Scientific Research Publishing

Open Journal of Business and Management, 2025, 13(1), 514-524
https://www.scirp.org/journal/ojbm
ISSN Online: 2329-3292
ISSN Print: 2329-3284

Research on the Construction of Financial Market Sentiment Index and Its Predictive Power for Asset Prices

Mohan Hou

Shenzhen Fuyuan British American School, Shenzhen, China
Email: mohanhou25@outlook.com

How to cite this paper: Hou, M. H. (2025). Research on the Construction of Financial Market Sentiment Index and Its Predictive Power for Asset Prices. *Open Journal of Business and Management, 13,* 514-524.
https://doi.org/10.4236/ojbm.2025.131029

Received: October 16, 2024
Accepted: January 23, 2025
Published: January 26, 2025

Abstract

Fluctuations in financial markets are not only influenced by fundamental factors, but investor sentiment also plays an increasingly important role. Accurately capturing and quantifying market sentiment is of great significance for understanding asset price dynamics. This study is dedicated to exploring the theoretical basis for constructing a comprehensive financial market sentiment index and evaluating its potential impact on asset price prediction. The research first reviews the theoretical developments of investor sentiment in behavioral finance, analyzing how emotional factors influence investment decisions and market dynamics. On this basis, the study proposes a multi-dimensional sentiment indicator framework, including aspects such as social media sentiment, news reporting tendencies, and trading behavior characteristics. Through theoretical analysis, the research discusses how these indicators comprehensively reflect the overall sentiment state of the market. The study also examines the sensitivity differences of various asset classes (such as stocks, bonds, foreign exchange) to sentiment factors, and the potential reasons for these differences. Furthermore, the research discusses the potential non-linear relationships and feedback mechanisms between market sentiment and asset prices. Through theoretical derivation, the study proposes hypotheses about the explanatory power and predictive potential of sentiment indices for short-term price fluctuations. However, the research also points out the theoretical challenges faced in quantifying sentiment impacts, such as the complexity of sentiment transmission mechanisms and the heterogeneity of market participants. This study not only deepens the theoretical understanding of investor behavior and market microstructure but also provides a theoretical framework for future empirical research and index construction.

Keywords

Market Sentiment, Asset Pricing, Sentiment Index, Behavioral Finance, Theoretical Analysis

1. Introduction

Financial markets are at the core of modern economies, and their operational mechanisms have long been a focus of attention in both academia and industry. Traditional financial theory assumes that market participants are fully rational and that market prices reflect all available information. However, with the rise of behavioral finance, there has been a growing recognition that investors' irrational behaviors and emotional factors play important roles in asset pricing. In recent years, the development of big data and artificial intelligence technologies has provided new tools and methods for quantifying market sentiment. The integration of multi-source information such as social media, news reports, and high-frequency trading data has made it possible to construct more comprehensive and accurate market sentiment indicators. Against this background, exploring methods for constructing market sentiment indices and their predictive power for asset prices has not only significant theoretical implications but also potential practical value. Existing research suggests that investor sentiment may cause asset prices to deviate from fundamental values, leading to anomalies such as overreaction or delayed reaction (Baker & Wurgler, 2006). However, accurately measuring and quantifying overall market sentiment remains a challenging issue. The sensitivity of different types of assets to sentiment factors may also vary, further increasing the complexity of research. This study aims to explore possible pathways for constructing comprehensive market sentiment indices through theoretical analysis and discuss their potential applications in asset price prediction. The research will start from the theoretical foundations of behavioral finance, combined with market microstructure theory, to propose a multi-dimensional sentiment indicator framework. Meanwhile, the study will also focus on the differences in the role of sentiment factors across various asset classes, as well as the potentially complex non-linear relationships between sentiment and prices. Through systematic theoretical analysis, this study hopes to provide theoretical support for subsequent empirical research and index construction work, and offer new perspectives for understanding the operational mechanisms of financial markets.

