Sentiment and Stock Characteristics: Comprehensive Study of Individual Investor Influence on Returns, Volatility, and Trading Volumes

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Abstract

Background: Traditional asset pricing models face challenges from financial anomalies, prompting exploration through behavioural finance theory. This study analyses the nuanced relationship between individual investor sentiment and key stock market variables. **Objectives:** To assess the impact of individual investor sentiment on stock returns, volatilities, and trading volumes using the American Association of Individual Investors (AAII) sentiment index. **Methods/Approach:** Using regression models, we examine the relationship between individual investor sentiment and various stock characteristics across 480 components of the Standard & Poor's 500 index. **Results:** We find a positive relationship between the AAII sentiment index and stock returns and a negative relationship with volatility and trading volume. **Conclusions:** Our study contributes to understanding the intricate role of individual investor sentiment in financial markets.

Keywords: investor sentiment; stock characteristics; behavioural finance; AAII sentiment index

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Introduction

For many years, traditional asset pricing models have dominated the assessment of risk-return trade-offs. However, the discovery of financial anomalies suggests that the efficient market hypothesis (Fama, 1970) may be challenged from the perspective of behavioural finance theory. Since the efficient market hypothesis (EMH) does not take into account the presence of investors' idiosyncratic behaviour (Haritha & Rishad, 2020), relying solely on EMH for asset pricing may lead to distortions. Investor sentiment, on the other hand, is popular for the empirical support it provides to asset pricing, emphasizing the impact of human biases on market behaviour. Because traditional theories do not account for the impact of abnormal investor behaviour on market outcomes, behavioural finance incorporates psychological perspectives into the description of financial markets so that we can gain a better understanding of why markets may deviate from the predictions of traditional theories such as EMH.

Baker and Wurgler (2007, p. 129) broadly defined investor sentiment as 'a belief about future cash flows and investment risks that is not justified by the facts at hand.' Both researchers and practitioners are interested in measuring market sentiment, reflecting the overall sentiment of market participants or their subgroups. González-Sánchez and Morales de Vega (2021) identified three main approaches to constructing investor sentiment indices: aggregation of market variables, investor surveys, or utilizing information from the media. Each of them has its own advantages and disadvantages. The potential drawback of constructing a sentiment index through the aggregation of market variables is that it may include unrelated information. Investor surveys, while widely used, suffer from low observation rates, usually monthly or with a lower frequency, and reliability issues when nonresponse rates are high (Sun et al., 2016). The third, rapidly evolving approach involves explaining the return on assets through textual analysis of news, but there is no clear evidence of its explanatory capacity (González-Sánchez & Morales de Vega, 2021).

In this paper, we focus on the second approach – measuring investor sentiment through investor surveys. Unlike other approaches, investor surveys provide a direct measurement of investor sentiment, as they involve directly asking and observing the sentiment among investors. Notable indexes for measuring investor sentiment in the US market include the monthly University of Michigan Consumer Sentiment Index, the weekly American Association of Individual Investors (AAII) sentiment survey, and the daily Investor Intelligence and Daily Sentiment Index. We concentrate our research on the AAII sentiment survey, which has a high number of survey participants and a long history of data since its inception in 1987.

The objective of this study is to explore the relationship between individual investor sentiments and characteristics of the stock market, such as stock returns, volatility, and trading volumes. The research question is whether there is any relationship between the AAII sentiment survey index and the characteristics of the stocks in the periods following the publication of the sentiment index data. According to the efficient market hypothesis, all relevant information should already be priced in, and the sentiment should have no predictive power for future returns, which is our null hypothesis.

The research addressed by this study also examines what should be used for prediction – whether the absolute value of the sentiment index or its change from the previous value. We hypothesize that changes in market sentiment are better predictors of future characteristics. For example, if sentiment improves from bearish to neutral, individual investors might start buying stocks and increase their bid and ask prices. On the contrary, if sentiment worsens from bullish to neutral, individual investors could start selling stocks. In both cases, the sentiment value is the same (neutral), but the actions taken by individual investors are different. Therefore, changes in the sentiment index are likely more significant than absolute values.

