Stock Exchange were listed and established successively, and China's capital market has seen vigorous development since then. Through 30 years of rapid development, the efficiency of China's securities market has improved at a speed that is obvious to all. It plays an increasingly important role in financing, optimizing capital allocation, and dispersing financial risks.

However, while affirming its positive role, we should calmly analyze the gap between China's capital market and the United States and other western developed economies. It is undeniable that compared with China's capital market, China's capital market still has many immature aspects, whether in terms of scale, information release, legal supervision or market effectiveness, there is a certain gap between China and the United States securities market. A prominent feature of China's securities exchange market is that the proportion of natural person investors is relatively high.

The traditional financial theory is based on the rational person hypothesis and the efficient market hypothesis. Because investors are "rational people" in the market, the market will automatically reach an efficient state. However, the traditional theory of finance lacks explanatory power in explaining the complicated market phenomena in today's financial market. Investors often show some irrationality, such as selective bias and conservative bias. This prompted financial scholars to adjust their research perspective, and on the basis of relaxing the basic assumptions of traditional finance, they tried to explain the various abnormal phenomena in the financial market from the perspective of behavioral, psychological and sociological. Behavioral finance, a new emerging discipline, emerged at the historic moment. As one of the pillars of behavioral finance theory, investor sentiment and its impact on the financial market have also been widely concerned by scholars. The investor sentiment was formally put forward by Lee, Shleifer and Thaler[1], and used it to explain the reason for the long-term discount of closed-end funds. Baker et al[2] believed that investor sentiment was an important factor affecting stock returns.

For China, a securities market with a majority of natural person investors, it is of practical significance to study investor sentiment and its impact on the return and volatility of the stock market. This paper mainly includes four aspects: firstly, it sorts out and comments on the literature of investor sentiment and its impact on the return and volatility of the stock market; The second is to calculate the volatility of the CSI 300 index by building the GARCH model; The third is to use Granger causality test to analyze the interaction between investor sentiment, the yield and volatility of the CSI 300 index, and then further analyze the interrelationship of variables through VAR model; Fourth, the research conclusions and policy recommendations of this paper.

2. Literature Review

The research on investor sentiment has been widely concerned by scholars. Brown et al[3]believed that investor sentiment was caused by investors' false expectations of the future price of stocks, which often showed excessive optimism or pessimism towards the stock market. As for the measurement of investor sentiment, there are currently two main methods used by the academic community: one is the direct indicator method, which is to collect investors' views on the stock market expectations through questionnaires. The investor sentiment measured by this method mainly includes investor sentiment index (Solt and Statman[4]), CCTV market data (Wang Mei and Sun Jianjun[5]), investor confidence index (China Securities Investor Protection Fund Co., Ltd) and China investor sentiment index (National Development Research Institute, Peking University). The other is the indirect indicator method, that is, selecting some objective indicators in the financial market and using principal component analysis, factor analysis, Kalman filter and other methods to form a comprehensive indicator to measure investor sentiment. The selected objective indicators include the number of new investor accounts (Lu Xunfa and Li Jianqiang[6]), the discount of closed-end funds (Delong[7]), the number of IPOs and the first day of listing (Baker and Wurgler[2]) and the turnover rate (Zhou Liang[8]).

As for the relationship between investor sentiment and stock market returns, there are differences in the conclusions drawn by domestic and foreign scholars. Foreign scholars have found that there is a significant correlation between investor sentiment and stock market returns. Ben-Rephael[9]research shows that there is a positive correlation between investor sentiment and the excess return rate of the stock market in the same period, while there is a negative correlation between investor sentiment and the excess return rate in the later period. Domestic scholars have found that investor sentiment has a one-way impact on stock market returns. Lu Xun Fa and Li Jianqiang[6] selected the number of new investor accounts as the measurement index of investor sentiment, and analyzed the asymmetric impact of investor sentiment on the yield of the Shanghai and Shenzhen 300 Index and the causal relationship between them through the construction of ARMA-TARCH model and Granger causality test. The result shows that the yield of the CSI 300 index is the Granger reason for the change of investor sentiment.

