

Investor Sentiment and Corporate Financial Fraud

Siyu Li

School of Business, The University of Sydney, Sydney, Australia

Email: lsy0801911@gmail.com

How to cite this paper: Li, S. Y. (2025). Investor Sentiment and Corporate Financial Fraud. *Modern Economy*, 16, 1254-1276. <https://doi.org/10.4236/me.2025.168059>

Received: February 10, 2025

Accepted: August 15, 2025

Published: August 18, 2025

Copyright © 2025 by author(s) and Scientific Research Publishing Inc.

This work is licensed under the Creative Commons Attribution International License (CC BY 4.0).

<http://creativecommons.org/licenses/by/4.0/>



Open Access

Abstract

In a market economy, investor sentiment may encourage managerial financial fraud to influence stock market prices, and generate profits. In this study, I examine whether investor sentiment induces financial fraud and investigate the differential impacts for various categories of firms. Using data on 1670 Chinese A-share listed companies for 2013-2022, I construct a probit model to analyze the relationship between investor sentiment and corporate financial fraud. The findings indicate that the likelihood of listed companies engaging in financial fraud is lower during periods of high investor sentiment. Moreover, I find that investor sentiment exhibits a stronger inhibitory effect on financial fraud in nonstate-owned enterprises than in state-owned enterprises. Financing constraints partially mediate this relationship, whereas the internal control index demonstrates a masking effect.

Keywords

Investor Sentiment, Financial Fraud, Chinese A-Share Listed Companies

1. Introduction

In recent years, with globalization and rapid advances in information technology, corporate financial fraud has increasingly attracted global attention. Financial fraud not only harms investors' interests but also undermines market fairness and transparency, threatening the stability of the economic system. Since the early 2000s, high-profile cases of financial fraud, such as those involving Enron (2001) and WorldCom (2002), have exposed critical loopholes in corporate financial reporting and regulatory oversight, severely eroding trust in international capital markets.

Corporate financial fraud significantly affects a firm's reputation, market value,

and business operations, and its employees' morale. Companies involved in financial fraud typically experience sharp declines in share prices and investor confidence, potentially leading to bankruptcy or takeover. For instance, the financial fraud committed by Kangmei Pharmaceuticals between 2016 and 2018 through revenue inflation and falsification of currency funds caused a severe decline in the company's share prices in 2019 and wiped out tens of billions of yuan in market capitalization. Financial fraud also adversely affects perceptions of industries and national economies, reducing external investors' willingness to invest and harming long-term economic growth. Investor sentiment significantly impacts financial market volatility, stock market pricing, corporate decision-making, and individual investor behavior. Managers may intentionally distort financial reports to exploit market misperceptions driven by investor sentiment, thus benefiting from fraudulent activities. A prominent example is the case of Xu Xiang's insider trading and stock manipulation involving China's Zexi Investment Company. Xu conspired with executives of 13 listed companies from 2010 to 2015, illegally controlling 139 securities accounts and generating 9.338 billion yuan in illicit profits. By manipulating market sentiment through fabricated announcements on hot market topics, Xu inflated stock prices to facilitate profitable transactions. Such cases illustrate how companies may influence investor sentiment to attract investment, ultimately leading to fraudulent activities detrimental to individual investors and market integrity.

Recognizing the severe consequences of financial fraud, researchers and practitioners have emphasized the need for deeper investigation of its causes, characteristics, and effects. Studies have explored the impact of investor sentiment on market behavior and corporate managerial decisions, highlighting the importance of enhancing financial transparency, and providing regulatory recommendations. Understanding the relationship between investor sentiment and corporate fraud assists enterprises in strengthening internal controls and risk management practices to protect investor interests.

Given China's unique institutional background, in this study, I explore the relationship between investor sentiment and corporate financial fraud, providing practical insights for management, regulatory bodies, and investors. My findings can guide regulators in policy formulation aimed at stabilizing investor sentiment, reducing excessive market volatility, and decreasing the occurrence of financial fraud. Enterprises can leverage these insights to improve internal controls and the authenticity of financial reporting, particularly during periods of heightened or diminished investor sentiment. Ultimately, research into the impact of investor sentiment on financial fraud is both theoretically significant and practically valuable, supporting the ongoing development and stability of capital markets.

2. Literature Review and Hypothesis Development

In this study, I primarily examine the two interconnected research fields of investor sentiment and corporate financial fraud, both of which are critical areas within

finance. Investor sentiment, the collective emotional states of market participants, significantly influences stock market trends and trading behaviors. Corporate financial fraud refers to the deliberate manipulation of financial reports by managers to mislead investors and markets. By collating data and studies, and conducting a comprehensive review of the literature, I provide a systematic summary and analysis of the relevant research on these two topics.

2.1. Investor Sentiment

Investor sentiment, a focal point in financial research, is defined as systematic biases in market expectations caused by investors' emotional responses or herd behavior. Emotions introduce uncertainty into economic activities, affecting investors' subjective judgments of future returns and investment behaviors. When aggregated, these sentiments significantly impact market dynamics. Investor sentiment influences trading behaviors and corporate decisions, and hence affects capital markets and the real economy. This complex and multidimensional concept encompasses investors' perceptions, interpretations, and reactions to market information. Changes in sentiment can lead to short-term managerial behaviors, such as financial report manipulation or misguided investments in research and development, potentially increasing the risk of financial fraud.

Investor sentiment involves biased asset price expectations driven by individual preferences, investment skills, and public opinion. Positive sentiment typically increases investment in high-risk emerging sectors, whereas negative sentiment fosters risk aversion, shifting investor preferences toward safer assets. Studies have demonstrated that investor sentiment affects corporate financing constraints, initial public offering (IPO) pricing, earnings forecasts, and accounting information quality. High investor sentiment can induce managers to engage in short-term manipulative activities, reducing financial transparency and accounting comparability. Consequently, understanding the multifaceted impacts of investor sentiment is crucial for comprehending corporate financial behaviors and fraud probabilities.

