

A Study of the Impact of Investor Sentiment on Stock Investment Returns

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Abstract. This study examines the influence of investor sentiment on stock investment returns in China's rapidly developing yet volatile securities market. Utilizing principal component analysis, a comprehensive investor sentiment index is constructed from six key indicators. The dynamic relationship between investor sentiment and stock market return volatility is explored through a Vector Autoregression (VAR) model and Generalized Autoregressive Conditional Heteroskedasticity (GARCH) models. The findings reveal a significant bidirectional correlation, with positive optimism exerting a greater impact on stock returns than negative pessimism. The findings of this study indicate that investor sentiment exhibits a heightened sensitivity to declining returns as opposed to rising ones, offering valuable insights for both investors and policymakers.

Keywords: investor sentiment; vector autoregressive (VAR) models; exponential generalized autoregressive conditional heteroskedasticity GARCH family models

1. Introduction

As the world's second-largest country by stock market capitalization, China is increasingly recognized as a compelling investment destination, drawing global interest. Currently, China's stock market is dominated by individual investors. This dominance makes the market more susceptible to fluctuations in individual investor sentiment, and their behavior may further amplify market volatility. Significant market fluctuations are closely mirrored by corresponding shifts in investor sentiment. Sharp market fluctuations, attributable to adverse factors, erode investor confidence and diminish their investment enthusiasm. This leads to a decrease in the degree of rationality when making investment decisions and often results in irrational emotions (Sun, 2022). Psychological biases, such as investor overconfidence and the herd effect, lead to an overreaction in the stock market as a whole. Moreover, the precarious state of investment confidence within the market is a contributing factor to an excessively bearish market, often marked by the formation of speculative bubbles (Sun, 2022). Investor sentiment not only molds individual investment decisions but also exerts a profound societal impact. This sentiment can contribute to the formation and bursting of stock market bubbles, trigger herd behavior, and other phenomena that ultimately impact the overall stock market trend. Therefore, it is necessary to study the impact of investor sentiment on the stock market and analyze the relationship between the two.

In 1970, FAMA proposed the Efficient Markets Hypothesis (EMH) for the first time. This assumes that every investor in the financial market is rational, and the study of financial market problems is based on the rationality assumption. However, in the actual investment market, not every investor exhibits rational behavior. Investor sentiment is a crucial element of behavioral finance, which delves into the psychological activities and decision-making behaviors of investors, elucidating their irrational behaviors (Gao and Liang, 2023). With the development of behavioral finance, research on investor irrationality is gradually deepening.

In recent years, Chinese and foreign scholars have conducted increasing research on investor sentiment, yielding fruitful results in the areas of measuring investor sentiment, constructing comprehensive indices, and exploring its relationship with stock investment returns. A substantial body of research has demonstrated a correlation between investor sentiment and stock market returns (Wen et al., 2014). De, Shleifer, Summers, and Waldman (1990) were among the first to

incorporate investor sentiment into stock price determination models. They highlighted that when investor sentiment influenced each other, arbitrageurs may not be able to correct mispricing resulting from irrational behavior, making investor sentiment a significant factor influencing financial markets. Therefore, investor sentiment has the potential to evolve into a systemic risk, significantly influencing the equilibrium pricing of financial assets.. Wen et al. (2022) utilized a dummy variable regression model, a GARCH model, and an RV-AR model to investigate the asymmetric impact of investor sentiment characteristics on stock price behavior. It was found that positive sentiment and upward changes in sentiment had a significant positive effect on stock returns. Meanwhile, the rational component dominated the market during periods of low sentiment, rendering the effect of negative sentiment changes insignificant. He et al. (2014) utilized principal component analysis to construct sentiment indicators and conducted regression analysis with panel data. Their study concluded that investor sentiment significantly influences stock price volatility. Liu et al. (2016) conducted a study on China's A-share market and found a strong positive correlation between investor sentiment and market trading. They observed that higher investor sentiment leads to more frequent market trading. Gao and Liang (2023) demonstrated that the negative pessimism of investors has a greater impact on stock market returns compared to positive optimism. Moreover, they found that investor sentiment had a more significant effect on the decline of returns than on the rise of returns.

