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Information, sentiment, and margin trading of Chinese stock market

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Abstract
This paper examines whether information or sentiment drives margin trading in the Chinese stock market. At the aggregate level, no conclusive evidence indicates a dominance of either information-driven or sentiment-driven margin trading activities. However, at the individual firm level, we observe both types of margin trading, underscoring the need to consider the heterogeneity of margin trading when reconciling previous research findings. Moreover, we find that the likelihood of sentiment-driven margin trading significantly declined following regulators' implementation of stricter rules for margin trading in 2015.

KEYWORDS
heterogeneity, information, margin trading, sentiment

JEL CLASSIFICATION
G12, G14

1 | INTRODUCTION

Existing literature has extensively examined the relationship between short-selling and informed investors. Numerous studies, including those by Bris et al. (2007), Boehmer et al. (2013), Rapach et al. (2016), and Kelley and Tetlock (2017), have established that short-selling activities can provide valuable information in predicting future stock returns.[1] However, margin trading, which shares similarities with short-selling regarding leverage use, has yet to be thoroughly investigated. This paper aims to illuminate the distinct characteristics and potential effects of margin trading.

[1]Prior research investigates various implications of short-selling. Saffi and Sigurdsson (2011) demonstrate that short-selling constraints, measured by a limited supply of lendable stocks, can reduce price efficiency. Karpoff and Lou (2010), Massa et al. (2015a), and Massa et al. (2015b) highlight the exceptional information processing ability of short sellers when it comes to detecting misconduct. Moreover, Geczy et al. (2002), D'Avolio (2002), Cohen et al. (2007), Kolasinski et al. (2013), and Aggarwal et al. (2015) explore the supply and demand dynamics of the short-selling market.

Furthermore, the impact of margin trading on various aspects of capital markets remains inconclusive. The lack of consensus may stem from previous studies neglecting the potential heterogeneity of margin trading across different stocks, thereby complicating the assessment of the margin trading market. In response, this paper considers the possible heterogeneity of margin trading to address the gap in the literature. By exploring the varied aspects of margin trading, we aim to deepen our understanding of leverage utilisation in capital markets.

The existing literature on margin trading presents mixed findings concerning its predictive power for returns and its impact on various aspects of capital markets. While some studies show that margin trading can forecast future returns, such as Hirose et al. (2009), who find predictive power in margin trading by retail investors in Japan, others, like Chang et al. (2014) and Lv and Wu (2019a), find no such evidence for the Chinese market.

Similarly, prior research on how margin trading influences price efficiency has produced inconsistent results. For example, Chang et al. (2014) reveal that buying decisions by margin traders enhance price efficiency, while their selling reduces it in the Chinese stock market. In contrast, Chen et al. (2016) find that margin trading correlates with an improved information environment.

The impact of margin trading on stock volatility also remains inconclusive. While Seguin (1990) concludes that margin trading has an insignificant impact on market volatility and liquidity in the US market, Hardouvelis and Peristiani (1992) illustrate that heightened margin trading requirements in Japan deter speculators, thus enhancing market stability. Additionally, Gui and Zhu (2021) document a decline in idiosyncratic volatilities for target stocks following the initiation of the margin trading program.

The lack of consensus in existing literature necessitates new perspectives to understand margin trading better. Extant studies typically evaluate margin trading at an aggregate level across different markets, overlooking the heterogeneity of the investor base and various stock characteristics. In contrast to short selling, margin buying is accessible to a broader range of investors, increasing the complexity of investor structures and their decision-making processes. Investors exhibit varying abilities to interpret public and private information, complicating the assessment of the margin trading market as a whole. Consequently, it may be advantageous to consider the heterogeneity of margin buyers across different stocks and examine their influence on a firm-by-firm basis.[2]

This paper investigates margin trading within the Chinese stock market, characterised by a predominance of retail investors and its growing significance in global financial markets. Before March 2010, leveraged trading was not permitted in the Chinese stock market. In March 2010, the Shanghai and Shenzhen Stock Exchanges initiated the designation of stocks eligible for margin trading and short selling, marking a crucial step towards enhancing the efficiency of the Chinese stock market. Furthermore, regulators publicly disclose comprehensive stock-level daily margin trading information, greatly facilitating research.[3] This policy change and the detailed data available provide an optimal environment for studying margin buyer behaviour and accounting for the heterogeneity of margin trading.

We explore the trading motives behind margin trading activities, specifically whether information or sentiment drives them and how these motives differ among various stocks. Information and sentiment are two crucial drivers of trading activities. The literature indicates that trading driven by information has distinct predictive power over future stock

[2]We define investors who use leverage to buy stocks as "margin buyers", reflecting that these investors are taking a long position.

[3]The pilot program offers a rich ground for examining the impact of margin trading on capital markets. Several recent studies have utilised this setting, such as Chang et al. (2014), Sharif et al. (2014), Chen et al. (2016), Lv and Wu (2019b), and Qian et al. (2020).

returns compared to trading driven by sentiment. If stock trading reflects information about the stock's future earnings or risk, it can positively predict returns (e.g., Hirose et al., 2009; Rapach et al., 2016; Kelley & Tetlock, 2017). Conversely, if investors are influenced by sentiment, their trading activities can increase market volatility (Baker & Wurgler, 2006; Mendel & Shleifer, 2012) and exhibit a negative association with future stock returns (Stambaugh et al., 2012; Huang et al., 2015).

Margin trading is a mechanism through which optimistic investors express their beliefs about a firm's performance or the overall stock market. We can contextualise the aforementioned distinction between information-driven and sentiment-driven trading within the margin trading market. If margin trading reflects relevant information, the margin trading balance will exhibit a positive relationship with future stock returns. Conversely, if margin trading is sentiment-driven, its balance will negatively affect future stock returns.

We begin our analysis by conducting predictive regressions at the aggregate level from 2010 to 2022. Specifically, we calculate the aggregate margin trading interest based on individual stocks' daily margin trading balance. We construct two groups of margin interest measures using different sample coverage and weighting schemes. The first group uses all eligible firms on the margin trading list and employs both equal- and value-weighted schemes to construct aggregate margin trading interest. In contrast, the second group of measures is based solely on the 70 eligible stocks on the margin trading list throughout our sample period.[4] These 70 firms have large capitalisation and can represent overall market conditions.

However, we find no evidence that market-level margin interest can predict stock market returns for either measure, aligning with the conclusions of Chang et al. (2014) and Lv and Wu (2019a). We then conduct sub-period analyses with different economic uncertainty and investor sentiment to test whether predictability changes with market conditions. Our results show that market-level margin interest can predict stock market returns when economic uncertainty or general investor sentiment is high. These results demonstrate information-driven margin trading activities under specific conditions.

There are two potential explanations for the insignificant results at the aggregate level. On the one hand, margin buyers might be unable to predict future market performance. On the other hand, both information- and sentiment-driven margin trading activities could exist, with their effects offsetting each other. To distinguish between these two explanations, we examine the predictability of margin interests at the individual firm level. We regress stock returns on stock-level margin trading interest for each firm. Our findings reveal that both information- and sentiment-driven margin trading activities coexist. The positive predictability by margin trading occurs in stocks with high price non-synchronicity (Chen et al., 2006) and Amihud illiquidity (Barardehi et al., 2021), aligning with the information-driven motivation. Conversely, sentiment-driven margin trading, characterised by a significant and negative association between stock-level margin trading interest and subsequent stock returns, is prevalent in stocks with low corporate transparency, as measured by more accrual-based earnings management and local auditors. These results are consistent with Firth et al. (2015), who document that stocks with low corporate transparency are more susceptible to being influenced by sentiment in the stock market.[5]

[4]These 70 stocks were chosen from the initial group of 90 stocks listed for margin trading during the entire sample period. Certain stocks were removed from the list during our sample period.

[5]Existing research recognises the crucial role of sentiment in explaining investor behaviour and anomalies, with sentiment defined as investors' perceptions regarding a firm's future cash flows and risks that cannot be explained by all available information (e.g., De Long et al., 1990). Pioneering research by Baker and Wurgler (2006) constructs a sentiment index widely used in the literature. Stambaugh et al. (2012) employ sentiment to investigate 11 anomalies and find that sentiment-driven behaviour leads to stock overpricing during high sentiment periods.

The regulators' response during the financial crisis has received increasing attention in the literature (Swagel, 2015). The granularity of data and stock-level predictive regressions enable us to evaluate the effectiveness of responses to the crisis in a market featured by retail investors. We assess the effectiveness of responses following the 2015 Chinese stock market crisis. Our findings reveal that sentiment-driven margin trading dropped significantly after the 2015 crisis. When predicting weekly returns, firms in the sentiment-driven category experienced a 54% decrease from 2015 to 2016. There is also a 33% increase in information-driven margin trading during the same period. We further employ a logit model and demonstrate that the decline in sentiment-driven trading and the increase in information-driven trading are statistically significant. Our results align with the findings of Qian et al. (2020), which show that the price delay after the 2015 crash is roughly half the price delay observed before the crash in the Chinese stock market. We propose several reasons to explain this decrease, including tighter rules on margin trading, more stringent risk management implemented by financial intermediaries, and conservative investment choices by investors.

