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Multiple time scales investor sentiment impact the stock market index fluctuation: From margin trading business perspective

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ABSTRACT

The stock market is viewed as a complex dynamic system, and investor sentiment has an important impact on index fluctuation. This study constructs investor sentiment from margin trading business perspective and investigates its impact on the Chinese stock market index fluctuation in multiple time scales. First, we utilize 12 indicators and two-stage PCA to construct a composite investor sentiment index of the margin trading business(ISMT). Second, based on TEI@I complex system theory, we use the VMD algorithm to decompose and reconstruct the ISMT, Shanghai Securities Composite Index(SSEC), and Shenzhen Securities Component Index(SZI), and obtain multiple time scale measurement sequences that reflect short-term, medium-term, and long-term fluctuation of each index, respectively. We provide evidence that the ISMT has an asymmetric impact on stock market index fluctuations. Specifically, for long-term trend, the ISMT has a significant positive impact on the SSEC, and a significant negative impact on the SZI. For medium and short-term trends, the ISMT has a significant positive impact on both the fluctuations of SSEC and SZI, and the impact degree on SSEC is greater than SZI. We also find that the impact degree of ISMT on SSEC and SZI decreases from short to long-term trend. In addition, we measure the fluctuation periodicity of ISMT in multiple time scales based on Fast Fourier Transformation, investigate the impact result during the COVID-19 pandemic, discuss the impact of ISMT on the other nine indexes commonly used in the Chinese stock market, and evaluate the predictive power of ISMT for 11 stock market index returns. This paper takes a new perspective and technology to investor sentiment research, and the results enrich relevant financial theories. The findings are crucial for investor decision-making and financial department regulation.

1. Introduction

Most conventional finance theories are based on the Rational Man Hypothesis and the Efficient Market Hypothesis, which hold that investors in the market are completely rational and their investment behavior is unaffected by various external uncertainties. However, according to behavioral finance theory, investor sentiment is a belief based on expectation for future asset value and investment risk that leads to irrational trading behavior, which has a substantial impact on the stock market and economic development (Haritha & Rishad, 2020; Long, Zhao, & Tang, 2021; Wurgler & Baker, 2006). Stock market index fluctuations indicate the market reaction to new information, which is affected by multiple factors, and investor sentiment is one of the most important influence factors (Gao & Zhao, 2023). On the one hand, investor sentiment serves as a risk factor affecting stock pricing and has

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become a vital inducement to stock price fluctuation (Gao & Zhao, 2023; Rupande, Muguto, & Muzindutsi, 2019). On the other hand, investor sentiment may lead to stock price frequent volatility and more uncertainty about future investment returns. In the above context, the relationship between investor sentiment and stock market index fluctuation has progressively become a hot topic.

Many traditional studies constructed investor sentiment in the forex market, futures market, or stock market from different perspectives such as volatility, advance-decline ratio, average turnover rate, price-earnings ratio, the number of IPOs, and overnight return, among others, and explored its impact on index fluctuation, company value, and market crash risk (Alnafea & Chebbi, 2022; Long et al., 2021). However, they all construct sentiment indicators from an overall market perspective and overlook the impact of sentiment on the market in specific business scenarios. Stock markets are complex systems comprising various types of trading entities and trading rules. For example, traders can be divided into individual investors and institutional investors; specific business scenarios can also be categorized into margin trading, funds, national debt, warrants, etc., all of which exert a significant impact on the market.

This study constructs investor sentiment from a new perspective that is margin trading business, and explores its impact on stock market index fluctuations. Margin trading business, also known as securities credit transactions, refers to investors providing collateral to securities companies to borrow funds and purchase securities (margin buying), or borrow securities to sell(short selling). It is a common practice in the majority of stock markets and an essential component of the modern financial system. As a propeller, stabilizer, and barometer in the development of the Chinese capital market, margin trading influences the market through leveraged trading and short selling mechanisms. Additionally, margin trading also has a function of counter-cyclical regulation. During market booms, it can prevent excessive bubbles. In times of recession, it can relieve the pressure on market funds and ameliorate insufficient liquidity conditions. Chang, Luo, and Ren (2014) and Lv and Wu (2019) pointed out that the margin trading business is widely concerned by traders, and its transaction data contain significant information content. It has an important influence on many aspects of the stock market, including market volatility, price discovery mechanisms, and stock price efficiency (Geraci, Garbaravičius, & Veredas, 2018; Li, Lin, Zhang, & Chen, 2018; Lv & Wu, 2020; Wan, 2020).

In March 2010, the China Securities Regulatory Commission (CSRC) lifted the ban on margin trading business and launched a pilot trading program for the first time. However, compared with developed countries, margin trading in the Chinese market is relatively new, immature, lagging in terms of marketization, and the impact mechanism on the financial market remains unclear. In the Chinese stock market, unlike regular investors, margin trading participants face strict requirements concerning capital and experience. Meanwhile, they face the risk of forced position liquidation under the leveraged trading regime. Generally, they are regarded as high-end investors, and some studies also classify them as investment experts. Intuitively, their investment behavior could potentially influence the market. The investor sentiment of margin trading business reflects the trading willingness of these so-called high-end investors, which is rich in valuable information. However, the majority of previous research about margin trading has focused on the influence of market liquidity, stability, and price efficiency. The margin trading business in the Chinese market is not mature and its impact mechanism on the market is not clear. Fewer studies have examined the quantification and construction of investor sentiment index from the margin trading business perspective and investigated its impact on the stock market index fluctuation.

In terms of research techniques, most studies about investor sentiment have focused on a single scale, limiting research and understanding to a single dimension. The concept of multiscale is widely found in finance literature (Alqaralleh, Canepa, & Uddin, 2023; Wang, Xie, Lin, & Stanley, 2017). Although much effort has been devoted to this topic, little attention has been paid to the multiple time scales of investor sentiment, especially in the margin trading business. We break this limitation and analyze it from a multiple time scales perspective. In general, long-term (large scale) fluctuation is associated with low-frequency information and value investing activities, whereas short-term (small scale) fluctuation is associated with high-frequency information and speculative trading activities (Caetano & Yoneyama, 2007; Gallegati, 2008). This is a significant issue because the investors with diverse investment cycle preferences and strategies differ across various time scales (Rua & Nunes, 2009). For example, investors who are enthusiastic about long-term value investment are uninterested in short-term sentiment or market index fluctuation, while short-term arbitrage investors are indifferent to long-term trend. However, for regulators, it is important to not only focus on short-term investor sentiment or stock market index fluctuations to prevent unhealthy development but also to consider medium or long-term fluctuations in order to formulate appropriate policies based on the market's operating environment.

Our study differs from most prior studies in that we emphasize the impact of investor sentiment on stock market index fluctuations across multiple time scales in specific business scenarios. Specifically, this study constructs investor sentiment from the margin trading business perspective, and investigates the impact on the Chinese stock market index fluctuation in multiple time scales. First, based on existing literature, we choose 12 indicators that reflect the margin trading operational state, and employ two-stage principal component analysis (PCA) to construct the investor sentiment of margin trading index (ISMT). Second, this paper utilizes sliding window sample entropy to analyze the fluctuation characteristics of ISMT. Then, based on the TEI@I complex system research theory, we use Variational Mode Decomposition (VMD) to decompose and reconstruct the ISMT, Shanghai Securities Composite Index(SSEC), and Shenzhen Securities Component Index(SZI) simultaneously. After that, in short, medium and long term time scales, we investigate the impact of ISMT on SSEC and SZI, respectively. A battery of robustness tests supports the relevant conclusions. Additionally, we also conduct four studies including clarifying the fluctuation periodicity of ISMT, investigating the impact of ISMT on stock market index fluctuation during the COVID-19 pandemic, discussing the impact of ISMT on other nine indexes commonly used in the Chinese stock market, and investigating the predictive power of ISMT for 11 stock market index returns.

This paper extends the research about investor sentiment from a new perspective and combines the TEI@I complex system research theory into traditional finance research paradigm. Relevant technology and conclusions fill the gaps in existing literature. The contributions of this paper include the following four aspects:

- This study extends the research scenario about investor sentiment to the margin trading business and utilizes 12 important indicators to construct the corresponding sentiment index called ISMT. However, most of the previous studies only focus on the overall market, rather than a specific business scenario.
- Based on the TEI@I complex system theory, we investigate the impact of ISMT on index fluctuation in multiple time scales, while previous studies rarely discuss this issue, especially for the Chinese stock market. Extensive robustness tests validate the conclusions.
- This paper measures the fluctuation periodicity of ISMT in multiple time scales, discusses the results during the COVID-19 pandemic, and analyzes the impact on more stock market indexes. These are important to understand the operation of the Chinese stock market and to dissect the impact of public health emergencies.
- This paper also evaluates the predictive power of ISMT for 11 stock market index returns commonly used in the Chinese market, such as SSEC returns, SZI returns, and CSI series returns, etc.

The remainder of this paper is organized as follows: The related work and motivation of the research are briefly introduced in Section 2. Section 3 introduces the research framework and method used in this paper. In Section 4, we provide a brief overview of the Chinese stock market margin trading business and construct the corresponding investor sentiment. Section 5 performs the main empirical results, while Section 6 concludes this paper.

2. Related work and motivation

2.1. Investor sentiment

In the 1990s, due to some phenomena in financial market that could not be explained by traditional financial theories, scholars began to pay attention to a fact that investment behavior is influenced by human being attributes, such as social environment, education, personal experience, preference, and habits, etc. Behavioral finance theory relaxes the rational man strictures of the Efficient Market Hypothesis and integrates the psychological factor into contemporary finance research framework. This theory suggests that investor sentiment, influenced by various factors such as risk perception, cognitive bias, and overconfidence, may prompt irrational trading behavior (Schmeling, 2007). As a result, behavioral finance scholars made huge efforts to analyze the investor behavior and found that investor sentiment has a significant impact on various markets. After that, a large number of literature about investor sentiment have subsequently emerged.

According to Haritha and Rishad (2020), investor sentiment impacts stock volatility, which determines the optimal portfolio. Kim and Ryu (2021a) believed that investor sentiment directly impacts trading behavior. Alnafea and Chebbi (2022) provided evidence that a high level of investor sentiment increases the risk of stock price crash, and Miwa (2016) found that it can lead to stock mispricing. Hudson, Yan, and Zhang (2020) documented that investor sentiment may also be a factor in fund managers' herding behavior. Kumari and Mahakud (2016) argued that investor sentiment influences stock market volatility, which influences future stock returns. Furthermore, an additional focus of investor sentiment research is on how to construct index. Since investor sentiment is difficult to measure and observe directly, there is no consensus on this matter. Typically, scholars utilize a variety of indicators as proxies for investor sentiment (Zhou, Cui, & He, 2020). There are three primary approaches: the first category uses subjective indicator as investor sentiment. Some scholars utilize indicators such as Wall Street Analyst Index(WSAI), Friendship Index(FI), Investors Intelligence(II), and Consumer Confidence Indices(CCI) to represent investor sentiment (Nartea, Bai, & Wu, 2020; Schmeling, 2009), although they are rarely used. The second category uses comprehensive sentiment index, which is constructed using some subjective or objective proxy indicators, such as closed-end fund discount(CEFD), share amount, the number and average first-day returns on Initial Public Offers(IPOs), the equity share in new issues, and the dividend premium, etc (Baker & Malcolm, 2007; Lee, Shleifer, & Thaler, 1991; Wurgler & Baker, 2006). Notably, principal component analysis (PCA) is the most commonly used method for constructing this type of investor sentiment, and many scholars construct sentiment index by this way (Alnafea & Chebbi, 2022; Kim & Ryu, 2021a, 2021b; Li, Tian, Ouyang, & Wen, 2021; Wurgler & Baker, 2006; Yang & Chi, 2023). Moreover, using machine learning, data mining, and text analysis to construct sentiment index has received a great deal of attention in recent years. Some scholars take Twitter, Facebook, Baidu Post Bar, and Yahoo Finance as data sources to obtain pictures, audio, and text documents to quantify (Antweiler & Frank, 2004; Goel & Dash, 2022; Obaid & Pukthuanthong, 2022; Siganos, Vagenas-Nanos, & Verwijmeren, 2017). Even though this method has certain data volume and technology requirements, it has become the direction of future development.

2.2. Margin trading

From the perspective of global economic development, as an important component and trading pattern, the margin trading business plays a crucial role in mature capital market. At present, many stock exchanges including NASDAQ, Tokyo, Hong Kong, and Taiwan are actively engaged in the margin trading business. Currently, research about margin trading mainly focuses on two aspects: one is to explore the impact on market liquidity and volatility, and the other is to explore the impact on stock price efficiency. On the one hand, Gui and Zhu (2021) pointed out that the underlying stocks of margin trading are usually under stricter regulation, and they are more liquid and less volatile. Wan (2020) analyzed the impact of margin buying and short selling on market liquidity by using limit order book data, which reflects market microstructure. The result revealed that considering the high proportion of uninformed traders and severe information asymmetry in the Chinese stock market, the margin trading has a negative impact on market liquidity. Ye, Zhou, and Zhang (2020) reached similar conclusions and refined the research on margin trading and liquidity. The results showed that under ordinary market conditions, margin buying is beneficial to stock liquidity, while short selling is harmful to stock liquidity. However, this tendency tends to reverse during market downturns.

Another research topic about margin trading is to explore the impact on price efficiency, although the conclusions are not unified. Some scholars, such as Alexander, Ors, Peterson, and Seguin (2004) and Chen, Kadapakkam, and Yang (2016) believed that margin trading can improve price efficiency. However, Rytchkov (2014) and Thurner, Farmer, and Geanakoplos (2012) hold opposite views that margin trading may decrease market efficiency. According to the research of Lv and Wu (2020), the reason for this divergence is due to the fact that different scholars employed diverse measurement techniques to represent price efficiency. As a result of the increased margin trading, the information content decreases which is not conducive to pricing efficiency. Meanwhile, the faster price adjustment speed, the positive impact on price efficiency. Encouragingly, some scholars have expanded the new direction of margin trading research. For example, Bian, He, Shue, and Zhou (2018) and Kahraman and Tookes (2020) connected margin trading to return spillovers. However, the research about investor sentiment in the margin trading business scenario is still a gap.

2.3. TEI@I complex system research theory used in financial market

The TEI@I is a new methodology for analyzing complex systems with emergent, unstable, nonlinear, and uncertain properties, proposed by Wang, Yu, and Lai (2005). At present, the TEI@I theory has been widely used in the research of price forecasting, foreign exchange rates, real estate markets, and other fields with good results (Tian et al., 2009; Wan, Xie, & Hu, 2021; Xiao, Kun, Zhenni, Gan, & Zhewen, 2020). The core idea of TEI@I is decomposition and integration, which argues that the trends of variables at different scales reflect different types of complex system operation rules. Interestingly, this concept can be well combined with investor sentiment research in multiple time scales.

In recent years, scholars have begun to realize that multiple time scales investor sentiment may have different effects on the market, although such literature is rare. Fang et al. (2015) utilized Ensemble Empirical Mode Decomposition (EEMD) to investigate the predictive power of investor sentiment in multiple time scales. The result provided evidence that the investor sentiment in different scales has significant difference impact on prediction result. Ftiti and Hadhri (2019) and Long et al. (2021) also used the same decomposition method to construct multiple time scales investor sentiment. Lao, Nie, and Jiang (2018) utilized wavelet decomposition to construct multiple time scales investor sentiment and analyzed its impact on stock returns. Moreover, Chen, Zhou, Zhang, and Sun (2021) used Bandwidth Empirical Mode Decomposition (BEMD) to decompose the investor sentiment index sequences and reconstruct them into short-term high-frequency components, medium-term important event low-frequency components, and long-term trend components. After that, they explored the interaction between investor sentiment and several financial market indexes in multiple time scales.

Based on the detailed summary and induction of related studies, we conduct some extension work to strongly supplement the gaps in existing literature. Simply, the margin trading business is an essential component of the financial market. It is rare to find literature about investor sentiment in such a specific business scenario. In addition, we utilize a research framework combined with TEI@I complex system research theory to explore the impact of multiple time scales investor sentiment on stock market index fluctuation.

3. Method

In this section, the research framework and main methodology used in this paper will be described. Specifically, in Section 3.1, we introduce the research framework used in this paper from theoretical level and technical level. In Section 3.2, we describe TEI@I complex system research theory and an interesting decomposition method called VMD. In Section 3.3, we provide the reconstruction method to obtain multiple time scales investor sentiment.

3.1. Research framework

The research framework can be roughly divided into theoretical level and technical level, with the detailed description shown in Fig. 1. On the theoretical level, based on behavioral finance theory, we choose 12 indicators that reflect the development of margin trading business to construct composite investor sentiment index. Moreover, according to the core idea of TEI@I complex system research theory, we discuss the impact of investor sentiment on the stock market index fluctuation in multiple time scales. On the technical level, we utilize two-stage PCA, sliding window sample entropy, VMD decomposition technology, Fast Fourier Transformation, and regression analysis to carry out research. A brief description of the research framework is as follows:

- First, this paper takes margin trading business as research object and constructs the investor sentiment based on finance theories.
- Second, we employ sliding window sample entropy to coarse-grained analyze the fluctuation characteristics of investor sentiment. Under different sliding window sizes, we effectively identify multiple periods of investor sentiment being positive and negative.
- Third, based on the idea of TEI@I complex system research theory, we use VMD to decompose and reconstruct the sentiment and stock market indexes.
- Fourth, we fine-grained discuss the impact of investor sentiment on the stock market index fluctuation in multiple time scales.
- Fifth, we carry out four additional studies including measuring the periodicity of ISMT fluctuation in multiple time scales, discussing the impact during the COVID-19 pandemic, investigating the impact result of ISMT on other nine indexes in the Chinese stock market, and evaluating the predictive power of ISMT for these index returns.