In addition, some scholars have conducted in-depth studies on the volatility characteristics of the stock market. Zhang and Yang (2009) analyzed the mechanism of how investor sentiment impacts stock returns using the modified noise trading theory model. Their theoretical model and empirical results demonstrated that investor sentiment was a systematic factor influencing stock prices, and stock prices fluctuate in response to changes in investor sentiment. In addition, there was asymmetry in the impact of rising and falling sentiment on stock prices. Rising sentiment had a much stronger impact on stock prices than falling sentiment. Stock return volatility, influenced by investor sentiment volatility, represented market systematic risk and was compensated with a risk premium. Lee et al. (2002) demonstrated an asymmetric effect of investor sentiment on stock market return volatility. Specifically, they found that investor optimism decreased return volatility, whereas investor pessimism heightened it.

In summary, both domestic and international scholars have analyzed the influence of positive and negative sentiment levels on stock price volatility from various perspectives. Many scholars focus their studies on the differential impact of upward and downward changes in sentiment on stock price behavior. This research helps to deepen our understanding of how investor sentiment influences stock price behavior. However, they have not clearly elaborated on the specific meaning of changes in investor sentiment in the market, nor have they considered the autocorrelation and heteroskedasticity of investor sentiment from the perspective of econometric modeling, as well as the theoretical and practical implications of the magnitude of changes in investor sentiment. Therefore, it is necessary to clearly define the connotations of investor sentiment and its changes at both theoretical and empirical levels. Furthermore, their theoretical analysis and explanation of the asymmetric impact of investor sentiment on stock returns are not sufficiently comprehensive. Based on this premise, the dissertation thoroughly examines the characteristics of the Chinese stock market. It utilizes principal component analysis to create investor sentiment indicators that mirror the general market sentiment. Additionally, it conducts empirical analyses using the vector autoregressive (VAR) model and the exponential generalized autoregressive conditional heteroskedasticity (GARCH) family model in econometrics. These analyses aim to explore the influence of investor sentiment on stock returns and the relationship between investor sentiment and the stock market. While previous literature has generally examined the impact of individual aspects of investor sentiment on the stock market, this paper offers a comprehensive analysis of the asymmetric relationship between investor sentiment characteristics and stock price behavior. It explores the connection between the basic statistical characteristics of stock returns and the investor sentiment index. The outcomes derived from this analysis are consistent, robust, and lend credibility

to the findings. This research aims to enhance investors' comprehension of the distinct dynamics within the stock market and lays a solid empirical foundation for scholarly inquiry.

2. Measurement of investor sentiment indicators

2.1 Selection of Investor Sentiment Indicators

Investor sentiment metrics are broadly classified into three categories: subjective, objective, and comprehensive indicators (Wen et al., 2014). Subjective indicators are derived from qualitative data, such as interviews and surveys, capturing investors' perspectives and expectations. They not only directly reflect investor sentiment but also indicate investors' expectations and judgments about the future stock market. However, due to factors such as survey samples, survey respondents, index compilation methods, and survey costs, the results of subjective indicators may not fully reflect the genuine sentiments of traders and may lack a certain degree of objectivity. On the contrary, objective indicators are measures that indirectly gauge investor sentiment through statistical market trading data. These data offer an intuitive reflection of prevailing market trends and investor engagement, while also providing insights into market dynamics. Both subjective and objective indicators are essentially single indicators. The biggest drawback of single indicators is that they cannot comprehensively measure investor sentiment. Therefore, it is necessary to extract common information from multiple single indicators using scientific and rational methods to construct a composite indicator. Comprehensive indicators contain more detailed information, making it more reasonable and accurate to use them to measure investor sentiment.

A more common approach is to obtain indicators that proxy for investor sentiment by collecting a variety of objective data from the marketplace. Baker and Wurgler utilize six variables, including the New York stock market turnover rate, the closed-end fund discount rate, the number of IPOs, the average first-day return on IPOs, the number of IPOs, IPO number of initial shares, and the logarithmic ratio of the average market capitalization of assets of dividend-paying to dividend-neutral firms, to construct a composite indicator of investor sentiment. A comprehensive indicator of investor sentiment is constructed. Several scholars in China have also researched the correlation between investor sentiment and these indicators in the Chinese stock market. For example, Wen Fenghua et al. (2022) selected the closed-end fund discount (CEFD), the number of IPOs (IPON), the first-day return of IPOs (IPOR), the number of new accounts opened in the A-share market (ACCOU), and the market turnover rate (TURN) as five indicators that can better reflect the investor sentiment of the domestic stock market.

