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Research article

Deep learning-based multi-dimensional investor sentiment and stock liquidity: Evidence from China

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Abstract: Investor sentiment has long been recognized as a critical driver of financial market fluctuations and liquidity. However, conventional approaches that rely on aggregated sentiment measures often obscure the intrinsic multidimensional heterogeneity of sentiment, which results in information obfuscation and a reduced explanatory power. This study introduces a deep learning framework to overcome this limitation. By analyzing 11 million investor posts from the Chinese A-share market, we decompose the sentiment into six thematic dimensions: policy, psychological, social, climate, technological, and company. Our empirical models demonstrate that this multidimensional approach substantially enhances the explanation of liquidity fluctuations compared to a single aggregate index. We uncover significant heterogeneity in these effects. For blue-chip stocks, social, psychological, and company-related sentiments provide a persistent positive impact on liquidity. In contrast, technology stocks exhibit a greater sensitivity to a broader range of themes, with psychological, technological, and company sentiments driving more pronounced and nonlinear dynamics. These findings establish that the thematic source of sentiment is a critical determinant of its market impact, a linkage which traditional measures have masked. Our framework provides a more granular understanding of the sentiment-liquidity nexus, thus offering key insights for risk management and market surveillance.

Keywords: behavioral finance; Chinese market; deep learning; investor sentiment; sentiment analysis; liquidity

JEL Codes: G12, D53, C45, D84

1. Introduction

Investor sentiment, a cornerstone of behavioral finance, represents a systematic, non-fundamental force that drives asset prices and shapes market dynamics (Baker & Wurgler, 2006; Barberis et al., 1998). Parallel to this, stock liquidity, defined as the ability to rapidly trade large quantities with minimal price impact, is a fundamental attribute of market quality and efficiency (Amihud & Mendelson, 1986). While traditional microstructure theories explain liquidity through rational mechanisms such as information asymmetry, a growing body of research establishes an important nexus between the two: investor sentiment is a key driver of liquidity fluctuations (Ammari et al., 2023; Glosten & Milgrom, 1985).

The behavioral mechanism is intuitive: optimistic sentiment can lower risk aversion, thus boosting trading participation and enhancing liquidity, while pessimism has the opposite effect (Brown & Cliff, 2005; Chordia et al., 2001). However, this straightforward narrative belies a more complex reality characterized by significant nonlinearity and heterogeneity (Da et al., 2015). This complexity is particularly pronounced in the Chinese A-share market, where the dominance of retail investors, who account for over 60% of the trading volume and are highly susceptible to social media discourse, renders sentiment an especially potent and multifaceted driver of market dynamics (Li & Ahn, 2024; Luo et al., 2020).

Compounding this market-level complexity is a fundamental limitation in how sentiment is traditionally measured. Conventional approaches, whether based on surveys or text, operationalize sentiment through the lens of its polarity (positive vs. negative). This unidimensional view is fundamentally misaligned with the nature of sentiment itself. Investor sentiment is not a monolithic construct; it is elicited by a diverse array of thematic drivers, from macroeconomic policies to firm-specific news. By collapsing this rich heterogeneity into a single score, the existing methods introduce significant aggregation bias, thus obscuring vital information and diminishing the explanatory power of empirical models.

To overcome the dual challenges of market complexity and methodological inadequacy, this study develops and deploys a deep learning framework to disaggregate investor sentiment into its core thematic dimensions. Using the Chinese A-share market as our empirical laboratory, we analyze over 11 million investor posts from online forums. We train a bespoke deep learning model to perform a six-fold thematic classification—policy, psychological, social, climate, technological, and firm-specific—which allows us to construct distinct daily sentiment indices for each dimension. Then, we employ a battery of econometric models to investigate the dynamic and heterogeneous impact of these theme-specific sentiments on stock liquidity.

Our findings reveal that disaggregating investor sentiment significantly enhances the explanatory power for liquidity fluctuations. While a conventional, unidimensional sentiment index only has a limited and transitory impact, the thematic dimensions exhibit highly heterogeneous effects in the direction, magnitude, and persistence. For blue-chip stocks, we find that social, psychological, and company-related sentiments exert a stable, positive influence on liquidity. In contrast, technology stocks are far more sensitive to a broader range of themes, with psychological, technological, and company sentiment showing particularly pronounced and nonlinear dynamics. These results uncover a rich structural linkage between the source of sentiment and its market impact—a linkage that standard aggregate metrics fail to detect.

This study makes several contributions to the literature. Methodologically, it pioneers a replicable framework for moving beyond the unidimensional treatment of sentiment via thematic decomposition. Theoretically, it deepens the understanding of the sentiment-liquidity nexus by documenting that the source of sentiment is a critical determinant of its market impact. Empirically, the findings uncover novel, heterogeneous liquidity responses across different market segments, thus enriching the behavioral finance literature. Finally, from a practical standpoint, this research offers crucial insights for asset managers who seek to refine risk models and for regulators who aim to design more sophisticated market monitoring systems.

The remainder of this paper is structured as follows: Section 2 reviews the relevant literature; Section 3 details the data sources and sentiment extraction methods; Section 4 analyzes the empirical results; Section 5 conducts robustness checks; Section 6 concludes the study; and Section 7 discusses its limitations.

2. Literature review

2.1. Theoretical foundation

The theoretical framework of this study draws upon two pillars of modern finance: behavioral finance and the market microstructure theory. Together, these fields provide the necessary lens to understand the mechanisms through which investor sentiment influences liquidity dynamics. Behavioral finance fundamentally challenges the classical assumption of the fully rational agent, thereby instead positing that investor decisions are systematically affected by cognitive biases, emotions, and social interactions (Barberis et al., 1998). Such deviations from pure rationality can generate persistent anomalies in asset prices, trading patterns, and, of central importance to this study, market liquidity.

Within this behavioral framework, investor sentiment functions as a systematic, non-fundamental force which shapes market outcomes. As defined by Baker & Wurgler (2006), sentiment reflects investor beliefs or speculations that are not justified by fundamentals and are instead driven by psychological heuristics and social contagion. These sentiment-driven behaviors manifest as market-level phenomena such as overreaction, herding, and excessive trading, all of which have direct implications for liquidity. During periods of optimism, declining risk aversion can fuel higher trading volumes and tighten bid-ask spreads, thereby improving liquidity. Conversely, prevailing pessimism can intensify the risk aversion and reduce market participation, thus leading to lower trading intensity and a deterioration in liquidity (Brown & Cliff, 2005; Chordia et al., 2001).

The market microstructure theory traditionally explains liquidity as an outcome of the interaction between informed and uninformed traders, with information asymmetry as the central friction (Glosten & Milgrom, 1985; Kyle, 1985). However, this paradigm requires adaptation in markets characterized by a high concentration of retail investors, such as the Chinese A-share market. In such environments, sentiment-driven trading can dominate or obscure the signals from information-based trading. The prevailing sentiment, even if noisy, becomes a key variable which influences the perceived risk and adverse selection costs. In this context, sentiment can be viewed as a widely observed (though non-fundamental) public signal that affects liquidity provision through its impact on order flow, inventory risk, and market-maker quote-setting behaviors.

Theories of bounded rationality and information complexity provide a compelling rationale to conceptualize sentiment as a multidimensional construct. Simon (1955) posits that decision-makers rely on heuristics and cognitive shortcuts because they are unable to process the universe of available data. This leads them to disproportionately weigh information that is salient, recent, or thematically coherent. When applied to financial markets, this implies that as investors are bombarded with diverse information, including macroeconomic announcements, political events, industry trends, and firm-specific news, where their sentiment response is not uniform but is instead filtered through distinct thematic lenses. Consequently, different dimensions of sentiment (e.g., policy-driven uncertainty versus technology-driven optimism) should theoretically exert differentiated effects on the trading behavior and, by extension, on liquidity (Pastor & Veronesi, 2012; Tetlock, 2007). Therefore, treating sentiment as a unidimensional variable fails to capture the complex cognitive and contextual mechanisms through which information is processed and priced by investors.

2.2. Measurement of investor sentiment

The accurate measurement of investor sentiment is foundational to understanding its role in asset pricing and market dynamics. As a latent psychological construct, sentiment is inherently unobservable and must be proxied through indirect indicators. Early research predominantly relied on two categories of proxies: survey-based indices and market-based variables. Survey indices, such as the American Association of Individual Investors (AAII) Sentiment Survey, provide direct gauges of investor expectations but are often limited by a low frequency, potential sampling biases, and questionable representativeness in fast-moving markets (Brown & Cliff, 2004). Market-based proxies, including trading volume, Initial Public Offering (IPO) first-day returns, and closed-end fund discounts, infer sentiment from aggregate investor actions (Baker & Wurgler, 2007). While timely, these indicators often conflate sentiment with either unrelated economic fundamentals or structural market factors, thereby lacking an interpretive precision.

The limitations of these traditional proxies motivated a turn toward a textual analysis, thereby leveraging advances in Natural Language Processing (NLP) to directly extract sentiment from unstructured data. A seminal contribution by Antweiler & Frank (2004) demonstrated that sentiment from online stock forum discussions could predict short-term market volatility and trading volumes. This line of inquiry was extended to formal media channels by Tetlock (2007), who showed that pessimistic sentiment derived from a Wall Street Journal column forecasted market downturns. Subsequently, researchers broadened the scope to social media, where Bollen et al. (2011) used sentiment from Twitter to predict daily changes in the Dow Jones Industrial Average (DJIA).

Despite their innovations, these early computational approaches, which primarily used lexicon-based methods or classical machine learning models (e.g., support vector machine (SVM)), were ill-equipped to handle the nuances of the financial language. Their inability to process contextual meaning, sarcasm, and domain-specific jargon limited their accuracy. This gap paved the way for deep learning models. For instance, Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks proved superior in capturing semantic features and long-range dependencies in sequential text (Kim & Kim, 2014; Ray et al., 2021). The advent of large-scale, pre-trained language models marked another leap forward. Models like Bidirectional Encoder Representations from Transformers (BERT) (Devlin et al., 2019) and its domain-specific adaptation, fine-tuned BERT (FinBERT) (Araci, 2019), have demonstrated a more profound understanding of context. Underscoring this progress, Liu et al. (2023) developed a FinBERT-based framework for StockTwits data that outperformed previous models by a significant 4–5% margin on the F1-score, thus highlighting the superior capability of modern NLP in financial sentiment classification.

2.3. Empirical evidence of the relationship between investor sentiment and market liquidity

A substantial body of literature has investigated the relationship between investor sentiment and market liquidity, yet the empirical findings remain highly inconsistent. Some studies suggest a positive linkage, thereby indicating that elevated sentiment enhances market liquidity through heightened trading participation and more efficient price discovery (Baker & Stein, 2004; Baker & Wurgler, 2007; Chordia et al., 2001). However, others report either insignificant or even negative relationships (Chiu et al., 2018; Debata et al., 2018; Dunham & Garcia, 2021). This lack of consensus underscores the notion that the sentiment–liquidity nexus is far from straightforward and is likely plagued by underlying methodological issues.