On the relationship between investor sentiment and stock market volatility, scholars at home and abroad have reached relatively consistent conclusions. He Ping, Wu Tian, et al[10] selected indicators such as the number of new A-share individual accounts opened, the net redemption rate of funds and the average market monthly trading volume, and used the principal component analysis method to construct the investor sentiment index, and took 2454 stock data from 2003 to 2011 as samples to quantitatively analyze the impact of investor sentiment on the volatility of the stock market. The results show that investor sentiment has a significant impact on stock market volatility. Zhou Yang[11] selected the closed-end fund price rate, the number of new investors opening accounts, the turnover rate, the average first-day yield of IPO and the number of IPO issuance as the proxy variables, constructed the investor sentiment index through the principal component analysis method, and established the EGARCH model to empirically analyze the impact of investor sentiment on the volatility of the stock market. The result shows that investor sentiment is one of the factors that lead to systemic risk in the stock market.

Many studies have been done to measure investor sentiment index using indirect index method, and analyze the relationship between investor sentiment and stock market yield and volatility on this basis. With the help of the daily investor sentiment index obtained by the National Development Research Institute of Peking University through big data and in-depth learning methods, this paper accurately analyzes the relationship between investor sentiment and the yield and volatility of the CSI 300 Index.

3. Research methodology

(1) Sample selection

For investor sentiment data, the National Development Research Institute of Peking University and the percentage company jointly collected the big data of financial texts and used the in-depth learning method to calculate and publish the Chinese investor sentiment index in December 2018. This paper directly uses the daily index data (expressed by IS) to analyze the relationship between investor sentiment and the yield and volatility of the CSI 300 Index. Since the National Development Research Institute of Peking University has released the daily investor sentiment index since January 2019, the sample range of this article is from January 2, 2019 to August 31, 2021, with a total of 649 data, which is from the collation of China Securities Network.

The Shanghai and Shenzhen 300 Index is selected as the stock market yield variable. The daily closing price data of the Shanghai and Shenzhen 300 Index in the same period can be obtained through the official website of Yahoo Finance (www.finance. yahoo. com), which is recorded as Pt.

The daily logarithmic rate of return of the CSI 300 index is calculated by the following formula:

$$\mathrm{HS_t} = \mathrm{In}\frac{\mathrm{P_t}}{\mathrm{P_{t-1}}} - 1 = \mathrm{InP_t} - \mathrm{InP_{t-1}} \quad (1)$$

where, HSt represents the daily logarithmic yield of the CSI 300 index; Pt represents the daily closing price of the CSI 300 Index.The descriptive analysis results show that the skewness value of HSt in the daily yield series of the Shanghai and Shenzhen 300 Index is -.409856, and the kurtosis value is 6.638939. The data distribution is left skewed and "peak thick tail". By testing the normality of the data, we can find that the skewness - kurtosis statistic of the data normality is 61.59, and the corresponding probability value is 0.000, which further verifies the non-normality of the daily yield series of the CSI 300 Index. Therefore, it is necessary to establish a GARCH model to describe the distribution characteristics of the yield series, and then measure the volatility of the CSI 300 Index.

(2) Calculation of the volatility of the CSI 300 index

The problem of data volatility aggregation needs special attention in the time series analysis of financial data, because the existence of this phenomenon will lead to the "peak and thick tail" of data, and then deviate from the normal hypothesis of efficient market. To solve this problem, we can build GARCH model.

The ARCH model, which is still widely used in the analysis of financial time series, was born in the early 1980s and was put forward by the economist Robert Engle. It can well solve the problems caused by the constant variance hypothesis of the traditional model. The basic form of variance of the model is as follows:

$$u_t^2 = \alpha_0 + \alpha_1 u_{t-2}^2 + \alpha_2 u_{t-2}^2 + \alpha_3 u_{t-3}^2 + \cdots + \alpha_p u_{t-p}^2 + \varepsilon_t \quad (2)$$

Based on this formula, the residual of a regression model can be directly tested for ARCH effect.