According to the characteristics of China's stock market, and taking into account the availability and representativeness of the data, this paper selects six indicators that better reflect investor sentiment in the domestic stock market. These indicators include the average discount rate of closed funds (DCEF), the average first-day return of IPOs (RIPO), the number of IPOs (NIPO), the number of new accounts opened (NA), the turnover rate of the market in the last month (TURN), and the consumer confidence index from the previous month (CCI). Domestic stock market investor sentiment indicators are used to construct a comprehensive index of investor sentiment through principal component analysis. The data sample interval used in the empirical analysis of this paper is from January 2009 to December 2023, comprising monthly data sourced exclusively from the Cathay Pacific database. ST stocks and financial samples are excluded from the sample selection. Additionally, both the first-day return and the number of IPOs during the period of IPO suspension are zero.

2.2 Principal Component Analysis of Investor Sentiment

Baker and Wurgler point out that each proxy variable of investor sentiment may have its own lead-lag effect, causing the variables to reflect investor sentiment in different periods. Drawing on their methodology, the study employs principal component analysis to synthesize 12 proxies, encompassing both current and lagged values of the six selected variables. Subsequently, the study

constructs a time series of investor sentiment indicators (FISI_{1t}) by computing the weighted average of the first four principal components. Finally, the paper conducts a correlation analysis between the constructed indicators and the 12 original proxies. In order to eliminate the influence of the scale, all variables are standardized in this paper.

Table 1 Correlation coefficient of FISI_{1t} with each proxy variable

	dceft	dcef_1t	ripot	ripo_1t	nipot	nipo_1t	nat	na_1t	turnt	turn_1t	ccit	cci_1t
FISI _{1t}	0.477	0.445	0.528	0.533	0.727	0.714	0.356	0.353	0.032	-0.004	0.631	0.642

According to Table 1, the correlation dceft, ripo_1t, nipot, nat, turnt, cci_1t are selected as the final sentiment variables, and the monthly return of the SSE Composite Index is utilized as a proxy for overall stock market performance. In order to eliminate bias caused by the influence of macroeconomic factors, the consumer price index (CPI), the industrial ex-factory price index (PPI), and the macroeconomic sentiment concordance index (MBA) are selected as macroeconomic proxy variables. The CPI and PPI data are from the RESSET database, and the MBA data are from the National Bureau of Statistics (NBS). The time interval for the control variables also spans from January 2009 to December 2023 to ensure data consistency. The six chosen sentiment proxies were regressed against macroeconomic indicators. The resulting residual series were analyzed as principal components of the sentiment variables with macroeconomic effects removed, showing a cumulative contribution of 86.67% from the first four variances.

Table 2 Contribution rate results

Component	Eigenvalue	Difference	Proportion	Cumulative
1	1.98917	0.595203	0.3265	0.3265
2	1.36396	0.262491	0.2273	0.5539
3	1.10147	0.325831	0.1836	0.7374
4	0.775642	0.364124	0.1293	0.8667
5	0.411219	0.023286	0.0686	0.9353
6	0.388233		0.0647	1.0000

Table 3 Factor Load Matrix

Variable	Factor1	Factor2	Factor3	Factor4
dceft	0.2544	0.8613	-0.1795	-0.0081
ripo_1t	0.4647	-0.0161	0.5715	-0.6740
nipot	0.7100	0.5078	-0.147	0.0368
nat	0.7975	-0.2926	-0.2066	0.1575
turnt	0.6736	-0.5252	-0.2631	0.0083
cci_1t	0.2908	0.0514	0.7803	0.5432

Table 4 Component Scoring Matrix

Variable	Factor1	Factor2	Factor3	Factor4
dceft	0.13984	0.63144	-0.16294	-0.01050
ripo_1t	0.23720	-0.01181	0.51885	-0.86895
nipot	0.36241	0.37228	-0.13405	0.04742
nat	0.40706	-0.21454	-0.18761	0.20310
turnt	0.34383	-0.38505	-0.23886	0.01066
cci_1t	0.14844	0.03768	0.70845	0.70033

Based on the above analysis, the following four principal component analysis formulas are constructed.