These inconsistencies are rooted in the coarse construction of sentiment indices, which often fail to account for the thematic richness of investor communication. Traditional indicators, whether from surveys, market proxies, or text-based metrics, typically reduce sentiment to a unidimensional construct. This simplification leads to an aggregation bias, where heterogeneous emotional and cognitive signals are compressed into a single scalar index, thus masking the diverse channels through which sentiment affects the market behavior (Da et al., 2015). This concern is amplified by evidence that different sentiment proxies (e.g., news vs. social media) capture weakly correlated dimensions of investor psychology with differentiated market effects (Dunham & Garcia, 2021; Nyakurukwa & Seetharam, 2025).

The problem of aggregation is particularly acute because major economic events rarely elicit a uniform response. For example, shifts in a macroeconomic policy can trigger divergent reactions across sectors: monetary tightening may be positively viewed by banking investors but negatively by those who face higher financing costs, while fiscal stimulus can boost infrastructure sectors but raise long-term sovereign debt concerns (Bernanke & Kuttner, 2005; Blanchard & Perotti, 2002). Similarly, adjustments to regulatory and geopolitical landscapes—such as antitrust actions or trade tariffs—can simultaneously create optimism for investors in protected industries and pessimism for those in targeted sectors or firms reliant on global supply chains (Caldara et al., 2020; Julio & Yook, 2012). A single aggregate sentiment score would inevitably conflate these opposing reactions.

By predominantly focusing on sentiment classification (i.e., polarity) rather than the thematic structuring of investor discourse, the existing research suffers from a critical blind spot: the inability to disentangle the source of sentiment from its market impact. To address this limitation, the present study constructs a set of topic-decomposed sentiment indices. This multidimensional framework enables a more granular examination of how specific categories of sentiment—from macro-policy outlooks to firm-specific news—affect market liquidity through differentiated transmission channels. By isolating these thematic drivers, our approach mitigates the aggregation bias inherent in prior measures, provides a clearer identification of sentiment-induced liquidity effects, and offers a scalable framework for future research in behavioral finance and market microstructure.

3. Data and methodology

3.1. Data

We obtained investor comments from the Guba Forum (http://guba.eastmoney.com), one of the most influential investment websites in China. Numerous studies on investor behavior and its impact on financial markets use data from this platform (Zhang et al., 2023; Zhang et al., 2024).

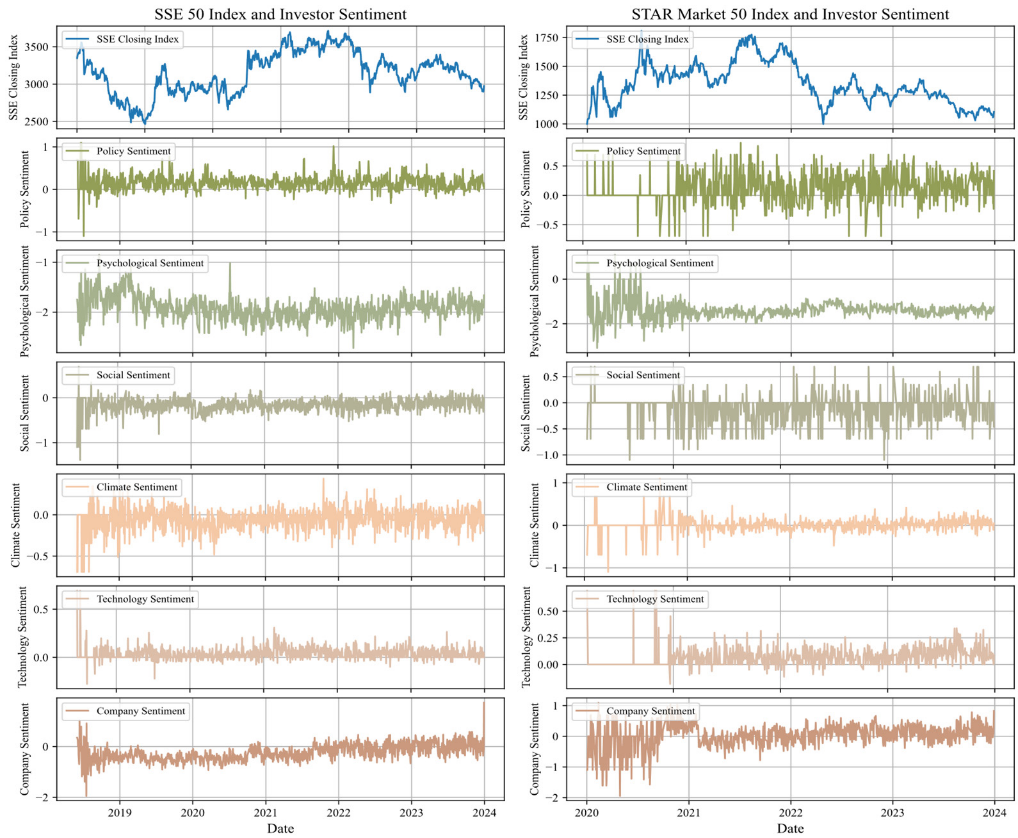

Figure 1. Sentiment dynamics across SSE 50 and STAR market 50.

Note: This figure presents the time series of six sentiment indicators—policy, psychological, social, climate, technology, and company sentiment—alongside the respective closing prices for two representative Chinese market indices: the SSE 50 (left) and the STAR Market 50 (right).

Using a web-scraping program, we collected all posts related to the Shanghai Stock Exchange 50 Index (SSE 50)[1] constituent stocks from January 1, 2018, to January 1, 2024 and all posts related to the STAR Market 50[2] Index constituent stocks from January 1, 2021, to January 1, 2024. The raw dataset consists of approximately 11 million records, thus providing a solid foundation for extensive data mining and research. Additionally, we sourced market transaction data from the CSMAR database (https://data.csmar.com/). The resulting daily sentiment indices for each category, together

[1] The Shanghai Stock Exchange 50 Index (SSE 50) consists of the 50 largest and most liquid stocks listed on the Shanghai Stock Exchange, representing major companies across various sectors in China.
[2] The STAR Market 50 Index is composed of the top 50 stocks listed on the STAR Market (Science and Technology Innovation Board) of the Shanghai Stock Exchange, which primarily includes technology-driven and innovative companies.

with the corresponding market index data, are visualized in Figure 1 to illustrate the temporal evolution of sentiment dynamics across the SSE 50 and the STAR Market 50.

3.2. Methodology

In this section, we detail the process of categorizing investor comments into six distinct categories and computing sentiment values for each category. The workflow is illustrated in Figure 2.

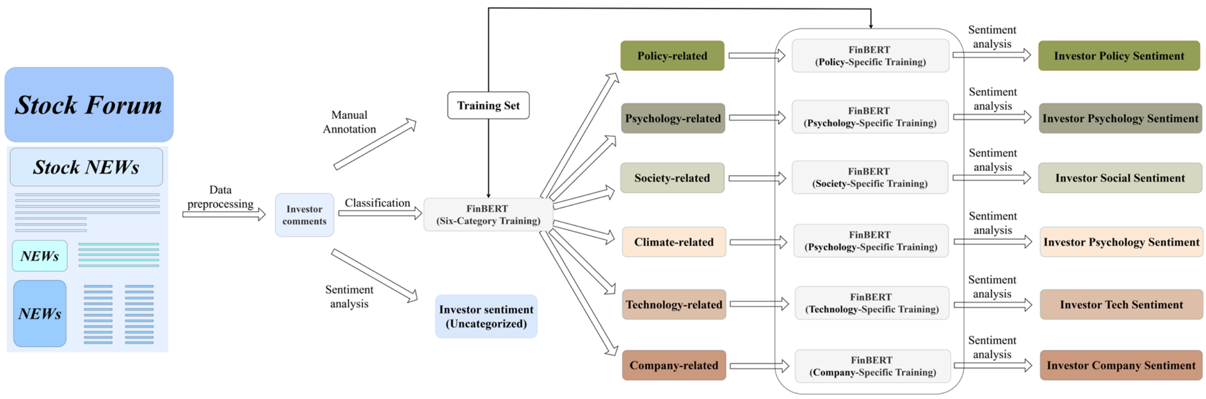

Figure 2. Workflow for categorizing investor comments into six distinct categories and computing sentiment values for each category.

3.2.1. Data preprocessing

Before performing the sentiment classification of investor comments, we first preprocessed the raw data. Our objective was to extract the investors' sentiment expressions; however, a significant portion of online content consists of comments and news published by various institutions. To ensure the accuracy and relevance of our analysis, we applied source-based filtering to remove comments and news that originated from institutional sources (Souma et al., 2019).

3.2.2. Investor comment categorization framework

To construct a classification framework that captures the salient drivers of investor attention, we began by evaluating the suitability of unsupervised topic models. Exploratory analyses with methods such as Latent Dirichlet Allocation (LDA) on our corpus of investor comments yielded themes that were diffuse and lacked substantive economic interpretability, largely due to the noisy and concise nature of the text data. This limitation highlighted the need for a more structured, theory-grounded approach.

Consequently, we developed our framework by systematically identifying the primary themes in the contemporary financial literature on investor focus. We conducted a comprehensive search of the Web of Science (WOS) database for studies published since January 2023 using the keyword "investor sentiment," which yielded 1,394 articles. Through a thematic analysis of the abstracts and keywords of these articles, we identified and ranked the most prevalent research topics by publication frequency. This process revealed five dominant themes that formed the core of our framework: Climate (151 articles), Social (143), Technology (142), Company-related (135), and Policy (103). Notably, “Real Estate” was the sixth most frequent theme (51 articles). However, our analysis revealed that discussions pertaining to this topic were predominantly confined to firms within the real estate sector, rather than reflecting a market-wide concern. Given our objective to establish a framework with a broad, cross-sectoral applicability, we excluded “Real Estate” to focus on more generalizable drivers of investor discourse.

Distinct from these five information-driven categories, we observed that a significant portion of comments conveyed pure emotional states or market outlooks without anchoring to a specific external topic. To capture this intrinsic dimension of market psychology, we established a sixth category: Psychological. This category includes direct expressions of fear, greed, optimism, or pessimism. Therefore, the resulting six-dimensional framework is grounded in a systematic review of academic literature that captures the direct, endogenous sentiment of market participants, thus providing a robust foundation for our subsequent analysis.

3.2.3. Data annotation and dataset construction

The accuracy of deep learning classifiers is heavily dependent on the quality of manually labeled training data. To build a high-quality dataset, we initially selected approximately 170,000 investor comments that were concise, readable, and easy to interpret.

This entire corpus was annotated by a team of 21 domain experts, including one professor, one associate professor, five doctoral students, and fourteen master’s students, all with backgrounds in finance and investment. The annotation was a unified process where each comment was simultaneously assigned to one of six predefined categories and labeled for sentiment using a four-class scheme: positive, neutral, negative, or uncertain. The detailed definitions and representative examples for each category are presented in Table 1.