Our results have important implications for investors. We find a positive relationship between sentiment and future returns and a negative relationship with future volatility, suggesting that sentiment could be a useful indicator in developing investment or trading strategies. The findings contribute to understanding the role of individual investor sentiment in financial markets and its implications for investment strategies. However, it is important to approach these results with caution. Although our findings indicate a relationship between sentiment and stock returns, the sentiment variable used in our study does not capture the full spectrum of influencing factors. Therefore, relying solely on sentiment indicators for investment decisions may not consistently yield high returns, and investors should consider sentiment as one of many factors in their decision-making process.

Our study differs from previous studies, which primarily concentrated on a single time series, usually the market index, see (Fisher & Statman, 2006; Y.-H. Wang et al., 2006; Kurov, 2008; Jacobs, 2015; Białkowski et al., 2023). We focus on a more robust dataset comprising the component stocks of the market index. Specifically, we use components of the Standard & Poor's 500 index. This approach allows for a comprehensive analysis that considers the dynamics and interactions within a broader range of securities, providing more robust results.

The remainder of the paper is structured as follows. In the next section, we provide a short review of the literature. Then we introduce the data and methods applied. In the next sections, we present the results and their discussion. The last section presents the conclusion of the paper.

Literature Review

The selection of stock returns, volatilities, and trading volumes as dependent variables in this study is based on their fundamental importance in financial market analysis. Stock returns are a primary measure of a stock's performance and are crucial for investors, as they directly relate to the gains or losses experienced. Volatility, on the other hand, serves as a key proxy of risk, reflecting the degree of uncertainty, with higher volatility indicating greater risk. Trading volumes provide an important measure of market activity and liquidity, and higher trading volumes typically indicate greater market interest and ease of transacting without significantly affecting stock prices. Together, these variables are crucial factors for investors, as they directly impact investment decisions (Hawaldar & Rahiman, 2019; Veld & Veld-Merkoulova, 2008).

These stock characteristics are also interrelated. A fundamental principle in finance is that investors require, or expect, higher returns for undertaking higher risks (represented by volatility). Research has also examined the relationship between trading volume and returns. Chen et al. (2001) and Naik and Sethy (2022) found a positive correlation between trading volumes and stock price changes, with trading volume contributing to the return process. Naik and Sethy (2022) also highlighted the asymmetric effect of stock returns on trading volume and the positive volume-volatility relationship.

However, stock returns can also be explained by other factors than trading volume and volatility. Traditional pricing models, such as the Fama-French five-factor model (Fama & French, 2015, 2017), explain the stock returns based on factors related to market return, company size, book-to-market ratio, profitability, and investment style. Macroeconomic indicators can also serve as predictors; for instance, Hjalmarsson (2010) identified the short interest rate and term spread as robust predictors in developed markets. In addition to these fundamental and macroeconomic factors, technical analysis provides another approach to understanding and predicting stock returns. Technical analysts believe that all relevant information is already reflected in stock prices and that price movements follow certain patterns that can be exploited. However, there is a broad academic debate on the applicability of technical analysis, as reviewed by Park and Irwin (2007).

Traditional asset pricing models face growing challenges in their explanatory power and research in behaviour finance theory has further demonstrated the role of investor sentiment in driving the stock markets. Johnson and Tversky (1983) suggested that people make risky decisions based on their sentiment state. Compared with traditional asset pricing models, one of the main arguments of behaviour finance is that imperfectly rational traders (known as noise traders) generate deviations from fundamental values (Uygur & Taş, 2014) and that these deviations can significantly affect investor behaviour and market prices (Daniel et al., 2002).

Focusing on investor sentiment is particularly important because this factor can lead to market anomalies that traditional models fail to explain. In recent years, research has increasingly explored the role of sentiment in returns, volatility, and trading volumes. Although the empirical results of Lee et al. (2002) suggest that sentiment is priced in systematic risk, the excess returns are still positively correlated with changes in sentiment. Additionally, the extent of bullish (bearish) sentiment changes leads to downward (upward) corrections in volatility and higher (lower) future excess returns. Uygur and Taş (2012) demonstrated that investor sentiment has a significant positive effect on the conditional volatility of the stock market during periods of high sentiment, whereas investor sentiment has a negative effect during periods of low sentiment.

