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Research on the Impact Of Investor Sentiment on Stock Returns

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ABSTRACT
Investor sentiment directly affects stock prices and yields, and is an important basis for investors to make investment decisions. Examine indicators of market sentiment among investors, primarily categorized as direct and indirect measures. Direct indicators are gathered directly from investor opinions, and the sentiment metrics developed based on these direct inputs reflect the collective mindset of investors toward the financial market—such as optimism or pessimism regarding future performance. Indirect indicators express investor sentiment in the form of proxy variables by calculating relevant data. This study examines the influence of investor sentiment on equity returns in the domestic market, thereby offering a theoretical foundation for both investment decision-making and regulatory oversight.

KEYWORDS
Stock market; Investor sentiment; Stock earnings

1 Introduction

1.1 Research background

Investor sentiment serves as a significant determinant influencing fluctuations in equity markets. While traditional financial theory posits that markets are efficient and security prices fully incorporate all publicly available information, empirical observations reveal that investors are often subject to psychological biases, emotional shifts, and prevailing social sentiment, leading to non-rational investment behaviors. Numerous studies have shown that investor sentiment can cause stock prices to deviate from their intrinsic value by influencing buying and selling behavior, resulting in short-term market anomalies [1]. In the case of information asymmetry or high market uncertainty, emotional factors have a more significant impact on individual stocks and the overall market. Exploring this influence mechanism not only helps explain market anomalies, but also provides an important reference for investors to formulate strategies and regulators to protect against market risks.

1.2 Research significance

Investigating the impact of investor sentiment on stock returns holds both theoretical and practical relevance. Theoretically, it contributes to the advancement of behavioral finance by uncovering the psychological drivers behind market anomalies unexplained by traditional finance, such as excessive volatility and asset bubbles, thereby addressing the limitations inherent in the efficient market hypothesis. At the practical level, studying the impact of investor sentiment can help investors better identify changes in market sentiment, optimize investment decisions, and avoid irrational trading behaviors caused by emotional fluctuations. At the same time, it also provides a reference for regulators to more effectively monitor market sentiment fluctuations, prevent systemic risks, and maintain financial market stability [2].

2 Review of literature at home and abroad

2.1 Research on the concept of investor sentiment

Foreign scholars have studied investor sentiment earlier. C.W. Chiu, R.D (2018) defines the connotation of investor sentiment from a new perspective, taking investors' subjective intuitive judgment of the future trend of asset prices in the capital market as the starting angle, and considers it to be a kind of judgment of investors on the trend of their investment prices. This judgment may come from whether investors' attitudes towards the company's future stock price are optimistic or pessimistic [3]. J. Benhabib (2016) conceptualized information as the fertile ground in which investor sentiment grows, defining such sentiment as the subjective belief shaped by investors after processing relevant historical and current information regarding an investment target. However, because investors lack a rigorous objective basis for estimating future cash flows and assessing various risks, this belief is often not grounded in objective reality [4].

Research on investor sentiment by domestic scholars gained significant momentum in the early 21st century. Yu Huijia (2025) further examined this type of systematic bias and suggested that it stems from individuals' subjective emotional assessments [5]. Ding Siqi (2023) emphasized that the presence of investor sentiment helps explain collective mispricing across the market from the perspective of deviations in asset pricing [6]. In contrast, Tian Yunzhu and Li Yawen (2023) argued that such systematic bias is more closely linked to individual investors knowledge and cognitive frameworks than to intense emotional influences [7]. Meanwhile, Zhou Haiyan (2023) framed the concept of investor sentiment within an asset-pricing context by comparing the current asset price, which is shaped by expectations of future values, with the price based on historical and current market information. She defined investor sentiment as the discrepancy between these two values [8].

2.2 Research on the impact of investor sentiment on stock returns

The determinants underlying investor behavior are multifaceted. Among these drivers, investor sentiment serves as a key factor, and the translation of such sentiment into action constitutes the primary direct contributor to actual market fluctuations. Thus, analyzing the influence of investor sentiment on the stock market holds considerable importance.

Feng Jing (2024) focused on the GEM stock market as the primary research subject. Using a text mining approach, the study predicted and analyzed returns of GEM stocks by applying a dictionary-based method to classify the sentiment tendencies of stock reviews from the East Money Stock Forum, collected between April 1, 2021, and April 1, 2023. An investor sentiment index was constructed, and a particle swarm-optimized support vector machine (PSO-SVM) model was developed to forecast returns. During the empirical phase, CATL, the largest stock by circulating market value on the GEM, was selected as a representative case. The PSO-SVM model was used to predict its returns, with multiple control models established for comparative analysis. The results indicated that the PSO-SVM model delivered superior predictive performance compared to other control models, and the version incorporating the sentiment index achieved better accuracy than the model without it [9].