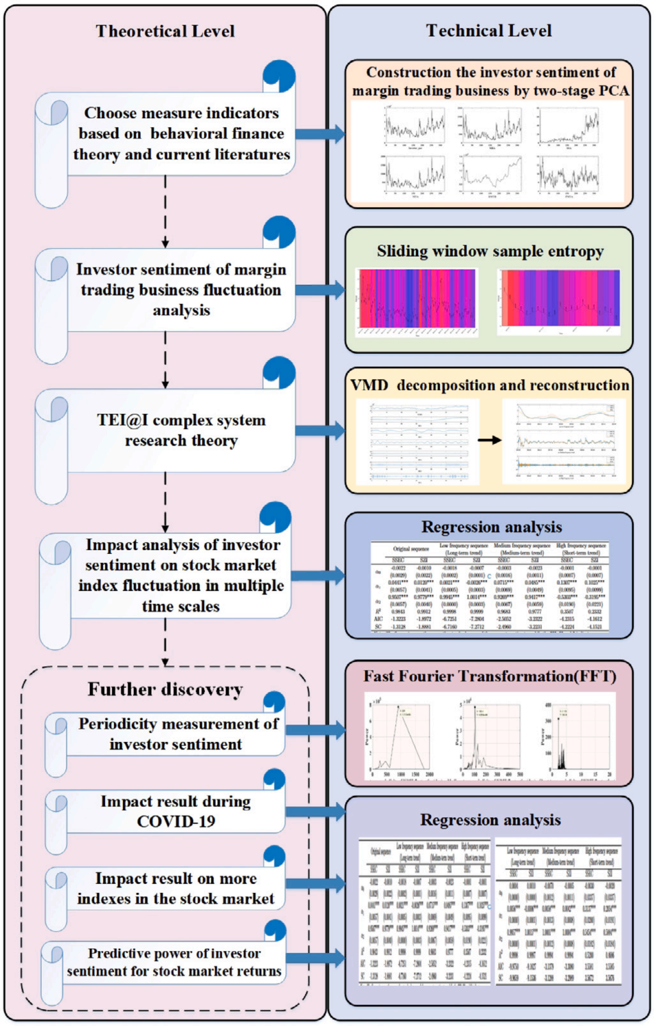


Fig. 1. Research framework.

3.2. TEI@I theory and VMD

The TEI@I complex system research theory believes that complex system is formed by coupling a series of things with different properties, the core idea is decomposition and integration (Wang et al., 2005). This theory focuses on how to effectively explore system's various characteristics. The investor sentiment is complicated to a certain extent, which is a typical complex system. From the perspective of system management and drawing on the idea of TEI@I theory, this framework decomposes the sentiment index by Variational Mode Decomposition and obtains the components in different scales.

Currently, the commonly used sequence decomposition methods such as wavelet decomposition (WD), Empirical Mode Decomposition (EMD), and Ensemble Empirical Mode Decomposition (EEMD), etc. Compared with the above methods, Variational Mode Decomposition (VMD) is an adaptive decomposition algorithm with higher robustness and is less affected by extreme values, which can effectively avoid mode mixing and is more sensitive to signals with different frequencies. The VMD decomposes a real-valued signal into some discrete sub-signals with specific sparsity properties (Dragomiretskiy & Zosso, 2014; Hassani, Mousavi, & Gandomi, 2022). These sub-signals, called Intrinsic Mode Functions(IMFs), are Amplitude-Modulated Frequency-Modulated(AM–FM) signals and have the following forms:

$$IMF_k(t) = A_k(t)\cos\left[\phi_k(t)\right] \tag{1}$$

where $A_k(t)$ and $\phi_k(t)$ denote its instantaneous amplitude and phase, respectively. The decomposition process of VMD can be viewed as a construction and solution of the variational problem (Liu, Yang, Huang, & Gui, 2019; Liu, Zhao, Yu, Zheng, & Liao, 2022). It can be given as follows :

$$\min_{IMF,\omega}\left\{\sum_k \left\| \partial_t \left[\left(\delta(t)+\frac{j}{\pi t}\right) * IMF_k(t)\right] e^{-j\omega_k t}\right\|_2^2\right\} \tag{2}$$

$$s.t. \sum_k IMF_k(t) = f(t) \tag{3}$$

where $f(t)$ is the original sequence; ∂_t is the partial derivatives; $*$ denotes the convolution operator; $\delta(t)$ is the Dirac distribution; t implicates the time script; $IMF = \{IMF_1, IMF_2, IMF_3, \cdots, IMF_k\}$ represent components obtained by VMD decomposition; $\omega = \{\omega_1, \omega_2, \omega_3, \cdots, \omega_k\}$ represent the central frequency of each IMF.

The VMD is to search for the optimal solution of the constrained variational model to decompose the signal adaptively. During the iterative solution, the algorithm gradually updates the center frequency and bandwidth of each component, and finally divides into different components according to the frequency domain characteristics of the signal itself. To convert the constrained variational problem into an unconstrained optimization problem and ensure the reconstruction fidelity, the quadratic penalty term, and the Lagrange multiplier term are utilized. Therefore, we introduce the augmented Lagrangian as Eq. (4):

$$\begin{aligned}\mathcal{L}(IMF,\omega,\lambda) = {}& \underbrace{\alpha \sum_k \left\| \partial_t \left[\left(\delta(t)+\frac{j}{\pi t}\right) * IMF_k(t)\right] e^{-j\omega_k t}\right\|_2^2}_{Gradient\ of\ squared\ L_2-norm\ of\ mode\ signal} + \\ & \underbrace{\left\| f(t) - \sum_k IMF_k(t)\right\|_2^2}_{Quadratic\ penalty\ term} + \underbrace{\left\langle \lambda(t), f(t) - \sum_k IMF_k(t)\right\rangle}_{Lagrangian\ multiplier\ term}\end{aligned} \tag{4}$$

where α represents the balancing parameter of the data-fidelity constraint, and $\lambda(t)$ is Lagrange multiplication factor for tightening restraint.

In addition, the Alternate Direction Method of Multipliers (ADMM) is used to address this unconstrained variational problem. The core of the algorithm is to update IMF_k^{n+1}, ω_k^{n+1}, and λ^{n+1} alternately by iteration to find the saddle point of the augmented Lagrangian(n is number of iterations). Finally, the optimal solution is found and the original sequence is decomposed into k IMFs. The update process can be express as Eq. (5) - Eq. (7).

$$I\hat{M}F_k^{n+1} = \frac{\hat{f}(\omega) - \sum_{i<k} I\hat{M}F_i(\omega) - \sum_{i>k} I\hat{M}F_i(\omega) + \frac{\hat{\lambda}(\omega)}{2}}{1+2\alpha\left(\omega-\omega_k\right)^2} \tag{5}$$

$$\omega_k^{n+1} = \frac{\int_0^\infty \omega \left|I\hat{M}F_k^{n+1}(\omega)\right|^2 d\omega}{\int_0^\infty \left|I\hat{M}F_k^{n+1}(\omega)\right|^2 d\omega} \tag{6}$$

$$\hat{\lambda}^{n+1}(\omega) = \hat{\lambda}^n(\omega) + \tau\left(\hat{f}(\omega) - \sum_k I\hat{M}F_k^{n+1}(\omega)\right) \tag{7}$$

where τ designates the dual ascent parameter; the $\hat{f}(\omega)$, $I\hat{M}F_k^{n+1}(\omega)$, and $\hat{\lambda}(\omega)$ are the Fourier transforms of $f(t)$, $IMF_k^{n+1}(t)$, $\lambda(t)$, respectively. Referring to Liu et al. (2022), Eq. (5) - Eq. (7) are updated iteratively until satisfy Eq. (8):

$$\sum_k \left\|I\hat{M}F_k^{n+1} - I\hat{M}F_k^n\right\|_2^2 / \left\|I\hat{M}F_k^n\right\|_2^2 < \epsilon \tag{8}$$

where ϵ represents the tolerance parameter of the convergence criterion and is usually small enough; we set 10^{-7} in this paper.

3.3. Index reconstruction

In this subsection, we introduce the reconstruction method of IMFs. In practice, the purpose of reconstruction is to get multiple time scale measurement sequences that reflect short-term, medium-term, and long-term fluctuation characteristics of the original data (Chen et al., 2021; Fang et al., 2015; Zhang, Lai, & Wang, 2008). The most commonly used decomposition techniques are based on EMD or EEMD (Fang et al., 2015; Zhang et al., 2008), and the corresponding reconstruction technique is usually to calculate the mean value for each component and identify this value departs from zero significantly. However, EMD or EEMD are known for limitations like sensitivity to noise and sampling (Dragomiretskiy & Zosso, 2014). In addition, these methods suffer from the problem of mode mixing (Liu, 2022). VMD overcomes these problems, however, reconstruction based on mean value is not suitable for VMD. On the one hand, EMD or EEMD treats the residual series as the long-term trend; therefore, they only divide IMFs into short-term and medium-term. On the other hand, the essence of reconstruction is to aggregate the IMFs with similar volatility, but the mean value cannot reflect the volatility of each component. Hence, we propose to use the standard deviation instead of the mean value. The algorithm is as follows:

Step 1: Calculating the standard deviation of the kth IMF, according to Eq. (9).

$$\sigma_{IMF_k} = \sqrt{\frac{1}{N}\sum_{t=1}^{N}(IMF_k^t - \overline{IMF}_k)^2} \tag{9}$$

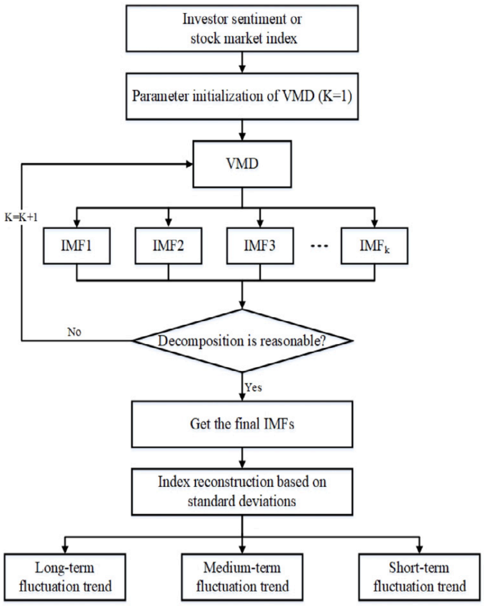


Fig. 2. The multiple time scales fluctuation sequences generation process based on TEI@I theory.

where $\overline{IMF_k}$ is the mean value of kth IMF.

Step 2: Identifying the inflection point of the standard deviation. Normally, the variability of standard deviation among IMFs with different fluctuation trends is large. The IMFs with the higher standard deviation are reconstructed as long-term fluctuation trend, denote as x^l_{IMF}. The IMFs corresponding to the standard deviation of the middle range are reconstructed as medium-term fluctuation trend, denote as x^m_{IMF}. The partial reconstruction with other IMFs are identified as the short-term fluctuations trend, denote as x^s_{IMF}. Multiple time scales fluctuation sequences can be calculated by Eq. (10) - Eq. (12), and the complete generation process shown in Fig. 2.

$$Long\_term(t) = \sum_l IMF^t_l \tag{10}$$

$$Medium\_term(t) = \sum_m IMF^t_m \tag{11}$$

$$Short\_term(t) = \sum_s IMF^t_s \tag{12}$$

4. Construction the investor sentiment of margin trading

In Section 4.1, we have a brief overview of the development of margin trading business in the Chinese stock market. Then, in Section 4.2, we introduce the data and investor sentiment measure indicators used in this research. After that, in Section 4.3, we provide how to construct investor sentiment in detail. Finally, in Section 4.4, we utilize sliding window sample entropy to analyze the fluctuation characteristics of investor sentiment.

4.1. Overview about margin trading business in China

Margin trading, as an emerging trading business, is permitted in most stock exchanges around the world, but it started relatively late in China. Until March 2010, the CSRC lifted its restriction for the first time (Lv & Wu, 2020). After that, the Shanghai Stock Exchange and Shenzhen Stock Exchange launched a trial program for margin trading business, and the CSRC stipulated that only stocks on the approved list could be purchased. Since the official launch of the margin trading business, there have been six major revisions of the approved list in December 2011, January 2013, September 2013, September 2014, December 2016, and August 2019, respectively. In August 2019, the approved list for margin trading business was extended to 1600 stocks, covering more than a third of the total stocks in the Chinese stock market. Until August 2021, there were 93 securities traders conducted margin trading business in China, involving 11,529 business departments, with the margin trading balance reaching RMB 1.87 trillion. As CITIC Securities, Guangfa Securities, Oriental Fortune, and other large financial institutions are actively engaged in relevant business.

It is worth mentioning that, from the perspective of participating in margin trading business, there are several remarkable characteristics. Compared with ordinary stock trading, investors who participate in margin trading will be affected by multiple

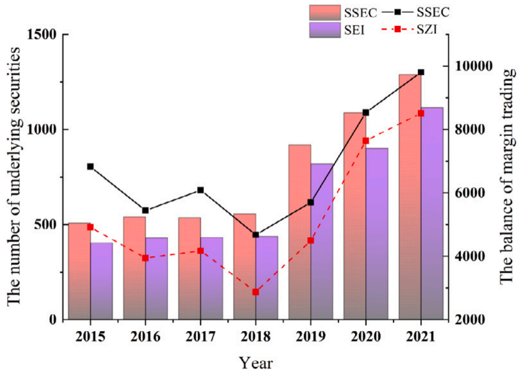


Fig. 3. Approved stocks and balance of margin trading business.

risk factors such as leverage risk, forced liquidation risk, credit risk, and transaction cost expansion. Therefore, the CSRC has more stringent criteria for investors. For qualified individual investors, in most securities companies, one of the prerequisites for creating a margin trading account is to have a trading history for more than six months, and the average daily securities assets should be more than RMB 500,000 during the last 20 trading days. Therefore, to a certain extent, investors who can participate in margin trading business are regarded as high-end traders with sufficient securities trading experience and risk tolerance. Fig. 3 shows the number of underlying securities and the balance of margin trading in Shanghai and Shenzhen stock markets, from 2015 to 2021, respectively. It can be seen that the margin trading business in the Chinese stock market is on the rise.

4.2. Data and measure indicators

The proxy indicator method is one of the most commonly used to construct investor sentiment (Haritha & Rishad, 2020; Li et al., 2021; Yang & Chi, 2023). The principle of selecting these indicators is to reflect the market operation as much as possible. In this paper, based on existing literature and data, we utilize 12 indicators which reflect the operation of margin trading to construct investor sentiment. The data are collected from 1 May, 2015 to 30 September, 2022, for a total of 1808 trading days. On the one hand, the sample spans a complete bull and bear market cycle. On the other hand, we also consider the availability of raw data and the release time of various indicators. The CSRC relaxed the restriction on margin trading business for the first time in 2010; hence, less information is available for prior years. The raw data are collected from the CSMAR database,[1] China securities finance corporation limited,[2] and Choice financial terminal.[3] Table 1 provides a brief description of each indicator and Table 2 displays descriptive statistics.

- **Number of individual investors (Investors individual):** According to the number of accounts, individual investors are still the main participants in margin trading business. Intuitively, the more individual investors participate in margin trading, the more optimistic in the stock market. Schmeling (2007) and Foucault, Sraer, and Thesmar (2011) pointed out that individual investors influence the volatility of stock returns.
- **Number of institutional investors (Investors institutional):** As another major participant in margin trading business, institutional investors have the advantage of capital and technology. In general, more institutional investors indicate a bullish market outlook. Schmeling (2007) believed that the institutional sentiment is proxy for “smart money”. Basak and Pavlova (2013) and Ferreira and Matos (2008) found that institutional investors have impact on stock market volatility, asset prices, and stock index.
- **Number of investors participate in trading (Investors par):** Investors decide whether or not to participate in margin trading business based on market environment and their personal circumstances. This indicator measures the number of investors who participate in trading during the current period.
- **Margin buying amount (MBA):** The amount of investors borrow funds from securities companies to purchase stocks. When the margin buying amount increases for a long time, the market heat is higher, and investors have a strong desire to invest, which belongs to a positive market environment. Gui and Zhu (2021) utilized MBA as independent variable to explore the relationship between margin trading and stock market volatility. Ye et al. (2020) believed that MBA impact on stock liquidity in the Chinese stock market.

1 https://cn.gtadata.com/
2 http://www.csf.com.cn/
3 https://choice.eastmoney.com/

Table 1
Indicator description.