We perform multiple tests to verify the robustness of the decline in sentiment-driven trading and the moderate increase in information-driven trading after the 2015 stock crisis. First, we divide our sample using a different definition of pre-crisis and post-crisis periods, and our results continue to hold. Second, we employ a multinomial logit model as an alternative specification, which enables the incorporation of more observations into the regression and enhances the test's power. The decrease in sentiment-driven trading and the increase in information-driven trading remain statistically significant under this new model specification.

Two recent studies conducted by Chang et al. (2014) and Lv and Wu (2019a) investigate related topics, but our paper diverges in several aspects. First, they evaluate the informativeness of margin trading at an aggregate level, while we consider the heterogeneity of margin trading by analysing individual stocks. Second, in addition to predictability, we examine the effectiveness of responses following the 2015 stock crisis.[6] Third, we adopt a different measure to capture margin trading activity in the Chinese stock market. We employ the daily balance scaled by firm capitalisation to capture the margin trading interest, complementing the measures employed in previous studies.[7]

Our paper contributes to the literature in several ways. First, we document the influences of information and sentiment on margin trading activities, providing empirical support for both rational and behavioural finance (Hirshleifer, 2015; Stambaugh et al., 2012). Second, we propose accounting for the heterogeneity of margin trading, which may offer a new perspective to reconcile the documented inconsistencies in the literature. While this paper examines margin buyers' skills in predicting returns, methods that account for the heterogeneity of margin trading are also valuable in addressing other critical issues, such as how margin trading affects price efficiency and stock volatility. Third, we contribute to the literature by analysing the responses of governments, financial intermediaries, and investors to sudden market crashes (Cong et al., 2020; He et al., 2020; Swagel, 2015). We demonstrate that sentiment-driven margin trading decreased dramatically after the 2015 Chinese stock market crisis, supporting tightened regulations in an emerging market characterised by retail investors.

The remainder of the paper is structured as follows: Section 2 provides institutional details about the margin trading program in China. Section 3 explains the sample selection process and the construction of stock-level and market-level margin trading interests.

[6]Lv and Wu (2019a) focus on potential strategies used by margin buyers, such as positive feedback and moving-average strategies.

[7]In contrast, Chang et al. (2014) utilise daily margin purchase volume (or daily covering volume of margin position) scaled by daily trading volume, and Lv and Wu (2019a) employ the margin-buying amount scaled by trading amount. Those measures might be affected by the high turnover of the Chinese market.

Section 4 reports the results of predictive regression at the aggregate and individual stock levels, respectively. Section 5 explores the change in information-driven and sentiment-driven behaviour after the 2015 stock market crisis. We also run panel logit models to investigate which firm characteristics affect information-driven and sentiment-driven margin trading. Section 6 presents the results of robustness tests, while Section 7 concludes the paper.

2 | INSTITUTIONAL BACKGROUND

This section begins by examining the history of the margin trading program in the Chinese stock market. Following this, we discuss the background of the 2015 stock market crisis and the policies implemented by regulatory bodies to stabilise the market.

2.1 | Margin trading program

The Chinese stock market's leverage trading program was implemented on 31 March 2010. Initially, entry standards were comparatively high, and the program was open only to selected stocks, securities companies, and qualified investors. First, a small group of stocks was chosen to participate in the program. The regulatory body selected eligible stocks based on market capitalisation and liquidity. The initial list comprised 90 large-capitalisation stocks with high liquidity. Second, only six securities companies could provide services, representing less than 10% of all securities companies in China. These companies used the assets and securities on their balance sheets to participate in the program. Third, to ensure market stability and protect retail investors, only investors with assets exceeding 500,000 Chinese Yuan (around US$80,000) could open margin trading or short-selling accounts. Finally, it was costly to participate in the margin trading program. Investors had to pay substantial loan fees, commissions, and stamp taxes. For example, the standard loan fee was around 8% for margin traders, though investors could negotiate with the securities companies to reduce the loan fees if the transaction size was large.[8]

Table 1 illustrates the evolution of China's margin trading and short-selling program. Several vital points need further discussion. First, the margin trading market experienced rapid growth after the program's inception. The regulatory body gradually added stocks with relatively high market capitalisation and liquidity to the eligible pool. The number of stocks on the list increased from 96 in 2010 to 3159 in 2022. Support for security companies participating in the program also expanded gradually. For instance, in October 2011, the Chinese Security Finance Corporation was established to provide financial support for security companies, aiming to increase the available funding for margin trading and lendable securities for short-selling. Second, investors use margin trading more actively than short-selling to take leverage in the Chinese stock market throughout our sample period.[9] In 2015, the margin trading and short-selling balances were 1117.30 and 1.55 billion Yuan, respectively. Third, more retail investors than institutional investors participated in the leverage trading program. By the end of 2022, 6,357,200 retail investors had joined, while only 46,500 institutional investors had entered the program.

According to regulatory policies, only investors who meet specific criteria can participate in the margin trading program. However, many non-eligible investors bypass these restrictions

[8]Data source: https://finance.sina.com.cn/stock/y/2019-09-10/doc-iicezueu4837789.shtml. The 8% figure is conservative when measuring loan fees at the beginning of the program implementation.

[9]This also justifies our focus on margin trading rather than short-selling in the Chinese stock market.

TABLE 1 Summary of the Chinese margin trading and short-selling program.

Variables	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**	**2016**	**2017**	**2018**	**2019**	**2020**	**2021**	**2022**
Number of eligible stocks	96	278	278	741	916	899	966	988	975	1689	1914	2287	3159
Margin trading balance (1 billion Yuan)	12.76	37.36	82.56	319.42	932.97	1117.30	892.95	922.56	655.37	885.05	1311.90	1555.40	1330.80
Short-selling balance (1 billion Yuan)	0.01	0.65	3.31	2.61	5.06	1.55	2.26	2.59	2.66	9.36	116.13	96.18	78.23
Retail investors number (10 thousand)	4.18	34.75	98.69	265.55	585.71	396.92	423.87	454.11	470.70	507.65	554.93	603.03	635.72
Institutional investors number (10 thousand)	0.02	0.11	0.34	0.64	1.00	0.77	1.02	1.41	1.72	2.25	3.14	4.00	4.65

Note: This table presents the summary statistics of China's margin trading and short-selling program from 2010 to 2022. The number of eligible stocks measures the number of stocks that have ever been on margin trading and short-selling lists in each respective year. The margin trading and short-selling balances represent the total end-of-year total balances. Other statistics are year-end figures from the China Securities Depository and Clearing Corporation Statistical Yearbook.

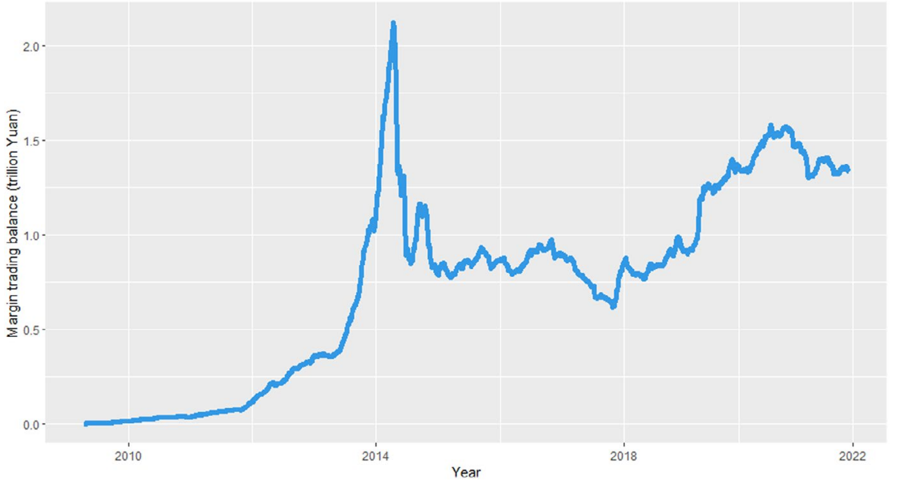

FIGURE 1 Historical margin trading balance. This figure plots the historical margin trading balance in the Chinese stock market from 2010 to 2022. We use the total amount of money borrowed by margin buyers for all eligible stocks each day, measured in trillions of Chinese Yuan.

by trading through third-party systems, such as the Homes system, which faces less regulation. Investors can achieve a much higher leverage ratio using the Homes system than the official margin trading market. The heightened enthusiasm in official and third-party systems contributes to excessive trading. Figure 1 illustrates the time series of the margin trading balance in the Chinese stock market from 2010 to 2022. The data reveals a significant increase in margin trading activity following the program's initiation in 2010, with the scale of margin trading exceeding 2 trillion Chinese Yuan in 2015.