Audrino et al. (2020) investigated the effect of sentiment and attention indicators on daily stock market volatility and showed that sentiment and attention variables have significant predictive power for future volatility and that the addition of the sentiment variable leads to a further decrease in the mean square prediction error, especially on days with high volatility. By distilling the sentiment of the news text, Zhang et al. (2016) found that changes in sentiment, especially those with negative views, affect volatility and volume.

Studies that investigate trading volume also show a relationship between investor sentiment and trading volume. From the results of So and Lei (2011), we can understand that the increase in the volatility index (VIX) is associated with an increase in trading volume, especially during periods when the VIX is high. This suggests that the higher the VIX level, the greater the change in trading volume. This is further confirmed by Lai et al. (2014), who found a positive correlation between investor sentiment and abnormal trading volumes. However, Kim and Ryu (2021) added a nuanced perspective by noting that the term structure of the impact of sentiment on trading volume is downward sloping, suggesting that instances of sentiment-induced trading anomalies are relatively short-living.

However, empirical studies that use the AAII sentiment survey as a sentiment measure are scarce. Previous studies involving data from the AAII sentiment survey have shown that sentiment-driven investors often trade based on data from the AAII sentiment survey (Chau et al., 2016). The AAII sentiment index not only affects the stock price (Bouteska, 2019) but also significantly affects both the stock return and volatility (Sayim et al., 2013). Additionally, the AAII sentiment index plays a crucial role in the performance of initial public offerings (Ibrahim & Benli, 2022).

Methodology

The sentiment index used in this study is obtained from the Investors Intelligence Survey (American Association of Individual Investors, 2024), which is conducted by the American Association of Individual Investors (AAII). The sentiment survey collects data from individual investors on their current market outlooks and investment decisions. Weekly, participants in the sentiment survey receive an email with a straightforward question: 'Do *you feel the direction of the stock market over the next six months will be up (bullish), no change (neutral), or down (bearish)?*' Participants can only submit one vote and their responses are used to calculate the indices, representing the percentages of bullish, bearish, and neutral market outlooks. By bullish outlook, we refer to the expectation of the participants that the stock market will grow in value. On the other hand, the bearish outlook represents the opinion of a future decline in the value of the stock market. Neutral perspectives are neither bullish nor bearish.

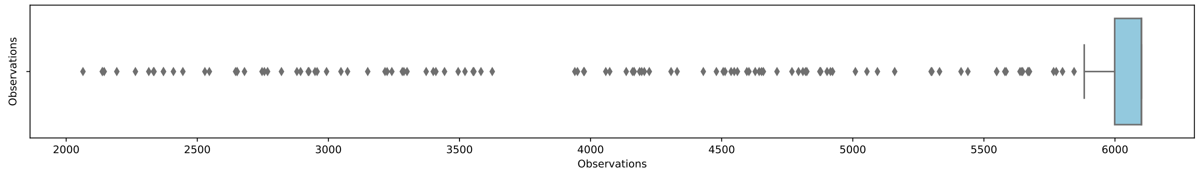
The sentiment index (AAII sentiment index) is then calculated as the spread between the bullish and bearish percentages of votes, ranging from –100% to 100%. Additionally, in our research, we experiment with an alternative construction of the sentiment index (the ratio of bullish to bearish) and their week-by-week differences or differences between the index and its moving average, as we believe that the change in sentiment can be more important than its absolute value.

It is crucial to note that this index is based on the opinions and investment decisions of individual investors and may not always align with broader market trends or sentiments. However, the survey offers valuable information on individual investors' perspectives and can help to understand the general outlook of the market.

