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Investor Sentiment and Market Risk in China: An Empirical Analysis Based on the CSI Sentiment Index

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Abstract: With the development of behavioral finance, the influence of investor sentiment on financial market risk has attracted increasing attention. Using data from the CSI 300 Index and the CSI Investor Sentiment Index, this study employs regression models to examine the effects of investor sentiment on market volatility and downside risk, measured by Value at Risk (VaR). The empirical results reveal a significant negative relationship between investor sentiment and subsequent VaR, suggesting that higher investor sentiment is associated with greater potential downside risk. Quantile regression analysis further confirms the robustness of this relationship across different risk levels. In addition, market conditions significantly moderate the relationship between investor sentiment and market risk, with the impact becoming more pronounced during bearish market periods. These findings suggest that investor sentiment may serve as a useful forward-looking indicator of financial market risk. Incorporating sentiment-based measures into financial risk monitoring and early-warning systems may therefore help improve market risk management and financial regulation.

Keywords: Investor Sentiment, Market Risk, CSI Sentiment Index, Value at Risk, Behavioral Finance.

1. Introduction

1.1. Research Background

With the rapid development of behavioral finance, the influence of investor sentiment on asset prices and financial market volatility has attracted considerable attention from both academics and practitioners. Unlike traditional financial theories, which assume fully rational investors and efficient markets, behavioral finance emphasizes that investment decisions are often influenced by psychological biases, misinterpretation of information, and herding behavior. These irrational factors may cause investors to deviate from optimal decision-making, thereby contributing to excessive fluctuations in asset prices [1].

As a typical emerging financial market, China's capital market is characterized by substantial participation from retail investors, relatively high market volatility, and continuously evolving regulatory and information disclosure systems. These characteristics make investor sentiment particularly relevant to market dynamics in China. For example, major policy adjustments, unexpected public events, and changes in macroeconomic expectations often trigger rapid shifts in investor sentiment in China's A-share market, resulting in asymmetric market reactions [2]. The accumulation and subsequent reversal of market sentiment may amplify price fluctuations and potentially contribute to broader financial instability.

Against this background, accurately measuring investor sentiment and identifying its influence on market volatility and potential downside risk have become important issues in financial risk management and policymaking. With advances in data analytics and the increasing availability of financial information, researchers have increasingly employed sentiment indices to capture changes in investor expectations and incorporate behavioral factors into financial risk assessment models [3].

1.2. Research Innovations and Contributions

Although previous studies have extensively examined the relationship between investor sentiment and asset prices, much of the existing literature has focused on the predictive power of sentiment for future stock returns. Relatively less attention has been paid to its direct influence on financial market risk, particularly market volatility and extreme downside risk. To address this gap, this study adopts a risk-oriented perspective and investigates the relationship between investor sentiment and market stability by incorporating both volatility and Value at Risk (VaR) into the empirical framework.

The contributions of this study are mainly reflected in four aspects.

First, this study extends the existing research perspective by shifting the focus from return prediction to downside risk assessment. By examining the relationship between investor sentiment and VaR, it provides additional empirical evidence on the potential role of behavioral factors in financial market risk.

Second, this study employs the CSI Investor Sentiment Index as the primary measure of investor sentiment in China's stock market. Compared with individual sentiment proxies, such as the Baidu Search Index and margin trading indicators, the composite sentiment index provides a broader representation of market sentiment and facilitates a more systematic empirical analysis.

Third, this study adopts a two-stage empirical approach. Ordinary Least Squares (OLS) regression is employed to examine the relationship between investor sentiment and market volatility, while quantile regression is further applied to investigate how the relationship between sentiment and VaR varies across different risk levels. This combination provides a more comprehensive assessment of the association between investor sentiment and financial market risk.

Finally, the findings of this study have practical implications for financial risk monitoring and market regulation. By identifying the potential relationship between

investor sentiment and downside risk, the study provides empirical insights that may help financial regulators and market participants improve risk assessment and early-warning practices.

1.3. Research Hypotheses

From the perspective of behavioral finance, the influence of investor sentiment on financial market risk can be explained through two main channels: the expectation bias channel and the trading-induced channel.