Indicator	Indicator symbol	Description
Number of individual investors	Investors_individual	The number of individual investors creating the margin trading accounts
Number of institutional investors	Investors_institutional	The number of institutional investors creating the margin trading accounts
Number of investors participate in trading	Investors_par	The number of investors participate in margin trading business
Margin buying amount	MBA	The total of margin buying amount for all stocks
Short selling amount	SSA	The total of short selling amount for all stocks
Margin trading amount	MTA	The total of margin buying and short selling amount for all stocks
Proportion of margin trading amount	PMTA	The proportion of margin trading amount in the total amount of A-share market
Margin buying balance	MBB	The total of margin buying balance for all stocks
Short selling balance	SSB	The total of short selling balance for all stocks
Margin trading balance	MTB	The total of margin buying and short selling balance for all stocks
Difference of margin trading balance	DMTB	The difference between the margin buying balance and the short selling balance
Proportion of margin trading balance	PMTB	The proportion of margin trading balance in circulation market capitalization of A-share market

- **Short selling amount (SSA):** The amount of investors borrow securities from company to sell stocks. When the short selling amount increases for a long time, the market heat is lower, and investors have a strong desire to sell stocks, which belongs to a negative market environment. Similar to MBA, Gui and Zhu (2021) also considered SSA would have an impact on stock volatility. Wang and Lee (2015) studied the short selling has an impact on stock price.
- **Margin trading amount (MTA):** The total of margin buying and short selling amount which reflects the overall development of margin trading business. According to Allen and Gale (1991), the margin trading business will increase stock market volatility and bring instability to the market. Chen et al. (2016) believed that MBA, SSA, and MTA have a significant on the Chinese stock market.
- **Proportion of margin trading amount (PMTA):** Measuring the proportion of margin trading amount to A-shares market trading amount. It is an important indicator for the margin trading business.
- **Margin buying balance (MBB):** The difference between the margin buying amount and its repayment, which reflects the strength of go-long in stock market. The larger MBB, the more people are optimistic about market. Li, Li, and Yuan (2017) and Ye et al. (2020) argued that MBB will impact on stock market liquidity and price.
- **Short selling balance (SSB):** The difference between the short selling amount and its repayment, which reflects the strength of short-sale in the stock market. The larger SSB, the more people are pessimistic about market. Li, Li, Li, and Wu (2018) pointed out that SSB in margin trading business is important for stock return.
- **Marging trading balance (MTB):** The total balance of margin buying and short selling, which is another important indicator and reflects the entire development of the margin trading business. Kahraman and Tookes (2020) used MTB as major factor, and the result believed that margin trading has a huge impact on financial market volatility.
- **Difference of margin trading balance (DMTB):** The difference between margin buying and short selling balance. A higher value indicates that investors are more optimistic about the stock market. Similar to Chen et al. (2016) considered MBB and SSB are important impact indicators on stock market.
- **Proportion of margin trading balance (PMTB):** Measuring the proportion of margin trading balance to circulation market capitalization. It is an important indicator, which reflects the activity of margin trading business in the A-share market.

Table 2 reports the descriptive statistics for 12 indicators. In particular, we need to point out that the skewness of all indicators is positive, but the kurtosis differs. The Investors_individual, Investor_institutional, MBB, SSB, and MTB have negative kurtosis, which indicates these indicators are more flatly distributed. While the kurtosis of the rest indicators is positive, which indicates the distribution of these indicators has the characteristics of sharp peaks. In addition, we report the correlation between the 12 indicators in Table 3.

4.3. Construction the investor sentiment of margin trading index(ISMT)

How to construct investor sentiment with different indicators under various market environments has been a hot issue in behavioral finance and financial market research. Previous section introduces 12 indicators, with rich market information content,

Table 2
Data descriptive statistical.

Indicator	Unit	Mean	Median	Max	Min	Skwness	Kurtosis
Investors_individual	million accounts	4.95	4.77	6.35	3.51	0.29	−1.02
Investors_institutional	thousand accounts	21.33	17.68	45.38	6.07	0.59	−0.96
Investors_par	thousand accounts	211.18	203.27	513.35	14.21	0.77	0.72
MBA	billion RMB	63.37	55.06	290.59	14.01	1.92	5.49
SSA	billion RMB	2.86	1.11	38.78	0.02	4.69	25.30
MTA	billion RMB	66.29	56.94	321.76	14.49	2.16	6.98
PMTA	percent	9.12	9.00	18.00	5.32	1.10	2.78
MBB	billion RMB	1158.26	996.87	2266.43	710.93	0.86	−0.29
SSB	billion RMB	40.32	7.89	173.74	1.82	1.17	−0.25
MTB	billion RMB	1198.59	1003.95	2272.80	716.97	0.77	−0.81
DMTB	billion RMB	1117.97	990.73	2260.23	704.89	1.06	0.89
PMTB	percent	2.42	2.35	4.73	1.83	2.85	10.86

Table 3
Correlation between 12 indicators.

Daily	Investors_ individual	Investors_ institutional	Investors_ par	MBA	SSA	MTA	PMTA	MBB	SSB	MTB	DMTB	PMTB
Investors_ individual	1.0000	0.9921	0.2278	0.0561	0.1090	0.0622	−0.4463	0.5681	0.8265	0.6215	0.4927	−0.2131
Investors_ institutional	0.9921	1.0000	0.2953	0.1309	0.1854	0.1397	−0.4117	0.6456	0.8597	0.6949	0.5746	−0.1080
Investors_ par	0.2278	0.2953	1.0000	0.9436	0.5759	0.9319	0.5560	0.6893	0.4343	0.6724	0.7022	0.5082
MBA	0.0561	0.1309	0.9436	1.0000	0.7048	0.9949	0.6731	0.6690	0.2955	0.6346	0.7047	0.6516
SSA	0.1090	0.1854	0.5759	0.7048	1.0000	0.7600	0.3947	0.7302	0.2771	0.6861	0.7775	0.7355
MTA	0.0622	0.1397	0.9319	0.9949	0.7600	1.0000	0.6638	0.6962	0.3016	0.6595	0.7344	0.6823
PMTA	−0.4463	−0.4117	0.5560	0.6731	0.3947	0.6638	1.0000	0.1265	−0.2250	0.0796	0.1847	0.4412
MBB	0.5681	0.6456	0.6893	0.6690	0.7302	0.6962	0.1265	1.0000	0.7711	0.9958	0.9931	0.6385
SSB	0.8265	0.8597	0.4343	0.2955	0.2771	0.3016	−0.2250	0.7711	1.0000	0.8261	0.6912	0.1546
MTB	0.6215	0.6949	0.6724	0.6346	0.6861	0.6595	0.0796	0.9958	0.8261	1.0000	0.9782	0.5873
DMTB	0.4927	0.5746	0.7022	0.7047	0.7775	0.7344	0.1847	0.9931	0.6912	0.9782	1.0000	0.6965
PMTB	−0.2131	−0.1080	0.5082	0.6516	0.7355	0.6823	0.4412	0.6385	0.1546	0.5873	0.6965	1.0000
Weekly	Investors_ individual	Investors_ institutional	Investors_ par	MBA	SSA	MTA	PMTA	MBB	SSB	MTB	DMTB	PMTB
Investors_ individual	1.0000	0.9924	0.2565	0.0842	0.1402	0.0930	−0.4167	0.5819	0.8274	0.6338	0.5079	−0.2015
Investors_ institutional	0.9924	1.0000	0.3214	0.1564	0.2140	0.1675	−0.3828	0.6559	0.8598	0.7038	0.5861	−0.1003
Investors_ par	0.2565	0.3214	1.0000	0.9447	0.5812	0.9317	0.5565	0.6992	0.4603	0.6842	0.7097	0.5079
MBA	0.0842	0.1564	0.9447	1.0000	0.7099	0.9968	0.6762	0.6809	0.3236	0.6482	0.7144	0.6532
SSA	0.1402	0.2140	0.5812	0.7099	1.0000	0.7635	0.3804	0.7446	0.3041	0.7017	0.7907	0.7416
MTA	0.0930	0.1675	0.9317	0.9968	0.7635	1.0000	0.6628	0.7082	0.3310	0.6734	0.7441	0.6824
PMTA	−0.4167	−0.3828	0.5565	0.6762	0.3804	0.6628	1.0000	0.1536	−0.1883	0.1083	0.2099	0.4705
MBB	0.5819	0.6559	0.6992	0.6809	0.7446	0.7082	0.1536	1.0000	0.7776	0.9958	0.9931	0.6365
SSB	0.8274	0.8598	0.4603	0.3236	0.3041	0.3310	−0.1883	0.7776	1.0000	0.8316	0.6984	0.1580
MTB	0.6338	0.7038	0.6842	0.6482	0.7017	0.6734	0.1083	0.9958	0.8316	1.0000	0.9783	0.5850
DMTB	0.5079	0.5861	0.7097	0.7144	0.7907	0.7441	0.2099	0.9931	0.6984	0.9783	1.0000	0.6950
PMTB	−0.2015	−0.1003	0.5079	0.6532	0.7416	0.6824	0.4705	0.6365	0.1580	0.5850	0.6950	1.0000

that provide a comprehensive description of margin trading business operation. We noticed that there may exist multiple linear correlations between partial variables, however, blindly removing some highly relevant variables may lead to information loss. Fortunately, based on maximum variance theory, the PCA can effectively address the multicollinearity and preserve the maximum information content. Hence, this paper uses a two-stage PCA to construct the investor sentiment of margin trading business in the Chinese stock market.

Considering an actual situation that economic indicators may have a lagging effect on investor sentiment. Hence, in this research, we choose 12 indicators and their first-order lag to calculate the first-stage sentiment index by PCA. Then, we calculate the correlation between the first-stage sentiment index and 24 indicators including the current and lagged values, as shown in Table 4. Finally, by using second-stage PCA, we select 12 indicators with the strongest links to the first-stage sentiment index and create the final sentiment index denoted as ISMT. It should be mentioned that, in order to retain more meaningful information, when constructing the sentiment index by PCA, the cumulative variance interpretation rate is set to 90% in each stage, and the final sentiment index is calculated using the weighted average of each principal component.

In Table 4, all indicators have a significant positive impact on the first-stage sentiment. In addition, we notice that Investors_individual, Investors_institutional, MBB, SSB, MTB, DMTB, and PMTB have a greater impact in the current period than in the lag period, which indicates the higher enthusiasm of these indicators in the current period. While other indicators are opposite, which indicates that the higher enthusiasm in the early stages stimulates investor sentiment more in the later stages. Consequently, we finally choose 12 indicators to extract the principal components, which are $\text{Investors\_individual}_t$, $\text{Investors\_institutional}_t$, $\text{Investor\_par}_{t-1}$, MBA_{t-1}, SSA_{t-1}, MTA_{t-1}, DMTB_t, PMTA_{t-1}, MBB_t, SSB_t, MTB_t, and PMTB_t. Then, we construct the investor sentiment of margin trading business by second-stage PCA, the Eq. (13) shows the final expression of the ISMT. We compare the fluctuation

Table 4
The correlation between first-stage ISMT and each indicator.

	Investors individual$_t$	Investors institutional$_t$	Investor par$_t$	MBA$_t$	SSA$_t$	MTA$_t$
ISMT	**0.1873*****	**0.2772*****	0.8525***	0.9066***	0.8462***	0.9282***
	PMTA$_t$	MBB$_t$	SSB$_t$	MTB$_t$	DMTB$_t$	PMTB$_t$
ISMT	0.5116***	**0.8714*****	**0.4679*****	**0.8384*****	**0.9028*****	**0.8086*****
	Investors individual$_{t-1}$	Investors institutional$_{t-1}$	Investor par$_{t-1}$	MBA$_{t-1}$	SSA$_{t-1}$	MTA$_{t-1}$
ISMT	0.1835***	0.2768***	**0.8535*****	**0.9138*****	**0.8517*****	**0.9352*****
	PMTA$_{t-1}$	MBB$_{t-1}$	SSB$_{t-1}$	MTB$_{t-1}$	DMTB$_{t-1}$	PMTB$_{t-1}$
ISMT	**0.5278*****	0.8668***	0.4677***	0.8346***	0.8973***	0.7930***

Note: The *, **, and *** denote significance at the 10%,5% and 1% levels,respectively.

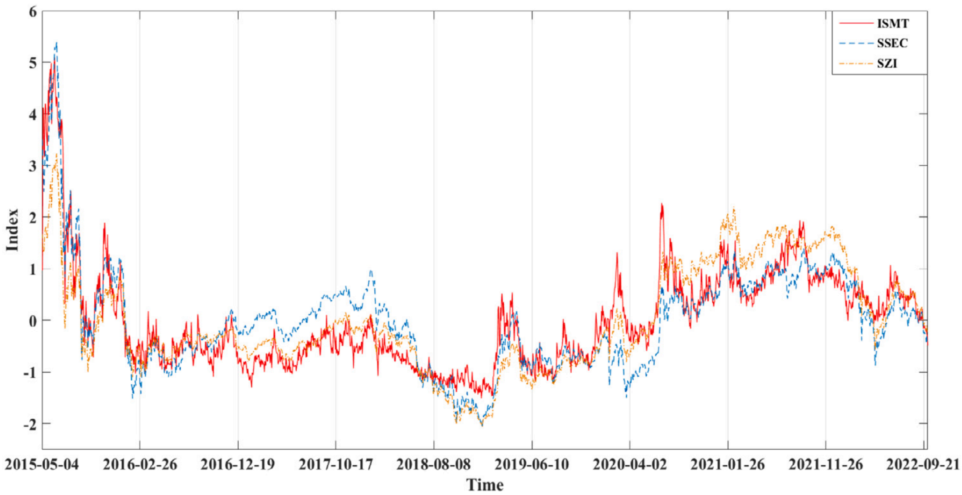


Fig. 4. The fluctuation of ISMT, SSEC, and SZI (Daily frequency data).

trends of ISMT, Shanghai Securities Composite Index(SSEC), and Shenzhen Securities Component Index(SZI) in Fig. 4.

$$\begin{aligned} ISMT\_Index = & -0.0086 Investors\_individual_t + 0.0156 Investors\_institutional_t + \\ & 0.2775 Investor\_par_{t-1} + 0.2936 MBA_{t-1} + 0.2080 SSA_{t-1} + 0.2930 MTA_{t-1} + 0.2318 PMTA_{t-1} + \\ & 0.1790 MBB_t + 0.0694 SSB_t + 0.1685 MTB_t + 0.1903 DMTB_t + 0.1822 PMTB_t \end{aligned} \tag{13}$$

It can be seen that the fluctuation trend of ISMT constructed in this paper is roughly consistent with the Chinese stock market index. Meanwhile, within our research interval, the margin trading business has generally experienced four development stages, and the ISMT has various degrees of fluctuation at each stage:

(1) In 2015, the CSRC issued the "Securities Company Margin Trading Management Measures" and made the specific requirement for creating trading account with average daily securities assets for more than RMB 500,000 in the previous 20 trading days. This means that the margin trading business has tightened; correspondingly, the ISMT had fallen sharply.

(2) From 2016 to 2018, the margin trading business in the Chinese stock market entered an adjustment stage under the influence of tightening supervision by government and financial deleveraging, while the ISMT remained sluggish.

(3) In 2019, the CSRC successively issued the "Implementing Rules for Securities Lending" and "Transfer Securities Business of Science and Technology Board and Implementation Rules for Margin Trading Business", which abolished the restriction on the minimum maintenance guarantee ratio and expanded the underlying stocks of margin trading from 950 to 1,600. Following the implementation of these policies, the ISMT became active rapidly.

(4) Since the outbreak of COVID-19 in December 2019, the ISMT has been more volatile and experienced several sharp pullbacks, but it has remained on the upswing as the economy has gradually recovered.

The ISMT not only corresponds to the major events of margin trading business in the Chinese stock market, but also provides a good representation of its fluctuation trends. The analysis also shows that the sentiment constructed in this paper is reasonable.

4.4. ISMT fluctuation analysis

In this section, we carry out coarse-grained analysis of fluctuation of ISMT based on sliding window sample entropy. Fig. 5(a) - Fig. 5(c) show the sample entropy with the sliding window size is 15, 30, and 60, respectively. The red area indicates high value, which means sharp fluctuation and the blue area indicates low value, which means gentle fluctuation. From May 2015 to September

Table 5
Result of ADP and PP test.

Variables	ADF	PP	Variables	ADF	PP
ISMT	−4.4968***	−3.6147***	ISMT_Medium	−7.1313***	−7.1699***
SSEC	−3.8073***	−3.8842***	SSEC_Medium	−8.0911***	−6.1118***
SZI	−2.3500**	−2.5119**	SZI_Medium	−7.9963***	−5.9317***
ISMT_Long	−6.4613***	−6.2945***	ISMT_Short	−17.007***	−219.3783***
SSEC_Long	−6.3412***	−4.0966***	SSEC_Short	−15.0749***	−392.3371***
SZI_Long	−4.9887***	−1.6205*	SZI_Short	−11.0805**	−269.8294***

2022, the ISMT experienced several fluctuations, with the sharp fluctuation occurring from May 2015 to March 2016, February to March 2019, and August 2020, respectively, while the other periods mostly showed a reciprocating trend.