2.2 | The 2015 Chinese stock market crisis and regulation tightening

During the crash in 2015, the Chinese stock market declined by more than 30% from June to August.[10] Leveraged trading was criticised as a critical driver behind this decline. In response, financial market regulators began tightening margin trading regulations.[11] On 13 November 2015, the China Securities Regulatory Commission (CSRC) increased the initial margin ratio from 50% to 100%, raising the collateral investors needed to post for trading. Additionally, various concentration-ratio-based measures were adopted. The new regulation mandated that a security company's margin trading business should not exceed four times its net capital. Security companies also had to strictly limit the maximum percentage a single security could account for in an investor's stock portfolio. The regulatory body imposed strict regulation on third-party trading systems, like the Homes system, effectively reducing speculation in the margin trading market. After implementing these new rules, the margin trading balance quickly decreased from over 2 trillion to 0.95 trillion Yuan, as depicted in Figure 1.

[10]The most representative index of the Chinese stock market, the CSI 300 index, dropped from 5335 points on 12 June 2015, to 3342 on 28 August 2015.

[11]Lin and Wang (2018) examine the effects of tightened trading rules on market quality in 2015. They find that the efficiency and price discovery within the Chinese stock index futures market did not deteriorate following these regulatory adjustments.

3 | DATA AND METHODOLOGY

In this section, we first describe the sample selection process. We explain the methodology employed to construct stock-level and market-level margin trading interests.

3.1 | Data and sample

We obtain relevant data from the China Stock Market and Accounting Research Database (CSMAR), a reliable and comprehensive financial data provider in China and a Wharton Research Data Services (WRDS) data vendor. A key advantage of this database is that it allows us to observe daily margin trading balances, enabling us to conduct stock-level analysis. Our sample covers the period from May 2010 to December 2022.[12] Our primary variable of interest is the daily margin trading balance, which measures the total borrowed amount by margin buyers up to the day of data collection. This stock-level margin trading balance forms the basis for our variable of interest in predictive regressions.

The sample selection involves three significant steps. First, we omit exchange-traded funds (ETFs) from our analysis since we focus on stocks. This step leaves us with 3260 firms on the margin trading list. Second, we exclude 134 firms that were delisted from the margin trading list and re-added later. We employ this filter for two reasons. On the one hand, these removals and re-addition events typically involve special treatment or the firms becoming unrepresentative of the Chinese stock market.[13] On the other hand, there is typically a gap of over 10 months between the removal and re-addition events, which creates missing values for our primary variable of interest. Third, we mandate that each firm has a minimum of 90 observations during our sample period to conduct reasonable predictive regressions. We ultimately include 2450 firms in our study.

3.2 | Stock-level margin trading interest

We employ a two-step procedure to generate stock-level margin trading interest (*SMTI*), which measures investor optimism about each stock. First, we collect the natural log of each stock's daily margin trading balance, representing the amount of money borrowed by investors from security companies normalised with each firm's circulated capitalisation. The margin trading balance of an individual firm will be naturally proportional to its capitalisation.

Second, we detrend the log margin trading ratio of each stock. Following Rapach et al. (2016), we use the time trend to detrend this log ratio, as there is a natural increasing trend with the improvement of the margin trading facility. For instance, the establishment of the China Securities Finance Corporation (CSFC) made accessing capital for margin trading easier. The regression used for the detrending process is specified as follows:

$$log\left(\frac{margin\_trading\ \ balance_{it}}{circulated\ \ cap_{it}}\right) = a + bt + u_t, \tag{1}$$

[12]The pioneering program officially commenced on 31 March 2010. During the first month of this policy (April 2010), 90 stocks were listed for margin trading and short-selling. Many of these firms had a margin trading balance of 0, presumably due to system preparation and investors' adaptation to the new policy. We exclude the first month's observations from our predictive regressions.

[13]Special treatment refers to firms experiencing two consecutive years of negative profit. The exchange dynamically adjusts the list of firms to ensure that those on the list are representative, with high capitalisation and good liquidity.

where $margin\_trading\ balance_{it}$ is the margin trading balance of stock i on day t, $circulated\ cap_{it}$ is the circulated capitalisation of firm i on day t, and t is the time trend. We collect the residual u_t from the above detrending regression. $SMTI$ is the standardised u_t with a mean of zero and a variance of one. In summary, $SMTI$ captures fluctuations in the beliefs of margin buyers and measures the actual change of beliefs, considering the evolution of the margin trading facility and the accessibility of borrowing more funds.

3.3 | Market-level margin trading interest

We employ two methods to measure the market-level margin trading interest ($MMTI$). In the first method, we calculate the aggregate margin trading measure, $MMTI_{all}$, based on all the stocks on the leverage trading list. We first collect the stock-level ratio by normalising the margin trading balance of each stock with the firm's circulated capitalisation. We then calculate the weighted market-level margin trading interest using an equal-weighted or value-weighted scheme. We take the log of this weighted ratio and detrend it. The normalised residual represents the final market-level margin trading interest with a mean of zero and a variance of one.

The first method's drawback is that several large-scale addition and deletion events during our sample period might result in a sudden decrease or increase in margin trading interest, reducing the measure's accuracy. To address this issue, in the second method, we only use the 70 stocks that were consecutively on the margin trading list from 2010 to 2022 to form the aggregate margin trading interest $MMTI_{70}$. These 70 firms comprise the largest and most liquid entities in the Chinese stock market and can represent the overall market condition. We follow similar steps as in the first method to obtain the equal- and value-weighted margin trading interest.

4 | MARGIN TRADING MOTIVES

In this section, we explore the existence of both information- and sentiment-driven margin trading in the Chinese stock market. We begin by discussing various potential scenarios concerning the predictive power of margin trading interest. Next, we run market-level predictive regressions to determine whether margin buyers are informative at the aggregate level. Finally, we conduct stock-level predictive regressions to account for the heterogeneity of margin trading.

4.1 | Information-driven or sentiment-driven

In their study, Rapach et al. (2016) report a negative correlation between aggregate short-sell interest and market return, indicating that short sellers, as a whole, possess information in the US stock market. Similarly, Kelley and Tetlock (2017) demonstrate that retail short-sellers can predict negative stock returns because they have information about the retail investor community and the fundamentals of small firms. As a counterpart to short-selling, it is intriguing to study whether margin buyers are informed.

Margin trading reflects investor beliefs about future stock returns. Theoretically, there are three possible associations between margin trading interest and future stock returns. First, if these beliefs are primarily based on information, margin trading is considered informed trading, and margin trading interest will positively correlate with future stock returns. Second, if these beliefs are mainly driven by the sentiment that does not contain information, margin trading interest will likely have a negative relationship with future stock returns.[14] During high

[14]Huang et al. (2015) demonstrate that the market sentiment index negatively predicts future stock returns.

sentiment periods, investors typically increase their margin trading positions as prices rise, while during low sentiment periods, investors reduce their margin trading positions as prices decline. Such trading is influenced by sentiment, which will be corrected shortly. Finally, if both information- and sentiment-driven margin trading coexist, and neither dominates the market, the relationship between the margin trading balance and future market returns will be insignificant. We test these three possibilities separately at the market and individual stock levels in the following subsections.

4.2 | Market-level analysis

We follow Rapach et al. (2016) to study the aggregate margin trading interest and its predictive power for index excess returns. Specifically, we use market-level margin trading interests $MMTI_{all}$ and $MMTI_{70}$ to predict the excess return of the CSI 300 index separately. The model is specified as follows:

$$Indexexcess_{t:t+h} = \alpha + \beta\, MMTI_t + \varepsilon_{t:t+h}, \tag{2}$$

where $Indexexcess_{t:t+h}$ represents the CSI 300 index return minus the corresponding one-year deposit rate from day t to $t + h$, and $MMTI_t$ is the market-level margin trading interest at time t, which can either be $MMTI_{all}$ or $MMTI_{70}$. We employ the Newey–West method to adjust the t-statistics. Our primary focus is on the future weekly return ($h = 5$). Additionally, we run predictive regressions for 1–4 days as a robustness check. We concentrate on the predictive power of margin trading interest regarding short-term future returns for two reasons. First, many speculators exist in the Chinese stock market, primarily focusing on short-term returns. Second, as another focus of this paper, the 2015 regulation tightening aimed to reduce speculation in the Chinese stock market. Analysing short-term returns helps us evaluate the effectiveness of these regulation measures.