First, the expectation bias channel. During periods of heightened investor sentiment, market participants tend to hold overly optimistic expectations about future market performance. Such optimism may lead investors to overestimate potential returns and underestimate underlying risks, thereby increasing their exposure to risky assets and contributing to the formation of asset price bubbles. When market sentiment subsequently reverses, the resulting price corrections may trigger substantial fluctuations and increase market instability.

Second, the trading-induced channel. Changes in investor sentiment may also influence trading behavior. Elevated sentiment can encourage excessive trading and frequent portfolio adjustments, potentially creating temporary liquidity pressures and disrupting the price discovery process. These behavioral responses may amplify market volatility, particularly during periods of heightened uncertainty or abrupt changes in market expectations.

Based on the above theoretical discussion, this study proposes the following hypotheses:

H1: Higher levels of investor sentiment are associated with greater stock market return volatility in the subsequent period.

H2: Extremely high or low levels of investor sentiment are associated with increased downside market risk, as measured by Value at Risk (VaR).

By empirically testing these hypotheses, this study aims to investigate the relationship between investor sentiment and financial market risk, providing additional evidence on the role of behavioral factors in market instability and risk assessment.

2. Literature Review

2.1. Theoretical Foundations of Investor Sentiment

Since the 1990s, behavioral finance has gradually developed into an alternative framework to traditional financial theories, offering explanations for financial market phenomena that cannot be fully accounted for by the assumption of investor rationality. Luu (2024) examines investors' underreaction and overreaction to unexpected events, highlighting how behavioral responses to new information may affect the efficiency of asset pricing [4]. In addition, the theory of noise trading suggests that investors' irrational beliefs and collective trading behavior may influence market dynamics, amplify price fluctuations, and potentially contribute to substantial market corrections [5].

These theoretical perspectives provide an important foundation for understanding investor sentiment and its role in financial markets. They also motivate further empirical research into the explanatory power of investor sentiment for asset prices, market volatility, and financial risk.

2.2. Measurement of Investor Sentiment

Since investor sentiment cannot be directly observed, researchers generally measure it using proxy variables or composite sentiment indices. Wang (2003) investigated investor sentiment in relation to market timing and futures returns [6]. Composite sentiment measures may incorporate multiple market indicators, such as the number of initial public offerings (IPOs), first-day IPO returns, closed-end fund discounts, and trading volume, to capture overall market sentiment.

In the context of China's stock market, Gao (2016) developed a framework for constructing an investor sentiment index based on the characteristics of the A-share market [7]. Lu and Li (2012) further examined the relationship between stock market indices and investor sentiment indices in China [8]. The original manuscript also discusses the incorporation of information from margin trading, stock index futures positions, exchange-traded fund (ETF) capital flows, and news coverage into sentiment measurement. These indicators reflect different aspects of market activity and investor expectations.

Compared with individual sentiment proxies, such as the Baidu Search Index, a composite sentiment index can capture information from multiple dimensions of investor behavior. Accordingly, this study employs the CSI Investor Sentiment Index as its primary explanatory variable to examine the relationship between investor sentiment and market risk in China's stock market.

2.3. Empirical Evidence on Investor Sentiment, Market Returns, and Volatility

Existing empirical studies have examined the relationship between investor sentiment and stock market performance from several perspectives. Regarding stock returns, previous research suggests that investor sentiment may have stronger predictive power for the future returns of certain categories of stocks, particularly small-cap and value stocks. During periods of extreme market sentiment, elevated sentiment may be associated with lower subsequent returns, reflecting the potential reversal of sentiment-driven mispricing [9]. In the Chinese stock market, Wang Yang's research also suggests that excessively optimistic investor sentiment may precede a decline in future stock returns, indicating a pattern of excessive optimism followed by subsequent market correction [10].

Beyond stock returns, researchers have increasingly investigated the relationship between investor sentiment and market volatility. Some studies suggest that investor sentiment may influence not only expected asset returns but also fluctuations in return volatility [11]. The original manuscript further discusses evidence based on GARCH models and the CSI 300 Index, suggesting that extreme sentiment may amplify market volatility, particularly during bearish market conditions. However, the bibliographic attribution of this finding requires verification before it can be included as a specific empirical claim.

Although the existing literature provides valuable insights into the relationship between investor sentiment, stock returns, and market volatility, research focusing specifically on downside tail risk remains an important area for further investigation. In particular, examining Value at Risk (VaR) alongside conventional volatility measures may provide a broader understanding of how investor sentiment is

associated with adverse market outcomes [12].