To quantitatively ensure annotation consistency and reliability, we first performed a cross-annotation on a randomly selected subset of the data and calculated the inter-annotator agreement. Given our multi-annotator team, we employed Fleiss’ Kappa (κ) as the evaluation metric. The calculation yielded a Kappa score of 0.81 for the six-category classification task and 0.72 for the sentiment labeling task. These results validate the clarity of our annotation guidelines and the high consistency among the annotators. On this basis, for any remaining disagreements, we adopted a dual-strategy approach: a majority voting mechanism followed by expert arbitration. This hybrid method is an established practice for resolving inter-annotator disagreements and ensuring reliable ground truth labels.

For model training, we used a subset of this dataset as the training set, which includes 12,214 policy-related comments, 65,536 psychological-related comments, 10,824 social-related comments, 9672 climate-related comments, 49,695 technology-related comments, and 30,905 company-related comments.

Since the selected dataset is inherently imbalanced across categories, we adopted a weighted loss adjustment approach to balance different category weights. Specifically, we assigned a weight inversely proportional to the number of samples in each category, thus ensuring that categories with fewer samples receive higher weights. This prevented the model from being overly biased toward huge categories during training.

To achieve this, we first computed the weight of each category, and then normalized all category weights using the following formula:

$$w_i = \frac{1}{n_i} \tag{1}$$

$$w_i' = \frac{w_i}{\sum_{i=1}^{C} w_i} \tag{2}$$

where w_i represents the weight of the category, n_i is the number of samples in that category, w_i' is the normalized weight, and C denotes the total number of categories.

Table 1. Definition and examples of investor sentiment classification.

Category	Definition	Representative Examples
Investor Policy Sentiment	Comments on government policies, central bank decisions, monetary policy, fiscal policy, tax adjustments, other macroeconomic topics.	"The expectation of a Federal Reserve rate hike has strengthened, intensifying market volatility." "The central bank has increased liquidity injections, potentially leading to a market rebound." "The securities regulator has tightened IPO oversight, which may put pressure on the ChiNext market."
Investor Psychology Sentiment	fear, greed, hesitation, optimism, pessimism.	"Market sentiment is in extreme panic, which could be a good opportunity for bottom fishing." "This bull market is definitely here—jump in quickly!" "This stock is about to drop below 10 yuan—sell now!"
Investor Social Sentiment	Focuses on the impact of social issues, geopolitics, international relations, social stability on the market.	"Rising geopolitical tensions in the Middle East may push oil prices higher." "A resurgence of the pandemic could impact the consumer sector." "Escalation of French workers' strikes raises market concerns over renewed supply chain disruptions."
Investor Climate Sentiment	Concerns about climate change, environmental policies, ESG, carbon trading, climate risk, climate change.	"The government's carbon neutrality targets bring positive prospects for the new energy sector." "The increase in extreme weather events may lead to higher insurance payout risks." "The EU's tighter carbon emission policies have impacted some manufacturing companies."
Investor Technology Sentiment	Discussions on emerging technologies, AI, blockchain, autonomous driving, Biotechnology, cryptocurrency.	"The AI frenzy has become excessive, with valuations detached from fundamentals." "The adoption of blockchain technology is increasing, making Web3.0 a promising prospect." "Autonomous driving has entered mass production, marking a turning point for the smart car industry."
Investor Company Sentiment	Comments on stock indicators, company financial reports, earnings expectations, management decisions, CEO influence.	"Alibaba plans a large-scale stock buyback, boosting market confidence." "Tesla is laying off 10% of its workforce, leading to a sharp drop in its stock price." "Apple has launched a new iPhone, with market reactions being highly polarized."

3.2.4. Deep learning model

We conducted a comprehensive analysis of the strengths and weaknesses of various models and compared their performance. Ultimately, we selected FinBERT, a model specifically designed for the financial domain, as it demonstrated the best performance. A detailed comparison of model results is presented in Table 2. FinBERT demonstrated superior performances across multiple tasks, making it the optimal choice for our research.

I. FinBERT

FinBERT is a fine-tuned version of BERT tailored for a financial text analysis. By being pre-trained and fine-tuned, it effectively handles tasks such as financial sentiment analyses and risk assessments. FinBERT retains the core structure and computational processes of BERT and incorporates domain-specific optimizations for financial text. The overall model architecture is shown in Figure 3.

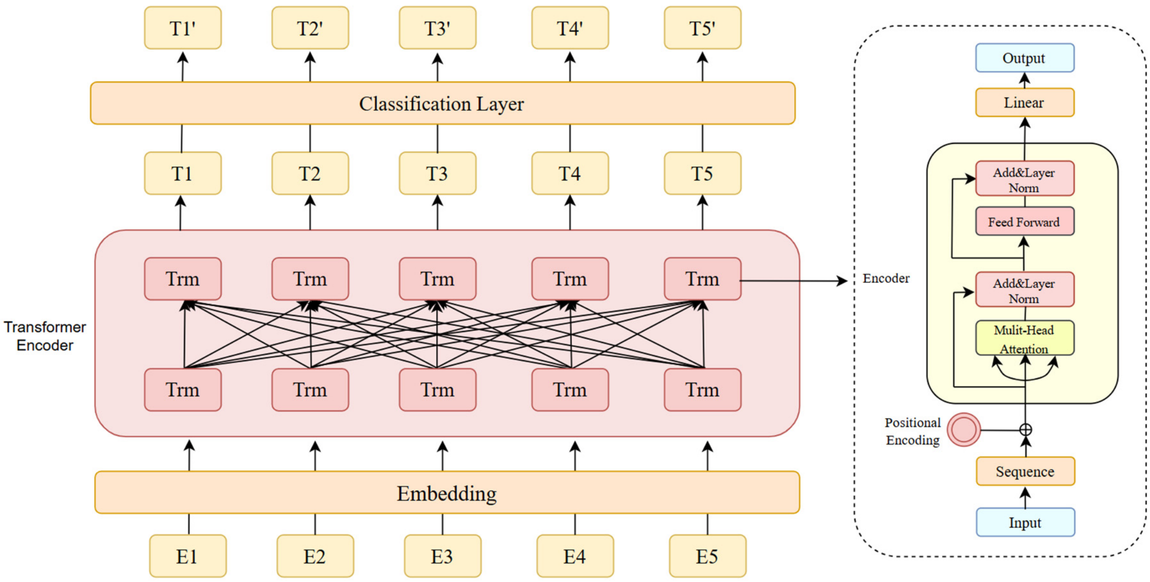

Figure 3. Architecture of the FinBERT.

II. Input Representation

In FinBERT, the input text is represented as a combination of word embeddings, positional embeddings, and segment embeddings. Suppose the i input word is w_i; its input vector E_i is computed as follows:

$$E_i = e(w_i) + p(i) + s(i), \tag{3}$$

where $e(w_i)$ represents the word embedding vector, $p(i)$ denotes the positional embedding, which indicates the position of the word in the sequence, and $s(i)$ is the segment embedding, which is used to distinguish different sentences.

III. Multi-Head Attention Mechanism

The Multi-Head Attention Mechanism (MHAM) is a core component of FinBERT, which enables the model to capture complex dependencies between elements in a sequence through parallel computations of self-attention heads. The key components of MHAM include the Query (Q), Key (K), and Value (V) matrices. The structure is illustrated in Figure 4. After a linear transformation, these matrices are used in scaled dot-product attention computations and are formulated as follows:

$$S_i(Q,K_i)=\frac{QK_i^T}{\sqrt{d_k}}, \tag{4}$$

$$\text{Attention}(Q,K_i,V_i)=\text{Softmax}\left(\frac{QK_i^T}{\sqrt{d_k}}\right)V_i\ , \tag{5}$$

$$\text{MHAM-Output}=\text{Concat}\big(\text{Attention}(Q,K_1,V_1),\ldots\ldots\text{Attention}(Q,K_h,V_h)\big). \tag{6}$$

Given a query Q, the similarity score S_i with multiple key vectors K_i is computed. Here, d_k is a scaling factor used to prevent numerical instability due to high dimensionality. Then, the Softmax function is applied to normalize the raw scores and obtain the attention weights. Finally, the output of the multi-head attention mechanism is obtained through a weighted sum of the value matrix. Here, h represents the number of attention heads.

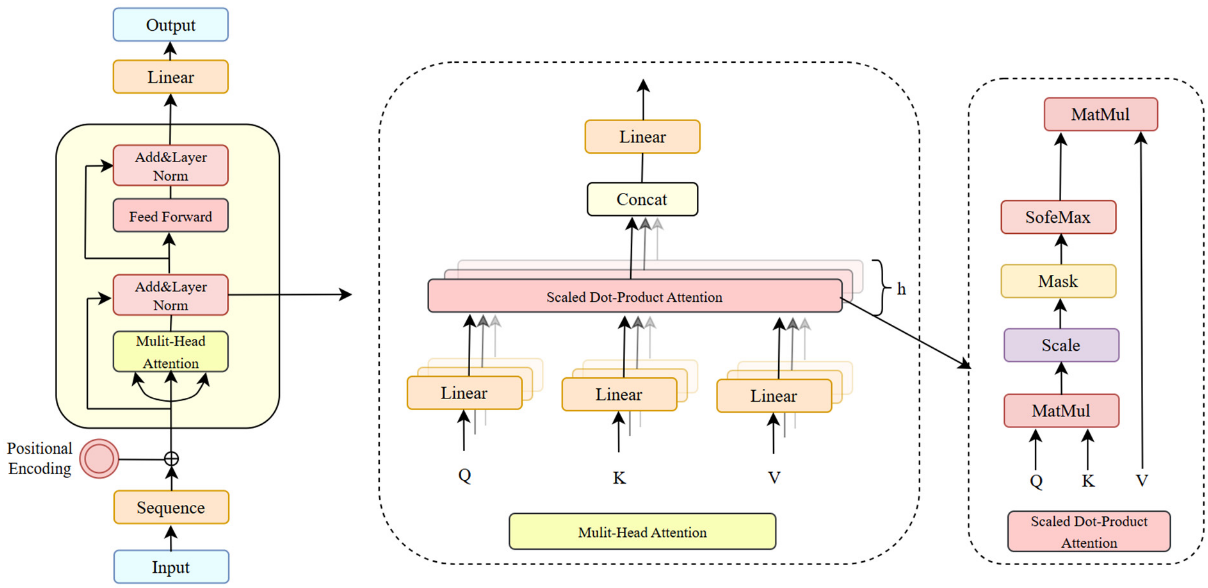

Figure 4. Structure of the Multi-Head Attention Mechanism.

IV. Transformer Layer

FinBERT employs multiple Transformer layers for sequence modeling. Each Transformer layer consists of a self-attention mechanism and a feedforward neural network. The output of the i word at the l layer, denoted as z_i^l, is processed through the feedforward neural network, which is computed as follows:

$$z_i^l = \text{LayerNorm}\left(x_i^{l-1} + \text{Attention}\big(Q_i^l, K_i^l, V_i^l\big)\right), \tag{7}$$

$$h_i^l = \mathrm{ReLU}(W_1 z_i^l + b_1), \tag{8}$$

$$z_i^l = \mathrm{LayerNorm}\,(z_i^l + W_2 h_i^l + b_2), \tag{9}$$

where W_1,W_2 are learnable parameter matrices, and b_1,b_2 are learnable bias terms.