$$F1 = 0.13984dcef_t + 0.23720ripo_1_t + 0.36241nipo_t + 0.40706na_t + 0.34383turn_t + 0.14844cci_1_t \quad (1)$$

$$F2 = 0.63144dcef_t - 0.01181ripo_1_t + 0.37228nipo_t - 0.21454na_t - 0.21454turn_t + 0.03768cci_1_t \quad (2)$$

$$F3 = -0.16294dcef_t + 0.51885ripo_1_t - 0.13405nipo_t - 0.18761na_t - 0.23886turn_t + 0.70845cci_1_t \quad (3)$$

$$F4 = -0.01050dcef_t - 0.86895ripo_1_t + 0.04742nipo_t + 0.20310na_t + 0.01066turn_t + 0.70033cci_1_t \quad (4)$$

In this paper, the ratio of the variance contribution of each extracted principal component to the total variance contribution is used as a weighting scheme to obtain the investor sentiment index.

$$FISI_{1t} = \frac{0.3265 \cdot F1 + 0.2273 \cdot F2 + 0.2836 \cdot F3 + 0.1293 \cdot F4}{0.8667} \quad (5)$$

3. An empirical Analysis of the Impact of Investor Sentiment on Stock Market Returns

3.1 The Impact of Investor Sentiment on Stock Returns Based on VAR Modeling

In order to explore the impact of investor sentiment changes on stock market return changes, the vector autoregressive (VAR) model in econometrics and the GARCH family model in time series are used to explore the relationship between the two. The monthly return of the SSE Composite Index is chosen to represent the stock market returns, and the sample data interval is from 2009 to 2023, unified as monthly data, and the data are from Wind database.

3.1.1 Stability test——ADF Test

Prior to model construction, a stability test is essential for each time series to prevent the occurrence of spurious regression. As can be seen from the results of the unit root test in Table 5, the Augmented Dickey-Fuller (ADF) test yielded significant results for both the composite stock market return (RETURN) and the macro-factor-adjusted market sentiment (FISI) at the 10% significance threshold, and the unit root test is smooth. Both indicators are smooth series and can be analyzed in time series.

Table 5 Unit Root Test Stability Results

Variables	ADF Test Statistic	P-value	Whether stable
RETURN	-5.606	0.0000	Yes
FISI	-2.838	0.0531	Yes

3.1.2 VAR Model Construction

This study constructs a Vector Autoregression (VAR) model to delve into the influence of investor sentiment on stock market returns. When building the VAR model, the first step is to determine the lag order of the VAR model. As the number of lags increases, the completeness of the dynamic information reflected by the VAR model improves. However, the number of lags is not as large as the better. Since the larger the number of lags, the smaller the degree of freedom. It is quite important to choose a lag and the degree of freedom of the lag period are reasonable. The analysis of the results in Table 4 yields a VAR lag order of P=3.

Table 6 VAR Model Lag Order

Lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
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0	-305.776				0.131	3.642	3.657	3.679
1	-217.83	175.89	4	0	0.048	2.649	2.69397*	2.76*
2	-212.313	11.034	4	0.026	0.048	2.631	2.706	2.816
3	-206.474	11.677*	4	0.02	.046584*	2.60916*	2.714	2.868
4	-205.524	1.901	4	0.754	0.048	2.645	2.781	2.979

After the VAR model is constructed, the stability of the model and the residual term should also be examined to determine the appropriateness of the model. If the mode inverses of the roots of the AR characteristic polynomials of the model all fall within the unit circle, the constructed model is stable and can be analyzed further.

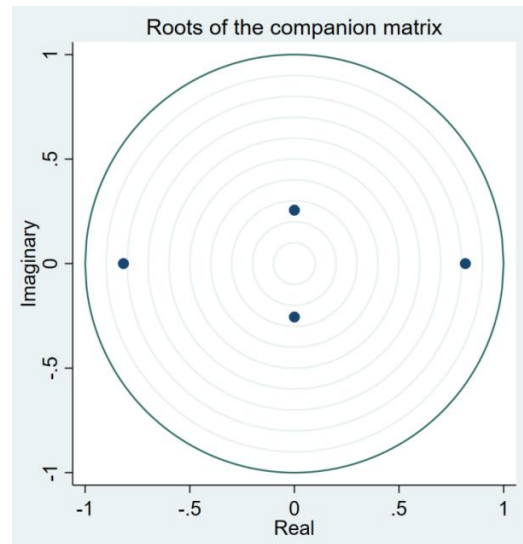


Figure 1 VAR model stability discrimination

As can be seen from Figure 1, the mode inverses of the roots of the AR characteristic polynomials of the VAR model all fall within the unit circle, and the model test is stable.

