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Research on AI Driven Investor Sentiment Recognition Mechanism and Dynamic Impact on Asset Pricing Bias

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Abstract. In tandem with the rise of platform-based financial communication, investor sentiment is now measurable as a behavioral factor affecting the behavior of equity markets. In social media messages and corporate news, there is information dispersion regarding investors' expectation of firm value, risk events, and policy uncertainty, whereas machine learning offers computable methods to capture the signals from text data. On the basis of 486,217 messages by investors, 18,604 announcements of listed companies, and 412,380 firm-level daily trading records in the years between 2021 and 2025, an investor sentiment recognition approach based on artificial intelligence is designed in order to detect sentiment polarity, strength, and uncertainty. FinBERT-Transformer fusion model exhibits optimal classification results with accuracy of 0.887±0.011, macro-F1 of 0.872±0.014, and AUC of 0.931±0.009. Through dynamic panel regression, it was found that one-standard deviation increase in positive sentiment leads to overpricing at day one by 12.6±2.1 basis points, while negative sentiment increases underpricing by 16.8±2.4 basis points. These effects diminish after five trading days and reverse somewhat at day ten in the two groups of size and liquidity. The results suggest that AI recognition of investor sentiment helps interpret asset pricing bias in terms of expectation adjustment, attention concentration, and trading pressure.

Keywords: AI-driven sentiment recognition, investor sentiment, natural language processing, asset pricing bias, behavioral finance

1. Introduction

With the development of digital trading platforms, there is a more direct relationship between public textual information and price adjustments. Investor sentiment emerges in social media prior to the processing of any information, while corporate disclosures affect revisions of beliefs through the disclosure tone, information uncertainty, and discourse framing. Modern asset pricing literature reveals that sentiment-based models can be helpful in explaining the excess return and anomalies [1]. From the evidence regarding managerial manipulation, it is clear that positive sentiment increases the overpricing effect when investors attach too much importance to disclosed information [2]. There is also evidence that sentiment beta includes price information under diverse states of the market [3]. The significance of sentiment is evident from current research, but the process of transferring AI-based recognition of textual sentiment into pricing bias requires an integrated

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approach combining computation and behavioral aspects. The proposed model links text mining using multiple sources, deep sentiment recognition, and dynamic bias estimation, showing how AI-generated investor sentiment affects asset prices through expectation adjustments and trading pressure.

2. Literature review

2.1. Investor sentiment and pricing bias in behavioral finance

Investor sentiment offers an explanation of pricing bias in terms of behavioral factors through linking of bounded rationality with temporary demand pressure. Contemporary studies on sentiment at the stock level claim that the overall mood of optimism and pessimism within the market affects the cross-section of expected returns since people do not revise their beliefs consistently among firms [4]. In addition, conditional anomaly results indicate that investor sentiment has value in asset pricing models due to changes in anomalies with regard to market moods [5]. This suggests that sentiment should be considered as a state variable that changes over time, but not a fixed psychological state. Pricing bias takes place as the result of attention-induced trading pressure that pushes prices more rapidly than fundamentals are updated.

2.2. NLP and deep learning for sentiment recognition

From dictionary scoring, financial sentiment recognition evolves to language modeling considering the context. From recent reviews, it is evident that the text mining in finance needs models capable of dealing with domain-specific lexicon, conventions of disclosures, sarcasm, negations, and event-specific tones [6]. FinBERT proves that the pre-training of a model on financial texts enhances its classification of sentences from analysts' reports and conference calls due to different context-specific meanings compared with general language meanings. Comparative research on financial sentiment analysis reveals that the deep learning models work better than the classical ones in case sentence structure and semantics play an important role [7]. In this way, AI sentiment recognition becomes relevant for the extraction of polarity, intensity, and uncertainty from diverse sources.

2.3. Dynamic transmission from sentiment signals to asset pricing bias

Dynamic Transmission Research Links Sentiment Extraction and Market Reaction. Multi-source sentiment analysis studies stress that single source opinion needs to be converted into the public sentiment which is indexed by time before it influences the price movement [8]. In multi-source designs, it is clear that the opinions from investors, news media, and corporate disclosure can create different effects with regards to timing since these are crowd reaction, information processing, and information revelation respectively. Sentiment might influence the order imbalance and abnormal returns through attention effect, abnormal return, valuation residual, or short term reversal [9]. The positive and negative sentiment could also create different effects since negative news tends to adjust more risk. A dynamic approach is therefore required to understand whether the sentiment identified by AI influences price bias.

