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Emotion in Motion: Hedge Fund Managers' Social Media Sentiment and Performance Across the COVID-19 Shock

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KEYWORDS

Hedge fund managers,
hedge fund performance,
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ABSTRACT

This study investigates the influence of hedge fund managers' moods on fund performance before and during the COVID-19 pandemic by analyzing approximately 560,000 English-language tweets from 230 active managers. Using BERT-based deep learning models and LDA topic modeling, we extract sentiment indices from both original tweets and interactive engagements (retweets, replies, and quotes). Results show that sentiment derived from interactive tweets has a significant and positive impact on hedge fund returns, particularly during the pandemic, while sentiment from original tweets exhibits a negative relationship with performance. Cointegration tests confirm a long-term relationship between managers' moods and fund performance, with stronger short-term effects observed during the COVID-19 period. The findings suggest that social interaction amplifies the predictive power of sentiment, possibly by mitigating biases associated with overconfidence or emotional contagion in isolated self-expression. This research highlights the role of digital discourse as a proxy for managerial sentiment and contributes to the growing literature at the intersection of behavioral finance, social media analytics, and fund management.

1. Introduction

Over the past several decades, the hedge fund (HF) investment industry has expanded at a dizzying pace. Furthermore, according to Hedge Fund Research (2021), for the first time in history, the hedge fund sector manages more than $4.5 trillion in assets, a 50% growth over 2018. As a consequence, hedge fund performance has piqued the curiosity of a broad spectrum of market players and scholars in recent years.

Contrary to the premise of conventional economic theory, humans are not always capable of making logical investment and trade choices. To shed light on the intricacy of real decision-making processes, psychological explanations are required. Lee and Chen (2020) found postitive sentiments via tweets are strong predictors of future ETF returns. Individually, investors' moods could also have substantial effects on trading decisions. Huang and Goo (2014) suggested that different types of happiness could create different investors' trading behaviors. They found that when satisfaction in the natural world is greater, investors are less prone to be overconfident. In contrast, investors are more prone to be overconfident when the investing environment is happier. However, given the profound impacts of psychological states and sentiments on individual investment decisions (Lee & Chen, 2020), it is surprising that there have been so few efforts to investigate hedge fund managers' sentiments and how they may affect the performance of hedge funds.

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In addition, despite growing evidence on the psychological and emotional consequences of the COVID-19 pandemic, limited research has been conducted on how these factors influence professional investment behavior, particularly among hedge fund managers. The pandemic not only caused extreme financial volatility but also triggered widespread emotional distress, anxiety, and uncertainty, all of which can deeply affect decision-making. While prior studies have examined individual investors' emotional responses during crises, the role of professional fund managers' sentiment—especially as publicly expressed on social media—remains underexplored. This gap is especially important given that hedge fund managers play a pivotal role in directing large volumes of capital, and their emotional resilience or vulnerability under crisis conditions can have significant implications for market dynamics. Therefore, this study seeks to fill this void by investigating how hedge fund managers' sentiment, before and during the COVID-19 pandemic, correlates with hedge fund performance, providing new insights into behavioral finance during periods of systemic stress.

In order to fill this research vacuum, this study investigates the most popular issues addressed by hedge fund managers on X, as well as the sentiment associated with them. Following Lee and Chen (2020), we use tweets' sentiment as the proxy for hedge fund managers' moods and examine whether it has any effect on hedge funds' returns. This study contributes to the existing behavioral finance in several ways. First, this study extracts the most commonly discussed issues on social media using text mining techniques (LDA) and the emotions of tweets using deep learning algorithms from about 560,000 English tweets from active fund managers, especially during the COVID-19 pandemic. We noticed that hedge fund managers significantly boosted their social media participation during the outbreak (from 2020 to 2021). Hedge fund managers primarily handled market information and, on occasion, social and political problems that may affect the funds' investments. As a result, the emotions of tweets might be used to reflect fund managers' moods and attitudes toward the markets, which could impact their trading decisions. Second, following the suggestion from Huang and Goo (2014), we divide fund managers' sentiments into two types: sentiments from interacted tweets (participating in discourse with others) and sentiments from original tweets created by hedge fund managers. Using these mood indices as a proxy for hedge fund managers' relevant investing attitude at a given period, we established a long-term cointegration between managers' sentiment and hedge fund performance from 2019 to 2021.