Hu Changsheng and Xia Guoxiao (2024) utilized transaction data from A-share listed companies between 2011 and 2020 to develop a new daily-frequency sentiment index. Based on this indicator, they examined the effects of cumulative changes in investor sentiment on short-term stock returns. The results show that investor sentiment has a cumulative effect, which initially brings significant positive returns, but will cause a large price correction after investor sentiment accumulates to a certain level, which has a more obvious impact on stocks that are difficult to arbitrage. The cumulative effect of high and low emotions has significant asymmetry, and under the continuous accumulation of high emotions, funds in the market will pour into assets with low volatility levels and good liquidity. while under the accumulation of sustained low sentiment, funds will choose more speculative assets [10].

Zhu Yixuan (2023) undertook a comprehensive investigation into the effects of investor sentiment on stock returns. The study analyzed the influence of market sentiment on both short-term fluctuations and long-term trends in equity markets, examined the relationship between sentiment and investor behavior, and assessed how sentiment-driven factors interact with macroeconomic variables. Additionally, the research explored the responsiveness of investor sentiment to macroeconomic policy changes. The results show that studying investor sentiment can help improve investment returns and reduce risks, provide a basis for government departments to formulate more accurate macroeconomic policies, promote economic development and stability, and promote theoretical research on investment behavior and market sentiment [11].

3 The impact of investor sentiment on stock returns

3.1 Model selection

The VaR (Value-at-Risk) model is a foundational tool in financial risk management, widely used to quantify potential losses in investment portfolios and regarded as a mainstream methodology for assessing market risk. It provides a concise and clear representation of risk exposure and helps standardize risk measurement practices across the industry, enabling both managers and investors to interpret and manage risk more effectively. Grounded in probability theory and mathematical statistics, the methodology is both scientifically rigorous and operationally straightforward. Furthermore, the VaR model addresses the historical lack of uniform risk assessment standards in finance, establishing a common framework that facilitates comparison across different financial sectors. This allows professionals from diverse fields to communicate using a shared language when evaluating market risks [12]. Following the standardization of risk reporting, financial institutions can calculate and disclose VaR values on a regular basis, thereby improving transparency in the market. This practice allows investors to better understand market conditions, strengthens investment confidence, and contributes to greater stability in financial markets. In contrast to traditional ex-post risk management approaches, the VaR model enables not only the risk assessment of individual financial instruments but also the evaluation of portfolio-level risk across multiple assets. By incorporating a comprehensive view of both risk and return factors, it assists investors in identifying the most efficient portfolio that maximizes returns for a given level of risk [13].

The empirical model employed in this study belongs to the GARCH family, which is well-suited for capturing the dynamic characteristics of financial volatility:

$$R_t = \alpha_0 + \alpha_1 \Delta IS_t + \mu_t$$

3.2 Unit root inspection

In the ADF test, the null hypothesis posits that the time series contains a unit root, while the alternative suggests a stationary process, which may include a constant term and/or a linear time trend. The test evaluates whether the estimated test statistic leads to rejection of the null hypothesis, allowing further inference regarding the presence of a unit root in the autoregressive structure. To ensure the validity of the test, the lag order must be appropriately selected during regression. This is typically accomplished using information criteria such as the SIC and AIC to determine the optimal lag length for the time series model. In addition, other factors need to be considered in practical applications, such as system stability, model fit, and other comprehensive factors.

Table 1 Unit root test

Sequence name	ADF test value	Prob	Stability	
IS	-10.8706	0.0000	stable	The 1% confidence level is -3.4825
Rt	-6.010	0.0000	stable	The 5% confidence level is -2.8843
∆RV2	-10.7076	0.0000	stable	The 10% confidence level is -2.5790

Based on the results of the ADF test, the unit root test indicates that the test statistics for the investor sentiment index, the monthly return of the Shanghai Stock Exchange, and its volatility all exceed the critical values at their respective significance levels. Therefore, the null hypothesis of a unit root is rejected. This suggests that the investor sentiment index, along with the monthly returns and volatility changes of the Shanghai Stock Exchange, do not exhibit unit roots. Consequently, the original time series of the yield and volatility for both the investor sentiment index and the Shanghai stock market are stationary.