2. Literature Review

2.1. Investor Sentiment Theory in Behavioral Finance

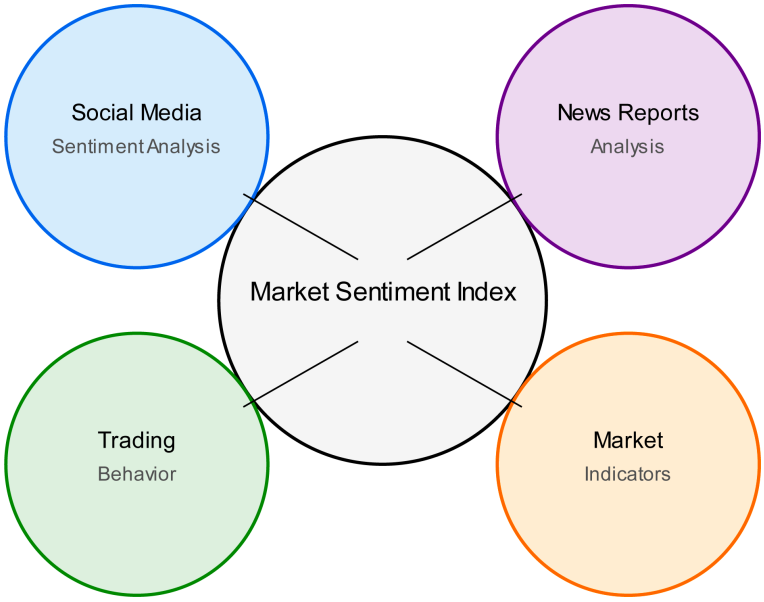
Investor sentiment, as one of the core concepts in behavioral finance, can trace its theoretical foundations to psychological and sociological studies on human decision-making behavior. The prospect theory proposed by Kahneman and Tversky (1979) revealed decision-making biases people face under uncertainty, providing

an important theoretical basis for understanding investor sentiment. Subsequently, the noise trader model proposed by De Long et al. (1990) further explained how irrational investors influence asset prices. These early theories laid the foundation for subsequent research on the role of investor sentiment in financial markets. In recent years, with the development of neurofinance, researchers have begun to explore the impact of emotions on investment decisions from physiological and neuroscientific perspectives (Lo & Repin, 2002). These studies have not only deepened our understanding of investor behavior but also provided new ideas for constructing sentiment indicators. However, how to link individual-level emotional biases with the overall sentiment state of the market remains an issue that needs further exploration.

2.2. Construction Methods of Market Sentiment Indicators

Methods for constructing market sentiment indicators have been continuously evolving with technological advancements. Early research mainly relied on indirect indicators such as closed-end fund discounts, IPO numbers, and first-day returns (Baker & Wurgler, 2006). While these indicators could reflect market sentiment to some extent, they often suffered from issues of lag and indirectness. With the popularization of the internet and social media, it became possible to extract sentiment information directly from investor expressions. The application of text analysis and natural language processing technologies has enabled researchers to extract sentiment information from a large number of news reports and social media posts (Bollen et al., 2011). Additionally, high-frequency trading data has also been used to construct market sentiment indicators, such as indicators based on order flow and trading volume (Lachanski & Pav, 2017). However, how to integrate sentiment information from these different sources to construct a comprehensive and real-time market sentiment index remains an unresolved issue. In particular, there may be contradictions or redundancies between different sentiment sources, and how to balance and filter this information is one of the main challenges faced in constructing comprehensive sentiment indices.

As shown in **Figure 1**, the construction of a market sentiment index requires the integration of information from multiple sources. This includes social media sentiment analysis, news report analysis, trading behavior characteristics, and traditional market indicators. Each component provides a unique perspective for capturing the overall sentiment state of the market. Social media sentiment reflects investors' immediate reactions and group emotions; news analysis can capture broader market information and professional opinions; trading behavior characteristics directly reflect investors' actual decisions; while traditional market indicators provide a benchmark for the overall market condition. These components interact with each other, jointly forming a comprehensive market sentiment index. However, how to effectively integrate information from these different sources and ensure the real-time nature and accuracy of the index remains a



Source: Adapted from Baker and Wurgler (2006) and modified based on current market structure analysis.

Figure 1. Components of market sentiment index.

major challenge in the construction process.

2.3. Relationship between Sentiment Indicators and Asset Prices

The relationship between sentiment indicators and asset prices has long been a focus of academic attention. Early research mainly concentrated on the stock market, finding significant correlations between investor sentiment and stock returns (Brown & Cliff, 2004). However, this relationship may vary depending on asset classes, market conditions, and time scales. For example, some studies have shown that sentiment factors have a more significant impact on small-cap stocks (Baker & Wurgler, 2006). In recent years, the scope of research has gradually expanded to other asset classes such as bonds, foreign exchange, and commodity markets. These studies have revealed that the mechanisms of sentiment factors may differ across different markets. For instance, in the foreign exchange market, sentiment may influence exchange rates by affecting risk preferences (Froot & Ramadorai, 2005). The relationship between sentiment and asset prices may be non-linear, with threshold effects or feedback mechanisms. For example, excessively optimistic or pessimistic sentiment may lead to the formation and bursting of market bubbles. However, how to accurately capture and quantify this non-linear relationship remains a challenge. Another issue worth noting is the predictive power of sentiment indicators. Although existing research suggests that sentiment indicators have some predictive power for short-term price fluctuations, their long-term predictive ability remains controversial. This may be related to market adaptability and efficiency; as investors' understanding of sentiment factors deepens, their impact on prices may weaken.