3.1.3 Granger Causality Tests

Granger causality not only describes the traditional causality but also determines the order of the 2 variables. The prerequisite for Granger causality test is that the variables are smooth. From the above analysis, it can be seen that the investor sentiment indicator and the stock market return have smoothness, so the Granger causality test can be directly carried out.

Table 7 Results of the Granger Causality Test

Equation	Excluded	chi2	df	prob>chi2
FISI	RETURN	4.3286	1	0.037
RETURN	FISI	2.7428	1	0.098

The results of the Granger causality test in Table 7 indicate that changes in the stock market return RETURN can cause changes in the investor sentiment index FISI at the 10% level of significance. Changes in the Financial Investor Sentiment Index (FISI) can lead to significant fluctuations in stock market returns, with a correlation of 10%, suggesting a causal relationship between the two. When the rate of return continues to increase, it stimulates investment interest, strengthens the willingness to invest, and boosts investment sentiment. When investor sentiment is high, it increases investors' demand in the stock market and boosts stock returns.

Behavioral finance and psychology research shows that in a positive emotional state, people tend to make optimistic judgments and decisions. Therefore, positive emotions can lead to an increase in investors' estimation of the expected rate of return on stocks and a decrease in their estimation of risk. In a positive mood state, emotional investors are less concerned about risk and pay more

attention to improving investment efficiency. Their investment behavior is more aggressive, and they are willing to buy a larger number of stocks. This active participation in the market pushes up the price of assets and positively affects stock returns. In the cycle of high market sentiment and rising emotions, new investors and funds continue to enter the market. These new investors often lack professional knowledge and experience, making them more likely to exhibit irrational characteristics. This exacerbates the rising market sentiment and creates a positive feedback effect in the stock market. On the contrary, in a state of negative sentiment, investors tend to make pessimistic judgments and decisions, leading them to reduce their estimate of the expected return on assets and increase their estimate of risk. In this case, emotional investors focus more on controlling risk, are willing to buy fewer stocks, market trading is light, and investors' willingness to participate in the market decreases.

3.2 Volatility Analysis Based on GARCH Family Models

The relationship between investor sentiment and stock market returns is analyzed through the GARCH family model to investigate whether there are symmetric and asymmetric effects between investor sentiment and stock market returns.

3.2.1 GARCH Family Modeling

3.2.1.1 GARCH Model

In ARCH(p) model, if p is very large, many parameters have to be estimated, which will lose the sample capacity. Bollerslev (1986) proposed GARCH model, which makes the surrogate estimation of parameters reduced, while the prediction of future conditional variance is more accurate.

The conditional mean equation constructed in this paper is:

$$\text{RETURN}_t = C + C_1 \text{FSIS}_t + u_t \quad (6)$$

$$\text{FSIS}_t = C + C_1 \text{RETURN}_t + u_t \quad (7)$$

$$u_t \sim N(0, \sigma_t^2) \quad (8)$$

Where RETURN_t denotes the stock market return, FSIS_t denotes the constructed investor sentiment indicator, C_1 denotes the coefficients, C is a constant term, u_t denotes the residual term, and Eq. 6 denotes the effect of investor sentiment on the volatility of stock market returns; and Eq. 7 denotes the effect of volatility of stock market returns on investor sentiment.

For a logarithmic time series r_t , let $a_t = r_t - \mu_t = r_t - E(r_t|F_{t-1})$ be its new interest series, $\{a_t\}$ is called service GARCH(m,s) model, a_t satisfies:

$$u_t = \sigma_t \sqrt{\varepsilon_t} \quad \sigma_t^2 = \omega + \sum_{i=1}^m \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^s \beta_j \sigma_{t-j}^2 \quad (9)$$

The GARCH (1, 1) model developed in this study features the following conditional variance equation:

$$\sigma_t^2 = \omega + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2 \quad (10)$$

Where $\{\varepsilon_t\}$ is the RETURN series of independently and identically distributed stock returns with zero mean and unit variance and the FISI series of investor sentiment index, σ_t^2 denotes the variance, the first-order lag term denoted by σ_{t-1}^2 , ε_{t-1}^2 is the disturbance term, ω , α and β are the coefficients. One of the main constraints of GARCH models is that they respond symmetrically to positive or negative shocks. However, for financial time series, negative shocks tend to cause greater volatility than positive shocks of the same magnitude. To explain this phenomenon, Engle (1993) plotted asymmetric information curves for good news and bad news, arguing that shocks to capital markets are asymmetric shocks.