2.4. Research Positioning and Contributions of the Present Study

In summary, previous studies have examined the relationship between investor sentiment and financial market performance from various perspectives, particularly its predictive role in future stock returns and market volatility. Nevertheless, further investigation is needed to understand how investor sentiment is associated with market risk, especially downside risk under adverse market conditions.

Building on the existing literature, this study extends the analysis in three respects. First, it shifts the research focus from stock return prediction to market risk assessment by examining the relationships between investor sentiment, return volatility, and downside risk, as measured by Value at Risk (VaR). This approach provides a broader perspective on the potential implications of investor sentiment for financial market stability.

Second, this study employs the CSI Investor Sentiment Index as its primary explanatory variable and combines it with market data from the CSI 300 Index. By incorporating information on market performance and trading activity, the study constructs a monthly dataset to investigate the relationship between investor sentiment and subsequent market risk in China's stock market.

Third, this study adopts a complementary empirical framework. Ordinary Least Squares (OLS) regression is first employed to estimate the relationship between investor sentiment and market risk indicators. Quantile regression is then used to examine whether the association between investor sentiment and VaR differs across the conditional distribution of downside risk. In addition, an interaction term between investor sentiment and market conditions is introduced to investigate whether the relationship varies between bearish and non-bearish market periods.

Through these analyses, this study seeks to provide additional empirical evidence on the role of investor sentiment in financial market risk and to offer insights into the potential application of sentiment indicators in risk monitoring and early-warning systems.

3. Model Specification, Data, and Variable Definitions

3.1. Model Specification

To investigate the relationship between investor sentiment and market risk in China's stock market, this study develops empirical models focusing on two dimensions of financial risk:

Model 1: The relationship between investor sentiment and market volatility (Volatility).

Model 2: The relationship between investor sentiment and downside risk (VaR).

3.1.1. Baseline OLS Regression Model

This study first employs ordinary least squares (OLS) regression to estimate the relationship between investor sentiment and market risk. The baseline regression model is specified as follows:

$$\text{Volatility}_t = \alpha_0 + \alpha_1 \cdot \text{Sentiment}_{t-1} + \alpha_2 \cdot \text{Turnover}_t + \alpha_3 \cdot \text{PE}_t + \alpha_4 \cdot \text{Volume}_t + \varepsilon_t$$

$$\text{VaR}_t = \beta_0 + \beta_1 \cdot \text{Sentiment}_{t-1} + \beta_2 \cdot \text{Turnover}_t + \beta_3 \cdot \text{PE}_t + \beta_4 \cdot \text{Volume}_t + u_t$$

In this specification, the core explanatory variable is the one-period lagged investor sentiment index (L1_Sentiment). Using lagged sentiment allows the analysis to examine its association with subsequent market risk and may help mitigate concerns about contemporaneous reverse causality.

The control variables include Turnover, which captures market trading activity; PE, which reflects market valuation; and Volume, which represents trading volume. The dependent variable is alternatively specified as Volatility or VaR to examine different dimensions of market risk.

3.1.2. Quantile Regression Model (Robustness Check)

To examine whether the relationship between investor sentiment and market risk varies across different levels of the conditional risk distribution, this study further employs quantile regression as a complementary empirical approach. The model is specified as follows:

$$Q_\tau\left(\text{Volatility}_t \mid X_t\right) = \gamma_0^\tau + \gamma_1^\tau \cdot \text{Sentiment}_{t-1} + \sum_{k=2}^{4} \gamma_k^\tau \cdot Z_{k,t}$$

$$Q_\tau(\text{VaR}_t \mid X_t) = \delta_0^\tau + \delta_1^\tau \cdot \text{Sentiment}_{t-1} + \sum_{k=2}^{4} \delta_k^\tau \cdot Z_{k,t}$$

In this model, τ denotes the conditional quantile level, with τ = 0.25, 0.50, and 0.75. By estimating the relationship between investor sentiment and VaR at different conditional quantiles, the quantile regression model provides additional evidence on whether the estimated association varies across the distribution of the dependent variable.