Table 2 reports the results of market-level predictive regressions. We do not find a significant relationship between any definition of market-level margin trading interest and future index excess returns of different horizons. We present the β coefficients and corresponding t-statistics of the market-level predictive regressions. The upper panel reports the results of using $MMTI_{all}$ to predict the index excess return in the upcoming 1–5 days. Most of the β coefficients are positive but not statistically or economically significant. For the equal-weighted (value-weighted) $MMTI_{all}$, the highest t statistic is only 0.97 (0.81) when predicting the index excess return in the upcoming 2 days. In terms of economic magnitude, in most cases, a one-standard-deviation change in $MMTI_{all}$ corresponds to less than three basis points change in return. The lower panel shows the results using $MMTI_{70}$ to predict the index excess return. The results are similar to those in the upper panel.

We do not find a significant link between margin trading and market returns. This relationship might vary with market conditions.[15] We run several sub-period analyses to test whether the predictability changes with market conditions. In particular, we consider economic uncertainty and investor sentiment. We use the economic policy uncertainty (EPU) index constructed by Baker et al. (2013) to measure economic uncertainty. We follow Han and Shi (2022) in employing the CICSI Composite Sentiment Index (CICSI) and ISI Composite Sentiment Index (ISI) as proxies for investor sentiment. We divide our sample period into two sub-periods based on the median values of EPU, CICSI, or ISI and run the market-level predictive regressions for high and low sub-periods separately.

[15]We thank the anonymous referee for this suggestion.

TABLE 2 Market-level predictive regressions.

		Equal-weighted		Value-weighted	
Predictors	h	β	t-statistics	β	t-statistics
$MMTI_{ALL}$	5	2.15	0.86	1.83	0.69
	4	2.22	0.88	1.91	0.72
	3	2.41	0.93	2.07	0.77
	2	2.65	0.97	2.28	0.81
	1	2.55	0.81	2.19	0.68
$MMTI_{70}$	5	1.09	0.39	1.15	0.40
	4	1.15	0.41	1.23	0.43
	3	1.36	0.48	1.41	0.49
	2	1.65	0.55	1.66	0.54
	1	1.53	0.44	1.58	0.45

Note: This table reports the β coefficients from the market-level predictive regressions from May 2010 to December 2022. The regression is specified as follows:

$$Indexexcess_{t:t+h} = \alpha + \beta MMTI_t + \varepsilon_{t:t+h},$$

where $Indexexcess_{t:t+h}$ is the CSI 300 index return minus the corresponding one-year deposit rate from day t to $t+h$, and $MMTI_t$ is the market-level margin trading interest at time t, which can be $MMTI_{all}$ or $MMTI_{70}$. We use both equal- and value-weighted methods in calculating $MMTI_{all}$ or $MMTI_{70}$. $MMTI_{all}$ includes all eligible firms on the margin trading list. In contrast, $MMTI_{70}$ includes stocks that were consistently on the margin trading list throughout our sample period, representing the overall market condition. We run the predictive regressions for the upcoming 1–5 days separately. We report the β coefficient in basis points (bps), which measures the impact on return induced by a one-standard-deviation increase in $MMTI_t$. Newey–West adjusted t-statistics are reported in parentheses.

Table 3 reports the results of market-level predictive regressions across different subperiods. In columns (1) and (2), the coefficients are positive and significant at the 10% level when economic uncertainty is high, while insignificant during low EPU periods. The results in columns (3) to (6) show that the margin trading balance can positively predict market returns during high sentiment periods. Our findings indicate that market-level margin interest can predict stock market returns when economic uncertainty or investor sentiment is high. Collectively, these results indicate that there are paradigm shifts in the predictive power of aggregate margin trading interest. Our findings are consistent with Chu et al. (2022), who show that non-fundamental predictors generally perform better in times of high sentiment.

The non-significant results in Table 2 at the market level could be attributed to two possible explanations. First, margin buyers may differ from short-sellers in their ability to predict future market performance. Second, both information-driven and sentiment-driven margin trading might coexist, with neither dominating the market, leading to their forecasting powers offsetting one another. We conduct a stock-level analysis in the following subsection to differentiate between these explanations.

4.3 | Stock-level analysis

To account for the potential heterogeneity of margin trading, we use individual stock-level margin trading interest ($SMTI$) to perform predictive regressions for each stock in this subsection. The specification for individual-level stock predictive regressions is as follows:

$$r_{i[t:t+h]} = \alpha + \beta SMTI_{it} + \varepsilon_{i[t:t+h]}, \tag{3}$$

TABLE 3 Sub-period analysis of market-level predictive regressions.

			(1)	(2)	(3)	(4)	(5)	(6)
Predictors	**Weights**	h	**High EPU**	**Low EPU**	**High CICSI**	**Low CICSI**	**High ISI**	**Low ISI**
$MMTI_{ALL}$	Equal-weighted	5	6.67*	1.18	8.16***	−1.79	5.97*	−2.86
		4	6.81*	1.27	7.95**	−1.56	6.22*	−3.12
		3	7.11*	1.49	8.05**	−1.3	6.79**	−3.56
		2	7.25*	1.79	8.08**	−0.92	7.27**	−3.78
		1	7.46	1.64	7.95*	−0.94	7.17	−3.87
	Value-weighted	5	6.96*	1.01	8.28**	−2.47	5.74*	−3.46
		4	7.09*	1.11	8.04**	−2.2	5.98*	−3.69
		3	7.50*	1.29	8.06**	−1.93	6.50*	−4.11
		2	7.58	1.57	8.03*	−1.56	6.89*	−4.23
		1	7.66	1.47	7.93*	−1.6	6.77	−4.29

Note: This table reports the β coefficients of sub-period market-level predictive regressions based on different proxies. We divide our sample into two periods (High or Low) based on the economic policy uncertainty (EPU) index, CICSI Composite Sentiment Index (CICSI), and ISI Composite Sentiment Index (ISI). We run the following regression for high and low sub-periods separately:

$$Indexexcess_{t:t+h} = \alpha + \beta MMTI_{all,t} + \varepsilon_{t:t+h},$$

where $Indexexcess_{t:t+h}$ is the CSI 300 index return minus the corresponding one-year deposit rate from day t to $t+h$, and $MMTI_{all,t}$ is the market-level margin trading interest at time t. We use equal- and value-weighted methods to calculate $MMTI_{all}$. $MMTI_{all}$ includes all eligible firms on the margin trading list. We report the results for future one-day ($h = 1$) to five-day ($h = 5$) returns, respectively. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

where $r_{i[t:t+h]} = \left(r_{i[t+1]} + \cdots + r_{i[t+h]}\right)/h$, and $r_{i[t+h]}$ is the daily adjusted return of firm i at day $t+h$, calculated by the daily stock return minus the corresponding day's CSI 300 index return. $SMTI_{it}$ is stock i's margin trading interest on day t. Our analysis spans from May 2010 to December 2022, excluding the specific crisis period from June 2015 to August 2015, and roughly divides the time into equal 12-month time intervals: 2011 (May 2010–May 2011), 2012 (June 2011–May 2012), 2013 (June 2012–May 2013), 2014 (June 2013–May 2014), 2015 (June 2014–May 2015), 2016 (September 2015–August 2016), 2017 (September 2016–August 2017), 2018 (September 2017–August 2018), 2019 (September 2018–August 2019), 2020 (September 2019–August 2020), 2021 (September 2020–August 2021), and 2022 (September 2021–December 2022). We focus on the forecast horizon of 1 week ($h = 5$) and run the regressions each year.

Table 4 presents the results of stock-level regressions. Panel A displays the number of firms with a significantly positive or negative β each year based on Equation (3). The results suggest the existence of both information- and sentiment-driven margin trading. Moreover, information-driven trading appears to be more prevalent than sentiment-driven trading. For instance, in 2017, the number of firms with significant positive and negative coefficients was 138 and 65, respectively, at the 10% level. However, many firms exhibit insignificant coefficients, suggesting that the relationship between margin trading and their future returns remains inconclusive.

To further compare the magnitudes of coefficients between information-driven and sentiment-driven firms, Panel B of Table 4 reports the mean β for both samples. In most sample periods except 2015, the average coefficients for the information-driven category are larger than those for the sentiment-driven category, indicating slightly higher profitability for information-driven margin trading.

TABLE 4 Firm-level predictive regressions.