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3. Experimental methods

3.1. Data sources and sample construction

The empirical framework includes a text-mining layer, a sentiment detection layer, and a price formation layer. The textual data are gathered from publicly accessible investor comments posted on StockTwits-like platforms, corporate announcements from listed firms, and time-stamped financial news from January 2021 to December 2025. After removing the duplicates, the bots' activities, and those postings which have been reposted or are containing less than five financial tokens, the resulting data consists of 486,217 postings and 18,604 announcements regarding 312 continuously listed firms. Every text is matched to a certain stock code using the process of named-entity recognition and ticker matching followed by allocation to the nearest trading window. The intraday texts posted after market closure are assigned to the next trading day. The market data consist of return, turnover, volatility, bid-ask spread, market capitalization, book-to-market ratio, and exposures to Fama-French factors, providing 412,380 observations on firms and days. The resulting dataset features three contemporaneous variables: text, sentiment variables generated by AI, and proxies for pricing biases. The training, validation, and testing splits occur chronologically at 70%, 15%, and 15%.

3.2. Sentiment recognition model design

In the classification layer, Loughran-McDonald scoring is used as the base, and subsequently FinBERT, BiLSTM-Attention, and Transformer-based fusion models are tuned using annotated financial sentences. Labels are classified into positive, neutral, negative, and uncertain, such that it becomes possible to disentangle the tone of the announcement and the sentiment of investors prior to aggregation. The token sequence is cut off at 256 tokens, and imbalanced classes are taken care of via weighted cross entropy [10]. For each firm-day, the final AI sentiment score aggregates source weights, token-level attention, and probabilistic polarity, as shown in Formula (1).

$$AIS_{i,t}=\sum_{s\in\{SM,CA,FN\}}\omega_s\left[\frac{1}{N_{i,t}^s}\sum_{j=1}^{N_{i,t}^s}\alpha_{i,j,t}^s\left(P_{i,j,t}^{pos}-P_{i,j,t}^{neg}\right)\left(1+P_{i,j,t}^{unc}\right)\right] \quad (1)$$

Formula (1) defines the AI-driven investor sentiment score for firm i on trading day t. SM, CA, and FN represent social media, corporate announcements, and financial news. The source weight is denoted by omega, the attention confidence by alpha, and the positive, negative, and uncertainty probabilities by P. This design retains source heterogeneity while converting sentence-level sentiment into a comparable firm-day signal for dynamic pricing analysis.

3.3. Dynamic impact testing and bias measurement

Bias is measured in the pricing dimension using abnormal returns, misvaluation residuals, and adjustment for reversal effects of price pressure. The abnormal returns are calculated relative to the Fama-French five-factor model. Misvaluation residuals are determined by applying a valuation model on a company-by-company basis based on size, book-to-market ratio, profitability, volatility, and liquidity. Sentiment shocks are standardized differently for positive and negative shocks, since

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people react differently to optimism and pessimism [11]. The dynamic effect of sentiment is then tested through a distributed-lag panel specification, as shown in Formula (2).

$$PB_{i,t+h}=\rho PB_{i,t-1}+\sum_{l=0}^{L}\beta_l^{+}AIS_{i,t-l}^{+}+\sum_{l=0}^{L}\beta_l^{-}AIS_{i,t-l}^{-}+\gamma^{T}X_{i,t}+\mu_i+\tau_t+\varepsilon_{i,t+h} \quad (2)$$

Formula (2) explains pricing bias for firm i at horizon h. PB denotes the pricing-bias proxy, AIS positive and AIS negative represent separated sentiment shocks, X contains control variables, mu captures firm fixed effects, and tau captures date effects. The lag coefficients beta identify whether sentiment produces immediate distortion, delayed amplification, or subsequent reversal in asset pricing. Standard errors are clustered by firm and date to control cross-sectional and temporal dependence.

4. Results

4.1. Results of sentiment recognition performance

As shown in Table 1, the Transformer-FinBERT fusion model produced the most stable recognition performance across the chronological test set. Its accuracy reached 0.887±0.011, macro-F1 reached 0.872±0.014, and AUC reached 0.931±0.009, exceeding the dictionary benchmark by 0.245, 0.279, and 0.236, respectively. The calibration error decreased to 0.041±0.006, indicating that predicted probabilities were closer to observed labels. Error inspection showed that the dictionary method frequently misclassified cautious positive announcements as neutral, while BiLSTM-Attention struggled with sarcasm and ticker-based abbreviations in social-media posts. Source-level ablation further showed that removing corporate announcements reduced uncertainty recall by 0.046±0.008, whereas removing social-media posts reduced negative-sentiment recall by 0.052±0.010. The fusion model improved negative-sentiment recall to 0.884±0.013 and uncertainty recall to 0.861±0.017, which is important because uncertainty-bearing sentiment later entered the pricing-bias equation as amplified pressure. These results support the use of AI-recognized sentiment as a structured explanatory variable.