3.1.3. Interaction Model: Investor Sentiment and Market Conditions

To investigate whether market conditions moderate the relationship between investor sentiment and downside risk, this study introduces an interaction term between investor sentiment and the market-state indicator.

$$\text{VaR}_t = \beta_0 + \beta_1 \cdot \text{Sentiment}_{t-1} + \beta_2 \cdot \text{Bear}_t + \beta_3 \cdot (\text{Sentiment}_{t-1} \times \text{Bear}_t) + \text{Controls} + \varepsilon_t$$

In this specification, Bear is a dummy variable representing bearish market conditions. The interaction term between L1_Sentiment and Bear is included to examine whether the association between investor sentiment and VaR differs during market downturns.

A statistically significant interaction coefficient would indicate that the relationship between investor sentiment and downside risk varies according to market conditions. In particular, a negative interaction coefficient would imply a more negative association between investor sentiment and the measured VaR during bearish market periods, subject to the definition and sign convention of VaR.

3.2. Data Sources

This study uses monthly data covering the period from January 2010 to December 2022 to investigate the relationship between investor sentiment and market risk in China's stock market. The analysis focuses on the CSI 300 Index (CSI300), a major benchmark of the Chinese equity market, and examines market movements, return volatility,

and downside risk over the sample period.

The core explanatory variable, investor sentiment, is measured using the CSI Investor Sentiment Index (China Sentiment Index). According to the original data description, this index is constructed using information related to market behavior, media coverage, and changes in trading accounts. The sentiment data are available at a monthly frequency and are used to capture changes in overall investor sentiment.

In addition to the sentiment index, this study uses daily CSI300 price data to construct monthly market risk indicators, including Volatility and VaR. The control variables consist of Turnover, PE, and Volume, which capture market trading activity, valuation levels, and trading volume, respectively. The relevant financial market data are obtained from sources including Wind and Eastmoney.

All variables are subsequently organized into a monthly dataset for empirical analysis.

3.3. Data Processing

To ensure consistency in the empirical analysis, this study follows a systematic procedure for constructing and organizing the research variables. The market risk indicators, including Volatility and VaR, are first calculated using daily return data from the CSI300. The resulting risk measures are then aggregated at the monthly level and matched with the monthly investor sentiment index and control variables.

The investor sentiment index is retained in its original scale without normalization or standardization. This treatment preserves the original measurement units of the index and allows the estimated coefficients to be interpreted in relation to changes in the observed sentiment measure.

Volatility is calculated using the standard deviation of daily returns within each month, while VaR is estimated using the historical simulation method based on the lower tail of the daily return distribution. Specifically, the monthly VaR measure is constructed from the fifth percentile of daily returns within the corresponding month.

In the regression analysis, the investor sentiment variable is lagged by one period to examine its relationship with subsequent market risk and to reduce the possibility of contemporaneous feedback between sentiment and risk. Finally, all variables are aligned at the monthly frequency to ensure consistency across observations and empirical specifications.

3.4. Variable Definitions and Calculation Formulas

The variables employed in this study are classified into three categories: dependent variables measuring market risk, explanatory variables capturing investor sentiment and market conditions, and control variables reflecting market characteristics. Their definitions and calculation methods are presented below.

3.4.1. Dependent Variables

(a) Return Volatility (Volatility)

Volatility measures the degree of fluctuation in stock market returns. In this study, monthly Volatility is calculated as the standard deviation of daily returns on the CSI300 within each month.

$$\text{Volatility}_t = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N}(r_{i,t} - \bar{r}_t)^2}$$

In this formula, the daily return refers to the return on the CSI300 on trading day i, the mean return represents the average daily return within the corresponding month, and the number of observations denotes the total number of trading days in that month.

A higher value of Volatility indicates greater fluctuations in daily market returns and, consequently, a higher level of market volatility.

(b) Downside Risk (VaR)

VaR is employed to measure downside market risk under adverse market conditions. This study estimates monthly VaR using the historical simulation method, which relies on the empirical distribution of daily returns rather than assuming a specific parametric return distribution.

$$\text{VaR}_t^{5\%} = \text{Quantile}_{5\%}\left(\{r_{1,t}, r_{2,t}, \ldots, r_{N,t}\}\right)$$

Specifically, VaR is defined as the fifth percentile of daily CSI300 returns within each month. Under this signed-return convention, a more negative VaR indicates a more severe potential downside return and therefore greater downside risk.