Significance level	Category	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022
Panel A: Number of stocks													
	Total eligible firms	82	209	210	620	797	795	866	880	897	1598	1890	2332
10%	*Positive β*	9	57	29	61	65	86	138	270	169	233	374	549
	Negative β	8	12	13	81	88	40	65	23	33	128	219	69
5%	*Positive β*	6	42	18	43	45	65	102	203	119	157	266	394
	Negative β	4	8	11	57	55	18	43	18	17	91	144	41
Panel B: Mean β													
10%	*Positive β*	0.18	0.34	0.66	0.67	0.57	1.03	0.91	1.13	0.88	0.87	0.98	0.66
	Negative β	−0.10	−0.17	−0.36	−0.45	−0.63	−0.77	−0.44	−0.61	−0.49	−0.42	−0.69	−0.43
5%	*Positive β*	0.23	0.38	0.81	0.70	0.60	1.11	1.02	1.23	0.99	0.96	1.05	0.74
	Negative β	−0.11	−0.16	−0.40	−0.47	−0.70	−0.89	−0.41	−0.66	−0.45	−0.42	−0.72	−0.49

Note: This table presents the results of the stock-level predictive regressions for each period. We roughly divide the sample into equal lengths of 12-month periods, excluding the specific crisis period from June 2015 to August 2015. The periods are as follows: 2011 (May 2010–May 2011), 2012 (June 2011–May 2012), 2013 (June 2012–May 2013), 2014 (June 2013–May 2014), 2015 (June 2014–May 2015), 2016 (September 2015–August 2016), 2017 (September 2016–August 2017), 2018 (September 2017–August 2018), 2019 (September 2018–August 2019), 2020 (September 2019–August 2020), 2021 (September 2020–August 2021), and 2022 (September 2021–December 2022). We regress the future weekly return on stock-level margin trading interest for each stock as follows:

$$r_{i[t:t+h]} = \alpha + \beta SMTI_{it} + \varepsilon_{i[t:t+h]}, h = 5,$$

where $r_{i[t:t+h]} = \left(r_{i[t+1]} + \cdots + r_{i[t+h]}\right) / h$, and $r_{i[t+h]}$ is the daily adjusted return of firm i at day $t + h$, calculated by the daily stock return minus the corresponding day's CSI 300 index return. $SMTI_{it}$ is the margin trading interest at day t for stock i. Panel A reports the number of stocks with a significantly positive or negative β in each period. Panel B reports the mean β of the significantly positive or negative stocks. We use 10% and 5% as significance thresholds, respectively. All the results are based on Newey–West robust t-statistics.

5 | REGULATION TIGHTENING AND MARGIN TRADING

This section evaluates the effectiveness of regulatory policies implemented in response to the 2015 stock crisis. We present preliminary evidence illustrating a decrease in sentiment-driven trading and an increase in information-driven trading following the crisis. We then employ a logit model to substantiate these results quantitatively. Furthermore, we investigate the firm attributes that impact the likelihood of sentiment-driven and information-driven trading.

5.1 | Preliminary analysis

5.1.1 | Analysis method

This analysis aims to determine whether significant changes occurred in the margin trading market following the 2015 stock crisis. We divide the time into 12-month intervals, as outlined in subsection 4.3. First, we conduct firm-level predictive regressions for each period and categorise firms as information-driven or sentiment-driven based on the stock-level predictive regressions. The information-driven (sentiment-driven) category comprises firms with a significantly positive (negative) relationship between their *SMTI* and future returns.

Next, we compute the proportion of firms exhibiting significantly positive or negative relationships between *SMTI* and future returns in each period.[16] We determine the overall positive and negative rates in each period as follows:

$$Positive\ \ rate_t = \frac{the\ \ number\ \ of\ \ firms\ \ in\ \ the\ \ information-driven\ \ category_t}{total\ \ number\ \ of\ \ eligible\ \ firms_t} \times 100, \tag{4}$$

$$Negative\ \ rate_t = \frac{the\ \ number\ \ of\ \ firms\ \ in\ \ the\ \ sentiment-driven\ \ category_t}{total\ \ number\ \ of\ \ eligible\ \ firms_t} \times 100. \tag{5}$$

5.1.2 | Preliminary results

Table 5 presents the annual percentage of information-driven and sentiment-driven stocks. The table shows a significant reduction in the proportion of sentiment-driven trading and an increase in information-driven trading following the 2015 stock crisis. We conjecture that these results are attributed to stringent regulatory policies enacted after the crisis (see subsection 2.2). These policies serve to curb speculation and promote investors' conservative investment decisions.

The upper panel of Table 5 reports the percentage of sentiment-driven margin trading for each period. We observe significant reductions in sentiment-driven trading from pre-crisis to post-crisis periods. When forecasting the weekly return and using 10% as the significance threshold, there is a 54% relative decrease in the sentiment-driven category from 2015 (11.04%) to 2016 (5.03%). These decreases are more pronounced for short-term returns. The ratios of sentiment-driven stocks declined by 61%, 64%, 71%, and 74% for four-, three-, two-, and

[16] We mandate that each firm has a minimum of 90 observations during each period. Most firms exceed this threshold during each period. We introduce this requirement to address dynamic adjustments since the exchange added some firms to the list towards the end of each sample period.

TABLE 5 The percentage of information-driven and sentiment-driven stocks.

Rate	Significance level	*h*	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022
Negative	10%	5	9.76	5.74	6.19	13.06	11.04	5.03	7.51	2.61	3.68	8.01	11.59	2.96
		4	9.76	5.74	6.19	13.06	10.66	4.15	6.81	3.07	3.79	7.38	11.32	3.00
		3	7.32	5.26	6.67	12.42	10.79	3.90	7.39	2.95	3.12	6.51	10.90	2.92
		2	3.66	3.35	5.71	11.29	10.04	2.89	6.47	2.61	3.46	6.95	10.16	2.62
		1	1.22	1.44	2.86	8.55	9.16	2.39	5.31	1.70	2.34	5.69	7.41	1.72
	5%	5	4.88	3.83	5.24	9.19	6.90	2.26	4.97	2.05	1.90	5.69	7.62	1.76
		4	3.66	2.87	3.81	8.55	7.03	1.89	4.62	1.93	1.56	5.01	7.57	1.67
		3	3.66	2.39	3.33	7.74	5.77	1.26	4.73	2.05	1.45	4.69	7.41	1.59
		2	1.22	0.96	3.33	6.29	6.02	1.26	4.27	1.25	1.34	4.07	6.46	1.20
		1	1.22	0.00	0.95	4.84	6.15	1.38	2.77	1.02	1.23	3.00	4.18	0.64
Positive	10%	5	10.98	27.27	13.81	9.84	8.16	10.82	15.94	30.68	18.84	14.58	19.79	23.54
		4	9.76	25.36	14.29	8.87	8.53	10.44	15.13	28.64	16.95	13.77	18.73	22.47
		3	10.98	23.92	12.38	8.39	8.16	10.82	13.51	26.25	15.27	13.83	17.41	20.54
		2	8.54	21.53	9.52	7.26	7.78	10.06	11.89	24.20	13.38	11.95	15.50	17.92
		1	6.10	15.79	5.71	3.23	5.77	7.80	7.74	17.27	8.03	7.95	10.63	10.46
	5%	5	7.32	20.10	8.57	6.94	5.65	8.18	11.78	23.07	13.27	9.82	14.07	16.90
		4	8.54	19.62	8.10	6.13	5.27	7.92	11.09	21.02	11.82	9.57	12.91	15.22
		3	7.32	16.75	6.67	4.84	5.02	7.42	9.12	18.30	10.59	8.89	12.22	13.55
		2	6.10	13.40	5.24	3.71	4.64	5.91	7.27	15.80	8.58	7.20	10.53	10.98
		1	2.44	10.05	2.38	0.48	2.38	5.66	3.58	9.32	4.35	4.26	6.72	5.96
Total number of eligible firms			82	209	210	620	797	795	866	880	897	1598	1890	2332

Note: This table presents the percentage of information-driven and sentiment-driven stocks for each sample period. Stocks with a significantly positive β are classified as information-driven, while those with a significantly negative β are considered sentiment-driven. We divide the time into equal 12-month periods, excluding the specific crisis period from June 2015 to August 2015: 2011 (May 2010–May 2011), 2012 (June 2011–May 2012), 2013 (June 2012–May 2013), 2014 (June 2013–May 2014), 2015 (June 2014–May 2015), 2016 (September 2015–August 2016), 2017 (September 2016–August 2017), 2018 (September 2017–August 2018), 2019 (September 2018–August 2019), 2020 (September 2019–August 2020), 2021 (September 2020–August 2021), and 2022 (September 2021–December 2022). We report results for future one-day ($h = 1$) to five-day ($h = 5$) returns using 10% and 5% as significance thresholds, respectively. All results are based on Newey–West robust t-statistics:

$$Positive\ \ rate_t = \frac{the\ \ number\ \ of\ \ firms\ \ in\ \ the\ \ information - driven\ \ category_t}{total\ \ number\ \ of\ \ eligible\ \ firms_t} \times 100,$$

$$Negative\ \ rate_t = \frac{the\ number\ of\ firms\ in\ the\ sentiment - driven\ category_t}{total\ number\ of\ eligible\ firms_t} \times 100$$

one-day returns from 2015 to 2016, respectively. When adjusting the significance criteria to 5%, the decline in sentiment-driven margin trading is even more substantial.