We assume that the individual investors are usually in a long position (Visaltanachoti et al., 2007), that is, they hold the stocks. As investor sentiment measures the beliefs of the market participant, we believe that the same market participants adjust their supply and demand for the stock accordingly. When they expect the market to soar, they increase the prices for which they are willing to buy and sell (ask and bid prices) as they consider the stocks to be undervalued at the current prices. They also increase the bid price, i.e., the price for which they are willing to buy because they speculate on the price increase. However, since there is positive market sentiment, fewer market participants are willing to sell, which decreases the trading volume and volatility. At the same time, we expect that as the sentiment in the market is negative or worsens, individual investors want to sell the stocks quickly, which both decreases the prices and increases the volatility and the trading volumes at the same time. Thus, we expect a positive relationship between sentiment and future returns and a negative relationship between sentiment and future return volatility and trading volume.

Furthermore, for the stocks, our dataset comprises the components of the S&P 500 index (Wikipedia, 2024), and we obtained the daily adjusted close prices and volumes from the Yahoo Finance website (Yahoo, 2024). All data were collected for the period from January 1, 2000, to December 31, 2023. We chose this period as the trade-off between the length of the data, as the longer length provides more robust results because all market phases (bullish, neutral, bearish) are present in the data, and data availability because the composition of the index is changing during the time and some companies become no longer publicly trading and the data are not available. At the same time, since the newcomers to the index do have shorter price histories, we excluded stocks with time series lengths of less than 2,000 observations, resulting in a database reduction from 502 stocks to 480 stocks. From these, for 357 stocks, we used the full history of 6,101 daily observations that covered the last 24 years, while for the rest the time series length was shorter; see Figure 1.

Figure 1
Boxplot of the Lengths of Time Series Applied



Source: Authors' work

As the sentiment data are weekly, we need to recalculate the daily data to weekly. The sentiment data are published each Thursday, and we assume that these data can be utilized to forecast the next week's characteristics; thus, we align the sentiment indexes published on Thursday with the subsequent Thursday-to-Thursday characteristics.

We employ several regression models, each estimated via the Ordinary Least Squares (OLS) method, incorporating a Newey-West heteroskedasticity and autocorrelation consistent covariance matrix (Newey & West, 1987). The general regression equation is expressed as follows,

$$E(y_{i,t}) = \alpha_i + \beta_i \cdot x_t, \tag{1}$$

were, *y* represents the chosen dependent variable, *i* is the index that specifies the stock, *t* is the time, α_i and β_i are regression coefficients for stock *i*, intercept and slope respectively, and x_t is the sentiment at time *t*.

In our research, we examine four dependent variables (*Y*): return, risk premium, volatility, and trading volume. We also assume different specifications of the independent variable (*X*): the value of the sentiment index, week-to-week differences, and the differences between the index value and its five-week moving averages for the sentiment index calculated as both the spread and the ratio of bullish and bearish percentages of votes. For all these sentiment index series, the null hypothesis of a unit root is rejected by the Augmented Dickey-Fuller unit root test at 0.01 significance level. In each model, sentiment indices are used as an independent variable, while stock returns, trading volumes, and volatilities are used as a dependent variable.

The first characteristic analysed is the one-week return calculated as a percentage change of the adjusted close prices *p* from Thursday to next Thursday,

$$r_{i,t} = \frac{p_{i,t}}{p_{i,t-1}} - 1. \tag{2}$$

According to the CAPM model, the returns can be divided into the risk-free rate and the risk premium. Thus, we also focus on one-week risk premiums, calculated as one-week returns minus the risk-free rates obtained from French (2024). The third dependent variable under consideration is the volatility of the returns. As it is not directly observable in the market, we estimate it ex-post from the returns using the generalized autoregressive conditional heteroskedasticity (GARCH) model (Bollerslev, 1986), specifically, we assume GARCH(1,1) specification:

$$r_{i,t} = \mu_i + \sigma_{i,t} \cdot \epsilon_{i,t}, \tag{3}$$
$$\sigma_{i,t}^2 = \omega_i + a_i \cdot \sigma_{i,t-1}^2 + b_i \cdot \epsilon_{t-j}^2, \tag{4}$$

where μ_i is the mean return of the *i*th stock, $\sigma_{i.t}$ is the standard deviation (volatility) for the *i*th stock modelled by the GARCH model and $\epsilon_{i,t}$ is a white noise. Parameters ω_i, a_i and b_i need to be estimated. Positive variance is ensured if $\omega_i > 0$, $a_i \geq 0$, and $b_i \geq 0$, and the model is stationary if $a_i + b_i < 1$. The fourth dependent variable considered is the volume in US dollars traded in one week from Thursday to Thursday.