The findings of this study are many folds. First, this study offers a novel integration of sentiment analysis derived from hedge fund managers' tweets by differentiating between original posts and interactive engagements (retweets, replies, and quotes). This distinction allows for a more nuanced understanding of how self-expressed sentiment versus socially engaged sentiment correlates with fund performance. Second, the paper provides empirical evidence on the differential impacts of sentiment on hedge fund returns before and during the COVID-19 pandemic, thereby contributing to the behavioral finance literature by contextualizing sentiment-performance dynamics under varying market conditions. Third, the study presents a methodological contribution by applying state-of-the-art natural language processing techniques—specifically BERT-based sentiment classification and LDA topic modeling—combined with Vector Error Correction Models (VECM) to uncover both short- and long-term relationships. Lastly, the research yields practical implications for fund managers and investors, suggesting that social media-derived sentiment, especially from interactive discourse, can serve as a predictive input for fund performance and decision-making, especially during periods of market stress. These contributions fill notable gaps in existing literature at the intersection of behavioral finance, social media analytics, and fund management.

The remainder of the paper is structured as follows: Section 2 reviews relevant literature on fund managers' emotions, market sentiment, and their impact on investment performance. Section 3 details the research data and methodology, including our approach to sentiment extraction and econometric modeling using VECM. Section 4 presents empirical results, encompassing content analysis of tweet topics and detailed regression results before and during the COVID-19 pandemic. Section 5 concludes the study with key findings, implications for theory and practice, limitations of the study, and avenues for future research.

2. Theoretical background

2.1. Fund Managers' Emotions and Investment Performance

Previous studies have shown that investor emotions can significantly influence their behavior in financial markets. According to Hirshleifer (2020), positive emotions such as happiness or excitement may lead to overconfidence, resulting in misjudgment and poor investment decisions. Conversely, negative emotions like anxiety or stress may make investors more cautious yet can also reduce investment performance if not properly managed. Prior studies have indicated that personal traits and behavioral factors can influence trading behavior, including increased overconfidence (Nguyen et al., 2023), herding behavior (Rubbaniy et al., 2022), or improved forecasting accuracy (Bonato et al., 2021).

Additionally, the emotions of fund managers—who play a crucial role in making investment decisions—can directly impact the performance of the funds they manage (Chen et al., 2021). Fund managers are responsible for asset allocation and investment direction, and their decisions are not only based on data analysis but are also influenced by their psychological and emotional states (Bonato et al., 2021). While positive emotions can foster decisiveness and a greater willingness to take risks, negative emotions often trigger overly cautious behavior, which may hinder the ability to maximize profits (Nguyen et al., 2025).

Nowadays, social media platforms such as Twitter have become important channels for fund managers to share their views and emotions about financial markets. Emotions expressed through social media posts can reveal the psychological states of fund managers and may affect their trading behavior. Sun et al. (2016) demonstrated that social media posts containing positive emotions tend to correlate with better market performance, whereas negative posts are often associated with declining performance. Based on this analysis, we propose the following hypothesis:

H1: The emotions of fund managers, as expressed through their posts on social media platforms, influence the abnormal returns of investment funds.

2.2. Market Sentiment and Investment Performance

Recent studies have increasingly highlighted the importance of market sentiment in shaping fund strategies and influencing their overall performance. Scholars have identified that investment funds can effectively leverage market sentiment as a key input for adjusting their strategies to capitalize on shifting market dynamics. For example, funds with higher sentiment betas—meaning their returns are more sensitive to market sentiment—tend to outperform those with lower sentiment betas on a risk-adjusted basis. This indicates that funds aligning their strategies with prevailing market sentiment can achieve superior performance (Chen et al., 2021).

This relationship between sentiment and performance is further supported by research showing that different fund styles exhibit varying levels of sensitivity to emotional shocks. Investor behavior, often irrational in nature, plays a crucial role in shaping fund returns. For instance, Zheng & Osmer (2018) found that funds tend to perform better during periods of optimistic sentiment, when investor behavior tends to drive markets upward, allowing funds to capitalize on trends and herding behavior.

In addition, the use of media-based macro sentiment indicators has emerged as a powerful tool for predicting fund returns and enhancing asset pricing models. Wang et al. (2021) emphasized how fund managers can adjust their funds' sensitivity to emotional fluctuations, positioning their portfolios to benefit from sentiment-driven market movements. By doing so, fund managers can better navigate periods of market volatility, ensuring that their strategies are not only aligned with market trends but are also optimized to capitalize on irrational investor behavior and sentiment-induced price shifts.

From this analysis, it is evident that sensing market sentiment is crucial for fund managers. Therefore, this study uses fund managers' interactions with others' posts on social media as a proxy for their sensitivity to market sentiment. Consequently, the following hypothesis is proposed:

H2: Fund managers' sensitivity to market sentiment, as reflected through their interactions with others' posts on social media, influences the abnormal returns of investment funds.