2.2. Financial Fraud

International organizations have offered various definitions of financial fraud. The Institute of Internal Auditors defines fraud broadly as encompassing intentional deception benefiting or harming organizations. Similarly, US auditing standards (Statement of Auditing Standards No. 82) characterize fraud as deliberate misrepresentation for illicit gain at others' expense. Chinese standards define fraud as intentional deception by organizational personnel to acquire improper benefits. Despite the differing definitions, there is universal agreement that fraud involves intentional misconduct that misrepresents financial statements, violates ethical standards, or breaches regulations, causing severe economic and reputational damage. Recent notable fraud cases, such as the 2020 Luckin Coffee scandal, underscore the persistent significance of financial fraud.

Research has emphasized the risk of fraud, primarily from auditing perspectives, highlighting its potential to superficially inflate corporate financial results and lead to severe long-term damage on exposure. Fraudulent companies face regulatory penalties, reputational damage, and shareholder lawsuits, with individuals subject to criminal liabilities for their involvements. Studies have also indicated that executive compensation, equity incentives, and delisting pressures influence the incidence of financial fraud. High-quality financial disclosures reduce information asymmetry, enhancing corporate investment efficiency and mitigating fraud risks. Effective board oversight, particularly by independent directors, significantly lowers fraud probabilities. Furthermore, increased media scrutiny and negative reporting can deter corporate financial misconduct.

2.3. Literature Summary

Studies have extensively explored investor sentiment, aiming to quantify it and its impact on corporate behaviors, and to determine fraud prevention mechanisms. However, few studies have analyzed the interaction between investor sentiment and corporate fraud across different enterprise categories. Through the current research, I aim to fill this gap by examining the relationship of investor sentiment with corporate financial fraud in varied institutional contexts, providing theoretical and practical insights to enhance financial reporting quality, investor risk awareness, and regulatory effectiveness.

The measurement of investor sentiment is a critical area in behavioral finance research. Scholars have employed various methodologies, including market transaction data analysis, investor surveys, and media report interpretation, to quantify investor sentiment and investigate its influence on corporate financial decisions. Empirical studies have demonstrated that investor optimism or pessimism significantly affects stock prices, market liquidity, capital structure, and dividend policy (López et al., 2017; Moshirian et al., 2017). Furthermore, Krishnamurthy and Muir (2017) revealed that systematic deviations in investor sentiment lead to substantial fluctuations in asset prices.

Research on financial fraud encompasses a wide range of topics from micro-level corporate governance to macro-level market regulation. Studies have extensively examined the role of internal controls, audit quality, legal frameworks, and market supervision in preventing and managing financial fraud. However, most of the literature has focused on the motivation, identification, and governance of corporate financial misconduct, with relatively limited attention given to the influence of investor sentiment on fraudulent behavior. Piñeiro-Chousa et al. (2021) conducted an in-depth analysis of investor sentiment through the theoretical lenses of prospect theory, expectancy theory, and regret theory, developing a comprehensive sentiment index to explore the impact of investor sentiment on financial behavior. Geng (2023) further established that investor sentiment is both identifiable and predictable, with investors exhibiting positive sentiment showing a greater propensity to invest in high-risk, emerging industries.

Several studies have underscored the multifaceted impact of investor sentiment on market perceptions of corporate cash holdings and firms' financing constraints. Wang et al. (2021) demonstrated that the positive asset pricing effect of cash holdings in publicly listed companies becomes more pronounced during periods of low investor sentiment. Li & Grundy (2023) identified a distinct phenomenon wherein heightened investor sentiment exacerbates the IPO price suppression effect in the growth enterprise market, an effect that remains independent of information asymmetry. Therefore, investor sentiment may influence corporate fraudulent behavior by shaping the external financing environment, market trust, and managerial pressure to meet short-term performance expectations.

2.4. Hypothesis Development

Research on the motivations underlying financial fraud has matured significantly, achieving fruitful insights. Studies have suggested that companies experiencing financial distress are more inclined to engage in fraudulent behavior to conceal their true conditions (Perols & Lougee, 2010). For example, the American Institute of Certified Public Accountants (1987) noted that newly listed companies facing substantial pressure to meet profitability expectations are particularly prone to financial misconduct. Similarly, firms under regulatory scrutiny by the Securities and Exchange Commission are more likely to manipulate earnings to secure external financing (Beaudry & Willems, 2022). In summary, financial fraud typically arises when a company's actual financial condition fails to satisfy internal or external stakeholders' expectations. Investors represent critical stakeholders whose sentiment fluctuations substantially impact stock prices, market returns, trading volume, and liquidity. Periods of low investor sentiment typically involve pessimistic market expectations, declining market returns, and falling stock prices, which may give firms incentives to engage in fraudulent behaviors as profitability pressures intensify. Conversely, high investor sentiment encourages investment and reduces firms' incentives to manipulate financial statements, given their easier access to financing. Thus, I hypothesize that investor sentiment is negatively correlated with corporate financial fraud. Reputation theory further posits that long-term corporate interests hinge on maintaining trust. Losing stakeholders' trust as a result of fraudulent activity can jeopardize ongoing business operations (Throckmorton et al., 2015). Therefore, when investor sentiment is high, market attention and scrutiny increase, motivating corporate management to protect reputational capital and avoid fraudulent actions. Moreover, according to risk management theory, high investor sentiment often coincides with increased market volatility. Consequently, companies adopt more cautious strategies, improving internal risk management practices to avoid potentially catastrophic financial decisions, including fraudulent activities (Li et al., 2024). On the basis of these theoretical insights, I propose the following hypothesis:

Hypothesis 1: Investor sentiment negatively influences the probability of corporate financial fraud.