V. Classification

As an optimized financial text classification model, FinBERT encodes input sequences using Transformer layers and employs the [CLS] token as a global representation of the text. The classification process is given by the following:

$$\mathrm{Logits} = W \cdot h_{CLS} + b, \tag{10}$$

$$\hat{y}_i = \frac{e^{z_i}}{\sum_{j=1}^{C} e^{z_j}}, i = 1,2,\ldots,C. \tag{11}$$

The token obtained through Transformer computation is used as the global representation of the text. Then, it is mapped to the classification space through a linear transformation, thus yielding the unnormalized classification score Logits. Here, C represents the total number of categories, and z_i corresponds to the specific category Logits.

VI. Loss Function

We employed the cross-entropy loss function to optimize the model, which is formulated as follows:

$$L_{classification} = -\sum_{i=1}^{C} y_i \log \hat{y}_i, \tag{12}$$

where y_i is the true label, and $\hat{y}_i$ is the predicted probability for class i.

3.2.5. Results analysis

To comprehensively evaluate the model's predictive performance, we utilized a confusion matrix and assessed its effectiveness from multiple perspectives. Table 2 presents the comparative results of different models, while Figure 5 illustrates the performance curves.

Table 2. Model performance comparison.

Task	Model	Precision	Accuracy	Recall	F1-score
Overall Sentiment Analysis	RNN	75.3%	0.76	0.74	0.75
	LSTM	78.7%	0.79	0.77	0.78
	Transformer	80.4%	0.80	0.79	0.80
	BERT	81.4%	0.82	0.81	0.81
	RoBERTa	81.2%	0.82	0.81	0.81
	FinBERT	81.6%	0.82	0.82	0.82
Overall Category Classification	RNN	81.6%	0.82	0.82	0.82
	LSTM	82.3%	0.83	0.82	0.82
	Transformer	85.8%	0.85	0.85	0.85
	BERT	87.7%	0.88	0.88	0.88
	RoBERTa	87.7%	0.88	0.88	0.88
	FinBERT	89.7%	0.90	0.90	0.90
Sentiment Analysis of Social-Related Comments	FinBERT	85.9%	0.86	0.86	0.86
Sentiment Analysis of Policy-Related Comments	FinBERT	92.0%	0.92	0.92	0.92
Sentiment Analysis of Climate-Related Comments	FinBERT	92.5%	0.93	0.93	0.93
Sentiment Analysis of Psychological-Related Comments	FinBERT	97.1%	0.97	0.97	0.97
Sentiment Analysis of Company-Related Comments	FinBERT	97.2%	0.97	0.97	0.97
Sentiment Analysis of Technology-Related Comments	FinBERT	97.4%	0.97	0.97	0.97

Note: The results presented in the table are the average prediction values obtained from running the task ten times.

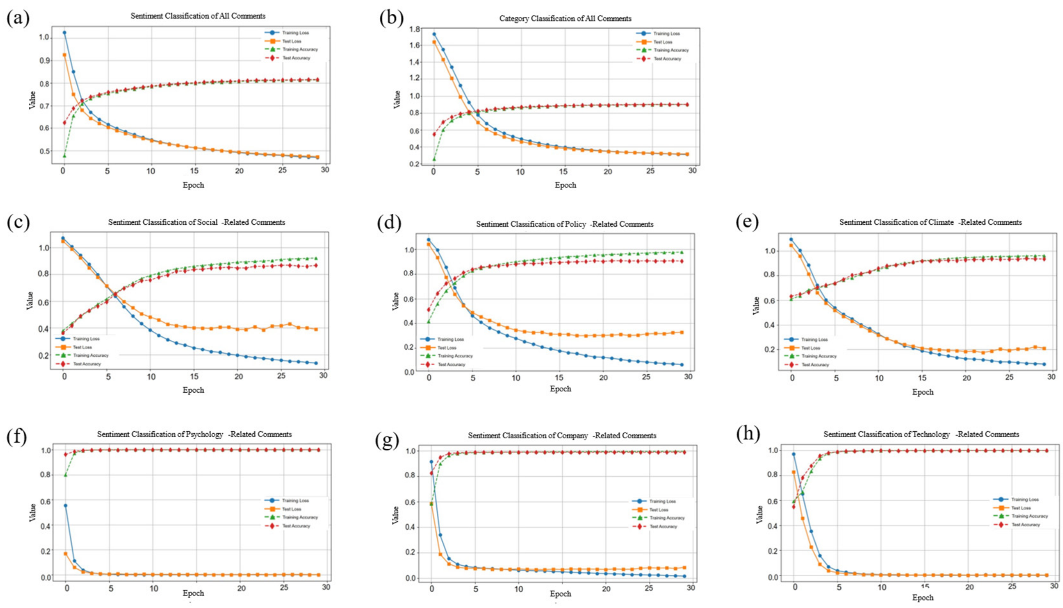

Figure 5. Model performance curve.

Note: Subfigure (a) presents the result curve of Overall Sentiment Analysis, while subfigure (b) shows the result curve of Overall Category Classification. Subfigures (c) to (h) sequentially illustrate the sentiment analysis result curves for comments related to the social (c), policy (d), climate (e), psychological (f), company (g), and technology (h) themes.

3.2.6. Ensemble learning

Although individual models achieved high classification accuracies, the vast size of the dataset means that even with very good performance, a considerable number of instances may still be misclassified. We adopted an ensemble learning strategy to improve the overall robustness and further reduce the error rate.

Ensemble learning is a technique that combines multiple base learners (models) to improve the overall classification performance. The core idea is to aggregate predictions from multiple independently trained models, thereby reducing bias and variance while enhancing the model's robustness.

In our study, we adopted a voting mechanism to integrate the predictions of multiple models. The specific voting formula can be expressed as follows:

$$\hat{y} = \mathrm{argmax}_k \left(\sum_{i=1}^{N} I\,(y_i = k) \right), \tag{13}$$

where y_i represents the model's prediction for a given sample, $I(y_i = k)$ is an indicator function, which takes the value 1 if $(y_i = k)$ and 0 otherwise, and $\hat{y}$ represents the final prediction result, which corresponds to the class k that receives the highest number of votes.

3.3. Variables

3.3.1. Liquidity

We used the Amihud illiquidity ratio (AMH) as a measure of the price impact of stock illiquidity (Amihud & Noh, 2021). The Amihud illiquidity ratio is defined as follows:

$$AMH_{i,t}=10^8\times\frac{VOLD_{i,t}}{D_{i,t}\sum_{t=1}^{D_{i,t}}|R_{i,t}|}, \tag{14}$$

$$LIQ=\ln\frac{1}{AMH_{i,t}}, \tag{15}$$

where $D_{i,t}$ represents the number of effective trading days for stock i during period y, $R_{i,t}$ is the return of stock i on day t, and $VOLD_{i,t}$ denotes the trading volume of stock i on day t.

3.3.2. Investor sentiment

Due to its robustness, many studies have adopted the following formula to calculate online investor sentiment (Wu et al., 2014):

$$IST_{i,t}=\ln\frac{1+pos_{i,t}}{1+neg_{i,t}}, \tag{16}$$

where $pos_{i,t}$ represents the number of optimistic posts about stock i on day t, and $neg_{i,t}$ represents the number of pessimistic posts about stock i on day t.

3.3.3. Investor attention

We used the daily volume of online posts to proxy for investor attention (Zhang et al., 2023). To handle days with zero posts and to mitigate the influence of extreme values, we applied a logarithmic transformation. The metric is formally defined as follows:

$$INAT_{i,t}=\ln(1+M_{i,t}), \tag{17}$$

where $M_{i,t}$ denotes the total number of posts on stock i on day t, and $INAT_{i,t}$ denotes the investor's attention on stock n on day t.

3.3.4. Market sentiment

To capture market-wide sentiment, we employed two complementary approaches.

(1) Baidu Search Index:

Following the methodology adopted in previous studies, we utilized the Baidu Search Index (BSI) as a proxy for market sentiment in the Chinese context (Fang et al., 2020). Specifically, we focused on two representative keywords that are widely used by investors to characterize market conditions: "Niushi" (bull market) and "Xiongshi" (bear market). After applying a natural logarithmic transformation, the daily Baidu search volumes associated with these terms were employed as sentiment indicators. This approach allows us to quantitatively capture fluctuations in investor sentiment and incorporate them into the empirical model to analyze their impact on stock market volatility.

(2) Average Sentiment Across SSE 50 Constituents:

In addition to the BSI, we constructed a "bottom-up" market sentiment index directly derived from investor discourse. This index is based on the rationale that the SSE 50 constituents, as the largest and most influential blue-chip companies, act as bellwethers for the entire A-share market. Therefore, the collective sentiment surrounding these systemically important firms provides a powerful proxy for the overall market mood, thus reflecting the views of active market participants.

Specifically, for each trading day t, we computed the market sentiment index, denoted as MS_t, by taking the equal-weighted average of the individual sentiment scores ($IST_{i,t}$) for all N=50 constituent stocks. The calculation is formalized by the following equation:

$$MS_t = \frac{1}{N}\sum_{i=1}^{N} IST_{i,t}, \tag{18}$$

where $IST_{i,t}$ represents the sentiment score for stock i on day t. This approach offers a complementary perspective to the BSI: while the BSI captures broad public attention which may not originate from active investors, our SSE 50-based index reflects sentiment that is grounded in discussions about the market's core economic engines. By employing both measures, we aim to capture a more comprehensive and robust picture of market-wide sentiment.

3.4. Regression models

To investigate the contemporaneous impact of investor sentiment on stock liquidity, the following fixed effects panel regression model is specified:

$$LIQ_{i,t} = \alpha + \beta_k \cdot Sentiment_{k,t} + \gamma \cdot X_{i,t} + \mu_i + \varepsilon_{i,t}, \tag{19}$$

where $LIQ_{i,t}$ denotes the liquidity measure of stock i on trading day t, $Sentiment_{k,t}$ represents the k-th category of sentiment indicators, $X_{i,t}$ is a vector of control variables, μ_i denotes stock-specific fixed effects, and $\varepsilon_{i,t}$ is the idiosyncratic error term.

To assess the isolated effects of lagged sentiment shocks, we estimated a series of distributed lag models, each including a single lag of the sentiment variable, as follows:

$$LIQ_{i,t} = \alpha + \sum_{l=1}^{4} \beta_{k,l} \cdot Sentiment_{k,t-l} + \gamma \cdot X_{i,t} + \mu_i + \varepsilon_{i,t}. \tag{20}$$

In this setting, each lag l is individually included in a separate regression, which allows for the estimation of the marginal effect of sentiment at each specific lag without interference from other periods.