3. Data and methodologies

230 accounts of Twitter-active-participant hedge fund managers with over 5000 retweets, 1000 likes, and 1000 responses are obtained using the Twitter search tool. From January 2019 to October 2021, roughly 730,000 tweets were crawled using Twitter APIv2. Taking into account just English-language tweets, 556,753 tweets remained and were utilized for further text mining and sentiment studies. Since March 2020, the overall number of tweets has increased dramatically from an average of 6,700 tweets per month to 11,000 tweets per month (Figure 1). This time frame was deliberately chosen to capture hedge fund managers' sentiment and behavioral patterns both before and during the COVID-19 pandemic, offering a natural quasi-experimental setting to compare fund managers' emotional expressions and corresponding fund performance under normal and crisis conditions. The onset of the pandemic in March 2020, marked by the World Health Organization's declaration of a global pandemic, led to unprecedented market volatility and emotional stress among financial professionals, making this period particularly relevant for examining mood-performance dynamics.

Devlin et al. (2018) established the Bidirectional Encoder Representations from Transformers (BERT) deep learning method for language understanding in Google A.I. Language, which is currently a cutting-edge language processing model. BERT was trained using English Wikipedia (2.5 billion words) and Books Corpus (800 billion words), enabling the model to acquire a deeper understanding of the language, uncover diversity in data patterns, and perform effectively on a variety of NLP tasks. The BERT-base model is a 12-layer, 768-hidden, 12-head neural network with 110M parameters, while the BERT-large model has 24 layers, 1024 hidden nodes, and 16 nodes with 340M parameters. In this study, we employed one hundred

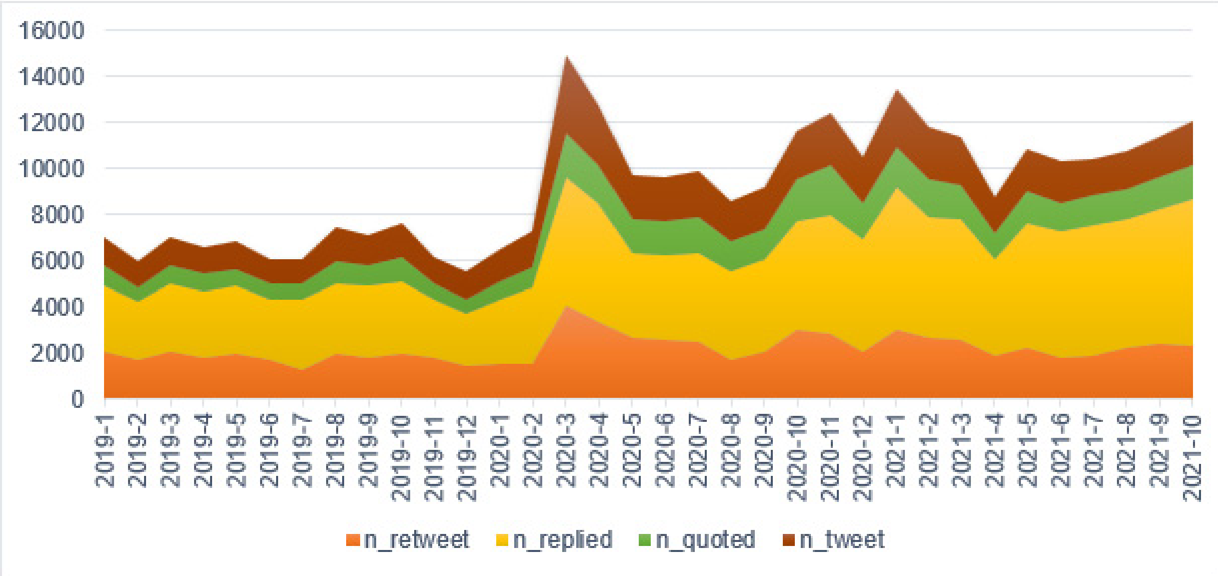

Figure 1. Number of retweeted tweets, replied_to tweets, quoted tweets and original tweets from 2019 to 2021

thousand annotated IMDB movie reviews to fine-tune a pre-trained BERT-based model for sentiment analysis. The revised model retains its edges while retaining exceptionally high accuracy metrics (about 93.78 % training accuracy and around 85 % validation accuracy).