Although China is currently transitioning toward a market economy, most Chinese listed companies remain either directly or indirectly controlled by the government (Ma et al., 2022). It is likely that the distinct governance structures and management incentives of state-owned and nonstate-owned enterprises result in differing influences of investor sentiment on the propensity to commit fraud. Thus, analyzing how investor sentiment differentially affects fraud incidence based on firm ownership characteristics is essential. Typically, state-owned enterprises in China are characterized by hierarchical management structures, internal promotions, and external administrative appointments (Wu & Du, 2022). Managers of state-owned enterprises hold dual roles, serving both as corporate executives and government officials, which weakens the incentives to maximize long-term corporate value (Chen & Zhang, 2022). In addition, the remuneration and career advancement opportunities of these managers are largely unaffected by short-term company performance, significantly reducing managerial accountability and incentive alignment (Hu et al., 2019). Consequently, the effectiveness of investor sentiment in constraining financial fraud within state-owned enterprises may be limited. In contrast, nonstate-owned firms are often perceived to have a more flexible and innovative corporate culture, which is able to positively capitalize on market sentiments in order to promote innovation and growth in the firm (Lan et al., 2023). Nonstate-owned enterprises are usually characterized by greater innovation and more diversified shareholder bases than state-owned enterprises, which fosters greater transparency and accountability (Guan et al., 2023). Furthermore, nonstate-owned enterprises frequently link managerial compensation directly to long-term corporate performance, thus incentivizing managers to adopt strategies that enhance long-term value rather than engage in short-term financial misconduct (An et al., 2023). Thus, nonstate-owned firms are expected to be more sensitive to investor sentiment, reducing their likelihood of financial fraud compared with state-owned enterprises. On the basis of this analysis, I propose the following hypothesis:

Hypothesis 2: Investor sentiment exhibits a stronger negative influence on financial fraud in nonstate-owned enterprises than in state-owned enterprises.

3. Research Design

3.1. Data Sources

In this study, I use data on Chinese A-share companies listed on the Shanghai and Shenzhen stock exchanges from 2013 to 2022, extracted from the “Violation Processing Research Database” of the China Stock Market and Accounting Research (CSMAR) database. The identification of financial fraud relies on penalties imposed for violating the Company Law, Securities Law, and regulations from relevant regulatory bodies, including the China Securities Regulatory Commission, Ministry of Finance, and stock exchanges. The specific types of financial fraud considered include fabricated profits, fictitious assets, false records, major omissions, delayed disclosures, false disclosures, and improper accounting treatments.

3.2. Sample Selection

To ensure accuracy, I select the earliest year of financial fraud as the observation year for each fraudulent company to avoid overestimating fraud occurrence. Next, I exclude firms from the financial industry, and firms that are delisted or nearing delisting. I also remove observations with missing data. Ultimately, following these selection procedures, I identify 835 fraudulent firms (**Figure 1**).

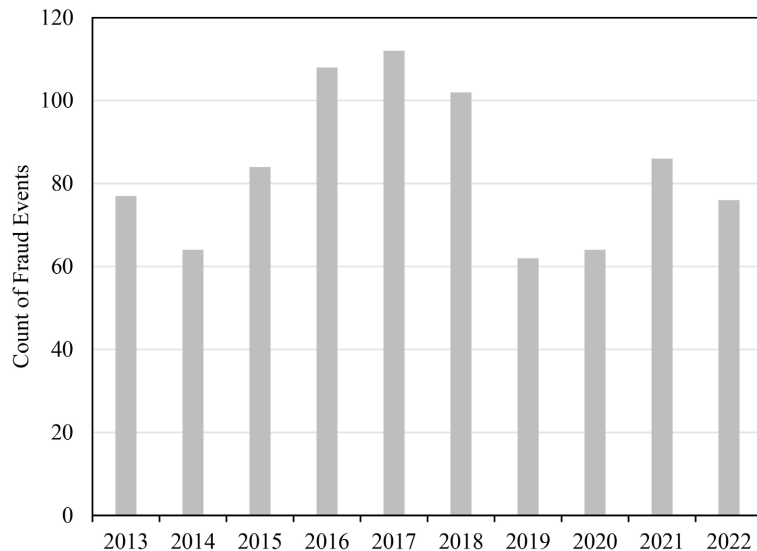


Figure 1. Statistics on fraud of listed companies.

Consistent with prior research methods (Beasley, 1996), I adopt matched sampling to form a control group of 835 nonfraudulent firms. Each fraudulent firm is matched with a nonfraudulent firm based on industry, firm size (total assets within $\pm 30\%$), and stock exchange listing. The observation year for control firms corresponds to the same fiscal year in which the matched fraud firm committed financial fraud. All explanatory variables are measured for both groups in this identical fiscal year. I require that the matched control firms have not received public condemnations from the stock exchanges and that they have complete data available throughout the observation period. Following the matching, the final sample comprises 1670 observations.

Investor sentiment data are sourced from the CSMAR China Investor Sentiment Indicators Research Database. To mitigate outlier effects, I winsorize all continuous variables at the 1% and 99% levels.

3.3. Variable Definitions

Table 1 presents the definitions of variables in this study. The dependent variable is financial fraud (Fraud), coded as a dummy variable (0, 1). Firms identified as fraudulent in a given year receive a value of one; otherwise, they are assigned a value of zero. Investor sentiment is the key independent variable. I primarily use the Composite Index of Chinese Investor Sentiment (CICSI) developed specifi-

cally for Chinese financial markets through natural language processing and deep learning methodologies. The CICI integrates multiple indicators, including the fund discount rate (DCEF), market trading volume (TURN), number of IPOs (IPON), IPO first-day returns (IPOR), new investor additions (NIA), and the consumer confidence index (CCI). Firm ownership (SOE) is included as a binary variable, coded as one if the ultimate controlling entity is government-related, and zero otherwise. Control variables comprise firm size (Size, log total assets), the proportion of shares held by the largest shareholder (Large), the proportion of independent directors (Indep), financial leverage (Lev), earnings per share (EPS), the long-term debt ratio (LTDBT), the book-to-market ratio (BTM), and the return on assets (ROA).

Table 1. Definitions of variables.