Furthermore, to capture the cumulative and dynamic transmission mechanism of sentiment, a progressive distributed lag model is constructed as follows:

$$LIQ_{i,t} = \alpha + \sum_{m=0}^{M} \beta_{k,m} \cdot Sentiment_{k,t-m} + \gamma \cdot X_{i,t} + \mu_i + \varepsilon_{i,t}\,,\ M = 0,1,2,3,4. \tag{21}$$

Only the contemporaneous sentiment is included when M=0, both contemporaneous and one-period lagged sentiment are included when M=1, and so forth, up to M=4.

4. Empirical results

4.1. Descriptive statistics

Table 3 presents the distributional characteristics of six sentiment components derived from the aggregate Sentiment measure. The decomposition yields systematically distinct patterns: Policy

Sentiment exhibits positive means (0.143 SSE 50, 0.303 STAR 50) with moderate dispersion (SD=0.157, 0.252), thus reflecting stable governmental influence; Psychological Sentiment shows pronounced negativity (−1.792, −1.960) and asymmetric ranges ([−2.720,3.044], [−2.752,−0.681]), thus indicating cognitive bias persistence; and Technology Sentiment maintains consistently positive values (0.035, 0.348) with tight dispersion (SD=0.056, 0.213), thus suggesting sustained sector optimism. The remaining components demonstrate intermediate characteristics: Company (−0.201, −0.237) and Social (−0.144, −0.242) Sentiments display negative baselines, while Climate Sentiment (−0.051, −0.050) approaches neutrality. Crucially, all sub−sentiments exhibit substantially lower standard deviations than the composite Aggregate Sentiment measure (SSE 50: 0.648; STAR 50: 0.806), which confirms the decomposition's capacity to isolate more stable behavioral signals. Cross−component correlations remain below 0.40 (unreported), thus validating their discriminant validity.

Table 3. Descriptive statistics.

Variables		Mean	Std	Min	Max
SSE 50	Aggregate Sentiment	−0.637	0.648	−3.434	3.044
	Policy Sentiment	0.143	0.157	−1.098	1.098
	Psychological Sentiment	−1.792	0.544	−2.720	0.000
	Social Sentiment	−0.144	0.138	−1.386	0.693
	Climate Sentiment	−0.051	0.120	−0.693	0.438
	Technology Sentiment	0.035	0.056	−0.277	0.693
	Company Sentiment	−0.201	0.308	−1.945	1.731
	Investor Attention	3.669	1.137	0	8.740
	Beta	0.823	0.410	−0.475	2.522
	Market Value (log)	25.94	1.091	21.74	28.81
	Book−to−Market Ratio	1.340	1.718	0.000	19.48
	Turnover Rate	0.059	0.092	0.001	0.258
	Liquidity	6.138	1.859	1.267	13.81
STAR 50	Aggregate Sentiment	−0.320	0.806	−2.944	2.708
	Policy Sentiment	0.303	0.252	−0.963	1.415
	Psychological Sentiment	−1.960	0.258	−2.752	−0.681
	Social Sentiment	−0.242	0.246	−1.609	1.039
	Climate Sentiment	−0.05	0.167	−0.895	0.693
	Technology Sentiment	0.348	0.213	−0.297	1.058
	Company Sentiment	−0.237	0.295	−1.167	1.245
	Investor Attention	2.954	0..978	0	8.401
	Beta	0.009	0.009	−0.037	0.063
	Market Value (log)	18.32	23.46	0.934	140.2
	Book-to-Market Ratio	1.547	1.491	0.071	10.07
	Turnover Rate	0.019	0.018	0.000	0.172
	Liquidity	6.886	1.272	1.442	13.81

4.2. Stationarity and multicollinearity diagnostics

Table 4 presents the results of the stationarity (Augmented Dickey-Fuller (ADF) test) and multicollinearity (Variance Inflation Factor (VIF)) diagnostics. All variables exhibit strong stationarity at conventional significance levels, with the ADF statistics significantly reject the null hypothesis of unit roots. The VIF values for both sentiment measures and control variables remain well below the standard threshold, which indicates no severe multicollinearity concerns. These results support the validity of our empirical specification.

Table 4. Stationarity and multicollinearity test results.

Variables	ADF test statistic	Test critical values			p value	VIF
		1% level	5% level	10% level		
Aggregate Sentiment	−20.41	−3.43	−2.86	−2.56	0.00	1.014
Policy Sentiment	−25.51	−3.43	−2.86	−2.56	0.00	1.046
Psychological Sentiment	−21.02	−3.43	−2.86	−2.56	0.00	1.251
Social Sentiment	−25.24	−3.43	−2.86	−2.56	0.00	1.149
Climate Sentiment	−26.74	−3.43	−2.86	−2.56	0.00	1.030
Technology Sentiment	−22.33	−3.43	−2.86	−2.56	0.00	1.042
Company Sentiment	−10.96	−3.43	−2.86	−2.56	0.00	1.091
Investor Attention	−21.75	−3.43	−2.86	−2.56	0.00	1.061
Beta	−11.37	−3.43	−2.86	−2.56	0.00	1.029
Market Value (log)	−6.43	−3.43	−2.86	−2.56	0.00	1.052
Book-to-Market Ratio	−8.93	−3.43	−2.86	−2.56	0.00	1.086
Turnover Rate	−13.99	−3.43	−2.86	−2.56	0.00	1.105

4.3. Lag order selection

Table 5 presents the lag order selection criteria, including the Akaike Information Criterion (AIC), the Bayesian Information Criterion (BIC), the Hannan-Quinn Information Criterion (HQIC), and cross-sectional dependence (CD) statistics, for all seven sentiment categories across both the SSE 50 and the STAR 50 indices at lag orders 1 through 4. The results provide systematic evidence for determining optimal lag lengths in our panel VAR specifications.

Table 5. Lag order selection criteria for sentiment variables.

		SSE 50				STAR 50			
Sentiment Category	Lag	AIC (×10³)	BIC (×10³)	HQIC (×10³)	CD	AIC (×10³)	BIC (×10³)	HQIC (×10³)	CD
Aggregate Sentiment	1	243.750	243.793	243.764	0.2001	25.809	25.851	25.823	0.2001
	2	243.749	243.799	243.766	0.2007	25.805	25.854	25.822	0.2007
	3	243.750	243.807	243.770	0.2007	25.806	25.863	25.825	0.2007
	4	243.749	243.813	243.771	0.2010	25.805	25.869	25.827	0.2010
Policy Sentiment	1	243.764	243.807	243.779	0.1989	25.823	25.865	25.837	0.1989
	2	243.766	243.816	243.783	0.1989	25.825	25.874	25.842	0.1989
	3	243.767	243.824	243.786	0.1990	25.826	25.883	25.845	0.1990
	4	243.769	243.833	243.791	0.1990	25.828	25.892	25.849	0.1990
Psychological Sentiment	1	243.765	243.808	243.780	0.1988	25.824	25.867	25.839	0.1988
	2	243.766	243.816	243.783	0.1988	25.826	25.875	25.843	0.1988
	3	243.768	243.825	243.787	0.1988	25.828	25.885	25.847	0.1988
	4	243.770	243.834	243.792	0.1988	25.829	25.893	25.851	0.1988
Social Sentiment	1	243.766	243.808	243.780	0.1988	25.824	25.867	25.839	0.1988
	2	243.767	243.817	243.784	0.1988	25.826	25.876	25.843	0.1988
	3	243.768	243.825	243.787	0.1988	25.827	25.884	25.846	0.1988
	4	243.763	243.827	243.785	0.1995	25.822	25.886	25.844	0.1995
Climate Sentiment	1	243.766	243.808	243.780	0.1988	25.824	25.867	25.839	0.1988
	2	243.767	243.817	243.784	0.1988	25.826	25.875	25.843	0.1988
	3	243.767	243.824	243.786	0.1990	25.826	25.883	25.845	0.1990
	4	243.770	243.834	243.792	0.1990	25.828	25.892	25.849	0.1990
Technology Sentiment	1	243.741	243.784	243.756	0.1992	25.820	25.863	25.834	0.1992
	2	243.738	243.788	243.755	0.1996	25.817	25.866	25.834	0.1996
	3	243.734	243.791	243.753	0.2002	25.812	25.869	25.832	0.2002
	4	243.736	243.800	243.758	0.2002	25.814	25.878	25.836	0.2002
Company Sentiment	1	243.734	243.777	243.749	0.1998	25.813	25.855	25.827	0.1998
	2	243.736	243.786	243.753	0.1998	25.815	25.864	25.832	0.1998
	3	243.738	243.795	243.757	0.1998	25.817	25.874	25.836	0.1998
	4	243.740	243.804	243.761	0.1998	25.818	25.882	25.840	0.1998

4.4. Regression results

We employed a systematic model selection procedure for the static panel analysis, which involved the following: (i) Chow tests for structural breaks; (ii) comparison of pooled OLS, fixed-effects (FE), and random-effects (RE) estimators; and (iii) formal specification testing via the Breusch-Pagan LM and Hausman tests. The FE specification is preferred based on standard diagnostic criteria.

4.4.1. Analysis of the impact of multidimensional investor sentiment on the liquidity of SSE 50 constituents

Table 6 presents the contemporaneous relationship between various sentiment indicators and stock liquidity. A pivotal finding emerged at the outset: the conventional, one-dimensional aggregate sentiment index (Aggregate) showed no statistically significant relationship with liquidity, as evidenced in Model 1 (coefficient = 0.004, t-statistic = 0.46). Similarly, the BSI, a common proxy for broad market attention, failed to exhibit a significant impact (Model 8). This result starkly exposes a critical limitation of traditional composite metrics—their propensity to obscure genuine market relationships through information obfuscation, thereby validating the primary motivation for this study's multidimensional decomposition. In stark contrast to the inertness of the aggregate index, the decomposition of sentiment reveals heterogeneous effects on liquidity. The empirical results demonstrate that four distinct dimensions—Policy, Psychological, Social, and Company sentiment—all exert a statistically significant positive influence on the liquidity of the SSE 50 constituents in the current period. Among these, the coefficient for Psychological sentiment is the largest (0.256), thus indicating the most pronounced immediate impact. However, the Climate and Technology sentiment dimensions did not show statistical significance in the contemporaneous regressions.

These immediate findings lend direct empirical support to our theoretical framework. The statistical insignificance of the aggregate index confirms that it suffers from a severe aggregation bias in measuring investor sentiment. Conversely, the significance of the decomposed dimensions aligns with the behavioral finance theory, which posits that sentiment, as a non-fundamental factor, influences market liquidity by affecting investor trading behavior. The significance of macro-level dimensions such as Policy, Psychological, and Social sentiment suggests that investor sentiment is systematically driven by the external information environment. Furthermore, this decomposition not only identifies the effective sources of sentiment's influence, but also enhances the model's explanatory power. For instance, the adjusted R^2 of Model 3 (Psychological, 0.054) shows an improvement over that of Model 1 (Aggregate, 0.049), which indicates that the dimensional decomposition contributes incremental information for explaining liquidity fluctuations that aggregate measures fail to capture.