3.4.2. Explanatory Variables

(a) Investor Sentiment (Sentiment)

Investor sentiment is measured using the CSI Investor Sentiment Index, denoted as Sentiment. The index is used to capture changes in the overall sentiment of investors in China's stock market.

In the empirical regressions, the one-period lagged sentiment index, L1_Sentiment, is employed as the core explanatory variable to examine the relationship between investor sentiment and subsequent market risk.

The sentiment index is retained in its original scale without standardization.

(b) Market Conditions (Bear)

Market conditions are measured using market returns as a proxy for the prevailing market environment. Based on this measure, a dummy variable, Bear, is constructed to distinguish bearish market periods from other market conditions.

$$\text{Bear}_t = \begin{cases} 1 & \text{if MarketReturn}_t < 0 \\ 0 & \text{else} \end{cases}$$

The Bear variable is further interacted with L1_Sentiment to examine whether the relationship between investor sentiment and VaR differs across market conditions.

3.4.3. Control Variables

To account for observable market characteristics that may be associated with market risk, this study includes three control variables: Turnover, PE, and Volume.

Table 1. Definitions of Control Variables

Variable	Symbol	Definition or Measurement
Turnover Rate	Turnover	Monthly trading value divided by total market capitalization, reflecting market trading activity
Price-to-Earnings Ratio	PE	Weighted average price-to-earnings ratio of CSI300 constituent stocks, reflecting market valuation
Trading Volume	Volume	Monthly total trading value, measured in units of RMB 100 million

These control variables are included in the regression models to account for differences in market activity, valuation, and trading conditions when examining the relationship

between investor sentiment and market risk.

4. Empirical Analysis

4.1. Baseline OLS Regression Results

To examine the relationship between investor sentiment and market risk in China's stock market, this study first estimates baseline OLS regression models using the one-period lagged investor sentiment index (L1_Sentiment) as the core explanatory variable. Volatility and VaR are employed as alternative dependent variables to capture overall market fluctuations and downside risk, respectively. The estimation results are reported in Table 2.

Table 2. Baseline OLS Regression Results: Investor Sentiment and Market Risk

Variable	Coef. (Sig)	Std. Error	Coef. (Sig)	Std. Error
	Volatility		VaR	
const	0.0583***	0.0091	-0.0395*	0.0201
L1_Sentiment	0.0001	0.0001	-0.0010***	0.0002
Turnover	0.0948	0.0836	0.0061	0.1852
PE	0.0002	0.0001	-0.0003	0.0003
Volume	-0.0000	0.0000	-0.0000	0.0000

The regression results reveal differences in the relationship between investor sentiment and the two market risk measures.

First, the coefficient of L1_Sentiment in the VaR regression is -0.0010 and is statistically significant at the 1% level. Given that VaR is defined as the fifth percentile of daily returns, a lower VaR value represents a more negative lower-tail return and therefore greater downside risk. Accordingly, the negative coefficient indicates that higher investor sentiment is significantly associated with more severe subsequent downside risk, holding the control variables constant. This finding is consistent with the view that elevated investor optimism may be accompanied by increased vulnerability to adverse market outcomes.

Second, the coefficient of L1_Sentiment in the Volatility regression is positive (0.0001), but it is not statistically significant. Although the estimated coefficient suggests a positive association between investor sentiment and market volatility, the available evidence is insufficient to establish a statistically significant relationship. Therefore, the baseline results provide stronger support for an association between investor sentiment and downside risk than for an association with overall return volatility.

Regarding the control variables, Turnover, PE, and Volume do not exhibit statistically significant coefficients in either regression model. This suggests that these variables do not demonstrate statistically detectable associations with the two risk measures under the current model specifications. However, their lack of statistical significance does not necessarily imply that market activity, valuation, or trading volume are economically irrelevant.

Overall, the baseline OLS results indicate that investor sentiment is significantly associated with subsequent downside risk, whereas its relationship with market volatility is not statistically significant. These findings motivate further analysis of whether the relationship between investor sentiment and VaR remains consistent across different conditional quantiles and market conditions.