The analytical strategy unfolds in three key stages. First, tweet data are cleaned, filtered for English language, and processed using the BERT model to generate monthly sentiment scores. Next, topic modeling via Latent Dirichlet Allocation (LDA) is applied to extract key discussion themes, enriching the interpretation of sentiment dynamics. Finally, monthly sentiment indices and hedge fund returns are analyzed using the Vector Error Correction Model (VECM). This includes unit root testing (ADF), Johansen cointegration testing, optimal lag selection using AIC, and robustness checks through alternative specifications. This multi-step approach enables a detailed examination of both immediate and long-term impacts of managerial sentiment on fund performance.

The dependent variables in this study are the monthly alpha returns of three widely recognized hedge fund performance indices, sourced from Hedge Fund Research, Inc. (HFR), a leading provider of global hedge fund data and analysis. Specifically, the indices include: (1) the HFRI Institutional Fund Weighted Composite Index (HFRINFWC), which represents a broad measure of institutional hedge fund performance across all strategies and asset classes; (2) the HFRI 500 Fund Weighted Composite Index (HFRI5FWC), which tracks the performance of the largest and most liquid 500 hedge funds, offering a more focused and investable benchmark; and (3) the HFRI World Index (HFRIWRLD), which reflects the performance of hedge funds operating globally, thus capturing international trends in fund management. These indices are reported monthly by HFR and are constructed using a fund-weighted methodology to reflect the real performance experienced by investors. To derive alpha returns, each index's return is adjusted by subtracting the corresponding monthly return of the S&P 500 Index, which serves as the market benchmark. This adjustment isolates the hedge fund-specific performance (excess return) that may be attributable to factors such as managerial skill or sentiment-driven decisions, independent of general market movements. Using these indices enables a robust and comprehensive evaluation of how hedge fund managers' sentiment relates to fund performance across various fund types and market exposures.

This research examines this alpha return as the independent variable in the Error Correction Model (ECM) to determine if hedge fund managers' social media activities are related to hedge fund performance. The Vector Error Correction Model (VECM) is a specialized form of the Vector Autoregression (VAR) model used for non-stationary time series that are cointegrated. VECM captures both the short-term dynamics and the long-term equilibrium relationships among variables by incorporating an Error Correction Term (ECT), which reflects the extent to which the previous period's disequilibrium is corrected in the current period. In this study, VECM is appropriate because the sentiment indices (derived from hedge fund managers' tweets) and hedge fund return indices are non-stationary but exhibit cointegration, as confirmed by unit root and Johansen cointegration tests. The use of VECM allows us to investigate not only how short-term shifts in sentiment affect fund performance, but also how deviations from the long-run equilibrium are corrected over time, providing a comprehensive understanding of the dynamic interactions between managerial sentiment and financial outcomes.

The model employed in this study builds upon existing work in behavioral finance and sentiment analysis. Specifically, the empirical framework extends prior research by Chen et al. (2021) on sentiment trading and hedge fund returns, and draws on Huang & Goo (2014), who emphasized how distinct emotional states influence trading behaviors. This synthesis of social media analytics, emotion-sentiment theory, and cointegration econometrics provides a theoretically sound and methodologically rigorous basis for our investigation.

Table 1 represents descriptive analyses of the main variables in the ECM equation as follows:

$$HF_{i,t}=c_t+\beta_1\ HF_{i,t-1}+\beta_2\Delta SENTIMENT_{l,t-1}\ +\varphi ECM_{t-1}+\varepsilon_t,\ (1)$$

Where:

$HF_{i,t}$: alpha return of hedgefund indexes i at time t,

$HF_{i,t-1}$: alpha return of hedgefund indexes i at time t at time t-1,

$\Delta SENTIMENT_{l,t-i}$: change in monthly sentiment l at time t-1,

ECT_{t-1}: Error correction term at time t-1.

Table 1. Descriptive analysis of variables in VECM regression

vars	n	mean	sd	min	max
Sent_interacted	34	0.458	0.061	0.345	0.598
Sent_original	34	0.480	0.084	0.339	0.776
S&P 500 Index	34	0.019	0.051	-0.125	0.127
HFRINFWC	34	-0.012	0.035	-0.098	0.068
HFRI5FWC	34	-0.010	0.034	-0.085	0.065
HFRIWRLD	34	-0.011	0.036	-0.092	0.064

Note: Sent_interacted: average probability of positive sentiment of retweeted, replied to or quoted tweets weighted by their number of interactions (retweeted, replied, quoted) using BERT algorithm; Sent_original: average probability of positive sentiment of original tweets weighted by their number of interactions (retweeted, replied, quoted) using BERT algorithm; HFRINFWC: monthly alpha return of HFRI Institutional Fund Weighted Composite Index; HFRI5FWC: monthly alpha return of HFRI 500 Fund Weighted Composite Index; HFRIWRLD: monthly alpha return of HFRI World Index. The benchmark used is S&P500 index.