To investigate the temporal persistence of these contemporaneous effects, we further examined the lagged impacts of the sentiment indicators, with results presented in Table 7. The analysis revealed significant heterogeneity in how the influence of different sentiment dimensions unfolds over time. The positive impact of Psychological sentiment demonstrates the strongest persistence, thereby remaining significant even at a lag of four periods. Additionally, the effects of Policy and Social sentiment exhibited meaningful durability, with their significance extending to the third and second lags, respectively. A noteworthy finding is the delayed reaction of Climate sentiment; while insignificant contemporaneously, its impact became significantly positive from the first to the third lag. In contrast, the lagged effects of both Company and Technology sentiment were insignificant, which suggests that their influence is largely transitory.

Table 6. Immediate Effects of Sentiment on SSE 50 Liquidity.

LIQ	(1) Aggregate	(2) Policy	(3) Psychological	(4) Social	(5) Climate	(6) Technology	(7) Company	(8) BSI	(9) MS
Sentiment	0.004	0.188***	0.256***	0.222***	0.012	0.074	0.075***	0.025	0.108**
	(0.46)	(4.32)	(8.76)	(4.31)	(0.22)	(0.62)	(3.48)	(1.21)	(2.45)
Attention	0.126***	–0.130***	0.104***	–0.039	–0.025	0.003	–0.025***	–0.019***	0.073***
	(13.80)	(–6.04)	(6.65)	(–1.59)	(–1.26)	(0.15)	(–3.26)	(–3.12)	(5.12)
Beta	0.066	0.061	0.054	0.062	0.063	0.065	0.066	0.065	0.063
	(1.67)	(1.53)	(1.34)	(1.55)	(1.57)	(1.63)	(1.65)	(1.64)	(1.58)
Market Value	1.066***	1.082***	1.071***	1.084***	1.091***	1.093***	1.082***	1.092***	1.085***
	(46.19)	(46.84)	(46.29)	(46.89)	(47.21)	(47.36)	(46.78)	(47.35)	(46.91)
BM	–0.002	0.007	0.008	0.005	0.002	–0.001	0.008	–0.001	0.004
	(–0.22)	(0.92)	(1.03)	(0.64)	(0.24)	(–0.07)	(1.07)	(–0.11)	(0.59)
Turnover	0.227***	0.274***	0.261***	0.277***	0.278***	0.278***	0.277***	0.278***	0.276***
Rate	(24.56)	(32.77)	(30.36)	(33.09)	(33.22)	(33.28)	(33.09)	(33.25)	(33.01)
Constant	–22.16***	–22.06***	–21.75***	–22.15***	–22.36***	–22.46***	–22.08***	–22.42***	–22.21***
	(–36.78)	(–36.35)	(–35.78)	(–36.47)	(–36.86)	(–37.06)	(–36.38)	(–37.15)	(–36.68)
Stock FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Groups	50	50	50	50	50	50	50	50	50
Observations	64,133	64,133	64,133	64,133	64,133	64,133	64,133	64,133	64,133
R^2	0.049	0.053	0.054	0.053	0.052	0.052	0.053	0.049	0.052

Notes: t statistics are in parentheses; ***, **, and * denote significance at the 0.01, 0.05, and 0.1 level respectively.

Table 7. Lagged Effects of Sentiment on SSE 50 Liquidity.

Lag(Days)	Aggregate Sentiment	Policy Sentiment	Psychological Sentiment	Social Sentiment	Climate Sentiment	Technology Sentiment	Company Sentiment	Baidu Search Index	Market Sentiment
Lag 1	0.049***	0.179***	0.252***	0.193***	0.205***	–0.103	0.066	0.018	0.085**
	(3.43)	(4.63)	(6.07)	(4.62)	(3.45)	(–0.98)	(1.45)	(0.95)	(2.21)
Lag 2	0.030***	0.190***	0.159***	0.210***	0.195***	–0.040	0.066	0.011	0.051*
	(2.64)	(4.57)	(3.58)	(4.35)	(3.14)	(–0.36)	(1.51)	(0.57)	(1.75)
Lag 3	0.019*	0.157***	0.178***	0.033	0.168***	0.062	0.066	–0.005	0.023
	(1.89)	(3.98)	(4.19)	(0.78)	(2.70)	(0.61)	(1.42)	(–0.26)	(0.88)
Lag 4	0.010	0.017	0.153***	0.009	0.072	0.062	0.067	0.008	0.009
	(1.14)	(0.39)	(4.06)	(0.18)	(1.20)	(0.55)	(1.45)	(0.41)	(0.35)
Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES
Stock FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Groups	50	50	50	50	50	50	50	50	50
R^2	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05

Notes: t statistics are in parentheses; ***, **, and * denote significance at the 0.01, 0.05, and 0.1 level respectively.

This heterogeneity in persistence reflects differential speeds at which the market absorbs and processes distinct types of information. The more enduring influence of macro-level sentiments such as Policy, Psychological, and Social may arise because such information shocks are broader in scope and more complex in their implications, thereby requiring a longer period for the market to reach a consensus. The delayed effect of Climate sentiment is particularly intriguing, possibly suggesting that for mature firms such as those in the SSE 50, investors are more deliberative when processing non-traditional information related to long-term fundamentals, which results in a lagged market response. The ephemeral impact of firm-level sentiment aligns with tenets of market efficiency, whereby company-specific information is rapidly impounded into prices. These findings underscore that sentiment's impact on liquidity is not an instantaneous event but rather possesses a complex temporal structure, which can only be accurately identified through a multidimensional lens.

Finally, Table 8 provides a more integrated test of sentiment's transmission channels by constructing a cumulative dynamic model that includes multiple lagged terms. The results confirm that Psychological and Social sentiment are robust drivers of liquidity, with their coefficients remaining significantly positive even after controlling for their own lagged effects. Policy sentiment exhibited an impulse-like effect, where its significant contemporaneous impact continued to exert influence over subsequent days. However, the most compelling evidence from this model is its definitive refutation of the aggregate sentiment index in a dynamic setting. The contemporaneous coefficient of the aggregate index is consistently insignificant across all specifications that include lagged terms. This result indicates that relying on an aggregate measure not only leads to flawed conclusions in static analysis but also induces a severe model misspecification in the dynamic analysis, as it fails to capture the true transmission mechanism of sentiment's influence.

The evidence presented in Table 8 offers the most potent support for our central thesis: the source of sentiment is a critical determinant of its market impact. Certain dimensions of sentiment, such as Psychological and Social, are not merely ephemeral market noise, but are systematic forces capable of producing persistent effects. This finding empirically demonstrates that any attempt to accurately forecast liquidity or to construct quantitative strategies based on sentiment will face a substantial risk of model misspecification if it relies on traditional, monolithic indices. Therefore, the multidimensional framework proposed herein offers significant theoretical and practical values for advancing the understanding of market dynamics, improving the precision of asset pricing models, and optimizing financial risk management.

Table 8. Dynamic Effects of Sentiment on SSE 50 Liquidity.

LIQ	(1) Lag 0	(2) Lag 0–1	(3) Lag 0–2	(4) Lag 0–3	(5) Lag 0–4
Aggregate Sentiment$_t$	0.004 (0.46)	–0.005 (–0.47)	–0.005 (–0.45)	–0.005 (–0.44)	–0.005 (–0.44)
Aggregate Sentiment$_{t-1}$		0.050*** (3.54)	0.046*** (3.44)	0.045*** (3.43)	0.045*** (3.43)
Aggregate Sentiment$_{t-2}$			0.023** (2.19)	0.021* (1.99)	0.021* (1.95)
Aggregate Sentiment$_{t-3}$				0.000 (0.02)	–0.002 (–0.27)
Aggregate Sentiment$_{t-4}$					0.012 (1.33)
Policy Sentiment$_t$	0.188*** (4.32)	0.142*** (3.17)	0.138*** (3.07)	0.138*** (3.07)	0.139*** (3.11)
Policy Sentiment$_{t-1}$		0.135*** (3.45)	0.094** (2.27)	0.090** (2.18)	0.092** (2.23)
Policy Sentiment$_{t-2}$			0.144*** (3.07)	0.116** (2.40)	0.118** (2.42)
Policy Sentiment$_{t-3}$				0.097** (2.34)	0.115*** (2.72)
Policy Sentiment$_{t-4}$					–0.050 (–1.16)
Psychological Sentiment$_t$	0.256*** (8.76)	0.153*** (3.97)	0.140*** (3.84)	0.139*** (3.83)	0.137*** (3.83)
Psychological Sentiment$_{t-1}$		0.169*** (4.77)	0.183*** (4.79)	0.167*** (4.18)	0.166*** (4.17)
Psychological Sentiment$_{t-2}$			–0.026 (–0.67)	0.057* (1.72)	0.055* (1.69)
Psychological Sentiment$_{t-3}$				–0.061* (–1.65)	0.012 (0.41)
Psychological Sentiment$_{t-4}$					–0.063* (–1.66)
Social Sentiment$_t$	0.222*** (4.31)	0.210*** (3.38)	0.213*** (3.44)	0.216*** (3.45)	0.219*** (3.49)
Social Sentiment$_{t-1}$		0.189*** (4.49)	0.178*** (4.23)	0.183*** (4.29)	0.179*** (4.09)
Social Sentiment$_{t-2}$			0.191*** (4.00)	0.194*** (4.05)	0.186*** (3.99)
Social Sentiment$_{t-3}$				–0.012 (–0.28)	–0.016 (–0.38)
Social Sentiment$_{t-4}$					–0.053* (–2.01)

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LIQ	(1) Lag 0	(2) Lag 0–1	(3) Lag 0–2	(4) Lag 0–3	(5) Lag 0–4
Climate Sentiment$_t$	0.012 (0.22)	–0.027 (–0.43)	–0.032 (–0.53)	–0.042 (–0.72)	–0.045 (–0.77)
Climate Sentiment$_{t-1}$		0.206*** (3.52)	0.192*** (3.34)	0.171** (2.81)	0.164** (2.75)
Climate Sentiment$_{t-2}$			0.182*** (3.12)	0.165** (2.90)	0.153** (2.65)
Climate Sentiment$_{t-3}$				0.040 (0.67)	0.024 (0.41)
Climate Sentiment$_{t-4}$					0.126** (2.01)
Technology Sentiment$_t$	0.074 (0.62)	0.085 (0.69)	0.080 (0.64)	0.076 (0.61)	0.073 (0.59)
Technology Sentiment$_{t-1}$		–0.112 (–1.07)	–0.108 (–1.04)	–0.115 (–1.09)	–0.115 (–1.09)
Technology Sentiment$_{t-2}$			–0.031 (–0.28)	–0.039 (–0.36)	–0.043 (–0.39)
Technology Sentiment$_{t-3}$				0.072 (0.70)	0.064 (0.64)
Technology Sentiment$_{t-4}$					0.060 (0.53)
Company Sentiment$_t$	0.057 (1.54)	0.048 (1.40)	0.043 (1.31)	0.039 (1.23)	0.054* (1.73)
Company Sentiment$_{t-1}$		0.035 (0.93)	0.024 (0.77)	0.015 (0.51)	0.020 (0.67)
Company Sentiment$_{t-2}$			0.028 (1.05)	0.018 (0.75)	0.027 (1.17)
Company Sentiment$_{t-3}$				0.022 (0.65)	0.022 (0.66)
Company Sentiment$_{t-4}$					0.056 (1.39)
Baidu Search Index$_t$	0.025 (1.21)	0.024 (1.18)	0.023 (1.13)	0.024 (1.17)	0.023 (1.14)
Baidu Search Index$_{t-1}$		0.017 (0.90)	0.015 (0.80)	0.016 (0.84)	0.015 (0.79)
Baidu Search Index$_{t-2}$			0.010 (0.52)	0.008 (0.42)	0.007 (0.36)
Baidu Search Index$_{t-3}$				–0.006 (–0.31)	–0.007 (–0.37)
Baidu Search Index$_{t-4}$					0.009 (0.47)