The lower panel of Table 5 presents the percentage of information-driven margin trading for each period. We observe a moderate increase in information-driven trading after the crisis. When forecasting the weekly return and using 10% as the threshold for significance, the proportion of firms in the information-driven category was 8.16% in 2015 and 10.82% in 2016. The percentage of information-driven trading for four- to one-day returns in 2016 is 10.44%, 10.82%, 10.06%, and 7.80%, respectively, showing an increase relative to their corresponding figures of 8.53%, 8.16%, 7.78%, and 5.77% in 2015.

5.2 | Panel logit model analysis

5.2.1 | Model and variables

The results from the preliminary analysis do not account for other variables or address the statistical significance of the findings. To supplement them, we employ logit models in this subsection. We implement a two-step procedure for this test. In the first stage, we conduct predictive regressions by regressing future weekly returns on stock-level margin trading interest. If the coefficient is significantly positive (negative), we assign that firm a $Categorydummy_{it}$ value of 1 (−1) for the corresponding period. Non-significant firms are assigned a value of 0. We choose a significance level of 10% to ensure an adequate sample for running the second-stage regression.

In the second stage, we collect the values (1, 0, −1) obtained from the first-stage regressions as the dependent variable for the panel logit model. We use two logit models to quantify the change in probability for information-driven trading and sentiment-driven trading following the 2015 stock crisis. The non-significant firms serve as the benchmark category in both models. The specification for the second stage is as follows:

$$Categorydummy_{it} = \alpha + \beta_1 \ \ Postcrisisdummy_t + \Gamma_i' X_{it}' + \varepsilon_{it}, \tag{6}$$

where $Categorydummy_{it}$ is the dummy variable obtained from the first stage stock-level predictive regressions, *Postcrisisdummy* is a dummy variable that takes a value of one for the period after the 2015 stock crisis and zero otherwise, and X_{it} denotes the control variables. We centre our sample on years before and after the 2015 crisis in all tabulated regressions. Moreover, we incorporate firm fixed effects into the model to mitigate the influence of omitted variables.

The control variables can be categorised into five groups. The first group comprises transaction-related variables. We use the price-to-book and price-to-sales ratios to measure firms' future growth opportunities (Kogan & Papanikolaou, 2014). The price-to-book ratio (*PB ratio*) is defined as the stock's market capitalisation normalised by its latest net asset value, while the price-to-sales ratio (*PS ratio*) is determined by dividing the market capitalisation by the previous year's revenue. We also control for turnover ratio (*Turnover ratio*) (Datar et al., 1998), which equals the trading amount divided by market capitalisation. We first compute the daily values of the three ratios mentioned above and then use their averages within each period in the regression.

The second group includes idiosyncratic volatility and Jensen's alpha, which measure a firm's risk and return (Campbell & Taksler, 2003). We use a CAPM model and regress a stock's daily excess return on the value-weighted average of the daily excess returns of Chinese A-share stocks.[17] The one-year deposit rate serves as the proxy of the risk-free rate. We utilise the inter-

[17]The Chinese A-share stocks include the A-share stocks listed in both Shanghai and Shenzhen Stock Exchanges.

cept of the CAPM model as Jensen's alpha (*Jensen's alpha*) and the residuals' standard deviation as idiosyncratic volatility (*Idiosyncratic volatility*).

The third group consists of fundamental-related variables. They include return on assets, debt ratio, and market capitalisation. Return on assets (ROA) is measured by revenue divided by total assets and serves as a control for operating performance (Core et al., 2006). The debt ratio (*Debt ratio*) assesses a firm's liability situation (Collin-Dufresne & Goldstein, 2001; Eom et al., 2004), computed as total liabilities divided by total assets. Firm size (*Size*) is calculated as the natural logarithm of circulated capitalisation and measures a firm's information environment. The fourth group includes variables that measure the informativeness of stock prices. Chen et al. (2006) use price non-synchronicity to measure the amount of private information in stock prices. To better understand information-driven trading, we follow Chen et al. (2006) and use price non-synchronicity to measure the degree of private information in the stock price. We regress daily stock return on market and industry return and obtain the regression R^2. Price non-synchronicity is calculated as $1 - R^2$. A larger value of price non-synchronicity means the stock price incorporates more private information. Additionally, we follow Barardehi et al. (2021) and employ a modified Amihud illiquidity measure to assess the information content of the stock price. A larger value of modified Amihud illiquidity indicates a higher level of asymmetric information.

The final group comprises variables associated with corporate transparency. Firth et al. (2015) show that corporate transparency could explain the sensitivity of stock price to sentiment in the Chinese stock market. To better understand sentiment-driven trading, we follow Firth et al. (2015) and employ several variables related to earnings management and auditor quality to measure corporate transparency. We calculate the absolute value of the residual from the modified Jones model (Dechow et al., 1995) to measure a firm's annual discretionary accruals, where a higher value indicates a greater likelihood of earnings manipulation. To supplement this measure, we also control for earnings smoothness (Bhattacharya et al., 2003). High earnings smoothness suggests that the firm has more flexibility to smooth earnings over multiple years. Finally, we include a foreign auditor dummy in the regression, as firms audited by foreign auditors generally exhibit better corporate transparency.

Table 6 presents the summary statistics of the independent variables used in our logit model. The sample comprises 6671 firm-year observations and includes firms with varying characteristics. For example, the average price-to-book and price-to-sale ratio are 3.67 and 5.86, respectively. The mean return on assets is 5%. Our sample is representative of the Chinese stock market.

5.2.2 | Empirical results

Table 7 presents the logit model results for the sentiment-driven category versus the non-significant category, as specified in Equation (6). We begin with the univariate regression in model (1) and progressively introduce more control variables. Our variable of interest, *Postcrisisdummy*, is significantly negative at the 1% level from model (1) to model (7), indicating a significant decrease in the likelihood of a firm being classified as sentiment-driven after the 2015 stock crisis. These findings corroborate the results discussed in subsection 5.1. Moreover, consistent with Firth et al. (2015), a firm is more likely to be sentiment-driven if it has low corporate transparency. Specifically, a firm is more likely to be sentiment-driven if it has high earnings smoothness, as indicated by the positive and significant coefficient of *Earnings Smoothness* in the full model (7). The coefficient of *Foreign Auditors* is negative and significant at the 10% level, suggesting that firms audited by foreign auditors are less likely to be sentiment-driven. Firms with a high level of information asymmetry, as measured by modified Amihud illiquidity, are also less likely to be sentiment-driven.

TABLE 6 Summary statistics of variables used in logit model.

Variables	N	Mean	Std dev	Minimum	Maximum
PB ratio	6671	3.67	8.71	0.32	381.52
PS ratio	6671	5.86	17.39	0.03	614.68
Turnover ratio	6671	0.02	0.02	0.00	0.15
ROA	6671	0.05	0.07	−0.74	0.68
Debt ratio	6671	0.49	0.21	0.01	1.41
Size	6671	16.43	1.01	13.64	21.21
Idiosyncratic volatility	6671	0.02	0.01	0.01	0.13
Jensen's alpha	6671	0.00	0.00	−0.01	0.01
Price nonsynchronicity	6671	0.51	0.19	0.00	0.99
Amihud illiquidity modified	6671	1.63	1.50	0.02	13.71
Accrued earnings management	6671	0.06	0.08	0.00	1.89
Foreign auditors	6671	0.08	0.27	0.00	1.00
Earnings smoothness	4844	5.26	12.10	0.05	306.17

Note: This table presents the summary statistics of variables used in the logit regressions. *PB ratio* is the market capitalisation divided by the latest net asset value. *PS ratio* is determined by dividing the market capitalisation by the previous year's revenue. *Turnover ratio* represents the trading volume in dollars divided by market capitalisation. *ROA* is measured by revenue divided by total assets, and *Debt ratio* is total liabilities divided by total assets. *Size* refers to the natural logarithm of circulated market capitalisation. We use the CAPM model to calculate each stock's *Idiosyncratic volatility* and *Jensen's alpha*. *Price nonsynchronicity* is $1 - R^2$, where R^2 is from the regression of daily stock return against market and industry return. *Amihud illiquidity modified* corrects the mismatch between stock return and trading volume in calculating the original Amihud illiquidity measure (Barardehi et al., 2021). *Accrued earnings management* is the absolute value of the residual from the modified Jones model (Dechow et al., 1995). *Foreign auditors* is equal to one when the firm uses a foreign auditor and zero otherwise. *Earnings smoothness* is calculated similarly to Bhattacharya et al. (2003). Since *Earnings smoothness* needs a four-year window and more data, its sample size is smaller than others.