3.2.1.2 TARARCH Model

Information asymmetry impacts on asset price volatility. As a simple extension of the GARCH model, the TARARCH model incorporates additional terms that explain possible asymmetries by adding a TARARCH term to the GARCH (1, 1) model.

$$\sigma_t^2 = \omega + \alpha_1 \varepsilon_{t-1}^2 + \gamma_1 |\varepsilon_{t-1}| I_{[\varepsilon_{t-1} < 0]} + \beta_1 \sigma_{t-1}^2 \quad (11)$$

where, σ_t^2 is the standard deviation, $I_{[\epsilon_{t-1} < 0]}$ is the indicative function, i.e., when $\epsilon_{t-1} < 0$, it takes the value of 1; and vice versa, it is 0, $|\epsilon_{t-1}|I_{[\epsilon_{t-1} < 0]}$ is the TARCH term, ω , α , and β are the coefficients.

3.2.1.3 EGARCH Model

In the standard GARCH model, there is a restriction on the values of the parameters, which is inconvenient for MLE. Nelson proposed Exponential GARCH model with conditional variance:

$$u_t = \sigma_t \sqrt{\epsilon_t} \quad (12)$$

$$\ln \sigma_t^2 = \omega + \sum_{j=1}^m [\alpha_j \epsilon_{t-j} + \gamma_j (|\epsilon_{t-j}| - E|\epsilon_{t-j}|)] + \sum_{i=1}^s \beta_i \ln(\sigma_{t-i}^2) \quad (13)$$

The conditional variance equation for the EGARCH (1, 1) model constructed in this paper is:

$$u_t = \sigma_t \sqrt{\epsilon_t} \quad (14)$$

$$\ln \sigma_t^2 = \omega + [\alpha_1 \epsilon_{t-1} + \gamma_1 (|\epsilon_{t-1}| - E|\epsilon_{t-1}|)] + \beta_1 \ln(\sigma_{t-1}^2) \quad (15)$$

Where $\epsilon_t \sim N(0,1)$, the order of this model is similar to GARCH(1,1), the model is actually an AR(1) model. As long as $\neq 0$, this model also contains asymmetric effects, similar to the TARCH model, for the EGARCH term, ω , α , γ and β are coefficients. The advantage of EGARCH is that no matter what value is taken, there is $\sigma_t^2 = \exp(\ln \sigma_t^2) > 0$, so there is no restriction on all the parameters in equation (15).

3.2.2 Comparison and Analysis of GARCH Family Model Results

Table 7 The effect of Stock Market Returns on the Volatility of Investor Sentiment

	GARCH model		TARCH model		EGARCH model	
	Coefficient	p-value	Coefficient	p-value	Coefficient	p-value
α_1	0.3839932	0.020	0.3868618	0.031	0.0118491	0.877
β_1	0.6497858	0.000	0.6496453	0.000	0.9261014	0.000
γ_1			-0.0052172	0.974	0.6164054	0.000
ω	0.5400203	0.395	0.5371794	0.395	0.2111929	0.208

According to the theory of stock market effectiveness, the volatility of stock prices reflects the continuous adjustment and interpretation of information by market participants. The application of GARCH, TARCH and EGARCH models can be regarded as a tool to reveal the relationship between market volatility and information shocks. These models can help us understand the dynamic mechanisms behind market volatility, including the absorption of information and the reaction of market participants, thus providing us with more in-depth explanations of market volatility.

The α coefficient measures the symmetric effect of stock return volatility on investor sentiment and the γ coefficient measures the asymmetric effect of stock return volatility on investor sentiment. Comparison of the analytical model results reveals that the significance of the symmetry effect of the coefficients of the GARCH model is better than that of the TARCH model and the EGARCH model, which is significant and the coefficients are positive at the 5% confidence level. It indicates that the volatility of stock returns has a significant positive impact on the investor sentiment index. However, the GARCH model fails to portray the asymmetry (leverage effect) of the volatility of the conditional variance of returns because in the GARCH model, the effects of positive and negative shocks on the conditional variance are symmetric. The GARCH model posits that conditional variance is determined by the squared lagged residuals, reflecting past market movements. Therefore, in the GARCH model, the positive and negative outcomes of the residuals are independent of volatility, i.e., the conditional variance responds symmetrically to price increases and decreases.