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LIQ	(1)	(2)	(3)	(4)	(5)
	Lag 0	Lag 0–1	Lag 0–2	Lag 0–3	Lag 0–4
Market Sentiment$_t$	0.108**	0.095**	0.092**	0.091**	0.091**
	(2.45)	(2.28)	(2.20)	(2.18)	(2.17)
Market Sentiment$_{t-1}$		0.081**	0.075*	0.076*	0.075*
		(2.15)	(1.98)	(1.99)	(1.97)
Market Sentiment$_{t-2}$			0.049*	0.045	0.044
			(1.70)	(1.56)	(1.53)
Market Sentiment$_{t-3}$				0.021	0.020
				(0.81)	(0.78)
Market Sentiment$_{t-4}$					0.011
					(0.42)
Controls	YES	YES	YES	YES	YES
Stock FE	YES	YES	YES	YES	YES
Observations	64,133	50,480	37,007	24,022	11,577
R^2 Range	0.04−0.06	0.04−0.06	0.04−0.06	0.04−0.06	0.04−0.06

Notes: t statistics are in parentheses; ***, **, and * denote significance at the 0.01, 0.05, and 0.1 level respectively.

4.4.2. Analysis of the impact of multidimensional investor sentiment on the liquidity of STAR 50 Constituents

Shifting the analytical focus to the STAR 50 index, which represents China's technology and innovation-driven firms, reveals a markedly different and more complex sentiment-liquidity nexus. Table 9 presents the contemporaneous regression results. A foundational contrast with the SSE 50 immediately emerged: the aggregate sentiment index, which was inert for blue-chip stocks, exhibited a statistically significant positive relationship with the liquidity of technology stocks (coefficient = 0.037, t-statistic = 2.42). This initial finding suggests that the investor base for STAR 50 firms, likely characterized by higher retail participation and a greater appetite for growth narratives, was more susceptible to broad, undifferentiated sentiment waves. However, the disaggregation of sentiment once again proved indispensable for uncovering the true underlying drivers. The analysis showed that Psychological, Social, Technology, and Company-specific sentiments were all potent, positive, and statistically significant determinants of contemporaneous liquidity. Notably, and in sharp contrast to the SSE 50, Technology sentiment registered as a powerful driver (coefficient = 0.152, t-statistic = 2.51), while Policy sentiment's impact became marginal (coefficient = 0.082, t-statistic = 1.88). This uncovers a critical heterogeneity: the liquidity of technology firms is intrinsically tied to sentiment surrounding innovation and firm-specific prospects, while being less sensitive to the macroeconomic policy discourse that heavily influences mature, blue-chip companies.

The examination of lagged effects, detailed in Table 10, further deepens the evidence of profound structural differences between the two market segments. The temporal dynamics for STAR 50 stocks are, in several respects, an inversion of those observed for the SSE 50. Most strikingly, the impacts of Technology and Company sentiment, which were purely transitory for blue-chips, demonstrated significant persistence for technology firms, with their positive influence extending to the third and fourth lags, respectively. This finding is consistent with the view that information related to technological breakthroughs and firm-specific growth trajectories is often complex, ambiguous, and subject to prolonged periods of investor debate and price discovery, thereby creating sustained effects on trading activity. Conversely, the highly persistent effect of Psychological sentiment on the SSE 50 stocks became entirely ephemeral for the STAR 50 firms, with its influence vanishing after the contemporaneous period. A particularly compelling, yet complex, dynamic was revealed for Social sentiment: while its contemporaneous effect was positive, it was followed by a significantly negative impact in subsequent periods (e.g., coefficient = −0.170, t-statistic = −5.54 at lag 4). This may reflect a "hype-and-correction" cycle endemic to technology stocks, where initial social media-fueled enthusiasm temporarily boosts liquidity, only to be followed by a sharp reversal as speculative narratives confront fundamental realities.

Table 9. Immediate effects of sentiment on STAR 50 liquidity.

LIQ	(1) Aggregate	(2) Policy	(3) Psychological	(4) Social	(5) Climate	(6) Technology	(7) Company	(8) BSI	(9) MS
Sentiment	0.037**	0.082*	0.151***	0.133***	–0.076	0.152**	0.145***	0.045**	0.105**
	(2.42)	(1.88)	(3.16)	(2.81)	(–1.19)	(2.51)	(4.00)	(2.25)	(2.33)
Attention	–0.003	–0.006	0.011	–0.067	–0.024	–0.001	–0.000	–0.015	–0.015
	(–0.18)	(–0.12)	(0.38)	(–1.41)	(–0.69)	(–0.05)	(–0.01)	(–0.39)	(–0.32)
Beta	0.511***	0.512***	0.487***	0.501***	0.508***	0.520***	0.516***	0.510***	0.505***
	(4.03)	(4.04)	(3.84)	(3.96)	(4.01)	(4.10)	(4.07)	(4.02)	(3.98)
Market Value	0.644***	0.652***	0.649***	0.680***	0.650***	0.635***	0.644***	0.648***	0.650***
	(18.91)	(18.31)	(18.12)	(18.74)	(18.39)	(17.26)	(17.85)	(18.85)	(18.15)
BM	–0.331***	–0.328***	–0.335***	–0.338***	–0.329***	–0.321***	–0.328***	–0.330***	–0.334***
	(–31.15)	(–30.47)	(–27.62)	(–30.74)	(–30.97)	(–27.04)	(–27.41)	(–31.10)	(–27.80)
Turnover	0.583***	0.589***	0.552***	0.620***	0.597***	0.588***	0.549***	0.585***	0.558***
Rate	(7.73)	(7.73)	(7.01)	(8.18)	(7.87)	(7.73)	(7.10)	(7.75)	(7.15)
Constant	6.925***	6.897***	7.187***	7.028***	6.942***	6.862***	6.961***	6.915***	7.150***
	(117.32)	(102.28)	(57.86)	(112.50)	(128.41)	(86.06)	(61.70)	(115.80	(59.55)
Stock FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Groups	50	50	50	50	50	50	50	50	50
Observations	27,525	27,525	27,525	27,525	27,525	27,525	27,525	27,525	27,525
R^2	0.171	0.171	0.172	0.172	0.171	0.171	0.172	0.171	0.171

Notes: t statistics are in parentheses; ***, **, and * denote significance at the 0.01, 0.05, and 0.1 level respectively.

Finally, the comprehensive dynamic models in Table 11 provide the most definitive evidence of the unique transmission channels of sentiment for technology stocks. The results confirm the robust and persistent positive influence of Company and Technology sentiment on liquidity, where their lagged coefficients remained significant. Additionally, the models substantiate the complex pattern of Social sentiment, thereby showing a strong positive immediate impact followed by a powerful, statistically significant negative lagged effect, thus reinforcing the hype-and-correction hypothesis. Moreover, this dynamic specification definitively demonstrates the weakness of the aggregate index: its initial contemporaneous significance (Table 9) deteriorated and became insignificant as lagged terms were introduced (e.g., t-statistic falls to 1.49 at lag 4), thus proving it to be a misspecified and unreliable indicator of the true underlying dynamics. In aggregate, the evidence from the STAR 50 constituents powerfully substantiate this study's central thesis. It shows that the market impact of investor sentiment is not uniform but is instead fundamentally conditioned by the nature of the firms being traded. For technology stocks, the sentiment-liquidity relationship is characterized by a distinct temporal structure, driven by persistent reactions to firm-specific and technological news and volatile, mean-reverting responses to social media discourse—a rich and nuanced reality entirely obscured by conventional, monolithic sentiment measures.

Table 10. Lagged effects of sentiment on STAR 50 liquidity.

Lag(Days)	Aggregate Sentiment	Policy Sentiment	Psychological Sentiment	Social Sentiment	Climate Sentiment	Technology Sentiment	Company Sentiment	Baidu Search Index	Market Sentiment
Lag 1	0.026	0.061	0.093	−0.069*	0.001	0.122**	0.196***	0.032	0.087*
	(1.72)	(1.38)	(1.15)	(−1.76)	(0.01)	(1.97)	(4.72)	(1.45)	(1.93)
Lag 2	0.014	0.029	0.055	−0.037	0.070	0.153**	0.136***	0.017	0.065
	(0.89)	(0.67)	(0.71)	(−1.16)	(1.16)	(2.09)	(3.82)	(0.74)	(1.28)
Lag 3	−0.010	−0.023	0.049	−0.083**	−0.063	0.181**	0.107***	−0.007	0.040
	(−0.71)	(−0.67)	(0.71)	(−1.97)	(−0.78)	(2.45)	(3.01)	(−0.33)	(0.85)
Lag 4	−0.004	−0.006	0.081	−0.170***	−0.002	0.065	0.127***	−0.003	0.031
	(−0.25)	(−0.13)	(1.17)	(−5.54)	(−0.03)	(0.93)	(3.75)	(−0.12)	(0.62)
Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES
Stock FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Groups	50	50	50	50	50	50	50	50	50
R^2	0.17	0.17	0.17	0.17	0.17	0.17	0.17	0.17	0.17

Notes: t statistics are in parentheses; ***, **, and * denote significance at the 0.01, 0.05, and 0.1 level respectively.

Table 11. Dynamic effects of sentiment on STAR 50 liquidity.