Variable Type	Variable Name	Variable Code	Variable definition and calculation method
The explained variable	Financial fraud	<i>Fraud</i>	If there was financial fraud in the year, the value is 1, otherwise is 0
The explanatory variable	Investor sentiment	<i>CICSI</i>	Constructed by principal component analysis
	State-owned enterprises	<i>SOE</i>	If the actual controller is a state-owned enterprise or a state-owned institution, the value is 1, otherwise is 0
The control variables	Total assets	<i>Size</i>	Log of total assets at the end of the period
	Shareholding ratio of the largest shareholder	<i>Large</i>	Number of shares held by the largest shareholder/total number of shares
	Proportion of independent directors	<i>Indep</i>	Number of independent directors/Total number of board members
	Financial leverage	<i>Lev</i>	Total liabilities/Total assets
	Long-term debt ratio	<i>LTDBT</i>	Total long-term liabilities/total assets
	Return on total assets	<i>ROA</i>	Net profit/total assets
	Earning per share	<i>EPS</i>	Net profit/total number of shares
	Book-to-market ratio	<i>BTM</i>	Market price/book value per share
	Year	<i>Year</i>	Dummy variable of year
Industry	<i>Industry</i>	Dummy variable of industry	

3.4. Model Specification

Following Beatty et al. (2013) and Wu et al. (2019), I construct the following model (1) to test Hypothesis 1:

$$\begin{aligned}
 Prob(Fraud = 1) = & \alpha_0 + \alpha_1 CICI + \alpha_2 Size + \alpha_3 Large + \alpha_4 Indep + \alpha_5 Lev \\
 & + \alpha_6 BTM + \alpha_7 ROA + \alpha_8 LTDBT + \alpha_9 EPS \\
 & + \sum Industry + \sum Year + \varepsilon
 \end{aligned} \tag{1}$$

where α_0 is the constant interception, $\alpha_1 - \alpha_9$ are coefficients, and ε is the residual error.

4. Empirical Analysis

4.1. Descriptive Statistics

Table 2 summarizes the descriptive statistics for all the variables used in this study. Because of the matched sampling method, the mean value of the dependent variable (*Fraud*) is 0.50. The mean value of the investor sentiment index (*CICSI*) is 7.663, indicating a generally optimistic sentiment among Chinese investors during the period of 2013-2022, although the substantial standard deviation (8.804) suggests that there were considerable fluctuations over the period.

Table 2. Descriptive statistics of variables.

Variable	N	Mean	Median	SD	Min	Max
Fraud	1670	0.500	0.500	0.500	0	1
CICSI	1670	7.663	6.240	8.804	-11.310	19.350
Size	1670	22.154	22.002	1.111	20.056	25.516
Large	1670	0.339	0.314	0.147	0.086	0.769
Indep	1670	0.377	0.364	0.053	0.333	0.571
Lev	1670	1.440	1.082	1.179	0.340	8.910
BTM	1670	0.344	0.325	0.156	0.053	0.763
ROA	1670	0.048	0.039	0.039	0.001	0.182
LTDBT	1670	0.177	0.123	0.167	0.001	0.734
EPS	1670	0.505	0.323	0.607	0.004	3.926
SOE	1670	0.354	0	0.479	0	1

Among control variables, average firm size (*Size*) is 22.154 with minor variance, reflecting relative homogeneity among the sampled companies. The mean shareholding of the largest shareholder (*Large*) is 33.9%, signifying moderate ownership concentration. The proportion of independent directors (*Indep*) exhibits minimal variance, suggesting uniform corporate governance structures across firms. Conversely, financial leverage (*Lev*) displays substantial variability, indicating diverse financial structures among companies. Other indicators, including the BTM, ROA, and EPS, demonstrate significant variability, reflecting differences in market perceptions and corporate profitability.

The result of the comparative analysis (shown in **Table 3**) reveals significant differences between fraudulent and nonfraudulent companies regarding investor sentiment, providing preliminary support for Hypothesis 1—higher investor sen-

timent correlates with lower fraud probability. Similarly, nonstate-owned enterprises exhibit significantly higher investor sentiment compared with state-owned enterprises (Table 4), preliminarily supporting Hypothesis 2.

Table 3. Comparative analysis of the means of fraud samples and nonfraud samples.

Variable	Fraud samples	Nonfraud samples	Difference of mean	T test	Sig.
CICSI	6.9531	8.3732	-1.4201	-3.3059	0.0010***
Size	22.1622	22.1463	0.0159	0.2923	0.7701
Large	0.3310	0.3461	-0.0152	-2.1047	0.0355**
Indep	0.3749	0.3793	-0.0043	-1.6694	0.0952*
Lev	1.5614	1.3182	0.2432	4.2371	0.0000***
BTM	0.3285	0.3586	-0.0301	-3.9486	0.0001***
ROA	0.0415	0.0547	-0.0132	-7.0935	0.0000***
LTDBT	0.1714	0.1834	-0.0119	-1.0120	0.1434
EPS	0.4109	0.5991	-0.1882	-6.4154	0.0000***

Standard errors are shown in parentheses. The symbols *, **, and *** denote that $p < 0.1$, $p < 0.05$, and $p < 0.01$, respectively. This also applies to the tables below. The mean difference = mean of fraud group – mean of nonfraud group.

Table 4. Comparison and analysis of the mean values of variables for state-owned vs. nonstate-owned samples.

Variable	State-owned samples	Nonstate-owned samples	Difference of mean	T test	Sig.
CICSI	6.3882	8.3634	-1.9752	-4.4100	0.0000***
Size	22.6966	21.8564	0.8402	15.8468	0.0000***
Large	0.3635	0.3249	0.0385	5.1533	0.0000***
Indep	0.3717	0.3802	-0.0085	-3.1260	0.0009***
Lev	1.6994	1.2973	0.4022	6.7578	0.0000***
BTM	0.3315	0.3503	-0.0189	-2.3619	0.0183**
ROA	0.0398	0.0526	-0.0127	-6.5390	0.0000***
LTDBT	0.2254	0.1511	0.0743	8.8956	0.0000***
EPS	0.4519	0.5342	-0.0822	-2.6544	0.0080***
Fraud	0.4611	0.5213	-0.0601	-2.3556	0.0186**

Mean difference = mean of state-owned group – mean of nonstate-owned group.

4.2. Correlation Analysis

The results of the correlation analysis (presented in **Table 5**) confirm the existence of a significant negative relationship between investor sentiment (*CICSI*) and corporate financial fraud (*Fraud*), providing initial support Hypothesis 1. Correlations among other variables are modest, with no severe multicollinearity detected (the variance inflation factor is less than five), confirming the robustness of the regression analysis.

Table 5. Correlation coefficients.