Table 1. Sentiment recognition performance across models

Model	Accuracy	Macro-F1	AUC	ECE	Negative Recall
Loughran-McDonald Dictionary	0.642±0.018	0.593±0.021	0.695±0.017	0.118±0.012	0.571±0.026
SVM-TF-IDF	0.728±0.015	0.704±0.019	0.781±0.014	0.091±0.010	0.692±0.021
BiLSTM-Attention	0.813±0.013	0.792±0.016	0.872±0.012	0.067±0.008	0.781±0.018
FinBERT	0.861±0.012	0.846±0.015	0.912±0.010	0.052±0.007	0.852±0.015
Transformer-FinBERT Fusion	0.887±0.011	0.872±0.014	0.931±0.009	0.041±0.006	0.884±0.013

4.2. Dynamic impact of sentiment shocks on pricing bias

As illustrated in Fig. 1, sentiment shocks triggered asymmetric and transient pricing biases. A positive sentiment shock by one standard deviation raised overpricing by 8.4±1.9 basis points on

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event day and reached a peak of 12.6±2.1 basis points on day one, especially in small-cap and high-turnover stocks. In the case of negative sentiment shock, its instantaneous impact was even more significant, causing underpricing to deepen by 16.8±2.4 basis points on day one but insignificant by day three. The biases became insignificant beyond day five, both below 5.0 basis points, and the day-ten coefficients were found to be weakly opposite, indicating some degree of price correction as attention pressure dissipated. The cumulative impacts of positive and negative sentiment shocks were measured to be 31.7±6.8 basis points and -42.5±7.3 basis points respectively using the VAR impulse-response test. Estimates based on subsamples revealed that highly attended firms experienced 1.31 times larger sentiment coefficient than their counterparts with low attention.

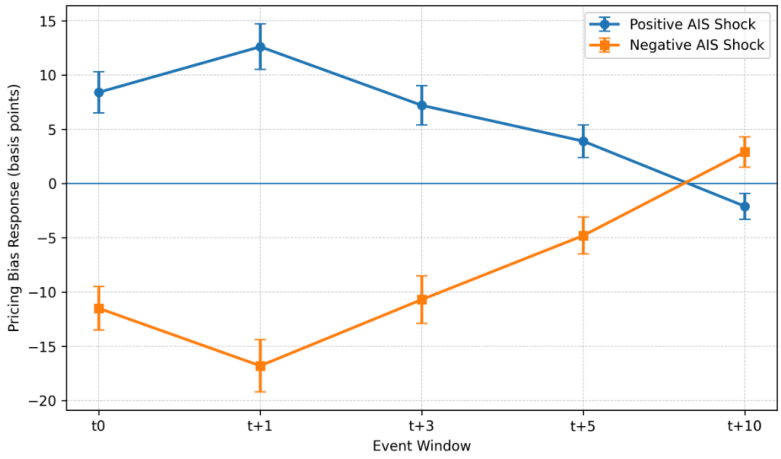


Figure 1. Dynamic response curve of pricing bias to one-standard-deviation sentiment shock

5. Discussion

From the analysis, it is clear that the technical benefits of using AI sentiment recognition lie primarily in the ability of the method to decrease semantic losses of the financial kind. Dictionary scores identify positive and negative words explicitly, but fail to detect cautious optimism, sarcasm, ticker expressions, and uncertainty included in disclosures. It is likely that the improved performance of the model that combines Transformer and FinBERT is due to the fact that the investor sentiment must be viewed as probabilistic and source-related. The pricing results also confirm a behavioral asymmetry. The negative sentiment led to deeper and more prolonged underpricing due to the fact that pessimism and liquidity withdrawal occurred quicker than an optimistic revaluation. In other words, the positive sentiment resulted in overpricing; however, its impact faded quickly since speculative attention disappeared in the presence of new trading information. The reversal after day ten shows that sentiment-induced pricing bias is temporary in nature, but the period is important from the economic point of view for active stocks. Concerning the governance function, sentiment analysis is useful for detecting abnormal volatility, but the output of the model must be used alongside liquidity, firm size, and disclosure type.

6. Conclusion

A model based on AI techniques was proposed to derive investor sentiment from social media, announcement and financial news data, and to analyze the impact of this dynamic factor on the bias of asset pricing. Empirically, the study integrates deep sentiment extraction with behavior propagation by arguing that the fusion of Transformer and FinBERT produces more reliable

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sentiment signal, and negative shocks have higher likelihood of generating short-run mispricing than positive shocks. The novelty of this work is its ability to relate unstructured financial texts, investor cognition, and asset pricing bias in a single analytical procedure. There are still issues related to the limited coverage of markets, reliance on manually labeled data, and potential language biases on certain platforms.

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