LIQ	(1) Lag 0	(2) Lag 0–1	(3) Lag 0–2	(4) Lag 0–3	(5) Lag 0–4
Aggregate Sentiment$_t$	0.037** (2.42)	0.033* (1.97)	0.034* (1.90)	0.028 (1.55)	0.026 (1.49)
Aggregate Sentiment$_{t-1}$		0.029 (1.31)	0.026 (1.10)	0.024 (1.03)	0.022 (0.98)
Aggregate Sentiment$_{t-2}$			0.021 (0.95)	0.020 (0.88)	0.018 (0.82)
Aggregate Sentiment$_{t-3}$				0.016 (0.72)	0.014 (0.66)
Aggregate Sentiment$_{t-4}$					−0.010 (−0.19)
Policy Sentiment$_t$	0.075 (1.49)	0.075 (1.44)	0.079 (1.52)	0.078 (1.49)	0.076 (1.46)
Policy Sentiment$_{t-1}$		0.048 (1.14)	0.048 (1.17)	0.049 (1.16)	0.048 (1.13)
Policy Sentiment$_{t-2}$			0.025 (0.54)	0.025 (0.54)	0.023 (0.50)
Policy Sentiment$_{t-3}$				−0.035 (−1.00)	−0.037 (−1.02)
Policy Sentiment$_{t-4}$					−0.009 (−0.19)
Psychological Sentiment$_t$	0.131** (2.10)	0.128** (2.13)	0.121** (2.08)	0.119** (2.09)	0.118** (2.09)
Psychological Sentiment$_{t-1}$		0.055 (0.77)	0.052 (0.89)	0.049 (0.90)	0.051 (0.99)
Psychological Sentiment$_{t-2}$			0.012 (0.21)	−0.002 (−0.03)	0.001 (0.01)
Psychological Sentiment$_{t-3}$				0.058 (1.11)	0.063 (1.30)
Psychological Sentiment$_{t-4}$					−0.024 (−0.42)
Social Sentiment$_t$	0.142*** (3.49)	0.144*** (3.48)	0.149*** (3.54)	0.159*** (3.79)	0.160*** (3.87)
Social Sentiment$_{t-1}$		−0.083** (−2.17)	−0.077* (−1.91)	−0.055 (−1.38)	−0.058 (−1.44)
Social Sentiment$_{t-2}$			−0.040 (−1.18)	−0.011 (−0.31)	−0.014 (−0.43)
Social Sentiment$_{t-3}$				−0.164*** (−5.85)	−0.164*** (−5.88)
Social Sentiment$_{t-4}$					0.034 (0.88)

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LIQ	(1) Lag 0	(2) Lag 0–1	(3) Lag 0–2	(4) Lag 0–3	(5) Lag 0–4
Climate Sentiment$_t$	−0.074	−0.076	−0.074	−0.087	−0.080
	(−1.18)	(−1.21)	(−1.19)	(−1.46)	(−1.35)
Climate Sentiment$_{t-1}$		0.007	−0.001	0.000	0.002
		(0.14)	(−0.02)	(0.00)	(0.03)
Climate Sentiment$_{t-2}$			0.073	0.079	0.082
			(1.18)	(1.23)	(1.27)
Climate Sentiment$_{t-3}$				−0.067	−0.066
				(−0.83)	(−0.83)
Climate Sentiment$_{t-4}$					−0.108**
					(−2.21)
Technology Sentiment$_t$	0.133**	0.112*	0.093	0.094	0.083
	(2.07)	(1.78)	(1.43)	(1.44)	(1.21)
Technology Sentiment$_{t-1}$		0.099	0.075	0.049	0.040
		(1.56)	(1.27)	(0.98)	(0.93)
Technology Sentiment$_{t-2}$			0.118*	0.094	0.078
			(1.75)	(1.42)	(1.22)
Technology Sentiment$_{t-3}$				0.136*	0.118*
				(2.02)	(1.90)
Technology Sentiment$_{t-4}$					−0.036
					(−0.80)
Company Sentiment$_t$	0.072***	0.059**	0.057**	0.050**	0.047**
	(3.00)	(2.77)	(2.63)	(2.25)	(2.21)
Company Sentiment$_{t-1}$		0.164***	0.147***	0.139***	0.138***
		(3.78)	(3.43)	(3.30)	(3.22)
Company Sentiment$_{t-2}$			0.046	0.029	0.025
			(1.47)	(1.03)	(0.92)
Company Sentiment$_{t-3}$				0.054*	0.043
				(1.82)	(1.41)
Company Sentiment$_{t-4}$					0.031
					(1.01)
Baidu Search Index$_t$	0.045**	0.042*	0.045*	0.031	0.034
	(2.15)	(1.90)	(1.73)	(1.60)	(1.55)
Baidu Search Index$_{t-1}$		0.038	0.035	0.032	0.030
		(1.52)	(1.45)	(1.36)	(1.31)
Baidu Search Index$_{t-2}$			0.031	0.029	0.027
			(1.33)	(1.25)	(1.22)
Baidu Search Index$_{t-3}$				0.026	0.024
				(1.19)	(1.16)
Baidu Search Index$_{t-4}$					0.022
					(1.12)

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LIQ	(1) Lag 0	(2) Lag 0–1	(3) Lag 0–2	(4) Lag 0–3	(5) Lag 0–4
Market Sentiment$_t$	0.105**	0.098**	0.090**	0.080*	0.085*
	(2.33)	(2.08)	(1.99)	(1.88)	(1.92)
Market Sentiment$_{t-1}$		0.043	0.037	0.034	0.040
		(1.56)	(1.41)	(1.36)	(1.45)
Market Sentiment$_{t-2}$			0.030	0.036	0.033
			(1.24)	(1.32)	(1.29)
Market Sentiment$_{t-3}$				0.029	0.026
				(1.18)	(1.12)
Market Sentiment$_{t-4}$					0.022
					(1.01)
Controls	YES	YES	YES	YES	YES
Stock FE	YES	YES	YES	YES	YES
Observations	27525	14335	7469	3848	1825
R^2 Range	0.10−0.17	0.09−0.17	0.10−0.17	0.10−0.17	0.10−0.17

Notes: t statistics are in parentheses; ***, **, and * denote significance at the 0.01, 0.05, and 0.1 level respectively.

5. Robustness tests

To establish the robustness of our core conclusions, we performed two distinct sets of tests.

First, we addressed the concern that the COVID-19 pandemic may have induced a structural break in financial markets. This period of unprecedented global uncertainty and market stress provides a rigorous setting to test the stability of the relationship we identify. Therefore, we re-estimated our baseline model using a subsample restricted to the pandemic period (2020–2023). The results, presented in Appendix A, confirm our core conclusions remain statistically and economically significant.

Second, to ensure our findings are not an artifact of our chosen liquidity proxy, we re-ran our entire analysis using an alternative, well-established measure: stock-level market depth. This test validates whether the observed relationship is fundamental rather than metric-specific. Appendix B presents results that fully corroborate our baseline findings, with key coefficients retaining their sign and statistical significance.

6. Conclusions

This study challenges the conventional, unidimensional view of investor sentiment by developing a deep learning framework to deconstruct it into six thematic dimensions: policy, psychological, social, climate, technological, and company-specific. By analyzing over 11 million posts from China's stock market, we demonstrated that this multidimensional approach fundamentally overcame the aggregation bias inherent in traditional indices, thus unlocking significant explanatory power for stock liquidity that monolithic measures obscure.

Our central empirical finding is the profound heterogeneity in sentiment's impact, which is contingent on both the sentiment's thematic source and the firm's characteristics. For blue-chip stocks, liquidity was primarily driven by a stable and sustained positive influence from social, psychological, and company-specific sentiments, while policy-related sentiment only created transient shocks. In stark contrast, technology stocks exhibited far more complex and volatile dynamics. For these firms, technology sentiment displayed a lagged amplification effect, social sentiment induced a "hype-and-correction" cycle, shifting from positive to negative over time, and climate sentiment acted as a persistent drag on liquidity. These intricate, often nonlinear patterns underscore that the sentiment-liquidity nexus is not uniform, but is instead dynamically shaped by the interplay between information type and firm-level attributes.

Methodologically, our work pioneers a scalable framework for moving beyond simple sentiment polarity to thematic decomposition, thus offering a more granular lens to test theories of behavioral finance and market microstructure. The practical implications are significant. The thematic indices we construct can serve as superior inputs for sophisticated risk management models, quantitative trading strategies, and regulatory surveillance systems designed to monitor market stability.

In conclusion, by reconceptualizing investor sentiment as a multidimensional construct, this paper provides a more accurate and nuanced understanding of its role in driving stock liquidity.

7. Limitations and future research

While this paper advances our understanding of the sentiment-liquidity nexus through a multi-dimensional framework, its conclusions should be interpreted in light of several limitations that also present opportunities for future inquiry.

(1) Endogeneity and Causal Inference

The primary limitation of this study is the challenge of endogeneity, which precludes a definitive causal interpretation of our results. Our panel fixed-effects and distributed-lag models, while controlling for unobserved firm heterogeneity and capturing temporal dynamics, cannot fully mitigate the risk of reverse causality. It is plausible that a deterioration in market liquidity—itself a salient market event—triggers negative investor sentiment. For example, a sudden liquidity drain or price shock could catalyze pessimistic discourse online, thus making sentiment an outcome of, rather than a driver of, market conditions.

Consequently, while our findings established a robust and nuanced correlation between specific sentiment dimensions and stock liquidity, we stopped short of claiming a strictly causal link. Thus, the paper's core contribution is to document and dissect this complex interrelationship, rather than to prove causation.

Future research must employ more robust identification strategies to disentangle this simultaneity. A promising avenue lies in the use of quasi-natural experiments. One could exploit exogenous shocks that plausibly affect investor sentiment without directly influencing individual stock liquidity. For instance, events such as major policy announcements on climate change could serve as instruments for "environmental" sentiment, thus allowing for a cleaner identification of its marginal impact on market dynamics. Such approaches are essential to move from correlation to credible causal inference.

(2) Sample Composition and External Validity

Second, due to time constraints and the high cost of data scraping, our sample was limited to constituent stocks of the SSE 50 and STAR 50 indices. Although these firms represent China's large-cap and high-growth technology sectors, they are not representative of the entire A-share market, which includes a vast number of smaller, less liquid, and less institutionally-held firms. The dynamics observed in our sample may not generalize to these other segments of the market.

Therefore, future work should extend the analysis to a broader and more diverse cross-section of stocks to verify the robustness and generalizability of our findings.

(3) Temporal Scope of Thematic Classification

Finally, our thematic classification scheme is based on contemporary market narratives reflected in literature published since 2023. This static, present-day lens may not capture the dominant investment themes of different historical eras. For example, the themes which drove markets in the early 2000s (e.g., the dot-com bubble's aftermath) significantly differ from today's focus on artificial intelligence (AI) or environmentasl, social, and governance (ESG) factors. This introduces a potential temporal bias, as the measured impact of sentiment may be contingent on the prevailing market regime. A valuable direction for future research would be a longitudinal analysis of investor sentiment. By constructing a textual corpus that spans several decades, one could track the evolution of sentiment themes and examine the time-varying nature of sentiment's influence on market microstructure across different economic cycles.

Author contributions

Zhiyi Wang: Conceptualization, Methodology, Software, Validation, Formal analysis, Writing - original draft, Writing - review & editing.

Jingru Guo: Software, Formal analysis, Writing - original draft.

Gaoshan Wang: Software, Formal analysis, Writing - original draft.

Xiaohong Shen: Software, Formal analysis, Writing - original draft.

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Use of AI tools declaration

The author declares they have not used Artificial Intelligence (AI) tools in the creation of this article.

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Conflict of interest

All authors declare no conflicts of interest in this paper.

Availability of data and material

The datasets used and/or analysed during the current study are available from the corresponding author on reasonable request.

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