	Fraud	CICSI	Size	Large	Indep	Lev	BTM	ROA	LTDBT	EPS	SOE
Fraud	1										
CICSI	-0.081***	1									
Size	0.007	0.040	1								
Large	-0.051**	-0.083***	0.151***	1							
Indep	-0.041*	0.043*	-0.037	0.056**	1						
Lev	0.103***	-0.065***	0.173***	-0.018	-0.009	1					
BTM	-0.096***	-0.083***	0.044*	0.112***	0.027	-0.186***	1				
ROA	-0.171***	0.060**	-0.102***	0.089***	0.033	-0.366***	0.047*	1			
LTDBT	-0.036	-0.014	0.303***	0.046*	0.019	0.147***	-0.002	-0.133***	1		
EPS	-0.155***	0.095***	0.163***	0.072***	0.013	-0.236***	0.077***	0.649***	-0.028	1	
SOE	-0.058**	-0.107***	0.362***	0.125***	-0.076***	0.163***	-0.058**	-0.158***	0.213***	-0.065***	1

4.3. Regression Analysis

4.3.1. Baseline Regression Results

The probit regression results (**Table 6**) indicate that investor sentiment (*CICSI*) has a negative and significant influence on corporate financial fraud (coefficient = -0.017 , $p < 0.1$), supporting Hypothesis 1. In addition, control variables, including ROA and BTM, are negatively and significantly associated with the likelihood of fraud.

To further assess the economic impact of investor sentiment (*CICSI*) on the probability of corporate financial fraud, this paper calculates the Average Marginal Effects (AME) of the probit model. The results show that for 1% increase in *CICSI*, the average probability of corporate financial fraud decreases by about 0.7%, which is statistically significant ($p < 0.1$), suggesting that investor sentiment is not only statistically significant, but also has a certain degree of economic significance.

Table 6. Regression results and average marginal effects for investor sentiment (CICSI) and financial fraud.

Continued table	(1)	(2)	(3)	(4)	(5)
	Fraud	Fraud	Fraud	Fraud	AME
CICSI	-0.012*** (0.004)	-0.011*** (0.004)	-0.018** (0.009)	-0.017* (0.009)	-0.007* (0.004)
Size		0.039 (0.032)	0.033 (0.032)	0.031 (0.035)	0.012 (0.014)
Large		-0.296 (0.218)	-0.289 (0.219)	-0.268 (0.234)	-0.107 (0.093)
Indep		-0.620 (0.598)	-0.592 (0.603)	-0.833 (0.625)	-0.332 (0.249)
Lev		0.034 (0.031)	0.033 (0.030)	0.033 (0.031)	0.013 (0.012)
BTM		-0.697*** (0.207)	-0.688*** (0.220)	-0.658*** (0.237)	-0.262*** (0.094)
LTDDBT		-0.520*** (0.197)	-0.504** (0.198)	-0.375 (0.229)	-0.150 (0.091)
ROA		-3.608*** (1.171)	-4.098*** (1.189)	-4.569*** (1.249)	-1.823*** (0.498)
EPS		-0.159** (0.074)	-0.105 (0.075)	-0.062 (0.080)	-0.025 (0.032)
Year			Control	Control	Control
Industry				Control	Control
_cons	0.088** (0.041)	0.091 (0.723)	0.130 (0.730)	-0.479 (0.837)	
N	1670	1670	1670	1657	1657
Prob > chi2	0.0010	0.0000	0.0000	0.0000	
Pseudo R ²	0.0047	0.0386	0.0484	0.0721	

AME is the average marginal effect at the sample mean; robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

4.3.2. Heterogeneity Analysis

Table 7. Financial fraud groups regression results and average marginal effects by control attributes.

Continued table	(1)	(2)	(3)	(4)
	Nonstate-owned enterprises	Nonstate-owned enterprises AME	State-owned enterprises	State-owned enterprises AME
CICSI	-0.026** (0.013)	-0.010** (0.005)	-0.031* (0.017)	-0.012* (0.007)
Size	0.083 (0.051)	0.033 (0.020)	0.097 (0.061)	0.038 (0.024)
Large	-0.452 (0.307)	-0.180 (0.122)	-0.170 (0.427)	-0.067 (0.169)
Indep	-1.663** (0.802)	-0.662** (0.320)	-0.320 (1.148)	-0.127 (0.455)
Lev	0.025 (0.050)	0.010 (0.020)	0.001 (0.042)	0.001 (0.017)
BTM	-0.775*** (0.297)	-0.309*** (0.118)	-0.651 (0.473)	-0.258 (0.187)
LTDBT	-0.276 (0.301)	-0.110 (0.120)	-0.699* (0.384)	-0.277* (0.152)
ROA	-4.632*** (1.564)	-1.845*** (0.623)	-5.562** (2.536)	-2.204** (1.005)
EPS	-0.039 (0.100)	-0.016 (0.040)	-0.304* (0.171)	-0.121* (0.068)
Year	Control	Control	Control	Control
Industry	Control	Control	Control	Control
_cons	-1.275 (1.216)		-1.903 (1.477)	
N	1064	1064	564	564
Prob > chi2	0.0000		0.0000	
Pseudo R ²	0.0766		0.1564	

Heterogeneity tests (shown in **Table 7**) demonstrate that investor sentiment has a stronger inhibitory effect on fraud among nonstate-owned enterprises (coefficient = -0.026 , $p < 0.05$) than among state-owned enterprises (-0.031 , $p < 0.1$), providing clear support for Hypothesis 2. The flexible corporate governance structures of nonstate-owned enterprises may contribute to this result by enabling rapid adaptation to investor sentiment shifts.

Across ownership subsamples, higher investor sentiment significantly reduces the likelihood of financial fraud: a 1% increase in CICSI lowers the fraud probability by 1% in nonstate-owned firms ($p < 0.05$) and by 1.2% in state-owned firms ($p < 0.1$), indicating economically meaningful deterrent effects in both groups.

To further control for firm-level dependence within the matched sample, I re-estimate **Table 6** and **Table 7** using firm-clustered robust standard errors. The results (see **Table 8**) indicate that the direction and significance of the CICSI coefficient remain essentially unchanged: it remains significantly negative in the all samples (coefficient = -0.017 , $p < 0.1$), and the deterrent effects in both nonstate-owned (coefficient = -0.026 , $p < 0.05$) and state-owned subsamples (coefficient = -0.031 , $p < 0.1$) remain significant. The significance of other control variables is also largely robust, confirming that the main conclusions are unaffected by firm-level clustering.

Table 8. Firm clustering robust standard errors of investor sentiment and financial fraud.