5. Empirical results

In this section, we show the empirical results. Specifically, in Section 5.1, we obtain the decomposition and reconstruction sequences of ISMT, SSEC, and SZI based on VMD; Then in Section 5.2, we analyze the fluctuation relationship among the ISMT, SSEC, and SZI in multiple time scales; After that, in Section 5.3, we carry out two robustness tests; Finally, in Section 5.4, we measure the periodicity of ISMT fluctuations in multiple time scales, discuss results during the COVID-19, investigate the fluctuation relationship with more indexes in the Chinese stock market, and reveal the predictive power of ISMT for 11 stock market index returns.

5.1. Index decomposition and reconstruction

The purpose of this paper is to investigate the impact of ISMT on the stock market index fluctuations under different time scales. Therefore, in order to ensure that the scales of each index series are consistent during the experiment, we need to decompose and reconstruct the ISMT, SSEC, and SZI simultaneously using VMD. The effect of VMD is limited by the number of IMFs, a smaller value will result in under-decomposition, which cannot effectively identify and separate the index fluctuation signal with different frequencies. However, a larger value will lead to over-decomposition, which mixes the different frequencies index fluctuation signal. In this paper, we determine this significant parameter by signal-energy based rule and center frequency. Huang and Deng (2021) proposed a improved signal-energy based rule to determine the number of IMFs, in which the core idea is to calculate the ratio of residual energy to the original signal. It can be expressed as Eq. (14):

$$E_{\text{res}} = \frac{\sum_{t=1}^{T} \left| f(t) - \sum_{k=1}^{K} IMF_k(t) \right|^2}{\sum_{t=1}^{T} f(t)^2} \times 100\% \tag{14}$$

where, E_{res} denotes the ratio of residual energy to the original signal; T is the length of sample; K is the number of IMFs; $f(t)$ is the original signal. The result with different IMFs of ISMT, SSEC, and SZI are provided in Fig. 6:

It can be seen in Fig. 6, the residual energy for three indexes tend to flatten around K=10. After that, we obtain the decomposition results and shown in Fig. 7. Next, we reconstruct the IMFs according to the variation interval of standard deviation value, mentioned in Section 3.3. We show the standard deviation of ISMT, SSEC, and SZI with different IMFs in Fig. 8.

We observe that for ISMT, IMF1 has the highest standard deviation with 0.8738, which is much larger than IMF2. In addition, the standard deviation from IMF7 to IMF10 tends to plateau. The change trends of standard deviation for the SSEC and SZI also show the same pattern roughly. Hence, for ISMT, SSEC, and SZI, the low-frequency scale can be reconstructed by $Low\_frequency(t) = IMF_1(t)$; the medium-frequency scale can be reconstructed by $Medium\_frequency(t) = IMF_2(t)+IMF_3(t)+IMF_4(t)+IMF_5(t)+IMF_6(t)$, and the high-frequency scale can be reconstructed by $High\_frequency(t) = IMF_7(t)+IMF_8(t)+IMF_9(t)+IMF_{10}(t)$. The reconstruction results of long-term, medium-term, and short-term fluctuations are shown in Fig. 9. For long-term fluctuation, all three indexes show a trend of decreasing first and then rising. For medium and short term, all three indexes show strong fluctuation characteristics.

5.2. Association analysis of fluctuations

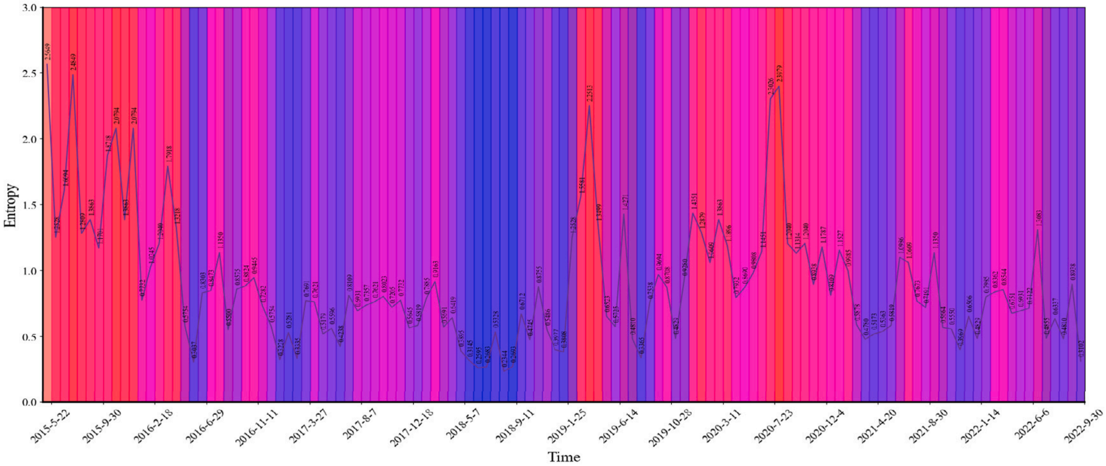
In this section, we develop a regression model to explore the fluctuation relationship between ISMT and stock market indexes at different scales:

$$Index_{i,t} = \alpha_0 + \alpha_1 ISMT_{i,t} + \alpha_2 Index_{i,t-1} + \mu_{i,t} \tag{15}$$

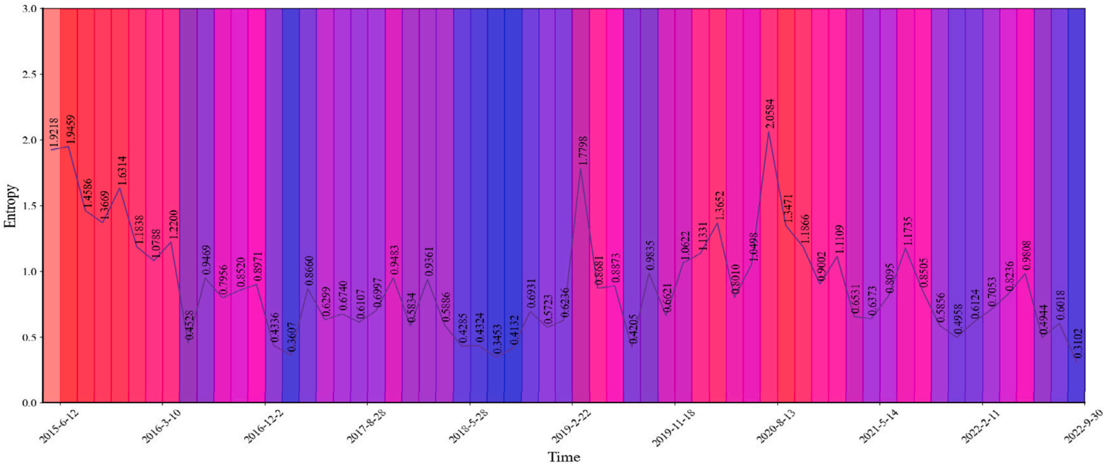
where $Index_{i,t}$ and $ISMT_{i,t}$ indicate fluctuation of stock market index and ISMT in the ith scale, respectively. In addition, we also consider the effect of first-order lag on the results.

We utilize ADF and PP test to carry out stationary test for the original sequence and multiple time scales sequence of ISMT, SSEC, and SZI. Table 5 reports the results and shows thaat all variables are stationary.

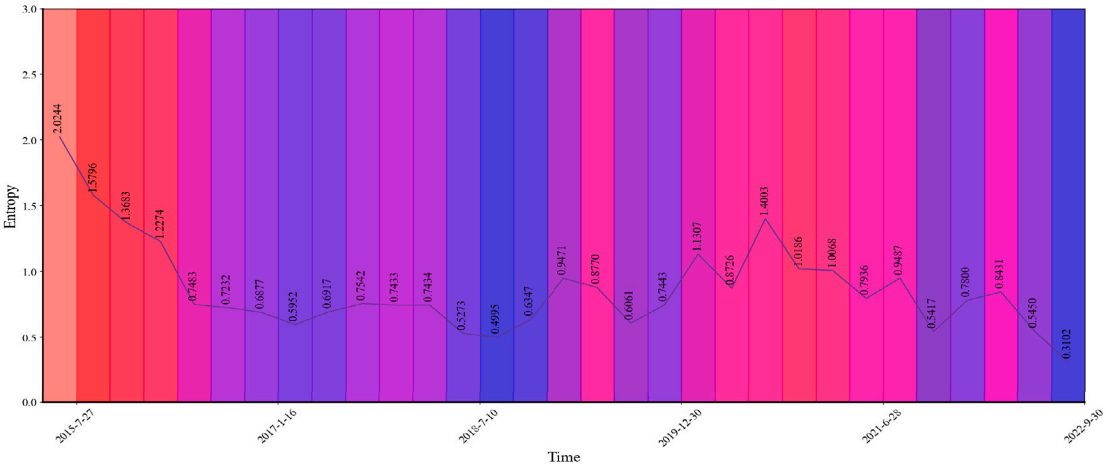
Table 6 shows the regression results. For original sequence, ISMT has a significant positive impact on the fluctuations of both SSEC and SZI, and the degree of impact on SSEC is greater than SZI. However, from a multiple time scales perspective, we observe



(a) Sliding window size is set to 15



(b) Sliding window size is set to 30



(c) Sliding window size is set to 60

Fig. 5. Sliding window sample entropy change trend of ISMT.

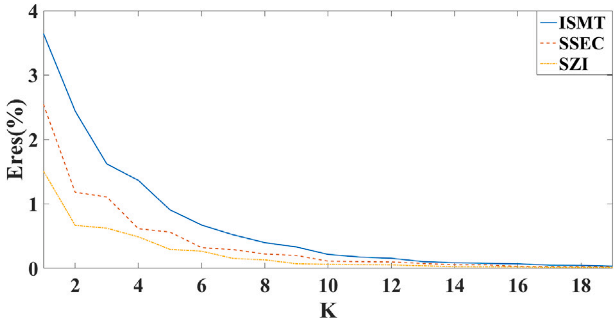


Fig. 6. The signal-energy change with different IMFs.

Table 6
Fluctuation impact of ISMT on SSEC and SZI in multiple time scales (Daily frequency data).

	Original sequence		Low frequency sequence (Long-term trend)		Medium frequency sequence (Medium-term trend)		High frequency sequence (Short-term trend)	
	SSEC	SZI	SSEC	SZI	SSEC	SZI	SSEC	SZI
α_0	−0.0022	−0.0010	−0.0018	−0.0007	−0.0003	−0.0023	−0.0001	−0.0001
	(0.0029)	(0.0022)	(0.0002)	(0.0001)	(0.0016)	(0.0011)	(0.0007)	(0.0007)
α_1	0.0441***	0.0120***	0.0021***	−0.0026***	0.0715***	0.0485***	0.1307***	0.1025***
	(0.0057)	(0.0041)	(0.0005)	(0.0003)	(0.0069)	(0.0049)	(0.0095)	(0.0099)
α_2	0.9507***	0.9779***	0.9945***	1.0014***	0.9269***	0.9417***	−0.5303***	−0.3195***
	(0.0057)	(0.0040)	(0.0000)	(0.0003)	(0.0067)	(0.0059)	(0.0190)	(0.0221)
R^2	0.9843	0.9912	0.9998	0.9999	0.9683	0.9777	0.3507	0.2332
AIC	−1.3223	−1.8972	−6.7251	−7.2804	−2.5052	−3.2322	−4.2315	−4.1612
SC	−1.3128	−1.8881	−6.7160	−7.2712	−2.4960	−3.2231	−4.2224	−4.1521

Note: The figures in parentheses are the standard errors of the parameter estimates, while the ***, ** and * indicate statistical significance at 1%, 5% and 10%,respectively.

some differences. Firstly, for the long-term trend, we discover that the ISMT has a significant positive impact on SSEC, and a significant negative impact on SZI. Secondly, for the medium-term trend and short-term trend, the ISMT has a significant positive impact on the fluctuations of both SSEC and SZI, and the impact on SSEC is greater than SZI still holds. Thirdly, from short-term trend to long-term, the influence of ISMT on SSEC and SZI gradually decreases, indicating that margin trading business have a greater impact on the stock market in a short period.

5.3. Robustness tests

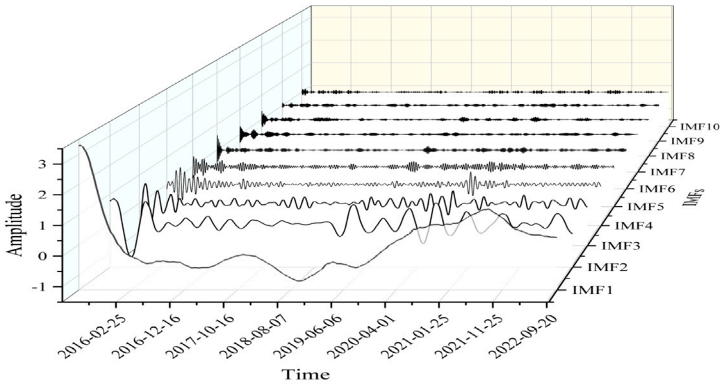
In the previous section, we use a regression model to discuss the impact of ISMT on SSEC and SZI. In this section, we conduct two robustness tests by using weekly frequency data and the EMD decomposition algorithm.

5.3.1. Empirical results with weekly frequency data

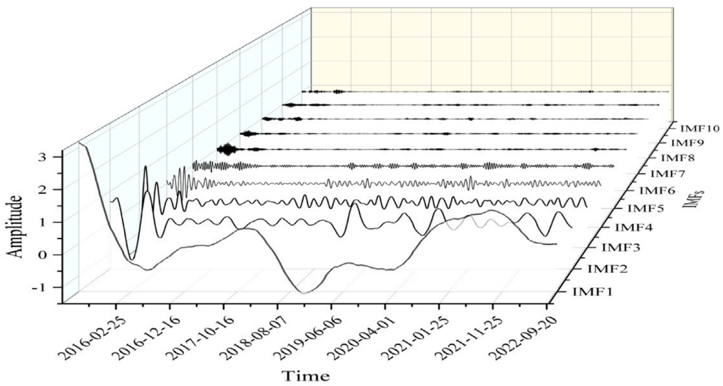
In this section, similar to the research using daily frequency data, we still utilize 12 indicators introduced in Section 4.2, and two-stage PCA mentioned in Section 4.3 to construct weekly frequency ISMT. The Eq. (16) displays the final computation of ISMT with weekly frequency data. Fig. 10 shows the fluctuation trend of ISMT, SSEC, and SZI with weekly frequency data. The three indexes are roughly consistent, which can also indicate that the weekly ISMT constructed in this paper is reasonable. After that, we decompose and reconstruct the weekly frequency ISMT, SSEC, and SZI by using VMD. The results are shown in Fig. 11 and Fig. 12, respectively.

$$\begin{aligned} ISMT\_Index = {} & 0.0063 Investors\_individual_t + 0.0395 Investors\_institutional_t + \\ & 0.2823 Investor\_par_{t-1} + 0.2965 MBA_{t-1} + 0.2147 SSA_{t-1} + 0.2960 MTA_{t-1} + 0.2254 PMTA_{t-1} + \\ & 0.1750 MBB_t + 0.0908 SSB_t + 0.1679 MTB_t + 0.1818 DMTB_t + 0.1554 PMTB_t \end{aligned} \tag{16}$$

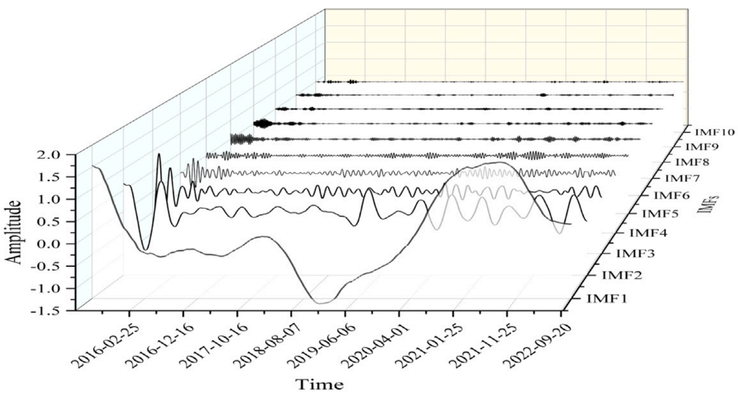
Table 7 reports the results with weekly frequency data. Specifically, for the original sequence, the ISMT has a significant positive impact on SSEC and SZI, and the impact on SSEC is greater than SZI. For the long-term trend, the ISMT has a significant positive impact on SSEC, and a significant negative impact on SZI. For medium-term trend and short-term trend, the ISMT has a significant positive impact on the fluctuations of both SSEC and SZI, and the impact on SSEC is greater than SZI. In addition, the impact of ISMT on SSEC and SZI decreasing from the short-term trend to the long-term still holds. These are consistent with results in Section 5.2.



(a) ISMT



(b) SSEC



(c) SZI

Fig. 7. Decomposition results by VMD (Daily frequency data).