The theory of leverage suggests that the market may show a relatively mild reaction in the face of good news and a more violent reaction in the face of bad news. Therefore, the TARCH and EGARCH models take into account this asymmetry, particularly the leverage effect, to more accurately capture the characteristics of market volatility.

The TARARCH model extends the GARCH framework by incorporating an additional term to account for potential asymmetries. Since $\beta > 0$, there is a leverage effect. While most of the parameters of the EGARCH model are better than the GARCH and TARARCH models in terms of the significance of the asymmetric effect and are significant at the 1% confidence level. All the coefficients of the conditional variance equation of the EGARCH model are significantly non-zero, which suggests that there is a certain amount of leverage effect, indicating that the fluctuations in stock returns have a significant asymmetric impact on the index of investor sentiment.

α_1 represents the impact of favorable information, γ_1 represents the impact of negative information. $|\alpha_1 + \gamma_1| = 0.06282545$ is the leverage effect of favorable information, and $|\alpha_1 - \gamma_1| = 0.6045563$ is the leverage effect of negative information. Since $0.6045563 > 0.06282545$, the shock effect of negative information is stronger than that of good information. The shock effect of rising stock market yields on investor sentiment is smaller than the shock effect generated by falling stock market yields. This phenomenon is consistent with the characteristics of financial time series.

Table 8 The impact of investor sentiment on the volatility of stock market returns

	GARCH model		TARARCH model		EGARCH model	
	Coefficient	p-value	Coefficient	p-value	Coefficient	p-value
α_1	0.2406725	0.003	-0.0072273	0.890	0.3236494	0.002
β_1	0.6758137	0.000	-0.1269176	0.156	-0.4274936	0.001
γ_1			0.4963403	0.017	0.4748053	0.002
ω	0.0003758	0.032	0.5371794	0.000	-8.069159	0.000

According to the theory of behavioral finance, emotional fluctuations in market sentiment may lead to inconsistent responses of investors to good and bad news, which in turn affects the volatility of the stock market. By analyzing the results of the above table, it is found that the significance of the symmetric and asymmetric effects of the coefficients of the EGARCH model is better than that of the TARARCH model and the GARCH model, both of which are significant and have positive coefficients at the 1% confidence level. It indicates that the investor sentiment index has a positive and significant symmetric and asymmetric effect on the volatility of stock returns. Stock returns are significantly affected by investor sentiment and this effect is positive, indicating that positive sentiment will promote investors to increase investment in stock returns, release favorable information about the stock market to the external market, attract more investors to invest in the stock market, and thus promote the increase in stock returns. On the contrary, negative investor sentiment reduces investor enthusiasm and creates a downturn environment in the stock market, which leads to a decrease in investor returns.

Each coefficient of the conditional variance equation of the EGARCH model is significantly non-zero, indicating the existence of a certain leverage effect, suggesting that the volatility of stock returns has a significant asymmetric impact on the investor sentiment index. The economic theory of the leverage effect suggests that the asymmetry of market participants' reaction to favorable and unfavorable news has different impacts on market volatility. $|\alpha_1 + \gamma_1| = 0.7984547$ is the leverage effect of favorable information and $|\alpha_1 - \gamma_1| = 0.1511559$ is the leverage effect of negative information. Since $0.7984547 > 0.1511559$, the shock effect of favorable information is stronger than that of negative information. It shows that positive sentiment has a stronger impact effect on stock return volatility than negative sentiment when positive sentiment is comparable to negative sentiment.

4. Conclusions and Policy Recommendations

The selection of investor sentiment metrics prioritizes the representativeness and availability of the indicators. Six indicators have been chosen to construct the comprehensive indicators of investor sentiment: the average discount rate of closed funds (DCEF), the average first-day return of IPOs (RIPO), the number of IPOs (NIPO), the number of new accounts opened (NA), the turnover rate of the market in the last month (TURN), and the consumer confidence index from the previous month (CCI). To address the impact of the same index on investor sentiment in various periods, the selected indexes are lagged by one period. Additionally, to mitigate the influence of macroeconomic factors, three macroeconomic variables (Consumer Price Index CPI, Industrial Ex-factory Price Index PPI, and Macroeconomic Prosperity Consensus Index MBA) are chosen as control variables. The investor sentiment composite index is then constructed using the Principal Component Analysis method. In analyzing the relationship between investor sentiment and stock market returns, the vector autoregressive (VAR) model in econometrics and the GARCH family model in time series are used. The research findings are mainly reflected in the following three aspects.