Other control variables also exhibit expected signs. The coefficient for return on assets is positively significant at the 5% level, implying that firms with high ROA are more likely to be associated with sentiment-driven margin trading. We conjecture that firms with solid past performance (high ROA) are more likely to attract media attention, leading margin buyers to over-interpret these firms' past performance and be swayed by sentiment to invest in them. Additionally, the probability of sentiment-driven trading is positively related to idiosyncratic volatility. In model (7), the coefficient of idiosyncratic volatility is 41.79 and is significant at the 5% level. This association is likely linked to retail investors' herd behaviour in the margin trading market. Our findings align with the notion that stocks with high idiosyncratic volatility face arbitrage constraints and are more likely to be influenced by herd behaviour (Stambaugh et al., 2015; Vo & Phan, 2019).

Table 8 reports the logit model results for the information-driven category versus the non-significant category, as specified in Equation (6). *Postcrisisdummy* is positively significant from model (1) to model (7). These results imply a notable increase in the likelihood of information-driven trading following the 2015 Chinese stock crisis. In line with Chen et al. (2006) and Firth et al. (2015), firms with more private information and high corporate transparency are more likely to be information-driven. The coefficients of both information proxies, price nonsynchronicity and modified Amihud illiquidity, are positive and significant at the 1% level. Moreover, the negative coefficient of discretionary accrual indicates that stocks with low corporate transparency are less likely to be information-driven.

Other control variables also deliver expected results. The turnover ratio has a significantly negative relationship with the probability of information-driven trading, with a coefficient of −19.40 significant at the 5% level. High turnover ratios indicate considerable investor

TABLE 7 Sentiment-driven category versus non-significant category.

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Postcrisisdummy	−1.183***	−0.967***	−1.058***	−0.985***	−0.913***	−0.905***	−0.825***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
PB ratio		0.112***	0.057	0.055	0.052	0.057	0.055
		(0.006)	(0.206)	(0.231)	(0.265)	(0.229)	(0.310)
PS ratio		−0.005	−0.005	−0.005	−0.005	−0.006	−0.005
		(0.547)	(0.538)	(0.523)	(0.559)	(0.501)	(0.528)
Turnover ratio		19.865***	21.009***	11.160	1.514	1.046	−4.253
		(0.000)	(0.000)	(0.108)	(0.846)	(0.894)	(0.633)
Debt ratio			0.807	0.726	0.824	0.840	1.841
			(0.422)	(0.470)	(0.416)	(0.413)	(0.145)
ROA			3.309*	3.930**	4.177**	4.456**	4.448**
			(0.075)	(0.036)	(0.027)	(0.021)	(0.040)
Size			0.283	0.217	−0.105	−0.110	0.048
			(0.121)	(0.244)	(0.627)	(0.613)	(0.863)
Idiosyncratic volatility				27.353*	34.762**	35.902**	41.788**
				(0.096)	(0.041)	(0.036)	(0.036)
Jensen's alpha				60.93	66.615	77.283	53.909
				(0.217)	(0.177)	(0.122)	(0.340)
Price nonsynchronicity					0.288	0.241	0.191
					(0.583)	(0.649)	(0.751)
Amihud illiquidity modified					−0.262***	−0.265***	−0.214**
					(0.003)	(0.003)	(0.031)
Accrued earnings management						−0.655	−0.266
						(0.503)	(0.792)
Foreign auditors						−2.045**	−1.571*
						(0.014)	(0.094)

(Continues)

TABLE 7 (Continued)

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Earnings smoothness							0.018*
							(0.074)
Adj. R^2	0.087	0.113	0.119	0.126	0.136	0.145	0.117
Observations	5614	5614	5614	5614	5614	5614	4124

Note: This table presents the results of the logit model, which includes both the sentiment-driven category and the non-significant category in the regression:

$$Categorydummy_{it} = \alpha + \beta_1 \ Postcrisisdummy_t + \Gamma_i' X_{it}' + \varepsilon_{it}.$$

$Categorydummy_{it}$ is assigned a value of −1 for stocks in the sentiment-driven category and 0 for stocks in the non-significant category. The non-significant category is set as the benchmark. The −1 value for the sentiment-driven category identifies the non-benchmark category, and its value of −1 is only symbolic. We determine the $Categorydummy_{it}$ every 12 months based on the stock-level predictive regressions that regress the future weekly stock return on *SMTI*. If the coefficient from the predictive regression is significantly negative at the 10% level, $Categorydummy_{it}$ is set to −1. If the coefficient is insignificant at the 10% level, $Categorydummy_{it}$ is assigned a value of 0. The sample centres on 5 years before and after the 2015 stock crisis. $Postcrisisdummy_t$ depends on the time relative to the 2015 stock crisis, equalling one for the period after the crisis (September 2015–August 2020) and zero otherwise. The model also accounts for firm fixed effects. The *p*-values based on Wald Chi-Square statistics are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

TABLE 8 Information-driven category versus non-significant category.

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Postcrisisdummy	0.649***	0.477***	0.496***	0.488***	0.456***	0.463***	0.470***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
PB ratio		−0.01	0.000	0.001	0.002	0.012	0.068*
		(0.647)	(0.991)	(0.976)	(0.920)	(0.602)	(0.056)
PS ratio		0.000	0.000	−0.001	−0.001	0.000	−0.015
		(0.949)	(0.981)	(0.750)	(0.822)	(0.967)	(0.258)
Turnover ratio		−33.271***	−33.180***	−36.421***	−21.016***	−20.714***	−19.403**
		(0.000)	(0.000)	(0.000)	(0.002)	(0.002)	(0.017)
Debt ratio			0.082	0.033	−0.012	−0.006	−0.533
			(0.893)	(0.958)	(0.985)	(0.993)	(0.493)
ROA			−1.097	−0.489	−0.163	−0.586	−1.405
			(0.247)	(0.610)	(0.866)	(0.556)	(0.297)
Size			−0.095	−0.122	0.179	0.169	0.165
			(0.443)	(0.331)	(0.229)	(0.259)	(0.401)
Idiosyncratic volatility				24.268**	11.187	9.574	3.068
				(0.023)	(0.309)	(0.385)	(0.822)
Jensen's alpha				−123.383***	−140.865***	−142.629***	−98.829***
				(0.000)	(0.000)	(0.000)	(0.008)
Price nonsynchronicity					0.929***	0.977***	1.014***
					(0.002)	(0.001)	(0.005)
Amihud illiquidity modified					0.190***	0.185***	0.206***
					(0.000)	(0.000)	(0.002)
Accrued earnings management						−2.231***	−3.264***
						(0.002)	(0.001)
Foreign auditors						−0.181	−0.062
						(0.651)	(0.917)

(Continues)

TABLE 8 (Continued)

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Earnings smoothness							−0.001
							(0.832)
Adj. R^2	0.024	0.051	0.052	0.059	0.068	0.073	0.066
Observations	6196	6196	6196	6196	6196	6196	4495

Note: This table presents the results of the logit model, which includes both the information-driven category and the non-significant category in the regression:

$$Categorydummy_{it} = \alpha + \beta_1 \ Postcrisisdummy_t + \Gamma_i' X_{it}' + \varepsilon_{it}.$$

$Categorydummy_{it}$ is assigned a value of 1 for stocks in the information-driven category and 0 for stocks in the non-significant category. The non-significant category is set as the benchmark. We determine the $Categorydummy_{it}$ every 12 months based on the stock-level predictive regressions that regress the future weekly stock return on *SMTI*. If the coefficient from the predictive regression is significantly positive at the 10% level, $Categorydummy_{it}$ is set to 1. If the coefficient is insignificant at the 10% level, $Categorydummy_{it}$ is assigned a value of 0. The sample centres on 5 years before and after the 2015 stock crisis. $Postcrisisdummy_t$ depends on the time relative to the 2015 stock crisis, equalling one for the period after the crisis (September 2015–August 2020) and zero otherwise. The model also accounts for firm fixed effects. The *p*-values based on Wald Chi-Square statistics are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

disagreement (Baker & Stein, 2004), making it challenging for margin buyers to assess firms' performance accurately. There is also a significantly negative association between Jensen's alpha and the probability of information-driven trading. In model (7), the coefficient for Jensen's alpha is −98.83 and significant at the 1% level.

Our empirical analysis reveals a significant drop in the likelihood of sentiment-driven trading and an increase in the likelihood of information-driven margin trading following the regulatory tightening in 2015. The tightening policies effectively regulated speculative behaviour in the Chinese financial market, leading to fundamental changes in margin trading.[18] Our findings underscore the positive impact of stringent regulatory responses to crises in a capital market characterised by retail investors.

6 | ROBUSTNESS CHECKS

In this section, we perform two robustness tests to demonstrate that the decrease in sentiment-driven margin trading and the increase in information-driven margin trading after the 2015 stock crisis are robust. First, we split our sample using a different definition of pre-crisis and post-crisis periods. Then, we employ an alternative multinomial logit model to test the robustness of our results.