Because ARCH model lacks the applicability of volatility analysis and detection to some extent, in order to make the model more close to the actual analysis needs, T. Bollerslev proposed the GARCH model in the late 1980s. Different from ARCH model, GARCH model adds 2t lag term on the basis of the former, and the specific formula is as follows:

$$y_t = \alpha + \beta_0 x_t + \beta_1 x_{t-1} + \beta_2 x_{t-2} + \cdots + \beta_p x_{t-p} + u_t, \quad u_t \sim N(0, \sigma_t^2) \quad (3)$$

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{p} \alpha_i u_{t-1}^2 + \sum_{j=1}^{p} \beta_j \sigma_{t-j}^2 \qquad (4)$$

As for the setting of the volatility equation, the analysis found that the asymmetric effect of positive and negative returns on the daily logarithmic returns of the CSI 300 index is not obvious in the sample range selected in this paper. Therefore, a GARCH (p, q) model can be fitted for the sequence. According to previous studies, the low-order GARCH model is more common for most financial time series. The LM test is carried out on the yield of Shanghai and Shenzhen 300 to determine whether there is ARCH effect. The results show that when the lag term is the first order and the second order p values are 0.0203 and 0.0593 respectively, there is no nihility assumption of rejecting ARCH effect at the significance level of 5%. Therefore, the coefficient can be estimated by specifying the model, and several GARCH models with different orders can be fitted, and the results are shown in Table 1.

Table 1. GARCH Model for Fitting the Daily Logarithmic Return of the CSI 300 Index.

Model	GARCH (1, 1)	GARCH (1, 2)	GARCH (2, 1)	GARCH (2, 2)
		HS		
_cons	0.0908 (1.82)	0.0819 (1.64)	0.0813 (1.61)	0.0798 (1.58)
		ARCH		
L1.arch	0.119*** (7.75)	0.151*** (8.09)	0.177*** (7.10)	0.177*** (6.65)
L2.arch			-0.0918* (-2.36)	-0.0740 (-0.92)
L1.garch	0.833*** (38.93)	0.364 (1.62)	0.884*** (25.24)	0.709 (1.36)
L2.garch		0.425 (1.95)		0.149 (0.34)
_cons	0.0993** (3.28)	0.122** (3.15)	0.0643* (2.30)	0.0797 (1.28)
AIC	2174.102	2173.733	2173.257	2175.025
BIC	2192.004	2196.11	2195.634	2201.877
N	649	649	649	649

Note:*p < 0.1, **p < 0.05, ***p < 0.01.

The order of GARCH model is determined according to Akaike info criteria (AIC) and Schwarz criteria (BIC). It can be seen from Table 1 that the GARCH (1,1) model is selected based on the AIC, BIC criteria and the significance of the corresponding coefficient, and the final fitting model is:

$$HS_t = 0.0908 + \alpha_t, \quad \alpha_t = \sigma_t \varepsilon_t \qquad (5)$$

$$\sigma_t^2 = 0.0993 + 0.119\alpha_{t-1}^2 + 0.833\sigma_{t-1}^2 \qquad (6)$$

After calculating the sample autocorrelation function (ACF) and partial autocorrelation function (PACF) of the standardized residuals of the above GARCH (1,1) model, it is found that the sample ACF and PACF of all lag orders are not significant at the significance level of 5%, indicating that the standardized residuals do not have sequence correlation. In addition, the p value corresponding to the statistics of the standardized residual is 0.728, which indicates that the GARCH (1,1) model constructed can fully describe the conditional heteroscedasticity of the daily logarithmic return series of the Shanghai and Shenzhen 300 Index. According to the fitted GARCH (1,1) model, the volatility series of daily logarithmic returns of the CSI 300 Index can be further calculated, which is recorded as VARt.