(1) The subjective sentiment indicators have been combined with the objective sentiment indicators, and the influence of macroeconomic factors has been eliminated. The FISCI constructed using principal component analysis is significantly correlated with each of the original indicators. The cumulative contribution rate of the four principal components extracted is 86.67%, indicating that the composite indicator FISCI contains most of the information from the original indicators, and the selected indicators are representative. In addition, the composite indicator FISCI is significantly correlated with RETURN. The fluctuation trend of RETURN is roughly the same as that of investor sentiment, which can reflect the changes in stock market returns to a certain extent. Further research can explore the relationship between the two.

(2) A VAR model is established to analyze the Granger causality between the investor sentiment index and stock market returns. The results show that the stock market yield is the Granger cause of the investor sentiment index, and vice versa, the investor sentiment index is also the Granger cause of the stock market yield, indicating a bidirectional causality between the two. When stock yields continue to rise, it stimulates the interest of investors, leading to an increase in their willingness to invest and boosting their investment sentiment. When there is a sustained increase in stock market returns, it stimulates investors' interest and leads to a rise in their willingness to invest, which in turn triggers a high level of investment sentiment. When investor sentiment is high, the demand for stocks in the market will increase accordingly, driving stock yields up further.

(3) The GARCH family of models has been applied to the study of the interaction between investor sentiment and stock market returns. The results indicate that the empirical findings of the GARCH model demonstrate a significant and positive symmetry effect between investor sentiment and stock market returns. Moreover, the EGARCH model outperforms the GARCH and TARCH models in terms of empirical results, suggesting a notable asymmetric effect between investor sentiment and stock market return volatility, which is highly significant. When investor sentiment is positive and optimistic, stock market returns tend to increase. Conversely, when investor sentiment is negative and pessimistic, stock market returns typically decrease. Conversely, an increase in stock market yields will stimulate high investor sentiment, while a decrease in yields will lead to low investor sentiment. However, it is worth noting that the stock market returns react less to positive optimism than to negative pessimism. In other words, the impact of positive news on the stock market is greater than that of negative news. This suggests that the impact of falling stock yields on changes in investor sentiment is greater than that arising from a rise in stock yields. Conversely, when examining the impact of investor sentiment on the volatility of stock yields, the impact of positive information is stronger. On the contrary, when studying the impact of investor sentiment on stock yield volatility, the impact of favorable information is stronger than that of negative information. This indicates that stock market yield volatility is much more affected by positive and optimistic investor sentiment than by negative and pessimistic investor sentiment.

Based on this, this paper presents the following policy recommendations:

(1) Investors should be encouraged to actively engage in financial education and training to enhance their financial literacy. This involves in-depth learning about securities trading, investment theories, and market behavior models, as well as improving investment skills through simulated trading and practical operations. It is advocated that investors adopt systematic investment analysis methods in the decision-making process. They should fully consider the impact of market sentiment on stock price behavior and conduct comprehensive analyses by combining fundamental and technical factors. This approach helps to avoid losses resulting from blindly following trends and making irrational investments, ultimately reducing the risk of irrational investment behavior.

(2) Financial institutions should also enhance risk management and product innovation to offer investors a variety of investment options and specialized investment services. This will help investors gain a better understanding of market sentiment and respond effectively to market fluctuations. Financial institutions can also actively engage in investor education activities. They can organize professional seminars and exchange forums to teach investors about investment concepts and risk management skills, aiming to cultivate rational investment awareness and behavior.

(3) Regulatory bodies should fortify the market regulatory framework, enhance market access protocols, and bolster information disclosure standards to ensure market transparency and fairness. This will help reduce information asymmetry, prevent market manipulation, and safeguard the legitimate rights and interests of investors. Urging regulatory bodies to bolster the development of market risk assessments and early warning systems to promptly mitigate the adverse impact of irrational investor sentiment on the capital market. Pay attention to the overall situation of investor sentiment and take active and effective measures to stabilize the market when investor sentiment fluctuates significantly. This will help regain investors' confidence in the market and improve the market regulatory system.

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