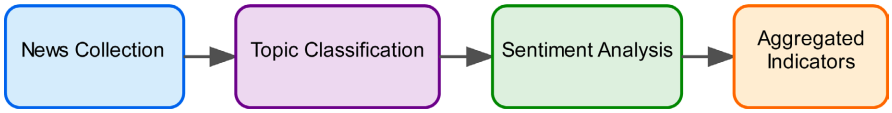
3. Multi-Dimensional Sentiment Indicator Framework

3.1. Social Media Sentiment Analysis

Social media platforms have become important channels for investors to express opinions and emotions, providing rich data sources for market sentiment analysis. Using natural language processing technologies, sentiment information can be extracted from a large number of social media posts. The advantage of this method lies in its real-time nature and broad coverage, capable of quickly capturing immediate reactions of market participants. However, social media data also faces challenges such as high noise and uncertain reliability. To improve the accuracy of analysis, a multi-level analysis framework can be adopted. Sentiment dictionaries and machine learning algorithms can be used to classify the sentiment of individual posts. The influence and credibility of users can be considered to weight sentiment information from different sources. The transmission patterns and group effects of sentiment can be analyzed, with how to quickly identify and quantify sudden changes in sentiment being a key issue. It is also necessary to consider the characteristics of different social media platforms and user group differences, as well as how to integrate sentiment information from multiple platforms. Future research directions may include using deep learning technologies to improve the accuracy of sentiment analysis, and exploring the impact of social network structures on sentiment transmission.

3.2. News Report Tendency Analysis

As an important channel for disseminating market information, news media and their reporting tendencies have a significant impact on the formation and changes of market sentiment. Compared to social media, news reports are usually more formal and professional, but may also have a certain lag. The key to news report tendency analysis lies in accurately identifying the sentiment tendency and topic importance of reports. This process can be achieved through the following steps: Using text classification techniques to categorize news, in order to filter out reports related to financial markets. Secondly, employing sentiment analysis algorithms to evaluate the sentiment tendency of each report, which can use methods such as Term Frequency-Inverse Document Frequency (TF-IDF) to extract keywords, combined with domain-specific sentiment dictionaries for analysis. Consider the credibility and influence of news sources to weight reports from different sources. It is also necessary to pay attention to the time series characteristics of news reports, such as changes in reporting frequency and trends in sentiment tendencies. Chen et al. (2019) found a significant correlation between news sentiment and stock market volatility. However, how to effectively integrate news report tendencies with other sentiment indicators remains an issue that needs in-depth research. Future research directions may include exploring the time lag relationship between news reports and market reactions, and how to use deep learning technologies to improve the accuracy and efficiency of news sentiment analysis.



Source: Developed based on Chen et al. (2019).

Figure 2. News sentiment analysis process.

As shown in **Figure 2**, news sentiment analysis is a complex multi-step process. Starting from news collection, it goes through topic classification and sentiment analysis, finally arriving at aggregated sentiment indicators. In this process, it is also necessary to consider the credibility of news sources, time series characteristics, and integration with other sentiment indicators. This systematic analysis method can more comprehensively capture the impact of news reports on market sentiment, providing important support for constructing comprehensive market sentiment indices.

3.3. Trading Behavior Characteristic Analysis

Investors' actual trading behavior is direct evidence reflecting market sentiment. By analyzing trading data, a series of characteristic indicators reflecting sentiment states can be extracted. These indicators include but are not limited to: trading volume, buy-sell ratio, order flow imbalance, volatility indicators, etc. Research by Lachanski and Pav (2017) shows that sentiment indicators constructed based on high-frequency trading data have significant predictive power for short-term price fluctuations. However, how to extract the most representative sentiment characteristics from massive trading data remains a challenging issue. One possible method is to use machine learning techniques such as Principal Component Analysis (PCA) or Autoencoders to extract potential factors that best reflect sentiment states from multi-dimensional trading characteristics. In addition, it is necessary to consider the differences in trading behaviors of different types of investors (such as institutional investors and individual investors), and how these differences affect overall market sentiment. Another issue worth noting is the relationship between trading behavior characteristics and other sentiment indicators. For example, can sentiment expressions on social media predict actual trading behaviors? Research on this relationship may help us better understand how emotions influence investment decisions. Future research directions may include exploring the application of non-linear methods (such as deep learning) in extracting trading behavior characteristics, and how to combine trading behavior characteristics with macroeconomic indicators to construct more comprehensive market sentiment indices.