6.1 | A different definition of pre-crisis and post-crisis

We employ a longer time frame for this test to define the pre-crisis and post-crisis periods. Table 9 presents the results of this exercise. In columns (1) and (2), we divide time into two equal 36-month periods: pre-crisis 1 (June 2012–May 2015) and post-crisis 1 (September 2015–August 2018). In columns (3) and (4), we divide time into two equal 60-month periods: pre-crisis 2 (June 2010–May 2015) and post-crisis 2 (September 2015–August 2020). We then re-run the analysis as in subsection 5.1 and examine the change in the percentage of information-driven and sentiment-driven stocks from pre-crisis to post-crisis.

Our conclusion remains valid when using a longer time frame to define the pre-crisis and post-crisis periods. The results confirm that the percentage of sentiment-driven firms decreased after the 2015 stock crisis. For instance, considering the 10% significance results in columns (1) and (2), the percentage of sentiment-driven firms changes from 11.77% ($h = 5$), 11.40% ($h = 4$), 11.15% ($h = 3$), 9.67% ($h = 2$), and 7.06% ($h = 1$) before the crisis to 5.05%, 4.84%, 5.49%, 5.49%, and 4.95% after the crisis, respectively. We also observe a moderate increase in the percentage of information-driven margin trading after the crisis. The results reported in columns (3) and (4) are consistent with this observation.

6.2 | A different logit model specification

In our analysis in subsection 5.2, we use two logit models to study whether the likelihood of information- or sentiment-driven margin trading significantly changed. We use the non-significant category as the benchmark in each model. To further verify our findings, we conduct a robustness check using a multinomial logit model that combines all data.

A key distinction in this robustness check is that the dependent variable can take values of −1 (sentiment-driven stocks), 1 (information-driven stocks), or 0 (non-significant category)

[18]We provide detailed information on the regulatory changes after the 2015 stock crisis in Section 2.

TABLE 9 The percentage of information-driven and sentiment-driven stocks: a robustness test.

			Pre-crisis 1	Post-crisis 1	Pre-crisis 2	Post-crisis 2
Rate	**Significance level**	*h*	**(1)**	**(2)**	**(3)**	**(4)**
Positive	10%	5	6.07	13.41	7.18	9.52
		4	5.95	13.08	6.56	9.58
		3	5.70	10.77	6.31	9.10
		2	5.08	10.00	5.69	7.94
		1	3.35	7.80	3.96	5.82
	5%	5	3.97	7.80	4.83	6.37
		4	3.59	7.36	4.46	6.43
		3	3.22	7.14	3.84	6.12
		2	2.73	5.16	3.84	4.85
		1	1.73	3.63	2.35	2.85
Negative	10%	5	11.77	5.05	12.38	10.61
		4	11.40	4.84	12.00	8.91
		3	11.15	5.49	11.63	9.58
		2	9.67	5.49	9.90	8.85
		1	7.06	4.95	7.05	6.37
	5%	5	7.68	3.08	8.29	6.61
		4	6.44	2.97	6.81	5.76
		3	5.70	2.86	6.06	5.46
		2	5.33	2.86	5.57	4.67
		1	3.84	2.86	4.21	3.27
Total number of eligible firms			807	910	808	1649

Note: This table presents the results for information-driven and sentiment-driven stocks using an alternative definition for pre- and post-crisis periods. In columns (1) and (2), we divide the time into two equal 36-month periods: pre-crisis 1 (June 2012–May 2015) and post-crisis 1 (September 2015–August 2018). In columns (3) and (4), we divide the time into two equal 60-month periods: pre-crisis 2 (June 2010–May 2015) and post-crisis 2 (September 2015–August 2020). The table reports the percentages of information-driven and sentiment-driven stocks in each sample period. Stocks with a significantly positive β are classified as information-driven, while those with a significantly negative β are considered sentiment-driven. We report results for future returns ranging from 1 day ($h = 1$) to 5 days ($h = 5$), using 10% and 5% as the significance thresholds. All results are based on Newey–West robust t-statistics:

$$Positive\ rate_t = \frac{the\ number\ of\ firms\ in\ the\ information-driven\ category_t}{total\ number\ of\ eligible\ firms_t} \times 100,$$

$$Negative\ rate_t = \frac{the\ number\ of\ firms\ in\ the\ sentiment-driven\ category_t}{total\ number\ of\ eligible\ firms_t} \times 100$$

within a single multinomial logit model. This model specification enables us to include more observations in the regression, thus enhancing the power of our test.

Table 10 presents the results of the multinomial logit model. The findings indicate that *Postcrisisdummy* is negative and significant for sentiment-driven trading. The coefficient of *Postcrisisdummy* is −0.63 and significant at the 1% level, indicating a substantial decrease in the likelihood of sentiment-driven margin trading following the 2015 stock crisis. For information-driven margin trading, the coefficient of *Postcrisisdummy* is 0.39, which is also significant at the 1% level, as shown in the second row of Table 10. Our findings remain robust under this alternative multinomial logit model specification.

TABLE 10 Multinomial logit model.

Variables	Category	Coefficient	*p* value
Postcrisisdummy	Sentiment	−0.634***	0.000
	Information	0.388***	0.000
PB ratio	Sentiment	−0.009	0.410
	Information	0.000	0.979
PS ratio	Sentiment	0.002	0.485
	Information	−0.001	0.849
Turnover ratio	Sentiment	15.483***	0.002
	Information	−7.877	0.129
Debt ratio	Sentiment	0.046	0.892
	Information	−0.122	0.638
ROA	Sentiment	−0.935	0.322
	Information	−0.62	0.438
Size	Sentiment	0.131	0.220
	Information	0.229***	(0.002)
Idiosyncratic volatility	Sentiment	19.468	0.124
	Information	8.217	0.392
Jensen's alpha	Sentiment	−10.838	0.783
	Information	−104.236***	0.001
Price nonsynchronicity	Sentiment	0.344	0.315
	Information	0.576**	0.020
Amihud illiquidity modified	Sentiment	−0.082	0.271
	Information	0.096**	0.015
Accrued earnings management	Sentiment	−0.283	0.691
	Information	−2.395***	0.001
Foreign auditors	Sentiment	−0.064	0.793
	Information	−0.215	0.210
Earnings smoothness	Sentiment	0.007**	0.043
	Information	0.002	0.500
Adj. R^2	0.053		
Observations	4844		

Note: This table presents the results of a multinomial logit model, which includes information-driven, sentiment-driven, and non-significant categories in the regression:

$$Categorydummy_{it} = \alpha + \beta_1 \ Postcrisisdummy_t + \Gamma_i' X_{it}' + \varepsilon_{it}.$$

$Categorydummy_{it}$ takes the values 1, 0, or −1. We set the non-significant category as the benchmark category. We obtain the $Categorydummy_{it}$ every 12 months based on stock-level predictive regressions of the future weekly stock return on *SMTI*. $Categorydummy_{it}$ equals one if the coefficient from the predictive regression is significantly positive at the 10% level, −1 if significantly negative at the 10% level, and 0 if not significant at the 10% level. The sample centres on 5 years before and after the 2015 stock crisis. $Postcrisisdummy_t$ is based on time relative to the 2015 stock crisis, equalling one for the time after the crisis (September 2015–August 2020) and zero otherwise. We also control for firm fixed effects. The *p*-values based on Wald Chi-Square statistics are reported in parentheses, while *, **, and *** denote the statistical significance at the 10%, 5%, and 1% levels, respectively.

7 | CONCLUSION

Margin trading represents an essential method for leveraging investments. Despite a large body of literature on short-selling, margin trading remains relatively under-explored. Utilising the

Chinese stock market's pilot program, we study the predictive power of margin trading interest across various levels, emphasising the need to account for the heterogeneity of margin trading.

We begin by examining the Chinese margin trading market as a whole. We develop various market-level margin trading interest measures, but none demonstrate predictive power at the aggregate level. The lack of significance at the aggregate level may stem from the heterogeneity of margin trading, potentially obscuring significant stock-level relationships.

To address the heterogeneity of margin trading, we investigate the association between margin trading interest and stock returns at the firm level. We document the existence of both information- and sentiment-driven margin trading and identify firm characteristics related to the likelihood of each type. The coexistence of information-driven and sentiment-driven margin trading supports both rational and behavioural finance perspectives.

Furthermore, we observe a significant decline in sentiment-driven margin trading and a moderate increase in information-driven trading after the 2015 stock crisis. These changes may be partially attributable to the stricter regulatory policies on margin trading implemented post-crisis. We demonstrate the effectiveness of regulatory tightening in an emerging market characterised by retail investors, contributing to the growing literature on post-financial crisis regulatory policies.

Our article offers a fresh perspective for reconciling the debate surrounding the predictive power of margin trading in various markets. More importantly, our methodology suggests the potential to consider the heterogeneity of margin trading in other unresolved issues, such as how margin trading affects price efficiency and stock volatility.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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