Variables	(1)	(2)	(3)
	Fraud	Fraud	Fraud
	All samples	Nonstate-owned enterprises	State-owned enterprises
CICSI	-0.017^* (0.009)	-0.026^{**} (0.013)	-0.031^* (0.017)
Size	0.031 (0.036)	0.083 (0.052)	0.097 (0.063)
Large	-0.268 (0.245)	-0.452 (0.317)	-0.170 (0.440)
Indep	-0.833 (0.645)	-1.663^{**} (0.829)	-0.320 (1.167)
Lev	0.033 (0.031)	0.025 (0.050)	0.001 (0.041)
BTM	-0.658^{***} (0.245)	-0.775^{**} (0.305)	-0.651 (0.482)
LTDBT	-0.375 (0.232)	-0.276 (0.306)	-0.699^* (0.386)

Continued

ROA	-4.569*** (1.284)	-4.632*** (1.615)	-5.562** (2.577)
EPS	-0.062 (0.082)	-0.039 (0.102)	-0.304* (0.173)
Year	Control	Control	Control
Industry	Control	Control	Control
_cons	-0.479 (0.865)	-1.275 (1.239)	-1.903 (1.552)
N	1657	1064	564
Prob > chi2	0.0000	0.0032	0.0000
Pseudo R ²	0.0721	0.0766	0.1564

4.3.3. Mechanism Tests

The financing constraints index (SA) was proposed by [Hadlock and Pierce in 2010](#) to measure the degree of financing constraints faced by firms. SA index is constructed using only two variables, enterprise size and enterprise age, which do not change much over time and are highly exogenous, effectively avoiding the endogeneity problem arising from the dependence on financial data of traditional indicators.

The specific calculation formula is as follows:

$$SA = -0.737 \times Size + 0.043 \times Size^2 - 0.040 \times Age \quad (2)$$

In the above, *Size* is the natural logarithm of inflation-adjusted total assets, and *Age* is the number of years since the firm's IPO. Higher SA values indicate more severe financing constraints. Data of SA are sourced from the CSMAR database.

Mechanism tests based on SA index reveal that financing constraints significantly mediate the relationship between investor sentiment and corporate financial fraud ([Table 9](#), [Table 10](#)). Higher investor sentiment eases financing constraints, reducing incentives for financial fraud.

Table 9. Regression results and Sobel test with financing constraints (SA) as the intermediate variable.

Continued table	(1)	(2)	(3)
	Fraud	SA	Fraud
SA			0.418*** (0.152)
CICSI	-0.017* (0.009)	-0.015*** (0.002)	-0.010 (0.010)

Continued

Size	0.031	-0.019***	0.039	
	(0.035)	(0.006)	(0.035)	
Large	-0.268	0.128***	-0.317	
	(0.234)	(0.042)	(0.235)	
Indep	-0.833	0.186*	-0.918	
	(0.625)	(0.110)	(0.628)	
Lev	0.033	-0.006	0.036	
	(0.031)	(0.004)	(0.031)	
BTM	-0.658***	-0.012	-0.653***	
	(0.237)	(0.040)	(0.237)	
LTDBT	-0.375	-0.011	-0.372	
	(0.229)	(0.038)	(0.229)	
ROA	-4.569***	-0.173	-4.504***	
	(1.249)	(0.200)	(1.251)	
EPS	-0.062	0.041***	-0.080	
	(0.080)	(0.014)	(0.081)	
Year	Control	Control	Control	
Industry	Control	Control	Control	
_cons	-0.479	-3.488***	0.964	
	(0.837)	(0.155)	(0.996)	
N	1657	1670	1657	
Prob > chi2	0.0000	0.0000	0.0000	
Pseudo R ²	0.0721	0.2103	0.0753	
Sobel Test	Coef	Std Err	Z	P > Z
Sobel	-0.00067542	0.00027732	-2.436	0.01486908
Goodman-1	-0.00067542	0.00027937	-2.418	0.01562212
Goodman-2	-0.00067542	0.00027525	-2.454	0.0141323
Proportion of total effect that is mediated: 0.15538469				
Ratio of indirect to direct effect: 0.18397096				
Ratio of total to direct effect: 1.183971				

Table 10. Bootstrap test with financing constraints (SA) as the intermediate variable.

Bootstrap Test	Coef	Std Err	Z	P > Z	[95% conf. interval]	
Indirect effect	-0.0006754	0.0002806	-2.41	0.016	-0.0012253	-0.0001255
Direct effect	-0.0036713	0.0013947	-2.63	0.008	-0.006405	-0.0009377

The internal control quality score is obtained from the DIB Internal Control Database. This index, which originally ranges from 0 to 1000, evaluates the effectiveness of a firm's internal control system across five dimensions: control environment, risk assessment, control activities, information communication, and internal supervision. To ensure consistent scaling and facilitate coefficient interpretation in regressions, the raw index is uniformly divided by 1000, transforming to a 0 - 1 scale. Higher values indicate stronger internal controls.

Results show that internal control quality exhibits a masking effect (**Table 11**, **Table 12**), partially offsetting the negative impact of investor sentiment on fraud. Poor internal controls weaken firms' responsiveness to investor sentiment changes, diminishing its role in inhibiting fraud.

Table 11. Regression results and Sobel test with the internal control index (Index) as the intermediate variable.

	(1)	(2)	(3)
	Fraud	Index	Fraud
Index			-1.624*** (0.467)
CICSI	-0.017* (0.009)	-0.002*** (0.000)	-0.020** (0.009)
Size	0.031 (0.035)	0.010*** (0.002)	0.048 (0.035)
Large	-0.268 (0.234)	0.013 (0.013)	-0.249 (0.234)
Indep	-0.833 (0.625)	0.044 (0.034)	-0.751 (0.629)
Lev	0.033 (0.031)	-0.005** (0.002)	0.024 (0.031)
BTM	-0.658*** (0.237)	-0.039*** (0.014)	-0.722*** (0.239)

Continued

LTDBT	-0.375 (0.229)	-0.007 (0.013)	-0.392* (0.229)	
ROA	-4.569*** (1.249)	0.331*** (0.067)	-4.071*** (1.253)	
EPS	-0.062 (0.080)	0.008* (0.004)	-0.049 (0.079)	
Year	Control	Control	Control	
Ind	Control	Control	Control	
_cons	-0.479 (0.837)	0.408*** (0.052)	0.159 (0.865)	
N	1657	1670	1657	
Prob > chi2	0.0000	0.0000	0.0000	
Pseudo R ²	0.0721	0.1322	0.0777	
Sobel Test	Coef	Std Err	Z	P > Z
Sobel	0.00047473	0.00018078	2.626	0.00864089
Goodman-1	0.00047473	0.00018391	2.581	0.00984394
Goodman-2	0.00047473	0.0001776	2.673	0.00751697
Proportion of total effect that is mediated: -0.10921457				
Ratio of indirect to direct effect: -0.09846117				
Ratio of total to direct effect: 0.90153883				

Table 12. Bootstrap test with the internal control index (Index) as the intermediate variable.