4.2. Robustness Check: Quantile Regression Results

To further examine the robustness of the relationship between investor sentiment and downside market risk, this study employs quantile regression to investigate whether the estimated association varies across different levels of the conditional distribution of VaR. Unlike OLS regression, which focuses on the conditional mean of the dependent variable, quantile regression allows the relationship between explanatory variables and market risk to be examined at different conditional quantiles.

Specifically, the quantile regression models are estimated at the 0.25, 0.50, and 0.75 quantiles. The estimation results are presented in Table 3.

Table 3. Quantile Regression Results: Heterogeneous Associations Between Investor Sentiment and VaR

Quantile	Coef. (Sig)	Std. Error	Significance
0.25	-0.0011***	0.0002	***
0.50	-0.0010***	0.0002	***
0.75	-0.0010***	0.0002	***

The quantile regression results indicate that L1_Sentiment is negatively associated with VaR across all three conditional quantiles, with the estimated coefficients statistically significant at the 1% level. Specifically, the coefficient is -0.0011 at the 0.25 quantile and -0.0010 at both the 0.50 and 0.75 quantiles. These estimates are also close to the coefficient obtained from the baseline OLS regression.

Given that VaR is defined as the fifth percentile of daily returns, the consistently negative coefficients suggest that higher investor sentiment is associated with more negative downside-return thresholds across the examined conditional quantiles. This finding provides additional evidence that the negative relationship between investor sentiment and VaR is not confined to the conditional mean.

Furthermore, the relatively small differences in coefficient magnitudes indicate that the estimated association remains broadly stable across the selected quantiles. Although the coefficient is slightly more negative at the 0.25 quantile, the reported results alone do not establish whether the differences between quantile-specific coefficients are statistically significant.

From a behavioral finance perspective, these findings are consistent with the possibility that elevated investor optimism may coexist with vulnerabilities that become apparent during adverse market conditions. Excessive optimism may lead investors to underestimate potential losses, thereby contributing to an environment in which downside risks are insufficiently recognized.

Overall, the quantile regression results reinforce the baseline finding of a statistically significant negative association between L1_Sentiment and VaR. They suggest that investor sentiment may contain useful information for assessing downside market risk across different parts of the conditional VaR distribution. Nevertheless, further out-of-sample testing would be required to establish its practical forecasting performance in a market risk early-warning system.

4.3. Moderating Effect of Market Conditions

Previous studies suggest that the relationship between investor sentiment and market risk may vary across different

market conditions. During bullish market periods, rising investor sentiment may reinforce prevailing market trends. In contrast, during bearish periods, changes in investor sentiment may be associated with stronger behavioral biases and increased vulnerability to downside risk.

To investigate the moderating role of market conditions, this study introduces the market-state dummy variable Bear and constructs an interaction term between L1_Sentiment and Bear. The interaction model is employed to examine whether the relationship between investor sentiment and VaR differs between bearish and non-bearish market periods. The regression results are presented in Table 4.

Table 4. Regression Results: The Moderating Effect of Market Conditions

Variable	Coef. (Sig)	Std. Error
const	-0.0372*	0.0213
L1_Sentiment	-0.0005	0.0003
Bear	-0.0041	0.0025
L1_Sentiment × Bear	-0.0019***	0.0004
Turnover	0.0031	0.1862
PE	-0.0004	0.0003
Volume	-0.0000	0.0000

The results indicate that the coefficient of the interaction term between L1_Sentiment and Bear is -0.0019 and is statistically significant at the 1% level. This finding suggests that market conditions significantly moderate the relationship between investor sentiment and downside risk.

Specifically, when Bear = 0, the estimated coefficient of L1_Sentiment is -0.0005, which is not statistically significant. When Bear = 1, the interaction coefficient indicates that the relationship between investor sentiment and VaR becomes more negative during bearish market periods. The estimated marginal coefficient of L1_Sentiment under bearish conditions is -0.0024, calculated as the sum of the main sentiment coefficient (-0.0005) and the interaction coefficient (-0.0019).

Given that VaR is measured as the fifth percentile of daily returns, a more negative coefficient corresponds to a stronger association between investor sentiment and adverse downside-return outcomes. Therefore, the significantly negative interaction coefficient suggests that higher investor sentiment is associated with greater downside risk during bearish market conditions than during non-bearish periods.