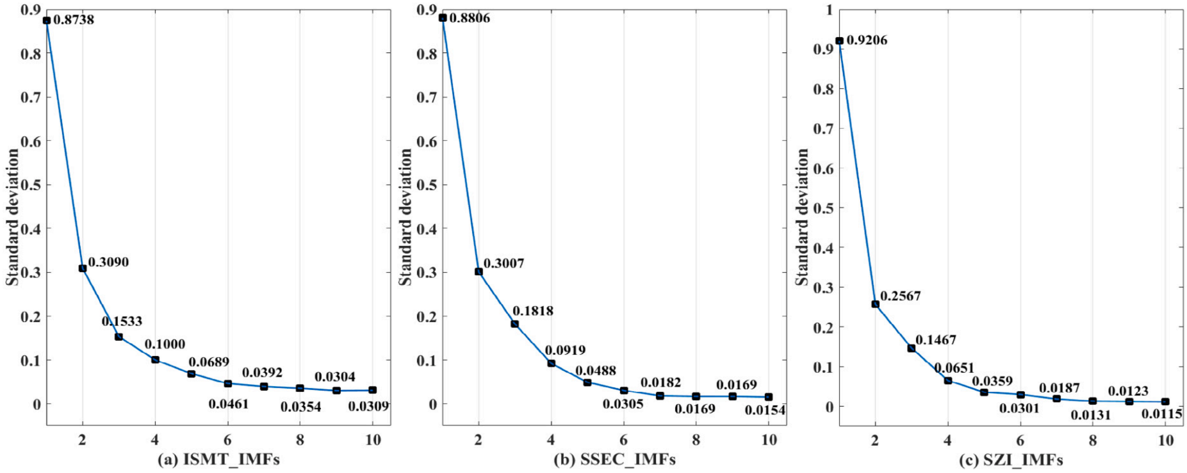


Fig. 8. Standard deviation of ISMT, SSEC, and SZI with different IMFs.

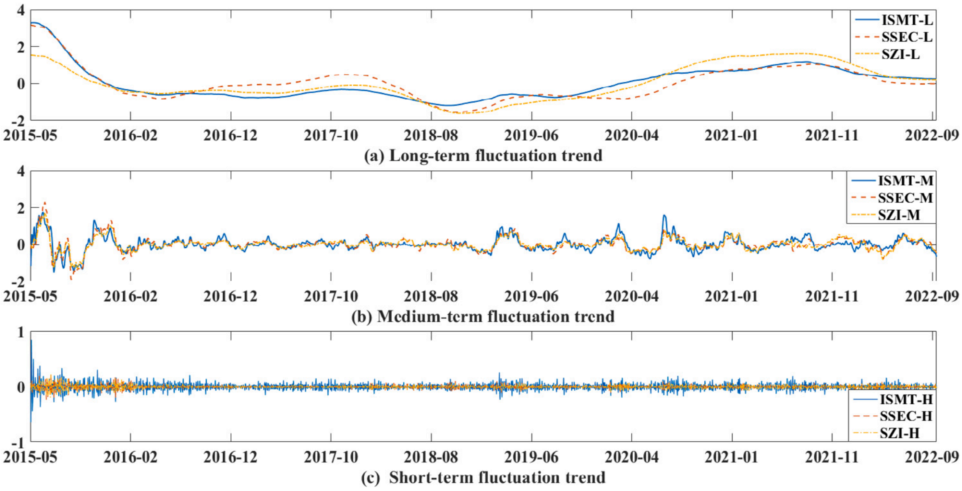


Fig. 9. Comparison of index reconstruction in multiple time scales (Daily frequency data).

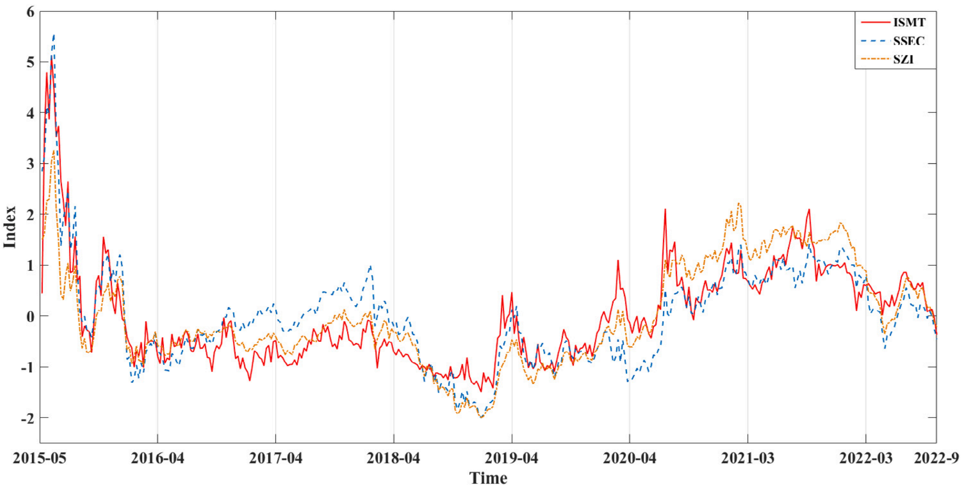
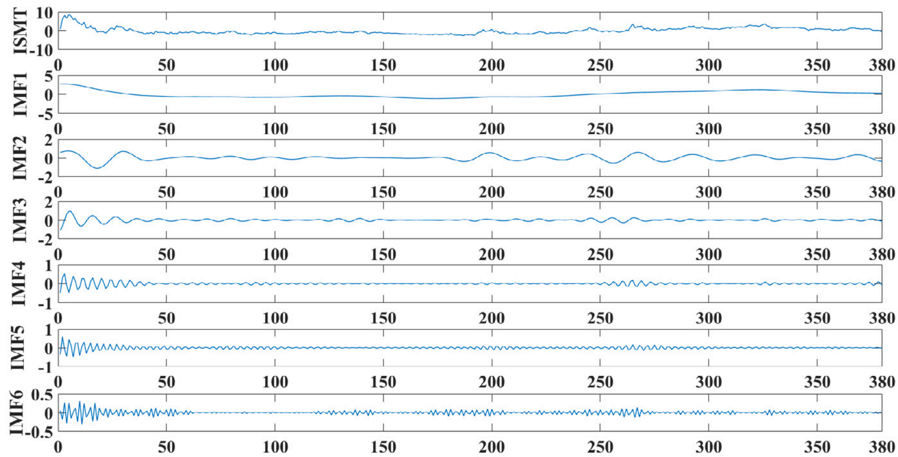
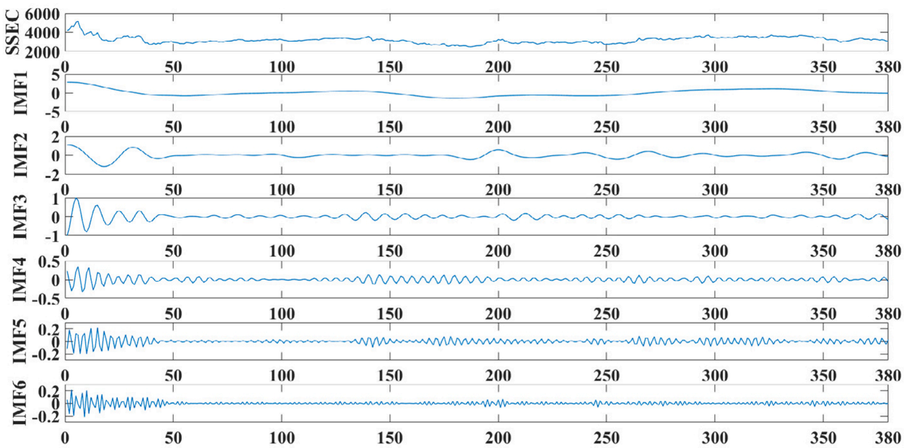


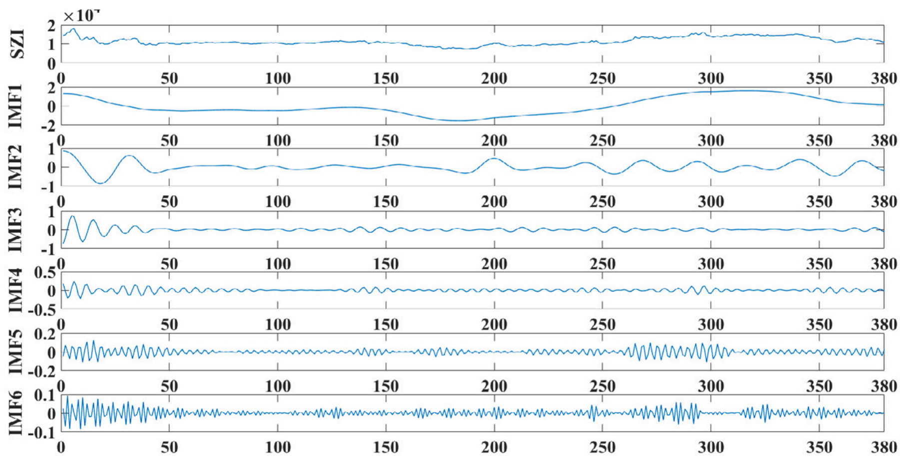
Fig. 10. The fluctuation of ISMT, SSEC, and SZI (Weekly frequency data).



(a) ISMT



(b) SSEC



(c) SZI

Fig. 11. Decomposition results by VMD (Weekly frequency data).

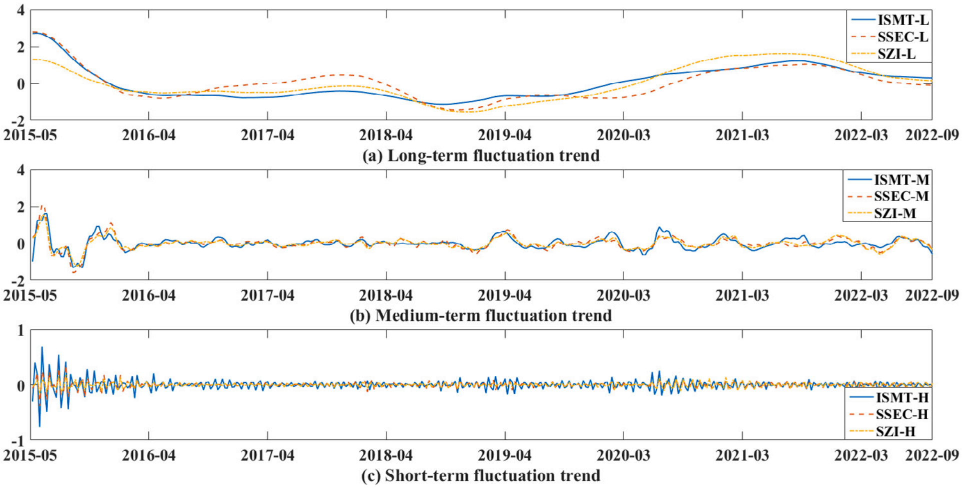


Fig. 12. Comparison of index reconstruction in multiple time scales (Weekly frequency data).

Table 7
Fluctuation impact of ISMT on SSEC and SZI in multiple time scales (Weekly frequency data).

	Original sequence		Low frequency sequence (Long-term trend)		Medium frequency sequence (Medium-term trend)		High frequency sequence (Short-term trend)	
	SSEC	SZI	SSEC	SZI	SSEC	SZI	SSEC	SZI
α_0	−0.0082	−0.0043	−0.0075	−0.0031	−0.0022	−0.0019	−0.0001	−0.0001
	(0.0131)	(0.0098)	(0.0018)	(0.0014)	(0.0069)	(0.0051)	(0.0024)	(0.0018)
α_1	0.1990***	0.1230***	0.0115***	−0.0096***	0.2800***	0.2098***	0.2629***	0.1261***
	(0.0225)	(0.0178)	(0.0043)	(0.0037)	(0.0327)	(0.0245)	(0.0265)	(0.0183)
α_2	0.7875***	0.8738***	0.9751***	1.0048***	0.6964***	0.7280***	−0.3352***	−0.3743***
	(0.0223)	(0.0178)	(0.0042)	(0.0034)	(0.0317)	(0.0292)	(0.0448)	(0.0457)
R^2	0.9345	0.9637	0.9982	0.9991	0.8568	0.8799	0.4767	0.3312
AIC	0.1094	0.4653	−3.8110	−4.3547	−1.1828	−1.7689	−3.2817	−3.8130
SC	0.1406	0.4341	−3.7798	−4.3235	−1.1516	−1.7377	−3.2693	−3.7818

Note: The figures in parentheses are the standard errors of the parameter estimates, while the ***, ** and * indicate statistical significance at 1%, 5% and 10%, respectively.

5.3.2. Index decomposition based on EMD

Although we have utilized the excellent decomposition method VMD to explore the impact of ISMT on SSEC and SZI in multiple time scales, different decomposition methods may lead to different conclusions. To eliminate the influence of this factor on the results as much as possible, we use Empirical Mode Decomposition (EMD) to test.

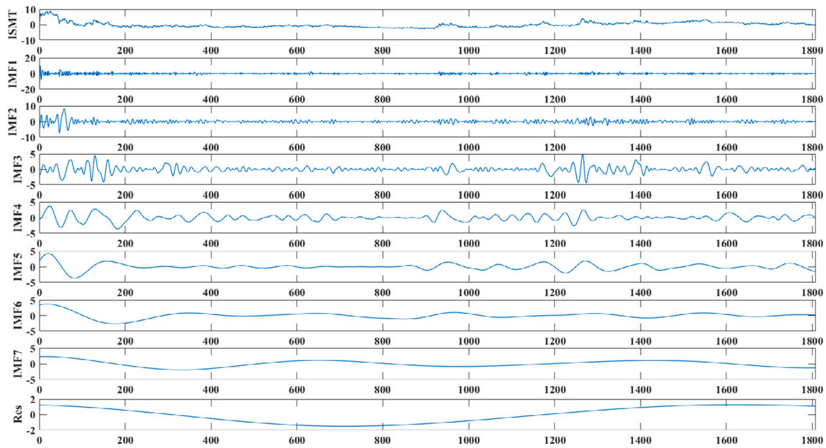
EMD is a commonly used signal decomposition method for nonlinear and non-stationary sequences. This method decomposes sequence into a series of independent intrinsic modes based on scale separation, and explains the generation of data from a novel perspective (Zhang et al., 2008). In this section, referring to decompose and reconstruct method by Zhang et al. (2008), we utilize daily frequency data to carry out robustness test. The results of decomposition and reconstruction are shown in Figs. 13 - 14.

It is worth mentioning that, by comparing Figs. 9 and 14, we find that VMD can depict index fluctuations in a finer granularity, which also demonstrates its superiority. Table 8 reports the regression results by EMD and the results are consistent with the VMD by using daily and weekly frequency data.

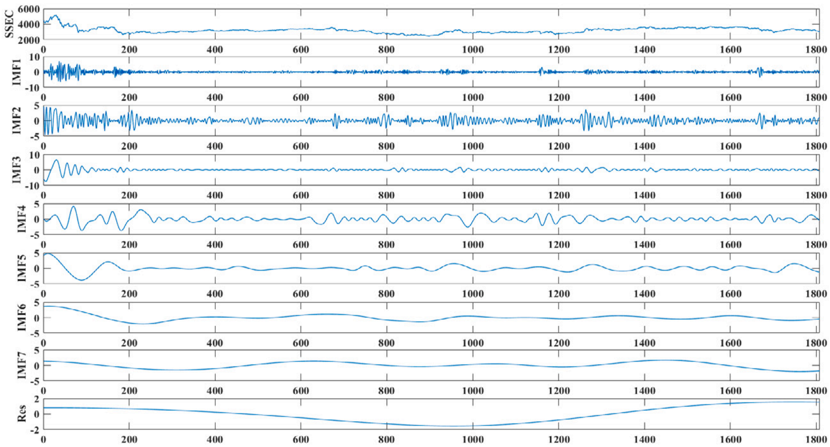
5.4. Further discovery and discussion

5.4.1. Periodicity measurement of ISMT fluctuation in multiple time scales

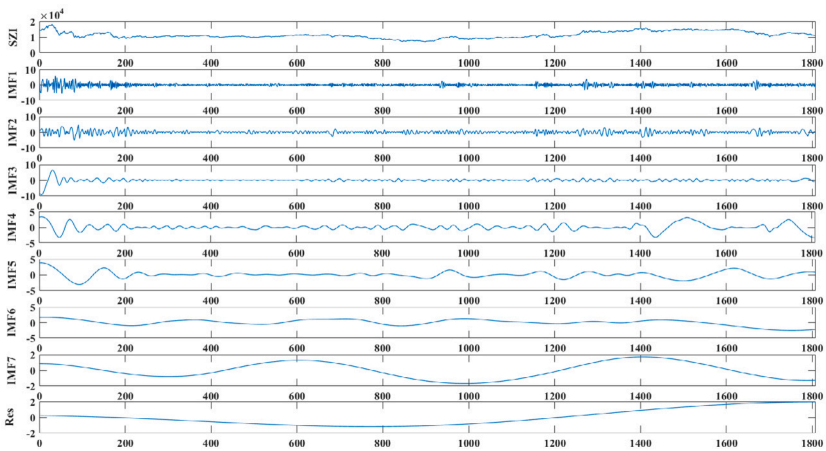
In the contemporary Chinese financial market, margin trading as a leveraged business plays an important role in stabilizing market function and ensuring the steady development of the financial system. Measuring the periodicity of sentiment will help investors or regulators to gain a deeper understanding of the margin trading business operation rules and grasp the market operation conditions in time. To the best of our knowledge, this is the first study to measure the periodicity of investor sentiment. However, for multiple time scales fluctuation of ISMT, it is difficult to directly observe periodicity by the naked eye. To clarify the fluctuation rule of ISMT, we utilize the Fast Fourier Transformation(FFT) (Mayor, Bietti, & Canales-Rodríguez, 2022; Ye et al., 2022) to measure the periodicity of ISMT in the long-term, medium-term, and short-term. The results are shown in Fig. 15. Moreover, we carry out the periodicity conversion and comparative analysis in Table 9.