Bootstrap Test	Coef	Std Err	Z	P > Z	[95% conf. interval]	
Indirect effect	0.0004747	0.0001776	2.67	0.008	0.0001266	0.0008228
Direct effect	-0.0048215	0.0013631	-3.54	0.000	-0.0074931	-0.0021499

4.4. Robustness Tests

I conduct robustness analyses employing an alternative measure of the investor sentiment index (ISI) and an alternative logit model. These analyses (see **Table 13**, **Table 14**) confirm the main findings, reinforcing their validity and generalizability. The direction and magnitude of the marginal effects are consistent with the main results.

Table 13. Regression results of investor sentiment (ISI) and financial fraud.

Variables	(1)	(2)	(3)
	Fraud	Fraud	Fraud
	All samples	Nonstate-owned enterprises	State-owned enterprises
ISI	-0.014* (0.008)	-0.021** (0.010)	-0.025* (0.014)
Size	0.031 (0.035)	0.083 (0.051)	0.097 (0.061)
Large	-0.268 (0.234)	-0.452 (0.307)	-0.170 (0.427)
Indep	-0.833 (0.625)	-1.663** (0.802)	-0.320 (1.148)
Lev	0.033 (0.031)	0.025 (0.050)	0.001 (0.042)
BTM	-0.658*** (0.237)	-0.775*** (0.297)	-0.651 (0.473)
LTDBT	-0.375 (0.229)	-0.276 (0.301)	-0.699* (0.384)
ROA	-4.569*** (1.249)	-4.632*** (1.564)	-5.562** (2.536)
EPS	-0.062 (0.080)	-0.039 (0.100)	-0.304* (0.171)
Year	Control	Control	Control
Industry	Control	Control	Control
_cons	-0.509 (0.839)	-1.322 (1.219)	-1.959 (1.483)
N	1657	1064	564
Prob > chi2	0.0000	0.0020	0.0000
Pseudo R ²	0.0721	0.0766	0.1564

Table 14. Regression results of logit model.

Variables	(1)	(2)	(3)
	Fraud	Fraud	Fraud
	All samples	Nonstate-owned enterprises	State-owned enterprises
CICSI	-0.028* (0.015)	-0.042** (0.020)	-0.053* (0.029)
Size	0.050 (0.057)	0.135 (0.084)	0.168 (0.105)
Large	-0.429 (0.382)	-0.737 (0.502)	-0.282 (0.730)
Indep	-1.412 (1.024)	-2.748** (1.330)	-0.413 (1.927)
Lev	0.051 (0.051)	0.039 (0.083)	0.002 (0.069)
BTM	-1.051*** (0.387)	-1.271*** (0.487)	-0.989 (0.810)
LTDBT	-0.596 (0.370)	-0.456 (0.485)	-1.123* (0.642)
ROA	-7.433*** (2.065)	-7.534*** (2.599)	-9.162** (4.544)
EPS	-0.108 (0.132)	-0.069 (0.165)	-0.515 (0.325)
Year	Control	Control	Control
Industry	Control	Control	Control
_cons	-0.809 (1.386)	-2.127 (2.026)	-3.494 (2.623)
N	1657	1064	564
Prob > chi2	0.0000	0.0102	0.0008
Pseudo R ²	0.0721	0.0769	0.1561

5. Conclusion

This study analyzes the relationship between investor sentiment and corporate financial fraud among Chinese A-share listed companies for the period of 2013 to 2022. The results show that higher investor sentiment significantly reduces the probability of corporate financial fraud. This suggests that during periods of high market optimism, corporate managers may have stronger incentives to maintain transparent financial practices owing to increased scrutiny from investors and regulatory bodies. In addition, I find that investor sentiment exerts a stronger inhibitory effect on financial fraud in nonstate-owned enterprises than in state-owned enterprises. It is probable that this difference stems from the more flexible decision-making processes and governance structures of nonstate-owned enterprises, which allows them to quickly adapt to fluctuations of market sentiment. Mechanism tests further reveal that investor sentiment reduces financial fraud primarily by alleviating financing constraints. Conversely, internal control quality exhibits a masking effect, as weaker internal control mechanisms limit firms' responsiveness to changes in investor sentiment, thereby partially reducing its preventive influence on financial fraud.

Based on these findings, I consider that several policy implications and recommendations emerge. First, regulators should enhance investor education and market transparency to ensure that timely and accurate financial information is provided to investors. Improved investor awareness can effectively enhance market discipline, ultimately reducing occurrences of corporate financial fraud. Moreover, firms should improve their internal control systems and external audit practices to ensure the authenticity of their financial reports. Especially in state-owned enterprises, reducing administrative interference and simultaneously enhancing internal accountability and oversight can significantly mitigate fraud risks. Furthermore, I encourage regulators to design targeted regulatory frameworks tailored to firm ownership structures. State-owned enterprises require stricter financial supervision and disclosure standards, whereas nonstate-owned enterprises can leverage their flexibility to proactively enhance internal governance and reduce fraud incentives. Finally, strengthening the legal system by imposing stricter penalties for financial misconduct can increase the cost of committing fraud, providing stronger deterrents against unethical financial practices. By implementing these measures, overall corporate transparency and governance quality can improve significantly, fostering a healthier and more sustainable capital market environment.