The timing chart of the volatility sequence is shown in Figure 1:

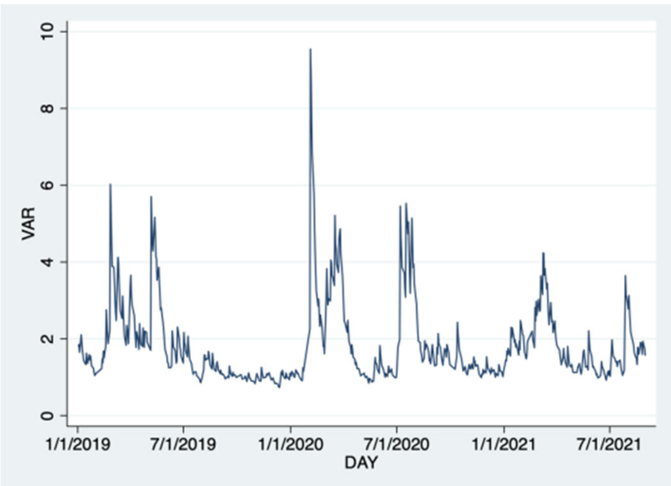

Figure 1. Daily Volatility Series of the CSI 300 Index.

The volatility of the CSI 300 index has obvious aggregation phenomenon, that is, the volatility between January 30, 2019 and July 9, 2019 is relatively large, and the volatility from then on to January 17, 2020 is relatively small. However, since late January 2020, the CSI 300 index has shown greater volatility, which may be due to the irrational behavior of investors in the stock market due to the impact of the COVID-19. It is relatively stable after 2020, and fluctuates again at the beginning of 2021, which may be due to the repeated epidemic and the impact of policy uncertainty.

4. Empirical Results

Granger causality test

Under the condition that the three time series of daily investor sentiment index ISt, daily logarithmic return HSt and volatility VARt of the CSI 300 index are stable, the Granger causality test can be used to quantitatively analyze the relationship between the three. The advantage of Granger causality test is that it can not only analyze the relationship between variables, but also determine the direction of interaction between variables. The Granger causality test results of ISt, HSt and VARt sequences are shown in Table 2.

Table 2. Granger causality test results

H0	Lag order	F statistics	Probability value
HSt is not the Granger reason for the change of ISt	1	31.76	0.0000
ISt is not the Granger reason for the change of HSt	1	1.40	0.2377
VARt is not the Granger reason for the change of ISt	2	3.51	0.0303
ISt is not the Granger reason for the change of VARt	10	2.96	0.0012
HSt is not the Granger reason for the change of VARt	1	22.94	0.0000
VARt is not the Granger reason for the change of HSt	10	1.45	0.1553

The Granger causality test results in Table 2 are expressed in the form shown in Figure 2, which can more intuitively see the relationship between the three time series of daily investor sentiment index ISt, daily logarithmic return HSt of the Shanghai and Shenzhen 300 Index and its volatility VARt and the direction of their impact.

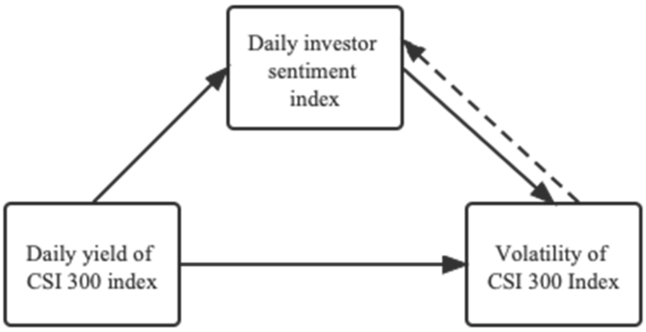

Figure 2. The relationship between investor sentiment and the yield and volatility of the CSI 300 Index.