4. Results and discussion

4.1. Content analyses

The actions of hedge fund managers on Twitter demonstrate a strong preference for utilizing Twitter as communication and interaction channels (accounting for over 80% of all tweets) as opposed to channels for self-posting information (Figure 1). In contrast to a number of businesses that use social media as a marketing channel, the majority of hedge fund managers have not viewed Twitter as the primary route for publishing and disseminating information about their companies' goods and services. Rather, the primary function of online social media is networking and social bridging.

Using the LDA topic modeling algorithm, we extracted the most important topic discussed in social media over time presented in Figure 2. In 2019, the four most prominent topics were the US-China trade war, the bearish market trend, monetary policy and other most noticeable social unrests like "anti Jewish" or "child sex". In the years of 2020 and 2021, the most popular topics were very similar and featured the "heavy volume" in stock market trading, which created the "market advances" in general. Another common topic was the fund managers' discussions on "insider activity" regarding the "director sale" of their company shares. In 2020, hedge fund managers focused more on the foreign exchange markets. While in 2021, one very prominent topic among hedge fund managers was the events of abnormal and aggressive trading behaviors in stocks like GameStop triggered by the "chatters" of "Wallstreetbets" in the Reddit platform.

4.2. Discourse' sentiment and impacts on hedge fund performances

We use March 2020 as the time marker to divide the samples of before and after the outbreak of the pandemic when The World Health Organization (WHO), on March 11, 2020, declared the novel coronavirus (COVID-19) outbreak a global pandemic. For the whole sample before and after the outbreak of COVID-19 pandemic, the Johansen cointegration test estimates in Table 2 reveal that both interacted and original managers' sentiment have long-term cointegrations with hedge fund monthly returns. Moreover, the coefficients of error correction terms (ECTs) in Table 3, the adjustment speeds increased from short- to long-term levels, demonstrated an expected negative and significant influence on returns in both the interacted and original tweet sentiment indices. This suggests that after the outbreak of COVID-19 pandemic, the fund managers' sentiment significantly affect their operations in terms of hedge funds' returns. However, before the outbreak, the adjustment term of long-term cointegration between fund managers' moods and funds' returns is only valid for the interacted tweets' sentiment (Table 4).

Following the outbreak of COVID-19 pandemic, results from Table 3 show that although interacted tweet feelings have positive effects (at 1% significant