From a behavioral finance perspective, this finding is consistent with the possibility that optimistic investor expectations may obscure underlying market vulnerabilities during downturns. When market conditions deteriorate, investors may underestimate potential losses or respond inadequately to unfavorable information, thereby increasing their exposure to downside risk. Such behavioral tendencies provide a possible explanation for the stronger negative association observed in bearish market periods.

Overall, the interaction analysis indicates that the relationship between investor sentiment and downside risk depends on prevailing market conditions. The findings highlight the importance of incorporating market-state information when evaluating the potential relevance of investor sentiment for financial risk monitoring.

5. Conclusions and Future Research

5.1. Main Findings

This study investigates the relationship between investor sentiment and market risk in China's stock market using data from the CSI300 and the CSI Investor Sentiment Index over the period from 2010 to 2022. By employing OLS regression, quantile regression, and an interaction model incorporating market conditions, the study examines the associations between investor sentiment, market volatility, and downside risk. The main findings are summarized as follows.

First, investor sentiment is significantly associated with downside market risk. The baseline OLS regression results show that the coefficient of L1_Sentiment on VaR is negative and statistically significant at the 1% level. Since VaR is measured as the fifth percentile of daily returns, a more negative VaR represents a more severe potential downside outcome. This finding suggests that higher investor sentiment is associated with greater subsequent downside risk, consistent with the possibility that excessive optimism may obscure underlying market vulnerabilities.

Second, the negative relationship between investor sentiment and VaR remains consistent across different conditional quantiles. The quantile regression results indicate that the coefficients of L1_Sentiment are significantly negative at the 0.25, 0.50, and 0.75 quantiles. These findings provide additional evidence of a relatively stable association between investor sentiment and downside risk across the examined conditional distribution.

Third, the conventional market control variables exhibit limited statistical significance in the estimated models. Turnover, PE, and Volume do not show statistically significant coefficients in the baseline regressions. In addition, although the coefficient of L1_Sentiment in the Volatility regression is positive, it is not statistically significant. Therefore, the empirical evidence is stronger for the relationship between investor sentiment and downside risk than for its relationship with overall market volatility.

Finally, market conditions play a significant moderating role in the relationship between investor sentiment and downside risk. The interaction term between L1_Sentiment and Bear is negative and statistically significant, indicating that the association between investor sentiment and VaR becomes more negative during bearish market periods. This result highlights the importance of considering prevailing market conditions when assessing sentiment-related financial risks.

Overall, the findings suggest that investor sentiment may provide useful information for understanding downside risk in China's stock market. Incorporating sentiment indicators alongside conventional market variables may therefore offer a complementary perspective for financial risk assessment and monitoring.

5.2. Policy Implications and Practical Significance

The empirical findings suggest that investor sentiment may provide additional information for assessing downside risk in China's stock market, particularly during bearish market periods. Although the results do not establish a causal relationship between investor sentiment and systemic financial crises, they highlight the potential value of incorporating behavioral indicators into financial risk monitoring. Based on these findings, several policy

implications can be proposed.

(1) Establishing a Regular Investor Sentiment Monitoring System

Financial regulators could consider developing a more comprehensive investor sentiment monitoring framework based on the existing CSI Investor Sentiment Index. In addition to conventional market-based indicators, the framework could incorporate sentiment-related information from Chinese social media platforms, such as Weibo, Zhihu, and Xueqiu, together with trading behavior indicators and net fund subscriptions.

Regular publication of market sentiment heat maps or sentiment-based risk indicators could help market participants and regulators identify unusual changes in investor expectations. Such information may serve as a supplementary reference for macroprudential monitoring and financial risk assessment.

(2) Incorporating Investor Sentiment into Financial Risk Assessment Frameworks

Financial regulatory authorities could explore integrating investor sentiment indicators with established risk measures, including VaR, CoVaR, and SRISK, to improve the comprehensiveness of financial risk monitoring.

For example, when investor sentiment rises persistently toward historically elevated levels while becoming increasingly disconnected from market fundamentals, regulators could consider strengthening risk communication, disclosure requirements, and market surveillance. Sentiment indicators should, however, be evaluated alongside conventional financial and macroeconomic indicators rather than treated as independent signals for regulatory intervention.

(3) Strengthening Behavioral Supervision of Financial Market Participants

Investor sentiment may be amplified by herding behavior and sentiment-driven trading, particularly when market participants respond similarly to changes in expectations. Therefore, financial regulators could strengthen the monitoring of trading behavior among institutional investors, including mutual funds and quantitative investment funds.