The results show that when the lag order is 1, the zero hypothesis that the return of the CSI 300 Index is not the Granger cause of investor sentiment change is rejected at the significance level of 1%, that is, the change of the return of the stock market will lead to the change of investor sentiment. This is easy to understand in common sense. When the yield is positive (or negative) and the stock market is in an upward (or downward) channel, investors will form a bullish (or bearish) judgment of the stock market based on this, and the investor sentiment will then tend to be optimistic (or pessimistic). When the lag order is 10 and 5 respectively, at the significance level of 5%, investors' sentiment is not the Granger reason for the change of the volatility of the CSI 300 Index, and the return of the CSI 300 Index is not the Granger reason for the change of the volatility, that is, the change of the return of the stock index and the investor's sentiment will lead to the change of the volatility. This can also be explained in common sense. Since the previous article has verified that changes in stock returns will lead to changes in investor sentiment, and changes in investor sentiment will inevitably affect their investment behavior, leading to changes in stock market volatility. This research result is also consistent with the conclusions of previous studies.

In addition, the research results also show that when the lag order is 1, under the significance level of 5%, investor sentiment cannot be rejected as the Granger reason for the change of the return of the CSI 300 Index, that is, the change of investor sentiment will not lead to the change of the return of the stock market. Although this conclusion deviates from the conclusions of some foreign scholars, it is mutually verified with the research conclusions of some domestic scholars.

(2) VAR model

The research on the relationship between investor sentiment and price volatility in China's stock market can be advanced to the construction of VAR model for further research.

Through reading the existing literature and the actual statistical analysis test, the order of VAR model is identified. Here, the SIC minimum criterion is used. The calculation shows that the AIC corresponding to the fourth order is 5.67318, which is the minimum value. The lag order selected for the model is the fourth order. The analysis results of VAR model are shown in the following table:

Table 3. VAR regression results

	ISt	VARt
_cons	10.50***	-0.136
L1.IS	0.450***	0.0391***
L2.IS	0.117**	-0.0236*
L3.IS	0.0661	-0.0117
L4.IS	0.118**	0.00378
L1.VAR	-0.326*	0.911***
L2.VAR	0.135	-0.0375
L3.VAR	0.0262	0.000800
L4.VAR	0.0918	0.0277

Note:*p < 0.1, **p < 0.05, ***p < 0.01.

According to the regression results, the following conclusions can be drawn:

There is a positive correlation between investor sentiment and stock price volatility, that is, the volatility of investor sentiment and the volatility of China's stock market price are in the same direction. It can be seen from Table 5 that the correlation coefficient between the investor sentiment composite index and the stock price volatility index is positive and statistically significant when the lag order is 1, so the interaction between the two is positive.

The fluctuation of investor sentiment will have an impact on the price fluctuation of China's stock market, and this impact has a cross-period nature, that is, the current investor sentiment fluctuation will affect the price volatility of the stock market in the next several periods, and this impact will decrease with the increase of the number of periods, and the impact of investor sentiment on the stock price will weaken with the passage of time. It can be seen from Table 5 that the correlation coefficient between the stock price volatility and the comprehensive index of investor sentiment with a lag of one period and two periods is 0.0391 and -0.0236. The correlation coefficient decreases with the increase of the lag order and decreases significantly, but it is completely insignificant in the third lag order. The reason for this result may be that investors' emotions fluctuate due to external information, and the impact of this event will last for a period of time, and the stock price will fluctuate for many days in the future by affecting investors' expectations of the future.

The fluctuation of stock price will also affect the fluctuation of investor sentiment in turn, but there will be no intertemporal nature, that is, the fluctuation of stock price in the current period will not affect the investor sentiment in the following periods. It can be seen from Table 5 that the correlation coefficients of the stock price volatility indicators of the investor sentiment composite index lagging behind the two periods are -0.135, but not statistically significant. When the current stock price volatility intensifies, due to the instability of the yield and the increase of risk information, investor sentiment will be restrained, that is, the common post-volatility consolidation in the market. Over time, the inhibitory effect of this stock price fluctuation on investor sentiment will weaken until it turns to a positive effect, that is, sentiment and market will warm up.

(3) Impulse response

In order to better explain the internal relationship between investor sentiment and price volatility in China's stock market, impulse response analysis is conducted for both, and the results are shown in the figure below.