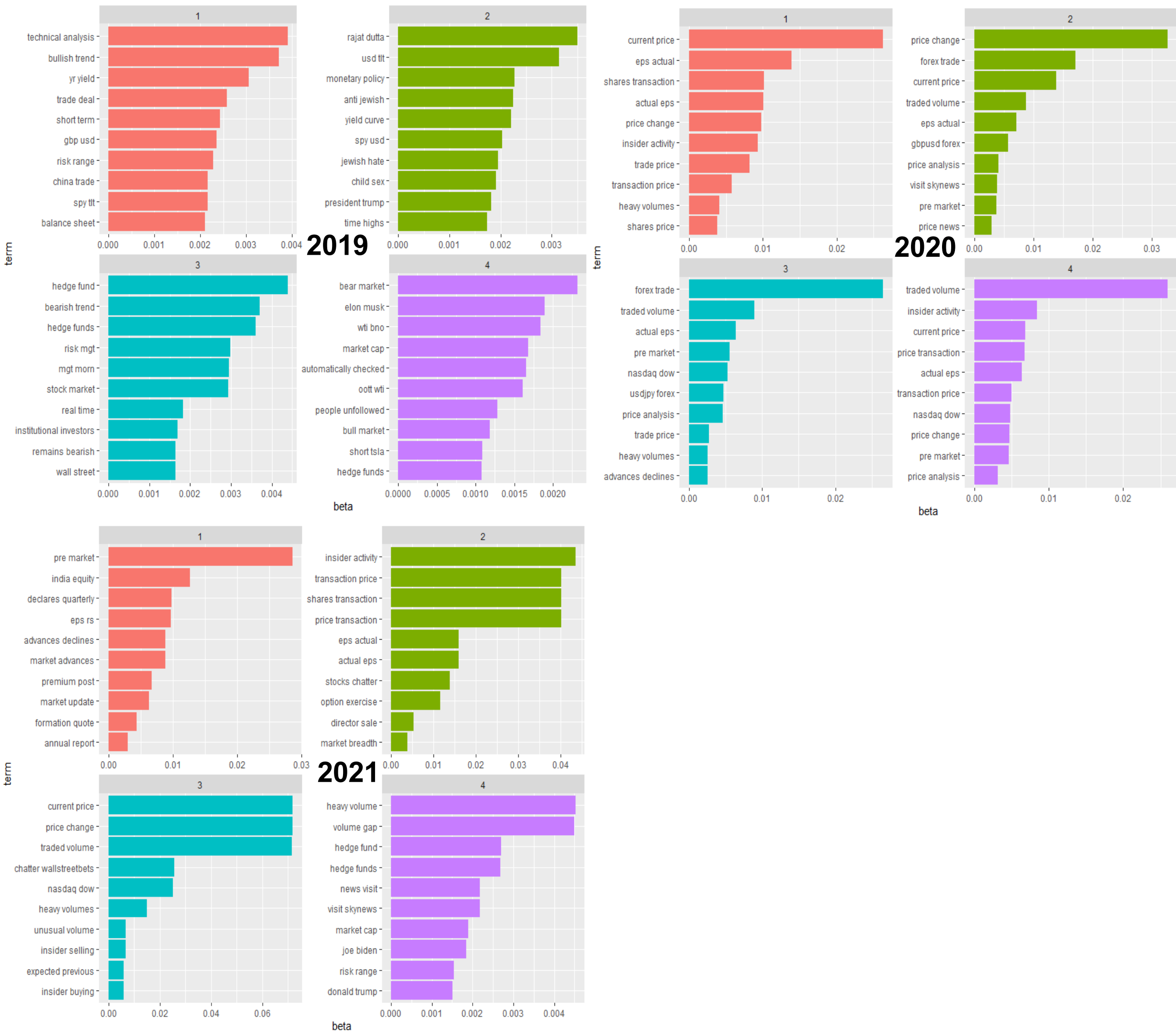

Figure 2. LDA topic modeling overtime on hedge fund managers' tweets

Table 2. Johansen and Juselius cointegration test

H_0: r = 0	Max-Eigen statistic		
	Sent interacted	Sent original	Critical value (Max-Eigen)
HFRINFWC	23.87	41.66	20.20
HFRI5FWC	22.69	39.59	20.20
HFRIWRLD	22.54	39.20	20.20

Note: The Trace statistics are also calculated and also indicate the presence of cointegrations between returns and sentiments. The cointegration tests are conducted without linear trend and constant. The chosen lag length to be included in the cointegration test is two based on the test of the optimal lag value using AIC criteria.

level) on all hedge fund return indices, original tweet emotions have considerable but negative impacts (at 1% significant level) on hedge fund returns. Specifically, when fund managers are members of a social network (interacting with and responding to social information), their interacted emotion is more likely to have good connections with their success in financial trading and investing. Even though the themes of engaged tweets are not always directly about financial markets and trading, the interactions within a network (at least two persons participate in the discussion) may elicit moods for fund managers and have positive and significant implications for hedge fund operations. The more favorable fund managers' discourses are when they participate in social networks, the better their success in making hedge fund profits. This conclusion adds to a newly emerging research area established by Hirshleifer (2020) that stresses the influence of social phenomena in finance and trade, such as network effects and transmission beliefs. Negative emotions and pessimism cause investors to withdraw their financial investments from the stock market, resulting in lower stock market returns.

In contrast, the impacts of original tweets' sentiment have negative correlations with the hedge fund indexes' returns. Regarding those original tweets are mainly about fund managers' views on financial market information and funds' operations, it could contain personal biases such as overconfidence and overreaction to market activities. For instance, when fund managers have strong positive sentiments towards market information and movements, it creates

Table 3. VECM estimations for short-run and long-run relationships between hedge fund performance and the fund managers' sentiment from March 2020 to October 2021

	HFRINFWC (1)	HFRI5FWC (2)	HFRIWRLD (3)	HFRINFWC (4)	HFRI5FWC (5)	HFRIWRLD (6)
ECT	-1.901***	-1.820***	-1.850***	-1.910***	-1.840***	-1.820***
	(0.220)	(0.220)	(0.223)	(0.300)	(0.290)	(0.280)
Sent_interacted_BERT	0.289**	0.326***	0.323***			
	(0.104)	(0.107)	(0.106)			
Sent_original_BERT				-0.460***	-0.420***	-0.410***
				(0.100)	(0.101)	(0.104)
LAG-1	0.624***	0.547***	0.537***	0.730***	0.632***	0.580**
	0.155	0.160	0.155	(0.211)	(0.204)	(0.197)
Intercept	-0.020***	-0.022***	-0.024***	-0.030***	-0.020***	-0.020***
	(0.002)	(0.003)	(0.001)	(0.003)	(0.001)	(0.003)