(a) ISMT



(b) SSEC



(c) SZI

Fig. 13. Decomposition results by EMD.

For daily frequency data of ISMT, the long-term, medium-term, and short-term periodicity are about 904 days, 106.4 days, and 2.165 days, corresponding to approximately 3.616 years, 0.4260 years, and 0.009 years, respectively. For weekly frequency data of ISMT, the long-term, medium-term, and short-term periodicity are about 190 weeks, 22.35 weeks, and 3.14 weeks, corresponding

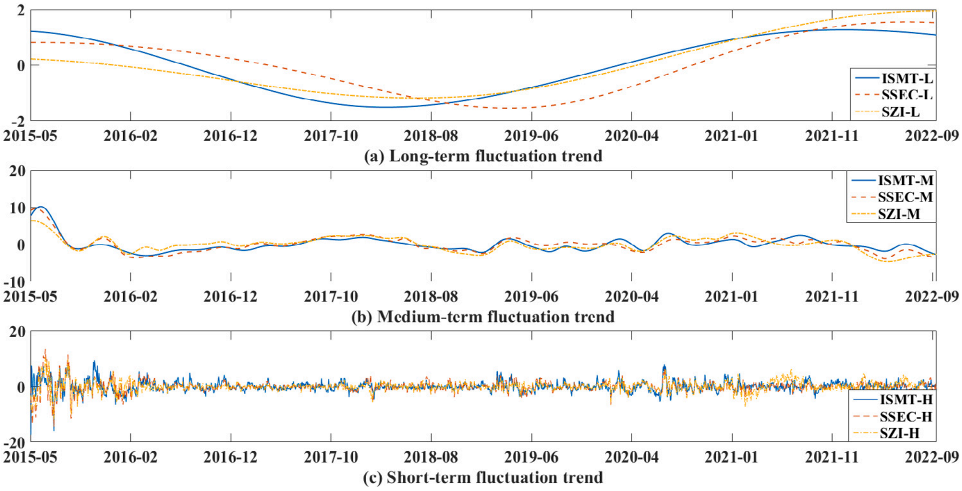


Fig. 14. Comparison of index reconstruction under multiple time scales conditions based on EMD.

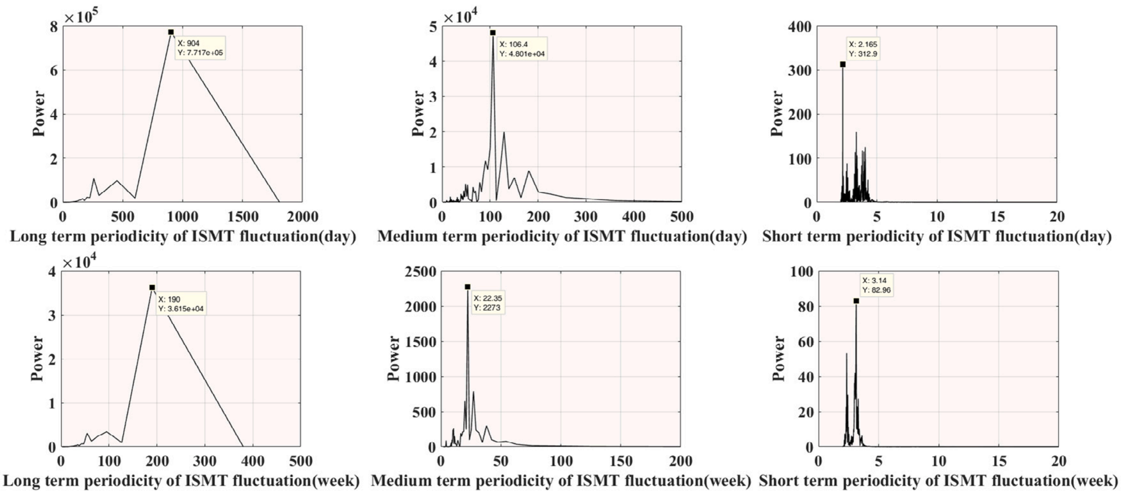


Fig. 15. Fluctuation periodicity of ISMT.

Table 8
Fluctuation impact of ISMT on SSEC and SZI with multiple time scales based on EMD.

	Low frequency sequence (Long-term trend)		Medium frequency sequence (Medium-term trend)		High frequency sequence (Short-term trend)	
	SSEC	SZI	SSEC	SZI	SSEC	SZI
α_0	0.0004	0.0010	−0.0070	−0.0005	−0.0030	−0.0020
	(0.0000)	(0.0000)	(0.0012)	(0.0011)	(0.0337)	(0.0337)
α_1	0.0056***	−0.0006***	0.0058***	0.0042***	0.3137***	0.2054***
	(0.0000)	(0.0001)	(0.0013)	(0.0008)	(0.0200)	(0.0191)
α_2	0.9957***	1.0015***	1.0001***	1.0004***	0.5454***	0.5884***
	(0.0000)	(0.0001)	(0.0012)	(0.0008)	(0.0182)	(0.0184)
R^2	0.9998	0.9997	0.9994	0.9994	0.5200	0.4686
AIC	−9.9750	−9.1627	−3.1379	−3.3080	3.5581	3.5585
SC	−9.9659	−9.1536	−3.1288	−3.2989	3.5672	3.5676

Note: The figures in parentheses are the standard errors of the parameter estimates, while the ***, ** and * indicate statistical significance at 1%, 5% and 10%, respectively.

to approximately 3.654 years, 0.4300 years, and 0.06 years, respectively. It is worth mentioning that the results of short-term periodicity measurement by using daily and weekly data has some differences, which may be caused by large volatility of daily frequency data. However, the results of medium-term and long-term volatility periodicity are generally consistent.

Table 9
Results of ISMT fluctuation periodicity measurement.

	Long term		Medium term		Short term	
Periodicity (daily)	904 days	3.616 years	106.4 days	0.426 years	2.165 days	0.009 years
Periodicity (weekly)	190 weeks	3.654 years	22.35 weeks	0.430 years	3.14 week	0.060 years

Table 10
Fluctuation impact of ISMT on SSEC and SZI in multiple time scales during COVID-19.

	Low frequency sequence (Long-term trend)		Medium frequency sequence (Medium-term trend)		High frequency sequence (Short-term trend)	
	SSEC	SZI	SSEC	SZI	SSEC	SZI
α_0	−0.0050	−0.0037	0.0009	0.0004	−0.0001	−0.0001
	(0.0002)	(0.0002)	(0.0020)	(0.0056)	(0.0009)	(0.0008)
α_1	−0.0030***	−0.0005***	0.0881***	0.0511***	0.1454***	0.1038***
	(0.0005)	(0.0003)	(0.0085)	(0.0056)	(0.0110)	(0.0116)
α_2	0.9969***	0.9964***	0.9185***	0.9407***	−0.5308***	−0.3197***
	(0.0005)	(0.0004)	(0.0073)	(0.0060)	(0.0190)	(0.0222)
α_3	0.0040***	0.0066***	−0.0029	−0.0016	0.0001	0.0001
	(0.0007)	(0.0004)	(0.0034)	(0.0023)	(0.0014)	(0.0015)
α_4	0.0082***	0.0027***	−0.0309***	−0.0058	−0.0582***	−0.0048
	(0.0009)	(0.0009)	(0.0096)	(0.0063)	(0.0219)	(0.0228)
R^2	0.9997	0.9998	0.9685	0.9778	0.3532	0.1332
AIC	−6.9349	−7.4431	−2.5092	−3.2307	−4.2332	−4.1590
SC	−6.9197	−7.4278	−2.4939	−3.2251	−4.2180	−4.1438

Note: Data frequency is daily; The figures in parentheses are the standard errors of the parameter estimates, while the ***, ** and * indicate statistical significance at 1%, 5% and 10%, respectively.

5.4.2. Results during COVID-19 pandemic

Since early 2020, the COVID-19 pandemic has severely affected the global economy and caused an unprecedented impact on stock market, development of human society, and resources. By February 2023, the COVID-19 still continues in some regions of China. In this context, it is necessary to understand the impact of ISMT on stock market index fluctuation during the COVID-19 pandemic (Goel & Dash, 2021; Van Hoang & Syed, 2021).

The National Health Commission of the People's Republic of China first issued "The Bulletin of Viral Pneumonia of Unknown Cause from Wuhan Municipal Health Commission" on January 11, 2020. Therefore, we use January 11, 2020 as the time point and introduce dummy variables to distinguish before and during the COVID-19 pandemic. For that, we consider the model defined as follow:

$$Index_{i,t} = \alpha_0 + \alpha_1 ISMT_{i,t} + \alpha_2 Index_{i,t-1} + \alpha_3 D + +\alpha_4 D * ISMT_{i,t} + \mu_{i,t} \tag{17}$$

$$D = \begin{cases} 0, Before\ COVID-19\ Pandemic \\ 1, During\ COVID-19\ Pandemic \end{cases} \tag{18}$$

where, the $Index_{i,t}$ and $ISMT_{i,t}$ are stock market index and investor sentiment fluctuation in ith scale, respectively. We consider the effect of first-order lag on the results. The D is the dummy variable and $D * ISMT_{i,t}$ is the interaction term; α_0 is the intercept term and $\mu_{i,t}$ is residual. Table 10 presents the results.

From Table 10, we find that the impact of the COVID-19 on the fluctuation between ISMT and two indexes is asymmetric. According to the interaction term coefficient, for the short and medium-term fluctuation trends, the COVID-19 pandemic has weakened the impact of ISMT on SSEC, while the impact on SZI is not significant. For the long-term fluctuation trend, the COVID-19 pandemic has a significant positive impact on the fluctuation between ISMT and two indexes, and the degree of impact on SSEC is stronger than SZI. All of this indicates that, in the long run, the COVID-19 pandemic is exacerbating the impact of ISMT on the stock market.

5.4.3. More indexes results in the Chinese stock market

In this section, we examine the impact of ISMT on more indexes in the Chinese stock market. It is a widely recognized fact that mainland China hosts two primary stock exchanges: the Shanghai Stock Exchange and the Shenzhen Stock Exchange. Indeed, the different stock exchanges construct various market indexes based on capitalization or liquidity of the listed companies. In this section, we chooses nine commonly used indexes in the Chinese stock market, and introduce them as follows:

- **SSE50:** The sample consists of 50 stocks with the largest and the most liquid in the Shanghai stock market, reflecting the overall situation of leading companies with the most market influence.
- **SSE380:** The sample consists of 380 stocks with moderate size, good growth, and strong profitability after removing the most influential 180 constituent stocks in the Shanghai stock market.

- **SSE100:** The top 100 stocks in SSE380 are selected as samples, reflecting the larger and better developed stocks in the Shanghai stock market.
- **SZ100:** Contains the 100 stocks with the largest market capitalization and the most active transactions in the Shenzhen stock market.
- **SZ200:** The other 200 stocks with larger market capitalization and active trading in addition to the SZ100 constituent stocks.
- **SZ700** The bottom 700 stocks in the SZ1000 constituent stocks, reflecting the overall situation of small and medium-sized companies.
- **CSI100:** The 100 stocks with the largest capitalization and the best liquidity in the Shanghai and Shenzhen stock market, reflecting the overall situation of top companies with the highest market influence ability.
- **CSI200:** The 200 constituent stocks, excluding the CSI100 stocks, reflecting the overall status of medium-sized companies in the Shanghai and Shenzhen stock market.
- **CSI500:** After excluding the constituents stocks of the CSI300, the top 500 stocks of total market capitalization, reflecting the overall situation of small and medium-sized companies in the Chinese A-share market.

Table 11 reports the regression results with different indexes. We find that no matter from Shanghai stock market, Shenzhen stock market or the overall Chinese stock market, the ISMT has less impact on the index composed of high-quality listed companies with large market capitalization and high liquidity than the composed of medium market value and low liquidity listed companies. More specifically, in Panel A and Panel B, from long-term trend perspective, the ISMT has a significant negative effect on SSE50 and SZ100, although the effect is weak. In addition, the ISMT has a significant positive effect on the other indexes in different scales. In Panel C, from long-term trend perspective, the ISMT has a significant negative effect on CSI100 and CSI200, and positive effect on the other indexes in different scales.[4]

We speculate that this is related to the robust risk tolerance and high liquidity of large-sized listed companies. In the Chinese A-share market, large-sized companies are often industry leaders, or important industries such as banking, real estate, infrastructure construction, and high-tech innovation, all of which are related to the lifeblood of the Chinese economy. They are usually more influenced by policies and have limited sensitivity to external funds. In contrast, small and medium-sized listed companies are more growth-type, eager to rapidly develop, expand and consolidate their advantages in the market. However, these companies have insufficient risk tolerance and lack the ability to adapt the dynamic environment in the stock market, which leads to magnify the effect through emerging business modes, such as margin trading.

5.4.4. Predictive power of ISMT for stock market returns

As mentioned earlier, ISMT is a novel investor sentiment indicator constructed under the margin trading business scenario. However, the precise mechanism of how ISMT has predictive power for Chinese stock market returns is unclear as well. In this subsection, we choose 11 stock market index returns including SSEC, SZI, SSE50, SSE100, SSE380, SZ100, SZ200, SZ700, CSI100, CSI200, and CSI500[5] to validate the predictive power of ISMT. In addition, we compare predictive power of ISMT with a composite investor sentiment index called CICSI (Yi & Mao, 2009) which is the most famous in the Chinese stock market. Different with Baker-Wurgler sentiment index (Wurgler & Baker, 2006), the CICSI is more suitable for the Chinese stock market (Han & Shi, 2022; Song, Gong, Zhang, & Yu, 2023). This index based on six single sentiment indicators, including closed-end fund discount (CEFD), turnover (TURN), first-day returns of IPOs (RIPO), the number of IPOs (NIPO), the number of newly opened individual investor accounts (NA), and consumer confidence index (CCI).

Usually, the traditional CICSI data could be collected from the CSMAR database and are updated monthly. However, this is not entirely applicable to the research in this paper. Specifically, our main works are carried out on the daily frequency of ISMT. On the one hand, the daily frequency data is more volatile and more granular; On the other hand, it can better reflect the dynamic characteristics of the stock market than monthly data. In the face of inconsistent data frequency, some literature chooses to fill daily data with monthly data. However, it reduces the information content to some extent. For this reason, considering the frequency of data updates, this paper uses daily turnover to replace monthly turnover and constructs the daily comprehensive sentiment index of the Chinese stock market called CICSI_D by referring to the method used in Yi and Mao (2009).[6] To investigate the predictive power of investor sentiment for stock market index returns, the regression model is described as:

$$R_{t+1} = \alpha_0 + \beta_1 Sent_t + \beta_2 lnVol_t + \beta_3 lnVal_t + \beta_4 lnAmo_t + \mu_{t+1} \tag{19}$$

where R_{t+1} is the return in month $t+1$ and $Sent_t \in \left\{ ISMT_t, CICSI\_D_t \right\}$ is investor sentiment in month *t*. Moreover, we choose log value of trading volume ($lnVol$), log value of trading amount ($lnAmo$), and log value of circulation market value ($lnVal$) as control variables that are widely used in the finance literature (Lv & Wu, 2019, 2020). For each index, we calculate four models, where Model1 and Model2 indicate the R_{t+1} are calculated by $R_{t+1} = (P_{t+1}/P_t) - 1$; Model3 and Model4 are calculated by $R_{t+1} = ln(P_{t+1}/P_t)$.

Table 12 shows that investor sentiment has predictive power for SSEC and SZI returns. Specifically, for Model1 and Model2 about SSEC, the coefficients of ISMT and CICSI_D as explanatory variables are 0.0029 and 0.0053, and both of which are significant at the

[4] Due to the limited length of the article, the decomposition results of the above indexes are not shown in this paper. The detailed decomposition results of each index can be obtained from the authors.

[5] SSEC, SZI, SSE50, SSE100, SSE380, SZ100, SZ200, SZ700, CSI100, CSI200, and CSI500 are introduced in Section 5.4.3.

[6] Due to the limited length of the article, the construction process of CICSI_D are not shown in this paper. The detailed results can be obtained from the authors.

Table 11
Fluctuation impact of ISMT on nine indexes in multiple time scales.