Despite providing valuable insights, this study has limitations that indicate directions for future research. The first limitation concerns the research scope; this study exclusively examines Chinese A-share listed companies, possibly limiting the generalizability of the conclusions to other market contexts or types of firms. Future studies could extend the analysis to broader samples, including firms listed on other markets or private companies, to enhance external validity. In addition, although I used established investor sentiment indices (CICSI and ISI), accurately

quantifying investor sentiment remains challenging because of its subjective and multifaceted nature. Further exploration of alternative sentiment indicators or advanced methodologies, such as textual sentiment analysis or behavioral indicators, could provide deeper insights and more robust findings. Addressing these limitations through expanded datasets, international comparisons, and improved sentiment measurement techniques would contribute to a more comprehensive understanding of the influence of investor sentiment on corporate financial fraud.

Conflicts of Interest

The author declares no conflicts of interest regarding the publication of this paper.

References

- An, S. Q., Yang, M. J., & Li, Y. T. (2023). Excess Goodwill, Financial Fraud Risk, and Audit Fees. *Finance and Accounting Monthly*, *44*, 86-93.
- Beasley, M. S. (1996). An Empirical Analysis of the Relation between Board of Director Composition and Financial Statement Fraud. *Accounting Review*, *71*, 443-465.
- Beatty, A., Liao, S., & Yu, J. J. (2013). The Spillover Effect of Fraudulent Financial Reporting on Peer Firms' Investments. *Journal of Accounting and Economics*, *55*, 183-205. <https://doi.org/10.1016/j.jacceco.2013.01.003>
- Beaudry, P., & Willems, T. (2022). On the Macroeconomic Consequences of Over-Optimism. *American Economic Journal: Macroeconomics*, *14*, 38-59. <https://doi.org/10.1257/mac.20190332>
- Chen, Y., & Zhang, W. Z. (2022). Can the Party Organization of State-Owned Enterprises Effectively Suppress Financial Fraud? A Quasi-Natural Experiment Based on the "Discussion Pre-Arrangement" Mechanism. *China Soft Science*, *No. 1*, 182-192.
- Geng, X. Y. (2023). Identification and Statistics of Investor Sentiment-Based on the Analysis of Unstructured Data. *Science Decision*, *No. 11*, 156-169.
- Guan, H. S., Li, S. Y., & Wang, Q. (2023). Fund Occupation and Financial Fraud Behavior Identification-Based on the Empirical Study of "Accounting Supervision Risk Tip No. 9". *Friends of Accounting*, *No. 14*, 90-97.
- Hadlock, C. J., & Pierce, J. R. (2010). New Evidence on Measuring Financial Constraints: Moving Beyond the KZ Index. *Review of Financial Studies*, *23*, 1909-1940. <https://doi.org/10.1093/rfs/hhq009>
- Hu, H. F., Ma, B., & Wang, A. P. (2019). What Kind of Equity Structure Is More Likely to Lead to Corporate Fraud? Based on Partially Observable Bivariate Probit Estimation. *Journal of Beijing Normal University (Social Sciences Edition)*, *No. 5*, 148-160.
- Krishnamurthy, A., & Muir, T. (2017). *How Credit Cycles across a Financial Crisis*. NBER Working Paper, No. 23850.
- Lan, Z. W., Li, Z. Q., & Hu, Z. Y. (2023). The Corporate Governance Effect of Social Capital-Empirical Evidence from the Relationship between Executive Localization and Accounting Information Quality. *Journal of Management Sciences in China*, *26*, 130-158.
- Li, H., & Grundy, B. (2023). The Effect of Investor Sentiment and the Structure of Shareholder Ownership on Corporate Investment. *International Journal of Managerial Finance*, *19*, 155-172. <https://doi.org/10.1108/ijmf-11-2021-0558>
- Li, P., Zhao, Q., Liu, Y., Zhong, C., Wang, J., & Lyu, Z. (2024). Survey and Prospect for Applying Knowledge Graph in Enterprise Risk Management. *Computers, Materials &*

Continua, 78, 3825-3865. <https://doi.org/10.32604/cmc.2024.046851>

López-Salido, D., Stein, J. C., & Zakrajšek, E. (2017). Credit-Market Sentiment and the Business Cycle. *The Quarterly Journal of Economics*, 132, 1373-1426.

<https://doi.org/10.1093/qje/qjx014>

Ma, L. F., Wang, B., & Song, J. N. (2022). Are Retail Investors More Fond of Digitization? A Study Based on the Heterogeneity of Investor Sentiment. *Economic and Management Research*, 43, 32-54.

Moshirian, F., Qian, X., Wee, C. K. G., & Zhang, B. (2017). The Determinants and Pricing of Liquidity Commonality around the World. *Journal of Financial Markets*, 33, 22-41.

<https://doi.org/10.1016/j.finmar.2017.02.004>

Perols, J. L., & Lougee, B. A. (2010). The Relation between Earnings Management and Financial Statement Fraud. *Advances in Accounting*, 27, 39-53.

<https://doi.org/10.1016/j.adiac.2010.10.004>

Piñero-Chousa, J., López-Cabarcos, M. Á., Caby, J., & Šević, A. (2021). The Influence of Investor Sentiment on the Green Bond Market. *Technological Forecasting and Social Change*, 162, Article ID: 120351. <https://doi.org/10.1016/j.techfore.2020.120351>

Throckmorton, C. S., Mayew, W. J., Venkatachalam, M., & Collins, L. M. (2015). Financial Fraud Detection Using Vocal, Linguistic and Financial Cues. *Decision Support Systems*, 74, 78-87. <https://doi.org/10.1016/j.dss.2015.04.006>

Wang, W., Su, C., & Duxbury, D. (2021). Investor Sentiment and Stock Returns: Global Evidence. *Journal of Empirical Finance*, 63, 365-391.

<https://doi.org/10.1016/j.jempfin.2021.07.010>

Wu, P., Lu, S., & Yang, N. (2019). Research on the Role of Corporate Governance in Media Attention from the Perspective of Financial Fraud. *Journal of Central University of Finance and Economics*, No. 3, 51-69.

Wu, X. G., & Du, S. Y. (2022). An Analysis on Financial Statement Fraud Detection for Chinese Listed Companies Using Deep Learning. *IEEE Access*, 10, 22516-22532.

<https://doi.org/10.1109/access.2022.3153478>