4. Sentiment Sensitivity Analysis of Asset Prices

4.1. Sentiment Sensitivity Differences across Asset Classes

The degree of influence of market sentiment on different asset classes may vary significantly. This difference is not only reflected in the importance of sentiment

factors but also in the sentiment transmission mechanisms and time characteristics. The stock market is generally considered to be the asset class most susceptible to sentiment influence, especially for small-cap and high-volatility stocks (Baker & Wurgler, 2006). In contrast, the bond market, especially the government bond market, has lower sensitivity to sentiment factors and may be more influenced by macroeconomic factors. The foreign exchange market is in an intermediate state, with its sentiment sensitivity possibly varying depending on currency pairs. Emerging market currencies may be more susceptible to sentiment fluctuations than major reserve currencies. Commodity markets, especially precious metals like gold, may exhibit unique sentiment sensitivity patterns by showing safe-haven or speculative properties under extreme market sentiment (such as panic or extreme optimism).

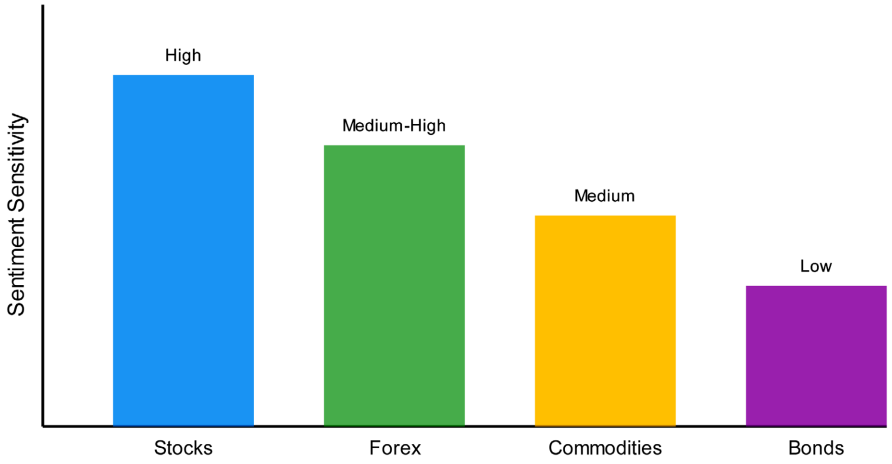


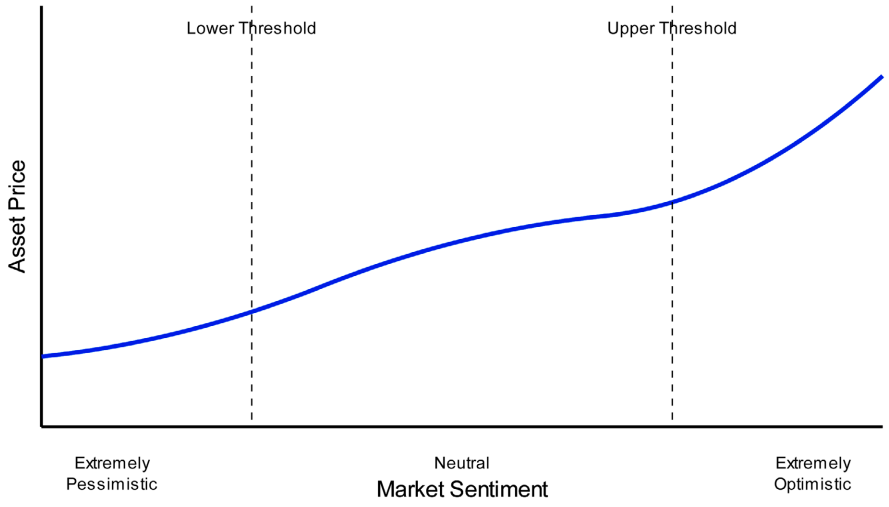
Figure 3. Sentiment sensitivity of different asset classes.