Panel A									
	SSE50			SSE100			SSE380		
	Long-term trend	Medium-term trend	Short-term trend	Long-term trend	Medium-term trend	Short-term trend	Long-term trend	Medium-term trend	Short-term trend
α_0	−0.0002	−0.0005	−0.0001	−0.0009	−0.0001	−0.0001	−0.0013	−0.0001	−0.0001
	(0.0001)	(0.0009)	(0.0007)	(0.0002)	(0.0015)	(0.0006)	(0.0002)	(0.0016)	(0.0006)
α_1	−0.0039***	0.0177***	0.0952***	0.0027***	0.0497***	0.1009***	0.0047***	0.0633***	0.1174***
	(0.0002)	(0.0035)	(0.0099)	(0.0003)	(0.0058)	(0.0082)	(0.0003)	(0.0062)	(0.0089)
α_2	1.0019***	0.9683***	−0.3227***	0.9961***	0.9465***	−0.5515***	0.9934***	0.9392***	−0.5384***
	(0.0002)	(0.0051)	(0.0218)	(0.0004)	(0.0060)	(0.0193)	(0.0003)	(0.0060)	(0.0194)
R^2	0.9999	0.9749	0.1426	0.9998	0.9709	0.3326	0.9999	0.9720	0.3287
AIC	−7.4732	−3.4941	−4.1562	−7.1532	−2.6671	−4.5447	−7.2415	−2.5577	−4.3753
SC	−7.4640	−3.4849	−4.1470	−7.1441	−2.6580	−4.5335	−7.2360	−2.5482	−4.3662
Panel B									
	SZ100			SZ200			SZ700		
	Long-term trend	Medium-term trend	Short-term trend	Long-term trend	Medium-term trend	Short-term trend	Long-term trend	Medium-term trend	Short-term trend
α_0	0.0002	−0.0002	−0.0001	−0.0019	0.0001	−0.0001	−0.0014	0.0002	−0.0001
	(0.0001)	(0.0008)	(0.0005)	(0.0001)	(0.0014)	(0.0006)	(0.0001)	(0.0013)	(0.0008)
α_1	−0.0019***	0.0231***	0.0723***	0.0029***	0.0562***	0.1110***	0.0016***	0.0565***	0.1172***
	(0.0002)	(0.0031)	(0.0069)	(0.0003)	(0.0059)	(0.0081)	(0.0002)	(0.0049)	(0.0107)
α_2	1.0013***	0.9576***	−0.3508***	0.9947***	0.9398***	−0.5269***	0.9970***	0.9468***	−0.3013***
	(0.0002)	(0.0026)	(0.0219)	(0.0003)	(0.0001)	(0.0195)	(0.0002)	(0.0049)	(0.0222)
R^2	0.9998	0.9762	0.1535	0.9997	0.9750	0.3143	0.9997	0.9802	0.1283
AIC	−7.7642	−3.9572	−4.8939	−7.4916	−2.8231	−4.5760	−7.6452	−2.9759	−4.0327
SC	−7.7550	−3.9480	−4.8848	−7.4824	−2.8139	−4.5668	−7.6361	−2.9667	−4.0237
Panel C									
	CSI100			CSI200			CSI500		
	Long-term trend	Medium-term trend	Short-term trend	Long-term trend	Medium-term trend	Short-term trend	Long-term trend	Medium-term trend	Short-term trend
α_0	−0.0001	−0.0004	−0.0001	−0.0009	−0.0002	−0.0001	−0.0016	0.0001	−0.0003
	(0.0001)	(0.0009)	(0.0006)	(0.0002)	(0.0012)	(0.0007)	(0.0002)	(0.0015)	(0.0006)
α_1	−0.0032***	0.0167***	0.0899***	−0.0020***	0.0587***	0.1176***	0.0037***	0.0666***	0.1199***
	(0.0002)	(0.0031)	(0.0088)	(0.0004)	(0.0054)	(0.0105)	(0.0003)	(0.0059)	(0.0097)
α_2	1.0015***	0.9693***	−0.3188**	1.0005***	0.9287***	−0.3056***	0.9941***	0.9344***	−0.5379***
	(0.0001)	(0.0050)	(0.0218)	(0.0003)	(0.0065)	(0.0222)	(0.0003)	(0.0059)	(0.0194)
R^2	0.9998	0.9766	0.1426	0.9998	0.9716	0.1315	0.9997	0.9741	0.3278
AIC	−7.4940	−3.7407	−4.3925	−7.2007	−3.1741	−4.0587	−7.2276	−2.7093	−4.4267
SC	−7.4848	−3.7316	−4.3834	−7.1915	−3.1649	−4.0495	−7.2185	−2.7001	−4.4176

Note: Data frequency is daily; Panel A reports the three indexes in Shanghai stock market, where, the SSE50, SSE100, SSE380 are consist of the most promising, well-developed stocks, and medium-size companies, respectively; Panel B reports the three indexes in Shenzhen stock market, where, the SZ100, SZ200, SZ700 are consist of the most promising, well-developed stocks, and small-size companies, respectively; Panel C reports the three indexes in the Chinese stock market, where, the CSI100, CSI200, CSI500 are consist of the most promising, well-developed stocks, and medium-size companies, respectively; The figures in parentheses are the standard errors of the parameter estimates, while the ***, ** and * indicate statistical significance at 1%, 5% and 10%, respectively.

1% level, respectively. For Model1 and Model2 about SZI, the coefficients of ISMT and CICSI_D as explanatory variables are 0.0022 and 0.0051, and both of which are significant at the 1% level, respectively. Model3 and Model4 in both SSEC and SZI show similar results. First, ISMT has a greater predictive power for SSEC than SZI, in other words, the impact on SSEC is larger. This finding corresponds to the conclusion in Section 5.2. Another interesting finding is that CICSI_D has greater predictive power than ISMT. This is normal, because ISMT is an investor sentiment index constructed in one of the specific business scenarios in the market, such as margin trading. However, CICSI_D is a comprehensive sentiment index that responds to the overall Chinese stock market. The two types of investor sentiment have different levels of information content. These two types of investor sentiments are analogous to the relationship between the whole and the part, where the information content is different, and reflecting the whole information may be higher.

We also evaluate the predictive power of investor sentiment for other nine stock market index returns, which the indexes are mentioned in Section 5.4.3. The Tables 13–15 report the regression results. First, for all nine index returns, both ISMT and CICSI_D have a significant predictive power. Second, the CICSI_D has better predictive power than ISMT in almost all situations (with the exception of CSI200 and CSI500). Third, there is an increasing predictive power of ISMT for the stock market index return which is composed of large-sized listed companies to composed of small and medium-sized listed companies. For example, for SSE50 to SSE380, the predictive power of ISMT increases from 0.0010 to 0.0036. For SZ100 to SZ700, the predictive power of ISMT increases from 0.0021 to 0.0029. For CSI100 to CSI500, the predictive power of ISMT increases from 0.0010 to 0.0034. To summarize, the ISMT has significant predictive power for the 11 Chinese stock market indexes returns. Although it is weaker than CICSI_D, but this is normal and understandable. This does not affect that we find a novel and interesting investor sentiment indicator. On the

Table 12
Predictive power of investor sentiment for SSEC and SZI returns.

	SSEC				SZI			
	Model1	Model2	Model3	Model4	Model1	Model2	Model3	Model4
ISMT	0.0029***		0.0028***		0.0022***		0.0021***	
	(0.0004)		(0.0004)		(0.0004)		(0.0004)	
CICSI_D		0.0053***		0.0050***		0.0051***		0.0047***
		(0.0013)		(0.0013)		(0.0011)		(0.0011)
*ln*Vol	0.0125***	0.0051*	0.0122***	0.0050*	0.0102***	0.0074***	0.0100***	0.0073***
	(0.0032)	(0.0029)	(0.0032)	(0.0029)	(0.0026)	(0.0024)	(0.0025)	(0.0024)
*ln*Val	0.0020***	0.0093***	0.0024***	0.0092***	−0.0082***	0.0006	−0.0075**	0.0007
	(0.0022)	(0.0031)	(0.0022)	(0.0032)	(0.0030)	(0.0030)	(0.0030)	(0.0030)
*ln*Amo	−0.0211***	−0.0119***	−0.0209***	−0.0116***	−0.0141***	−0.0107***	−0.0138***	−0.0105***
	(0.0036)	(0.0033)	(0.0036)	(0.0033)	(0.0027)	(0.0024)	(0.0027)	(0.0024)
α_0	0.253***	−0.0792	0.2395***	−0.0818	0.4309***	0.1170	0.4097***	0.1095
	(0.0634)	(0.0622)	(0.0640)	(0.0627)	(0.0937)	(0.0742)	(0.0944)	(0.0748)
N	1808	1808	1808	1808	1808	1808	1808	1808
R^2	0.028	0.012	0.026	0.011	0.018	0.0154	0.0166	0.0138

Note: The figures in parentheses are the standard errors of the parameter estimates, while the ***, ** and * indicate statistical significance at 1%, 5% and 10%, respectively.

Table 13
Predictive power of investor sentiment for SSE50, SSE100, and SSE380 returns.

	SSE50				SSE100				SSE380			
	Model1	Model2	Model3	Model4	Model1	Model2	Model3	Model4	Model1	Model2	Model3	Model4
ISMT	0.0010***		0.0010***		0.0030***		0.0029***		0.0036***		0.0035***	
	(0.0003)		(0.0003)		(0.0005)		(0.0005)		(0.0005)		(0.0005)	
CICSI_D		0.0039***		0.0037***		0.0036**		0.0032**		0.0040**		0.0035**
		(0.0011)		(0.0010)		(0.0014)		(0.0014)		(0.0016)		(0.0016)
*ln*Vol	−0.0087***	−0.0103***	−0.0088***	−0.0101***	0.0047*	0.0015	0.0045*	0.0014	0.0111***	0.0059*	0.0109***	0.0057*
	(0.0023)	(0.0024)	(0.0024)	(0.0025)	(0.0026)	(0.0025)	(0.0025)	(0.0026)	(0.0035)	(0.0035)	(0.0035)	(0.0035)
*ln*Val	−0.0177***	−0.0142***	−0.0173***	−0.0138***	−0.0010	0.0050	−0.0003	0.0051	−0.0044*	0.0044	−0.0037	0.0046
	(0.0047)	(0.0046)	(0.0047)	(0.0047)	(0.0027)	(0.0032)	(0.0027)	(0.0032)	(0.0025)	(0.0027)	(0.0037)	(0.0027)
*ln*Amo	0.0060**	0.0064**	0.0058**	0.0062**	−0.0141***	−0.0064**	−0.0142***	−0.0063**	−0.0204***	−0.0101***	−0.0203***	−0.0098***
	(0.0026)	(0.0026)	(0.0026)	(0.0025)	(0.0030)	(0.0028)	(0.0029)	(0.0737)	(0.0036)	(0.0034)	(0.0037)	(0.0034)
α_0	0.5544***	0.4573***	0.5431***	0.4482***	0.2856***	−0.0280	0.2676***	−0.0362	0.4478***	0.0049	0.4281***	−0.0046
	(0.1270)	(0.1214)	(0.1275)	(0.1220)	(0.0819)	(0.0730)	(0.0827)	(0.0737)	(0.0878)	(0.0649)	(0.0887)	(0.0656)
N	1808	1808	1808	1808	1808	1808	1808	1808	1808	1808	1808	1808
R^2	0.0153	0.0176	0.0153	0.0172	0.024	0.0051	0.0231	0.005	0.0308	0.0067	0.0294	0.0061

Note: The figures in parentheses are the standard errors of the parameter estimates, while the ***, ** and * indicate statistical significance at 1%, 5% and 10%, respectively.

Table 14
Predictive power of investor sentiment for SZ100, SZ200, and SZ700 returns.

	SZ100				SZ200				SZ700			
	Model1	Model2	Model3	Model4	Model1	Model2	Model3	Model4	Model1	Model2	Model3	Model4
ISMT	0.0021***		0.0021***		0.0024***		0.0023***		0.0029***		0.0028***	
	(0.0004)		(0.0004)		(0.0005)		(0.0004)		(0.0005)		(0.0005)	
CICSI_D		0.0031***		0.0029***		0.0052***		0.0049***		0.0061***		0.0058***
		(0.0011)		(0.0011)		(0.0011)		(0.0012)		(0.0012)		(0.0012)
*ln*Vol	−0.0040	−0.0045*	−0.0041	−0.0046*	0.0089***	0.0054**	0.0087***	0.0052*	0.0122***	0.0089***	0.0120***	0.0087***
	(0.0026)	(0.0027)	(0.0027)	(0.0023)	(0.0029)	(0.0027)	(0.0029)	(0.0027)	(0.0026)	(0.0025)	(0.0027)	(0.0022)
*ln*Val	−0.0089*	−0.0063*	−0.0085*	−0.0061*	−0.0068**	0.0018	−0.0061**	0.0021	−0.0154***	−0.0032	−0.0147***	−0.0028
	(0.0051)	(0.0053)	(0.0052)	(0.0053)	(0.0027)	(0.0027)	(0.0027)	(0.0028)	(0.0032)	(0.0027)	(0.0032)	(0.0027)
*ln*Amo	0.0015	0.0020	0.0016	0.0019	−0.0124***	−0.0083***	−0.0122***	−0.0082***	−0.0145***	−0.0103***	−0.0144***	*0.0101***
	(0.0029)	(0.0028)	(0.0029)	(0.0028)	(0.0029)	(0.0025)	(0.0030)	(0.0025)	(0.0025)	(0.0022)	(0.0026)	(0.0023)
α_0	0.3863***	0.2237	0.3752***	0.2182	0.3620***	0.0498	0.3404***	0.0407	0.6222***	0.1903**	0.6001***	0.1799**
	(0.1370)	(0.1370)	(0.1379)	(0.1379)	(0.0883)	(0.0699)	(0.0891)	(0.0706)	(0.1077)	(0.0761)	(0.1087)	(0.0737)
N	1808	1808	1808	1808	1808	1808	1808	1808	1808	1808	1808	1808
R^2	0.0198	0.0071	0.0188	0.0062	0.0152	0.0125	0.014	0.011	0.0247	0.0181	0.023	0.0163

Note: The figures in parentheses are the standard errors of the parameter estimates, while the ***, ** and * indicate statistical significance at 1%, 5% and 10%,respectively.

one hand, the constructed ISMT is valid; on the other hand, it is essential to consider the impact of margin trading business in the Chinese stock market.

6. Conclusion

Although the margin trading is a emerging business in the securities market, its impact on the market cannot be ignored. This paper takes margin trading business as a research scenario, and seeks to understand the impact of investor sentiment on stock market index fluctuation in multiple time scales. Firstly, we construct investor sentiment index of margin trading business in the Chinese stock market (ISMT) based on behavioral finance theory and two-stage PCA. Secondly, we decompose the ISMT, SSEC, and SZI original index sequences based on VMD. After that, we reconstruct decomposition results into multiple time scale sequences that reflect the long-term, medium-term, and short-term fluctuation characteristics. Thirdly, we investigate the impact of ISMT on SSEC and SZI fluctuations in different time scales. We find that, for long-term trend, the ISMT has a significant positive impact on SSEC, and a significant negative impact on SZI. For medium-term trend and short-term trend, the ISMT has a significant positive impact

Table 15
Predictive power of investor sentiment for CSI100, CSI200, and CSI500 returns.

	CSI100				CSI200				CSI500			
	Model1	Model2	Model3	Model4	Model1	Model2	Model3	Model4	Model1	Model2	Model3	Model4
ISMT	0.0010***		0.0010***		0.0022***		0.0020***		0.0034***		0.0020***	
	(0.0003)		(0.0003)		(0.0005)		(0.0005)		(0.0004)		(0.0005)	
CICSI_D		0.0030***		0.0028***		0.0015**		0.0011**		0.0025**		0.0013**
		(0.0011)		(0.0010)		(0.0013)		(0.0014)		(0.0013)		(0.0014)
*ln*Vol	−0.0066**	−0.0077***	−0.0066**	−0.0075**	0.0008**	0.0029**	0.0006**	0.0030*	0.0141***	0.0070*	0.0007***	−0.0030
	(0.0029)	(0.0030)	(0.0029)	(0.0029)	(0.0035)	(0.0034)	(0.0036)	(0.0030)	(0.0029)	(0.0027)	(0.0035)	(0.0035)
*ln*Val	−0.0127**	−0.0094*	−0.0122**	−0.0090*	−0.0013**	−0.0017*	−0.0008*	−0.0016*	−0.0112***	−0.0016	−0.0008***	−0.0016
	(0.0053)	(0.0053)	(0.0033)	(0.0054)	(0.0035)	(0.0039)	(0.0035)	(0.0040)	(0.0029)	(0.0030)	(0.0035)	(0.0039)
*ln*Amo	0.0037	0.0044	0.0035	0.0042	−0.0071*	−0.0010*	−0.0070*	−0.0009*	−0.0203***	−0.0080***	−0.0070*	0.0010
	(0.0032)	(0.0032)	(0.0032)	(0.0032)	(0.0038)	(0.0034)	(0.0038)	(0.0034)	(0.0031)	(0.0027)	(0.0038)	(0.0034)
α_0	0.4208***	0.3162**	0.4077***	0.3062**	0.2063**	0.0832**	0.1906**	0.0781**	0.6031***	0.1212**	0.1906**	0.07807**
	(0.1393)	(0.1363)	(0.4001)	(0.1370)	(0.0887)	(0.0909)	(0.0089)	(0.0916)	(0.1011)	(0.0762)	(0.0089)	(0.0916)
N	1808	1808	1808	1808	1808	1808	1808	1808	1808	1808	1808	1808
R^2	0.0109	0.0103	0.0101	0.01	0.0127	0.0021	0.012	0.0018	0.0294	0.0053	0.0118	0.0018

Note: The figures in parentheses are the standard errors of the parameter estimates, while the ***, ** and * indicate statistical significance at 1%, 5% and 10%, respectively.

on the fluctuations of both SSEC and SZI, and the impact on SSEC is greater than SZI. In addition, we discover that the impact of ISMT on SSEC and SZI decreases from short to long-term. The robustness test also supports the above conclusions.