Greater transparency regarding material portfolio adjustments, enhanced monitoring of sentiment-sensitive trading strategies, and closer observation of securities experiencing unusual sentiment fluctuations may help identify potential market vulnerabilities. These measures could contribute to a more transparent trading environment and reduce the possibility of destabilizing trading behavior.

(4) Improving Investor Education and Financial Literacy

Behavioral biases, including overconfidence, herding behavior, and the misinterpretation of market information, may influence investment decisions and risk perceptions. Investor education programs should therefore place greater emphasis on the relationship between psychological biases, market sentiment, and financial risk.

Regulators and industry associations could develop educational materials and simulation-based tools to help investors understand how changes in market sentiment may affect risk exposure. In addition, measures that encourage long-term investment, improve information transparency, and promote fundamental analysis may help investors make more informed decisions and reduce excessive reliance on short-term market sentiment.

Overall, incorporating investor sentiment into market monitoring and investor education may complement existing approaches to financial risk management. Nevertheless, the practical effectiveness of these proposals requires further empirical evaluation, particularly through out-of-sample forecasting and assessments of their implementation costs and benefits.

5.3. Limitations and Directions for Future Research

Despite its contributions to understanding the relationship between investor sentiment and market risk, this study has several limitations that should be acknowledged.

First, the frequency of the data imposes certain restrictions on the analysis. Although daily market returns are used to construct the risk measures, the empirical regressions are based on monthly observations. Consequently, the models may not fully capture high-frequency fluctuations in investor sentiment or the immediate effects of unexpected market events.

Second, the measurement of investor sentiment relies primarily on the CSI Investor Sentiment Index. While this index provides a quantitative measure of overall market sentiment, the study does not incorporate alternative information sources, such as social media sentiment, retail investor trading activity, or other behavioral indicators. This limitation may restrict the ability of the analysis to capture differences in sentiment across investor groups.

Third, the study focuses on market-level risk indicators, particularly Volatility and VaR, without examining the underlying behavioral mechanisms at the institutional or individual investor level. As a result, the analysis does not directly identify how changes in investor sentiment are transmitted through portfolio adjustments, leverage decisions, or trading behavior to affect market risk.

Finally, the empirical methodology is relatively conventional. Although OLS and quantile regression provide useful evidence on the statistical relationship between investor sentiment and market risk, the models may not fully capture complex nonlinear relationships, dynamic interactions, or potential endogeneity. Furthermore, the study does not conduct out-of-sample forecasting tests, which limits the extent to which the practical predictive performance of sentiment indicators can be evaluated.

Building on these limitations, future research could be extended in several directions.

First, incorporating high-frequency data and heterogeneous sentiment indicators. Future studies could employ daily or intraday data and integrate alternative sentiment measures derived from social media platforms, such as Weibo and Xueqiu. Constructing multidimensional sentiment indices may help capture differences in behavioral responses across investor groups and market conditions.

Second, investigating micro-level mechanisms and risk transmission channels. Future research could incorporate institutional holdings, fund subscriptions and redemptions, and leverage-related indicators to examine the potential transmission process from investor sentiment to trading behavior and market risk. Mediation models or structural vector autoregression (SVAR) models could be considered to investigate these relationships, subject to appropriate identification assumptions.

Third, introducing machine learning and nonlinear modeling approaches. Advanced methods, such as long short-term memory (LSTM) neural networks and XGBoost, could be employed to explore nonlinear patterns and complex interactions between investor sentiment and market risk.

Their forecasting performance could be assessed through out-of-sample evaluation and compared with conventional econometric models.

Fourth, extending the analysis across markets and asset classes. Future studies could investigate whether sentiment-related risk patterns also appear in bond markets, commodity markets, and international financial markets. Cross-market comparisons may provide additional insights into sentiment spillovers, financial market interconnectedness, and the transmission of risk across different asset classes.

Overall, future research that combines richer sentiment measures, more detailed behavioral data, and advanced empirical methods may provide a more comprehensive understanding of the relationship between investor sentiment and financial market risk. Such extensions could also help evaluate the practical usefulness of sentiment-based indicators in financial risk monitoring and early-warning systems.

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