As shown in Figure 3, there are significant differences in sentiment sensitivity across different asset classes. The stock market exhibits the highest sentiment sensitivity, possibly due to stock prices being more easily influenced by investor expectations and risk preferences. Foreign exchange and commodity markets show medium levels of sentiment sensitivity, which may reflect that these markets are influenced by both fundamental factors and are not completely immune to investor sentiment fluctuations. The bond market, especially government bonds, shows lower sentiment sensitivity, possibly because bond prices are more determined by factors such as interest rate expectations and credit risk. This differentiation suggests that when constructing comprehensive market sentiment indices, we need to consider the characteristics of different asset classes and may need to design specific sentiment indicators for different asset classes. Future research can further explore the reasons for these sensitivity differences and how to utilize these differences to optimize investment portfolio management and risk control strategies.

4.2. Non-Linear Relationship between Sentiment and Price

The relationship between market sentiment and asset prices is often complex and

non-linear. This non-linearity may stem from multiple factors, including the heterogeneity of investor behavior, the complexity of market microstructures, and changes in the macroeconomic environment. Research by Zhu et al. (2020) found that the impact of sentiment on stock returns exhibits significant threshold effects, meaning that when the sentiment indicator exceeds a certain critical value, its impact on prices suddenly intensifies. This non-linear relationship may cause traditional linear models to fail in predicting market dynamics. To capture this complex relationship, non-parametric methods or machine learning techniques such as Support Vector Machines (SVM) or neural network models can be considered. These methods can better adapt to non-linear patterns in data, improving prediction accuracy. Another issue worth noting is the feedback mechanism between sentiment and prices. Price movements themselves may affect market sentiment, while changes in sentiment in turn influence prices. This bidirectional causal relationship may lead to self-reinforcing cycles in the market, and in extreme cases, may even trigger market bubbles or crashes. Therefore, when constructing sentiment indicators and prediction models, this dynamic feedback mechanism needs to be considered. One possible method is to use Vector Autoregression (VAR) models or Granger causality tests to analyze the mutual influence between sentiment and prices. The impact of sentiment on prices may vary depending on the time scale. In the short term, sentiment may have a significant impact on price fluctuations; but in the long run, fundamental factors may be more important. Therefore, when analyzing the relationship between sentiment and prices, different time windows need to be considered. Time-frequency analysis methods such as Wavelet Analysis may help reveal the temporal characteristics of sentiment influence.



Source: Based on Zhu et al. (2020) and modified with additional theoretical analysis.

Figure 4. Non-linear relationship between sentiment and asset prices.

As shown in **Figure 4**, there exists a complex non-linear relationship between market sentiment and asset prices. In extremely pessimistic and extremely optimistic

sentiment ranges, price sensitivity to sentiment may be higher, manifested as steeper slopes of the curve. While in the neutral sentiment range, price response to sentiment may be relatively flat. The figure also shows possible threshold effects, meaning that when the sentiment indicator breaks through a certain critical value, prices may experience rapid changes. This non-linear relationship implies that when constructing sentiment indicators and prediction models, more complex methods need to be adopted to capture the dynamic relationship between sentiment and prices.

4.3. Evaluation of the Predictive Power of Sentiment Indicators

Evaluating the predictive power of sentiment indicators for asset prices is a key step in constructing effective market sentiment indices. This evaluation not only needs to consider the accuracy of predictions but also needs to focus on the timeliness and stability of predictions. Traditional evaluation methods usually include using indicators such as Mean Squared Error (MSE) and Mean Absolute Error (MAE) to measure prediction accuracy. However, considering the special nature of financial markets, focusing solely on these statistical indicators may not be sufficient to comprehensively evaluate the predictive power of sentiment indicators.

Firstly, the economic significance of predictions needs to be considered. Even if predictions are statistically significant, if they cannot generate excess returns, their value in practical applications may be limited. Therefore, portfolio backtesting can be considered to evaluate the actual predictive value of sentiment indicators. By constructing trading strategies based on sentiment indicators and comparing them with benchmark strategies (such as buy-and-hold), the predictive ability of sentiment indicators can be more intuitively evaluated.

Secondly, the time scale of predictions is also an important consideration. Different sentiment indicators may exhibit predictive power on different time scales. For example, sentiment indicators based on high-frequency trading data may be more suitable for short-term predictions, while indicators based on news analysis may perform better in medium to long-term predictions. Therefore, multiple time windows need to be considered in the evaluation process to comprehensively understand the predictive characteristics of sentiment indicators.