Based on the correlation coefficients reported in Table 2, a clear relationship is observed between the investor sentiment index (IS) and both the return and volatility of the SSE A-share market. Specifically, there is a positive correlation between the investor sentiment index and stock market returns (R), with a correlation coefficient of 0.0067. This suggests that a one-unit increase in the sentiment index is associated with an increase of 0.0067 units in market returns. Similarly, a positive correlation exists between investor sentiment and return volatility (RV), with a stronger coefficient of 0.0929. This indicates that a one-unit change in sentiment corresponds to a 0.0929-unit change in volatility. Overall, the results show that investor sentiment has a more pronounced effect on market volatility than on returns.

Table 2 Statistical analysis and correlation coefficients of each index

	R	RV			IS	R	RV
mean	0.0050	0.0069	correlation coefficient	IS	1		
median	0.0167	0.0048		R	0.0067	1	
maximum	0.2438	0.0352		RV	0.0929	-0.1832	1
minimum	-0.2824	0.0006					
standard deviation	0.0865	0.0066					

3.3 Long-term impact analysis

In order to measure the magnitude and direction of the impact of investor sentiment on stock yields, the hypothetical model:

$R_t = \alpha_0 + \alpha_1 \Delta IS_t + \mu_t$

ΔIS_t represents a change in investor sentiment indicators. Investor sentiment uses data from the Yale-CCER China Investor Confidence Index range from March 2008 to April 2012, the monthly yield of R_t SSE A-shares.

The logarithmic value of the real volatility of the Shanghai Composite Index selected in this paper is used as the interpreted variable. Examine the interrelationship between volatility and investor sentiment. The hypothetical model is:

$\log RV_t = \beta_0 + \beta_1 \Delta IS_t + \mu_t$

Table 3 Regression results

Regression equation	Adjusted-R^2	F-statistic	Prob
$R_t = \alpha_0 + \alpha_1 \Delta IS_t + \mu_t$ t=(0.0076) (0.45×10^5)	0.7127	0.6238	0.1078
$\log RV_t = \beta_0 + \beta_1 \Delta IS_t + \mu_t$ t=(0.1579) (0.0009)	0.6020	2.2871	0.1355

R^2 indicates the degree of fit of the regression equation, and closer to 1 indicates the degree of fit

According to the regression results of Equation 1, the estimated coefficient is -7.35×10^{-5}, indicating a negative relationship between market returns and the investor sentiment index. Specifically, returns move in the opposite direction to changes in sentiment. The regression coefficient of 0.0015 in Equation 2 suggests a positive relationship between return volatility and investor sentiment. A one-percentage-point increase in the composite sentiment index corresponds to a rise in return volatility. This result implies that during bull markets, heightened investor enthusiasm amplifies market volatility, whereas during bearish or stagnant market conditions, subdued sentiment is associated with more stable return patterns. These regression outcomes align with the correlation analysis presented earlier.

If the variables become stationary after being differenced d times, they are considered to exhibit a cointegration relationship. Although the time series ΔR_t and $\Delta(\Delta IS_t)$ are non-stationary first-order single integer sequences, a linear combination of them may still be stationary. This combination captures a long-term equilibrium relationship between the variables, known as cointegration. Using the Engle–Granger two-step method, the variables were first regressed on one another. The residuals from this regression were then tested for stationarity using the ADF test. If the residuals are found to be stationary, it indicates a cointegration relationship between the variables, and the estimated equation represents a cointegrating relationship.

The regression method is performed using the OLS method to obtain the regression equation between R_t and ΔIS_t:

$R_t = 0.0042\text{-}7.35\times10^{-5}\ \Delta IS_t + \mu$

The stationarity of the regression residuals was examined using the ADF test, and the corresponding results are presented in Table 3-5:

Table 4 Results of investor sentiment and stock return cointegration test

ADF	Types of inspections (c,t,k)	Critical value			conclusion
		1%	5%	10%	
-2.411846	(0,0,0,)	-2.692358	-1.960171	-1.607051	smooth

According to the stationarity test results presented in Table 4, the ADF test statistic is lower than the critical value at the 5% significance level, leading to the conclusion that the series is stationary. This indicates a cointegration relationship between investor sentiment and stock returns, confirming a long-term equilibrium between these variables. Furthermore, the results suggest that stock market returns exhibit a negative impact on investor sentiment. The estimated coefficient of investor sentiment is -7.35×10^{-5}, implying that a one-percentage-point increase in the investor sentiment index is associated with a decrease in stock market returns of -7.35×10^{-5} percentage points.