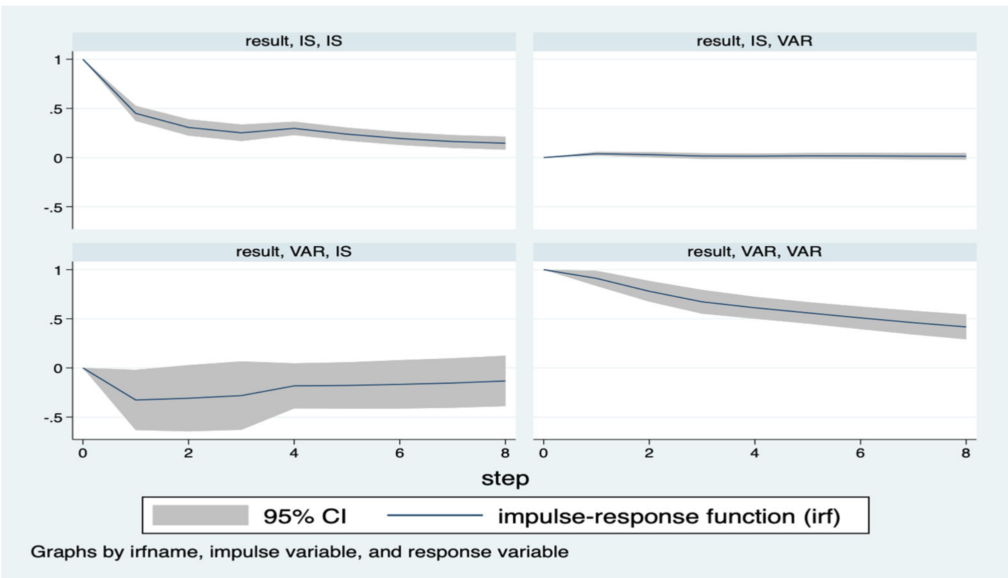

Figure 3. Impulse response diagram.

The upper right corner shows the impulse response of investor sentiment to stock price fluctuations. It can be seen that in the current period, the investor sentiment was positively impacted, and the stock price fluctuations showed a positive response, and weakened after the first period of the study period. This indicates that the high investor sentiment will positively affect the volatility of stock prices and weaken in the following time.

The lower left corner shows the impulse response of stock price fluctuations to investor sentiment. It can be seen that when the current positive impact on stock price fluctuations, investor sentiment presents a reverse reaction, and changes direction after the first period in the research period, and gradually eases and tends to disappear. This indicates that the intensification of stock price fluctuations will inhibit investor sentiment, but will usher in a rebound in the next period, that is, after one month's adjustment, investor sentiment will tend to rise and the market will tend to warm up.

5. Conclusion

This paper uses Granger causality test to further judge the direction of the interaction between investor sentiment, the yield of the CSI 300 Index and its volatility. The results show that the return of the CSI 300 index is the reason for the change of investor sentiment under the significance level of 1%; Both investor sentiment and the yield of the CSI 300 Index at the 5% significance level are the reasons for the volatility change; However, at the significance level of 5%, the change of investor sentiment is not the reason for the change of the yield of the CSI 300 Index. And there is a significant relationship between daily investor sentiment and stock index volatility.

Through the detailed analysis of the mechanism between the two through the VAR model, the overall conclusions are as follows: (1) The effect of investor sentiment on stock price volatility is positive, the rise of investor sentiment will lead to the increase of stock price volatility, and the fall of investor sentiment will lead to the reduction of stock price volatility, and this effect has a cross-period nature, that is, the current investor sentiment volatility will affect the stock price volatility in the following periods, Moreover, this impact will decrease with the number of spanning periods, and the impact will weaken with time. (2) It is not only investor sentiment that has a one-way impact on the price fluctuation of China's stock market, but also the price fluctuation of China's stock market will in turn affect the volatility of investor sentiment, but this impact is reversed at the initial stage, and then will turn positive.

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