*Note: ECT: error correction terms; *p-value < 0.1, **p-value <0.05, ***p-value < 0.01. LAG-1: lag variables of hedge fund indexes performance. HFRINFWC: monthly alpha return of HFRI Institutional Fund Weighted Composite Index; HFRI5FWC: monthly alpha return of HFRI 500 Fund Weighted Composite Index; HFRIWRLD: monthly alpha return of HFRI World Index. The benchmark used is S&P500 index. Sent_interacted_BERT: average probability of positive sentiment of retweeted, replied to or quoted tweets weighted by their number of interactions (retweeted, replied, quoted) using BERT algorithm; Sent_original_BERT: average probability of positive sentiment of original tweets weighted by their number of interactions (retweeted, replied, quoted) using BERT algorithm*

Table 4. VECM estimations for short-run and long-run relationships between hedge fund performance and the fund managers' sentiment before the global COVID-19 pandemic

	HFRINFWC (1)	HFRI5FWC (2)	HFRIWRLD (3)	HFRINFWC (4)	HFRI5FWC (5)	HFRIWRLD (6)
ECT	-2.610***	-2.590***	-2.560**	0.342	0.367	0.294
	(0.541)	(0.542)	(0.550)	(0.206)	(0.218)	(0.195)
Sent_interacted_BERT	0.523***	0.470***	0.532***			
	(0.142)	(0.130)	(0.145)			
Sent_original_BERT				-0.500	-0.502*	-0.460*
				(0.210)	(0.212)	(0.211)
LAG-1	0.675*	0.647*	0.667*	-0.530*	-0.570**	-0.500**
	(0.311)	(0.312)	(0.324)	(0.232)	(0.221)	(0.210)
Intercept	-0.010*	-0.011*	-0.013*	0.011	0.011	0.011
	(0.001)	(0.001)	(0.002)	(0.010)	(0.010)	(0.010)

*Note: ECT: error correction terms; *p-value < 0.1, **p-value <0.05, ***p-value < 0.01.*

overconfidence and leads to worse trading behaviors than expected. Thus, original tweets' sentiments which are closely related to fund managers' traits could have negative impacts on investment returns.

This study shows that there are several ways in which participation in online social media discourses influences real-life occurrences. This finding aligns with Bouri et al. (2023), who suggested that different types of happiness can result in diverse trading behaviors among investors. They discovered that when investors are more satisfied with the natural environment, they are less likely to be overconfident. Investors are more likely to be overconfident when the financial climate is more favorable.

Before the outbreak of the COVID-19 pandemic, the short-term effects of managers' sentiments on funds' returns are only significant at 1% level when fund managers participated in interacted discourses with others (Table 4). The managers' sentiment only marginally affects return indices at 10% level when the sentiment is extracted from their original tweets. These results indicate that the occurrence of the COVID-19 pandemic plays a crucial role and aggravates the effects of fund managers' moods on their trading performances. This finding is corroborated by results from Talwar et al. (2021), stating that the changes in financial attitude during the COVID-19 pandemic significantly impacted an individual's trading behaviors.

5. Conclusion and Limitation

Using a nearly 560,000 tweets dataset, we found a long-term cointegration between hedge funds' tweets sentiments and hedge fund performances. After the outbreak of COVID-19 pandemic, when hedge fund managers participate in network discourses on online social media (interacted tweets), what they say and feel is positively aligned with their performances in investment and trading activities. In contrast, their original tweets' sentiments are opposite to their trading performance, indicating biases in their views about markets. These effects before the COVID-19 are only valid for the fund managers' sentiment when interacting with others. In overall, hedge fund managers' sentiments on online social media could be used as inputs to predict and explain hedge fund performance. These results argue for the use of hedge fund managers' activities on social media as one of the critical inputs and contribute to emerged research stream of combining social science into the research of financial behaviors.

5.1. Implications and Recommendations

Beyond its empirical findings, this study offers several practical implications and policy-relevant recommendations for both hedge fund practitioners and financial researchers. First, the results highlight the importance of integrating behavioral data, such as sentiment extracted from social media, into investment decision-making frameworks. Hedge fund managers and institutional investors may benefit from systematically monitoring digital discourse—not only their own, but also that of peers and market influencers—to detect early signals of emotional contagion, overconfidence, or shifts in market sentiment that may impact portfolio performance.

Second, investment firms could consider incorporating sentiment indicators as part of their risk management and asset allocation processes. For instance, high positive sentiment in original tweets could serve as a cautionary signal for potential overconfidence, while increasing positivity in interactive discourse may reflect broader consensus or validation, which correlates positively with fund performance. By distinguishing between isolated expressions and socially mediated interactions, firms can build more nuanced behavioral dashboards to support trading strategies. Third, this study suggests the value of training programs for fund managers that promote emotional regulation, especially under crisis conditions such as the COVID-19 pandemic. Developing awareness of how public emotional expression correlates with performance can support more disciplined decision-making and communication strategies.