Thirdly, the stability of predictive power is also a key issue. The dynamic nature of financial markets means that the performance of prediction models may change over time. Therefore, rolling window methods or other dynamic evaluation methods need to be adopted to examine the time-varying characteristics of the predictive power of sentiment indicators. This dynamic evaluation not only helps understand the long-term effectiveness of sentiment indicators but may also reveal important information about market structure changes or the evolution of investor behavior.

Fourthly, the interaction between sentiment indicators and other predictive factors needs to be considered. Sentiment indicators may have correlations or complementarities with traditional technical indicators or fundamental factors. By

constructing multi-factor models, the marginal predictive power of sentiment indicators after controlling for other factors can be evaluated, thereby more accurately judging their importance in asset pricing.

Overall, the evaluation of the predictive power of sentiment indicators should be a multi-dimensional, dynamic process. This not only helps verify the effectiveness of sentiment indicators but also provides an important basis for further improving and optimizing sentiment indices. Future research can explore more advanced evaluation methods, such as cross-validation techniques in machine learning, or consider introducing Bayesian methods that incorporate model uncertainty, to provide more comprehensive and reliable evaluation results.

5. Conclusion

This study discussed the theoretical basis for constructing financial market sentiment indices and their predictive power for asset prices. Through systematic analysis, we proposed a multi-dimensional sentiment indicator framework, covering aspects such as social media sentiment, news report tendencies, and trading behavior characteristics. The research found that different asset classes have significant differences in sensitivity to market sentiment, providing a theoretical basis for constructing sentiment indicators specific to particular asset classes. Meanwhile, we also explored the potential non-linear relationships and feedback mechanisms between sentiment and asset prices, offering new perspectives for understanding market dynamics. In evaluating the predictive power of sentiment indicators, we emphasized the need to consider multiple dimensions such as economic significance, time scale, and stability of predictions. These findings not only deepen our understanding of investor behavior and market microstructures but also provide important theoretical guidance for future empirical research and index construction work. However, this study also reveals challenges that still exist in quantifying sentiment impacts, such as how to effectively integrate sentiment information from different sources, and how to handle the time-varying characteristics of sentiment indicators. Future research can further explore these issues and consider applying advanced machine learning techniques to sentiment analysis and the construction of prediction models. Overall, with the continuous development of big data and artificial intelligence technologies, market sentiment analysis will play an increasingly important role in asset pricing and risk management, providing more comprehensive and in-depth insights for investment decision-making.

Conflicts of Interest

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

References

Baker, M., & Wurgler, J. (2006). Investor Sentiment and the Cross-Section of Stock Returns. *The Journal of Finance, 61,* 1645-1680. https://doi.org/10.1111/j.1540-6261.2006.00885.x

Bollen, J., Mao, H., & Zeng, X. (2011). Twitter Mood Predicts the Stock Market. *Journal of Computational Science, 2,* 1-8. https://doi.org/10.1016/j.jocs.2010.12.007

Brown, G. W., & Cliff, M. T. (2004). Investor Sentiment and the Near-Term Stock Market. *Journal of Empirical Finance, 11,* 1-27. https://doi.org/10.1016/j.jempfin.2002.12.001

Chen, C. Y., Després, R., Guo, L., & Renault, T. (2019). *What Makes the Market Jump? Volatility Forecasting Using News Sentiment*. Working Paper.

De Long, J. B., Shleifer, A., Summers, L. H., & Waldmann, R. J. (1990). Noise Trader Risk in Financial Markets. *Journal of Political Economy, 98,* 703-738. https://doi.org/10.1086/261703

Froot, K. A., & Ramadorai, T. (2005). Currency Returns, Intrinsic Value, and Institutional-Investor Flows. *The Journal of Finance, 60,* 1535-1566. https://doi.org/10.1111/j.1540-6261.2005.00769.x

Kahneman, D., & Tversky, A. (1979). Prospect Theory: An Analysis of Decision under Risk. *Econometrica, 47,* 263-293. https://doi.org/10.2307/1914185

Lachanski, M., & Pav, S. (2017). Shy of the Character Limit: "Twitter Mood Predicts the Stock Market" Revisited. *Econ Journal Watch, 14,* 302-345.

Lo, A. W., & Repin, D. V. (2002). The Psychophysiology of Real-Time Financial Risk Processing. *Journal of Cognitive Neuroscience, 14,* 323-339. https://doi.org/10.1162/089892902317361877

Zhu, B., Niu, F., & Zhao, Y. (2020). The Nonlinear Impact of Investor Sentiment on Stock Returns: Evidence from China. *International Review of Economics & Finance, 69,* 424-438.