Moreover, this study carries out further discussion from four aspects. Specifically, we measure the fluctuation periodicity of ISMT and find the long-term roughly 3.6 years and the medium-term roughly 0.42 years. Then, we discuss the results during the COVID-19 pandemic. The results show that the COVID-19 pandemic is exacerbating the impact of ISMT on the stock market, and has a greater impact on SSEC than SZI. In addition, we explore the impact of ISMT on more commonly used indexes in the Chinese stock market. The results show that the ISMT has less impact on the index composed of high-quality and large-sized listed companies than composed of medium-sized and low-liquidity listed companies. Moreover, we reveal that the ISMT has significant predictive power for 11 stock market index returns, including SSEC and SZI. The ISMT has less predictive power for the index returns composed of high-quality and large-sized listed companies than index returns composed of medium-sized and low-liquidity listed companies.

Overall, investor sentiment of margin trading business is an important part of financial market, and this indicator helps investor better understand the financial market operation. The asymmetric impact of ISMT on several indexes fluctuations will assist different types of investor in better conducting margin trading business and performing effective risk management. It is also beneficial for regulators to timely master the development of margin trading business, effectively conduct financial supervision, and ensure the stable operation of the macroeconomic system. According to our results, although the ISMT has predictive power for market index returns, there is still a gap compared with the overall investor sentiment in the market. Hence, the margin trading business in the Chinese stock market has a large space for development. We believe that regulators must reinforce the critical role of margin trading in the Chinese financial market, improve the investor sentiment monitoring mechanism, optimize investor structure, and further drive the rational development of the stock market. Meanwhile, the relevant departments should focus on the balanced development of margin trading business and effectively support the smooth operation of stock market.

This paper is a starting work in a series of researches and the future study will be conducted from the following aspects: first, constructing ISMT is the foundation for research, and we will attempt to use pictures and text to quantify sentiment index. Second, due to limitations in available data, we only obtain the overall margin trading business data of the stock market, without focusing on a specific company. Hence, we do not provide an in-depth analysis about influence mechanism. Third, short selling in the Chinese stock market is strictly restricted, while margin buying business is relatively easy. In this scenario, future research will focus on whether the two businesses have different impacts on stock market index fluctuation. Fourth, ISMT is a novel investor sentiment indicator developed against the backdrop of the margin trading business. Exploring its predictive power for stock returns is an important issue in the future research, including prediction the returns of specific stocks and portfolios, as well as how it combine with Fama–French model to form a new asset pricing factor.

CRediT authorship contribution statement

Xinxin Chen: Investigation, Data curation, Methodology, Software, Writing – original draft, Validation. **Yanhong Guo:** Investigation, Visualization, Writing – review & editing. **Yingying Song:** Investigation, Data curation, Funding acquisition, Methodology, Software, Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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References

Alexander, Gordon J., Ors, Evren, Peterson, Mark A., & Seguin, Paul J. (2004). Margin regulation and market quality: A microstructure analysis. *Journal of Corporate Finance*, *10*(4), 549–574.

Allen, Franklin, & Gale, Douglas (1991). Arbitrage, short sales, and financial innovation. *Econometrica*, *59*(4), 1041–1068.

Alnafea, Maryam, & Chebbi, Kaouther (2022). Does investor sentiment influence stock price crash risk? Evidence from Saudi Arabia. *The Journal of Asian Finance, Economics and Business*, *9*(1), 143–152.

Alqaralleh, Huthaifa, Canepa, Alessandra, & Uddin, Gazi Salah (2023). Dynamic relations between housing markets, stock markets, and uncertainty in global cities: A time-frequency approach. *The North American Journal of Economics and Finance*, *68*, Article 101950.

Antweiler, Werner, & Frank, Murray Z. (2004). Is all that talk just noise? The information content of internet stock message boards. *The Journal of Finance*, *59*(3), 1259–1294.

Baker, & Malcolm (2007). Investor sentiment in the stock market. *Journal of Economic Perspectives*, *21*(2), 129–152.

Basak, Suleyman, & Pavlova, Anna (2013). Asset prices and institutional investors. *American Economic Review*, *103*(5), 1728–1758.

Bian, Jiangze, He, Zhiguo, Shue, Kelly, & Zhou, Hao (2018). *Leverage-induced fire sales and stock market crashes*: *Technical report*, National Bureau of Economic Research.

Caetano, Mal, & Yoneyama, T. (2007). Characterizing abrupt changes in the stock prices using a wavelet decomposition method. *Physica A. Statistical Mechanics and its Applications*, *383*(2), 519–526.

Chang, Eric C., Luo, Yan, & Ren, Jinjuan (2014). Short-selling, margin-trading, and price efficiency: Evidence from the Chinese market. *Journal of Banking & Finance*, *48*, 411–424.

Chen, Jun, Kadapakkam, Palani-Rajan, & Yang, Ting (2016). Short selling, margin trading, and the incorporation of new information into prices. *International Review of Financial Analysis*, *44*, 1–17.

Chen, Weiguo, Zhou, Shufen, Zhang, Yin, & Sun, Yi (2021). A study of multi-scale relationship between investor sentiment and stock index fluctuation based on the analysis of BEMD spillover index. *Journal of Systems Science and Information*, *9*(4), 399–420.

Dragomiretskiy, K., & Zosso, D. (2014). Variational mode decomposition. *IEEE Transactions on Signal Processing*, *62*(3), 531–544.

Fang, Yong, et al. (2015). A study on the correlations between investor sentiment and stock index and macro economy based on EEMD method. *Journal of Financial Risk Management*, *4*(03), 206.

Ferreira, Miguel A., & Matos, Pedro (2008). The colors of investors' money: The role of institutional investors around the world. *Journal of Financial Economics*, *88*(3), 499–533.

Foucault, Thierry, Sraer, David, & Thesmar, David J. (2011). Individual investors and volatility. *The Journal of Finance*, *66*(4), 1369–1406.

Ftiti, Zied, & Hadhri, Sinda (2019). Can economic policy uncertainty, oil prices, and investor sentiment predict Islamic stock returns? A multi-scale perspective. *Pacific-Basin Finance Journal*, *53*, 40–55.

Gallegati, Marco (2008). Wavelet analysis of stock returns and aggregate economic activity. *Computational Statistics & Data Analysis*, *52*(6), 3061–3074.

Gao, Yang, & Zhao, Chengjie (2023). Investor sentiment and stock price jumps: A network analysis based on China's carbon–neutral sectors. *The North American Journal of Economics and Finance*, *68*, Article 101954.

Geraci, Marco Valerio, Garbaravičius, Tomas, & Veredas, David (2018). Short selling in extreme events. *Journal of Financial Stability*, *39*, 90–103.

Goel, Garima, & Dash, Saumya Ranjan (2021). Investor sentiment and government policy interventions: Evidence from COVID-19 spread. *Journal of Financial Economic Policy*, *14*(2), 242–267.

Goel, Garima, & Dash, Saumya Ranjan (2022). GREEDS and stock returns: Evidence from global stock markets. *Journal of Behavioral Finance*, (1), 1–16.

Gui, Pingshu, & Zhu, Yifeng (2021). Margin trading and stock idiosyncratic volatility: Evidence from the Chinese stock market. *International Review of Economics & Finance*, *71*, 484–496.

Han, Chunmao, & Shi, Yongdong (2022). Chinese stock anomalies and investor sentiment. *Pacific-Basin Finance Journal*, *73*, Article 101739.

Haritha, P. H., & Rishad, Abdul (2020). An empirical examination of investor sentiment and stock market volatility: Evidence from India. *Financial Innovation*, *6*(1), 1–15.

Hassani, Sahar, Mousavi, Mohsen, & Gandomi, Amir H. (2022). Damage detection of composite laminate structures using VMD of FRF contaminated by high percentage of noise. *Composite Structures*, *286*, Article 115243.

Huang, Yusheng, & Deng, Yong (2021). A new crude oil price forecasting model based on variational mode decomposition. *Knowledge-Based Systems*, *213*, Article 106669.

Hudson, Y., Yan, M., & Zhang, D. (2020). Herd behaviour & investor sentiment: Evidence from UK mutual funds. *International Review of Financial Analysis*, *71*, Article 101494.

Kahraman, Bige, & Tookes, Heather (2020). Margin trading and comovement during crises. *Review of Finance*, *24*(4), 813–846.

Kim, Karam, & Ryu, Doojin (2021a). Does sentiment determine investor trading behaviour? *Applied Economics Letters*, *28*(10), 811–816.

Kim, Karam, & Ryu, Doojin (2021b). Term structure of sentiment effect on investor trading behavior. *Finance Research Letters*, *43*, Article 102005.

Kumari, Jyoti, & Mahakud, Jitendra (2016). Investor sentiment and stock market volatility: Evidence from India. *Journal of Asia-Pacific Business*, *17*(2), 173–202.

Lao, Jiashun, Nie, He, & Jiang, Yonghong (2018). Revisiting the investor sentiment–stock returns relationship: A multi-scale perspective using wavelets. *Physica A. Statistical Mechanics and its Applications*, *499*, 420–427.

Lee, Charles M. C., Shleifer, Andrei, & Thaler, Richard H. (1991). Investor sentiment and the closed-end fund puzzle. *The Journal of Finance*, *46*(1), 75–109.

Li, Rui, Li, Nan, Li, Jiahui, & Wu, Chongfeng (2018). Short selling, margin buying and stock return in China market. *Accounting & Finance*, *58*(2), 477–501.

Li, Rui, Li, Jiahui, & Yuan, Jinjian (2017). Short-sale prohibitions, firm characteristics and stock returns: Evidence from Chinese market. *China Finance Review International*.

Li, Zhisheng, Lin, Bingxuan, Zhang, Ting, & Chen, Chen (2018). Does short selling improve stock price efficiency and liquidity? Evidence from a natural experiment in China. *The European Journal of Finance*, *24*(15), 1350–1368.

Li, Zhuo, Tian, Meiyu, Ouyang, Guangda, & Wen, Fenghua (2021). Relationship between investor sentiment and earnings news in high-and low-sentiment periods. *International Journal of Finance & Economics*, *26*(2), 2748–2765.

Liu, C. (2022). An enhanced variational mode decomposition based on correntropy and a periodicity-assisted log-cycligram for bearing fault diagnosis. *Measurement Science & Technology*, *33*(6), 065108 (10pp).

Liu, Y., Yang, C., Huang, K., & Gui, W. (2019). Non-ferrous metals price forecasting based on variational mode decomposition and LSTM network. *Knowledge-Based Systems*, *188*(5), Article 105006.

Liu, Shuaishuai, Zhao, Rui, Yu, Kaiping, Zheng, Bowen, & Liao, Baopeng (2022). Output-only modal identification based on the variational mode decomposition (VMD) framework. *Journal of Sound and Vibration*, *522*, Article 116668.

Long, Wen, Zhao, Manyi, & Tang, Yeran (2021). Can the Chinese volatility index reflect investor sentiment? *International Review of Financial Analysis*, *73*, Article 101612.

Lv, Dayong, & Wu, Wenfeng (2019). Are margin traders informed? *Accounting & Finance*, *59*(5), 3105–3131.

Lv, Dayong, & Wu, Wenfeng (2020). Margin trading and price efficiency: Information content or price-adjustment speed? *Accounting & Finance*, *60*(3), 2889–2918.

Mayor, Eric, Bietti, Lucas M, & Canales-Rodríguez, Erick Jorge (2022). Text as signal. A tutorial with case studies focusing on social media (Twitter). *Behavior Research Methods*, 1–26.

Miwa, K. (2016). Investor sentiment, stock mispricing, and long-term growth expectations. *Research in International Business & Finance*, *36*(1), 414–423.

Nartea, Gilbert V., Bai, Hengyu, & Wu, Ji (2020). Investor sentiment and the economic policy uncertainty premium. *Pacific-Basin Finance Journal*, *64*, Article 101438.

Obaid, Khaled, & Pukthuanthong, Kuntara (2022). A picture is worth a thousand words: Measuring investor sentiment by combining machine learning and photos from news. *Journal of Financial Economics*, *144*(1), 273–297.

Rua, A., & Nunes, L. C. (2009). International comovement of stock market returns: A wavelet analysis. *Journal of Empirical Finance*, *16*(4), 632–639.

Rupande, Lorraine, Muguto, Hilary Tinotenda, & Muzindutsi, Paul-Francois (2019). Investor sentiment and stock return volatility: Evidence from the Johannesburg Stock Exchange. *Cogent Economics & Finance*, *7*(1), Article 1600233.

Rytchkov, Oleg (2014). Asset pricing with dynamic margin constraints. *The Journal of Finance*, *69*(1), 405–452.

Schmeling, Maik (2007). Institutional and individual sentiment: Smart money and noise trader risk? *International Journal of Forecasting*, *23*(1), 127–145.

Schmeling, Maik (2009). Investor sentiment and stock returns: Some international evidence. *Journal of empirical finance*, *16*(3), 394–408.

Siganos, A., Vagenas-Nanos, E., & Verwijmeren, P. (2017). Divergence of sentiment and stock market trading. *Journal of Banking & Finance*, *78*(MAY), 130–141.

Song, Ziyu, Gong, Xiaomin, Zhang, Cheng, & Yu, Changrui (2023). Investor sentiment based on scaled PCA method: A powerful predictor of realized volatility in the Chinese stock market. *International Review of Economics & Finance*, *83*, 528–545.

Thurner, Stefan, Farmer, J. Doyne, & Geanakoplos, John (2012). Leverage causes fat tails and clustered volatility. *Quantitative Finance*, *12*(5), 695–707.

Tian, Xin, Cao, Zhigang, Luo, Jiawei, Bao, Bo, Lu, Fengbin, & Wang, Shouyang (2009). Forecasting the container through put of Hong Kong through TEI@I. *Operations Research and Management Science*, *18*(04), 82–89.

Van Hoang, Thi Hong, & Syed, Qasim Raza (2021). Investor sentiment and volatility prediction of currencies and commodities during the COVID-19 pandemic. *Asian Economics Letters*, *1*(4), 18642.

Wan, Xiaoyuan (2020). The impact of short-selling and margin-buying on liquidity: Evidence from the Chinese stock market. *Journal of Empirical Finance*, *55*, 104–118.

Wan, Jiang Ping, Xie, Le Qi, & Hu, Xue Fang (2021). Study on the electric vehicle sales forecast with TEI@I methodology. *International Journal of Knowledge Engineering and Data Mining*, *7*(1–2), 1–38.

Wang, S. F., & Lee, K. H. (2015). Do foreign short-sellers predict stock returns? Evidence from daily short-selling in Korean stock market. *Pacific-Basin Finance Journal*, *32*, 56–75.

Wang, Gang-Jin, Xie, Chi, Lin, Min, & Stanley, H. Eugene (2017). Stock market contagion during the global financial crisis: A multiscale approach. *Finance Research Letters*, *22*, 163–168.

Wang, S. Y., Yu, L., & Lai, K. K. (2005). Crude oil price forecasting with TEI@I methodology. *Journal of Systems Science and Complexity*, *18*(2), 145–166.

Wurgler, J. A., & Baker, M. P. (2006). Investor sentiment and the cross-section of stock returns. *Economic Management Journal*, *61*(4), 1645–1680.

Xiao, Cui, Kun, Guo, Zhenni, Jin, Gan, Yang, & Zhewen, Liao (2020). Analysis of multi-scale volatility features of interest rate in China based on TEI@ I methodology. *Management Review*, *32*(7), 111.

Yang, Chunpeng, & Chi, Jun (2023). Investor sentiment and volatility of exchange-traded funds: Evidence from China. *International Journal of Finance & Economics*, *28*(1), 668–680.

Ye, Lin, Li, Yilin, Pei, Ming, Zhao, Yongning, Li, Zhuo, & Lu, Peng (2022). A novel integrated method for short-term wind power forecasting based on fluctuation clustering and history matching. *Applied Energy*, *327*, Article 120131.

Ye, Qing, Zhou, Shengjie, & Zhang, Jie (2020). Short-selling, margin-trading, and stock liquidity: Evidence from the Chinese stock markets. *International Review of Financial Analysis*, *71*, Article 101549.

Yi, Z., & Mao, N. (2009). Measurement study of China's stock market investor sentiment- construction of CICSI. *Journal of Financial Research*, *11*, 174–184.

Zhang, Xun, Lai, Kin Keung, & Wang, Shou-Yang (2008). A new approach for crude oil price analysis based on empirical mode decomposition. *Energy Economics*, *30*(3), 905–918.

Zhou, X., Cui, Y., & He, Q. (2020). Investor sentiment index based on intuitionistic fuzzy analytic network process method and empirical analysis. *Journal of Intelligent & Fuzzy Systems*, *39*(1), 1–16.