Finally, for academic and regulatory audiences, this research reinforces the need for further interdisciplinary exploration at the intersection of behavioral finance, artificial intelligence, and financial communication. Future studies may build upon this foundation to develop predictive models or early-warning systems that incorporate sentiment dynamics. Regulators may also consider monitoring public-facing sentiment data as part of systemic risk assessment frameworks, particularly during periods of market stress.

5.2. Limitation

While this study offers novel insights into the relationship between hedge fund managers' moods and fund performance, several limitations should be acknowledged. First, the dataset is limited to English-language tweets from Twitter-active hedge fund managers, which may not fully represent the broader hedge fund population or include managers who are less active or non-users of social media. Second, the sentiment analysis relies on the accuracy of machine learning models trained on general-purpose datasets (e.g., IMDB reviews), which may not fully capture the nuance or context of financial language and investor discourse. Third, although interactions on social media are used as a proxy for market sentiment sensitivity, this measure may oversimplify the complexity of social influences on decision-making. Lastly, this study focuses on the COVID-19 period, a time of heightened uncertainty and volatility, which may limit the generalizability of the findings to more stable market conditions. Future research could explore alternative sentiment extraction techniques, extend the analysis to other social media platforms, and include cross-cultural or multilingual data to enhance robustness and external validity.

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REFERENCES

Bonato, M., Gkillas, K., Gupta, R., & Pierdzioch, C. (2021). A note on investor happiness and the predictability of realized volatility of gold. *Finance Research Letters*, 39, 101614.

Bouri, E., Demirer, R., Gabauer, D., & Gupta, R. (2022). Financial market connectedness: The role of investors' happiness. *Finance Research Letters*, 44, 102075.

Chen, Y., Han, B., & Pan, J. (2021). Sentiment trading and hedge fund returns. *The Journal of Finance*, 76(4), 2001-2033.

Devlin, J., Chang, M. W., Lee, K., & Toutanova, K. (2019, June). Bert: Pre-training of deep bidirectional transformers for language understanding. In *Proceedings of the 2019 conference of the North American chapter of the association for computational linguistics: human language technologies*, *Volume 1 (long and short papers)* (pp. 4171-4186).

Hedge Fund Research (2021). *Hedge Fund Industry Capital Surpasses Historic Milestone*. Access at https://www.hfr.com/news/hedge-fund-industry-capital-surpasses-historic-milestone

Hirshleifer, D. (2020). Social Transmission Bias in Economics and Finance. *Journal of Finance*, 75(4), 1779–1831.

Huang, C. L., & Goo, Y. J. (2014). Are happy investors likely to be overconfident? *Emerging Markets Finance and Trade*, 44(4), 33-39.

Lee, C. C., & Chen, M. P. (2020). Happiness sentiments and the prediction of cross-border country exchange-traded fund returns. *The North American Journal of Economics and Finance*, 54, 101254.

Nguyen, H. H., Ngo, V. M., Le, T. T. P., & Van Nguyen, P. (2023). Do investors' personalities predict market winners? Experimental setting and machine learning analysis. *Heliyon*, 9(4).

Nguyen, H. H., Ngo, V. M., Pham, L. M., & Van Nguyen, P. (2025). Investor sentiment and market returns: A multi-horizon analysis. *Research in International Business and Finance*, 74, 102701.

Rubbaniy, G., Tee, K., Iren, P., & Abdennadher, S. (2022). Investors' mood and herd investing: A quantile-on-quantile regression explanation from crypto market. *Finance Research Letters*, 47, 102585.

Sun, A., Lachanski, M., & Fabozzi, F. J. (2016). Trade the tweet: Social media text mining and sparse matrix factorization for stock market prediction. *International Review of Financial Analysis*, 48, 272–281.

Talwar, M., Talwar, S., Kaur, P., Tripathy, N., & Dhir, A. (2021). Has financial attitude impacted the trading activity of retail investors during the COVID-19 pandemic? *Journal of Retailing and Consumer Services*, 58, 102341.

Wang, J., Yi, S., Wang, X., & Yang, J. (2021). Fund sentiment beta and delegated investment. *Applied Economics Letters*, 28(11), 902-905.

Zheng, Y., & Osmer, E. (2018). The relationship between hedge fund performance and stock market sentiment. *Review of Pacific Basin Financial Markets and Policies*, 21(03), 1850016.