Table 5 Results of investor sentiment and stock volatility cointegration

ADF	Types of inspections (c,t,k)	Critical value			conclusion
		1%	5%	10%	
-1.725685	(0,0,0,)	-2.4582146	-1.8524561	-1.545124	smooth

Based on the stationarity test results in Table 5, the ADF statistic is lower than the critical value at the 5% significance level, indicating that the series is stationary. This supports the presence of a cointegration relationship between investor sentiment and stock volatility, confirming a long-term equilibrium between these variables. The results further suggest that stock market volatility has a positive effect on investor sentiment. With an estimated coefficient of 0.0015 for investor sentiment, a one-percentage-point increase in the sentiment index is associated with an increase in stock market volatility of 0.0015 percentage points.

3.4 Short-term impact analysis

While a cointegration relationship captures the long-term equilibrium between variables, short-term imbalances may still arise due to external disturbances. To integrate these long-run dynamics with short-term adjustments, an error correction model is employed. In this study, an error correction model describing the interaction between investor sentiment and stock market returns was estimated using ordinary least squares (OLS) regression:

$R_t = 0.0034\text{-}4.02\times10^{-5}\ \Delta IS_t\ \text{-}0.527\ \mu$

Table 6 Error correction model of investor sentiment and stock market yield

variable	Regression coefficient	standard error	t-statistic	probability
C	-0.0034	0.077320	-0.450075	0.6587
Δ(ΔISt)	-0.0000402	0.270858	1.0484912	0.1570
UT(-1)	-0.527170	0.230793	-2.284172	0.0364

In the above equation, the coefficient of Δ(ΔISt) is -0.0000402, indicating that for every 1 percentage point increase in the investor sentiment index in the short term, the stock market yield decreases by 0.0000402 percentage points; The error correction term has a coefficient of -0.527170, which is in line with the reverse mechanism, indicating that when short-term fluctuations deviate from long-term equilibrium, they will return to equilibrium at a rate of -0.527170.

The error correction model of investor sentiment and stock market yield is established by using the OLS regression model:

$\log RV_t = \text{-}4.1287 + 0.0023\Delta IS_t \text{-}\ 0.9854\mu_t$

In the equation above, the coefficient of Δ(ΔISt) is -0.0023, suggesting that a 1 percentage point increase in the investor sentiment index in the short term is associated with an increase in stock market returns of 0.0023 percentage points. The coefficient of the error correction term is –0.9854, which is consistent with the reverse adjustment mechanism. This

Table 7 Error correction model of investor sentiment and stock market yield

variable	Regression coefficient	standard error	t-statistic	probability
C	-4.1287	0.056854	-0.385475	0.3657
Δ(ΔISt)	-0.0023	0.198542	0.8568491	0.2317
UT(-1)	-0.9854	0.270283	-1.984172	0.0034

indicates that when short-term fluctuations deviate from the long-term equilibrium, the system corrects toward equilibrium at an adjustment speed of 0.9854.

4 Empirical summary

Building on a rigorous research framework and employing multiple analytical perspectives, this study integrates empirical models with quantitative methods to examine the intrinsic relationship between investor sentiment and stock market returns. Based on the analysis, it is concluded that:

First, in the short term, investor sentiment exerts a significant negative impact on contemporaneous stock returns. As investors' optimism about the current economic outlook deepens, so does their sentiment, which leads to a decline in current stock market returns. Conversely, if investors are in a low mood, current stock earnings may show signs of recovery. Second, at the current stage, investor sentiment shows a significant positive correlation with the volatility of contemporaneous stock returns; When investors face a slowdown in economic growth or a recession, they tend to show a lower enthusiasm for investment. This negativity may lead to reduced volatility in the current stock, making yield changes more stable. On the other hand, if investor sentiment is unusually high, the current sector liquidity will increase and yield changes will become more uncertain. Finally, there is also a lag effect in future forecasts: monthly data analysis of the A-share market shows that investor sentiment will still significantly affect yields and volatility in the next one to three months. Such effects diminish over time and tend to be positively correlated.

In general, the research shows that investor mentality plays an important role in our examination of stock returns; When we make any judgment or decision, we must rely on irrational participation in subjective judgment factors, and analysts need to think deeply about risk management techniques and methods.

5 Conclusion

When analysing the impact of investor sentiment on equity market returns, we should take a comprehensive look at investor sentiment composition and size indices, and combine research theories to gain broader utility. Doing so can help create more economic gains and enable the stock market to effectively integrate investor sentiment changes. In addition to existing indicators, factors such as options implied volatility, futures premiums, and funding data should be considered when studying investor sentiment to enrich investor sentiment indicators and mitigate the potential negative impact of sentiment on the stock market.

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