In all characteristics, we align the newly announced values of the sentiment indices at time *t*, with the characteristics of the following week, that is, return, premium, volatility, and trading volume in the period from *t* to *t*+1.

Results

In this section, we present the results of the estimated regression models (1), which are carried out for the 480 component stocks of the S&P 500 index. The reported results include the number of stocks for which the estimated parameters are considered statistically significant at significance levels of 10%, 5% and 1% by means of the t-test and box plots of the parameter values.

First, we focus on returns, where the dependent variable in Equation (1) is the weekly return. Table 1 illustrates the number of stocks for which the estimated parameters are statistically significant. As can be seen, the sentiment index calculated as the spread is a better predictor than the index calculated as the ratio. In fact, when using the spread, the slope is statistically significant in the case of 242 stocks out of 480, that is, for around half of the stocks, compared to only 107 in the case of ratio. When we transform the independent variable to differences, either week-to-week or value-to-average, the number of statistically significant parameters increases. We can observe that for 390 stocks from 480, the difference between the index calculated as spread and its previous month's average is statistically significant in predicting the future one-week return.

Figure 2 shows the box plots of the parameters for all stocks. As can be seen, for all dependent variables except the ratio, both the intercept and the slope are positive in most of the stocks. We can conclude that there is a positive relationship between sentiment and subsequent one-week returns. Therefore, investors can use sentiment as a predictor of the return next week.

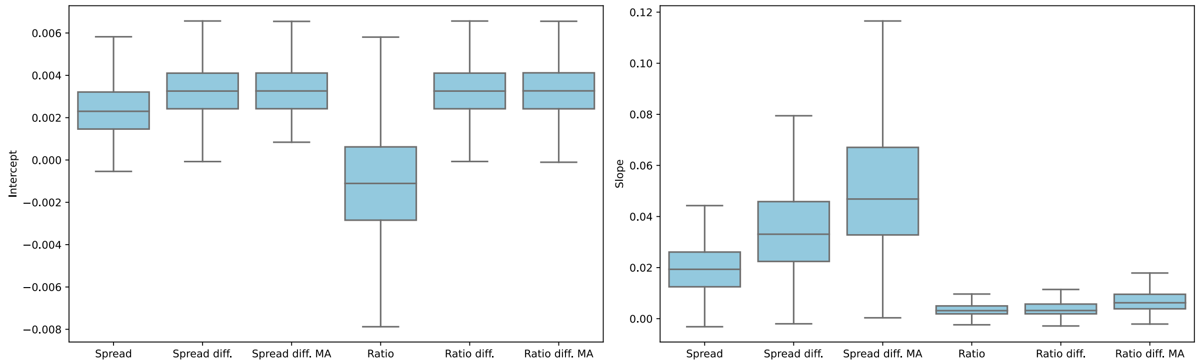
Considering the best model (difference of spread to its MA), the median values can be interpreted as follows. The expected value of the weekly return from Thursday to Thursday is 0.33% (intercept) plus 4% (slope) for every 100 bps of the difference between the sentiment index value and its average in the previous four weeks. Alternatively, we can annualize the returns for better comparability. Then, the expected value of the next-week return is 16.96% p.a. plus 2.44% p.a. for every 1 bps of the difference between the sentiment value and its average in the previous four weeks.

Table 1
Quantities of Statistically Significant Parameters of Regression of Return on Sentiment

Independent variable	10% significance level		5% significance level		1% significance level	
	Intercept	Slope	Intercept	Slope	Intercept	Slope
Spread	254	375	175	339	63	242
Spread diff.	404	443	343	420	202	349
Spread diff. MA	406	447	344	439	202	390
Ratio	48	296	27	223	3	107
Ratio diff.	403	289	342	225	201	129
Ratio diff. MA	403	369	342	333	202	225

Source: Authors' work

Figure 2
Parameter Values of Return Regressions



Note: Outliers positioned significantly far from the median have been excluded for the sake of clarity. Source: Authors' work

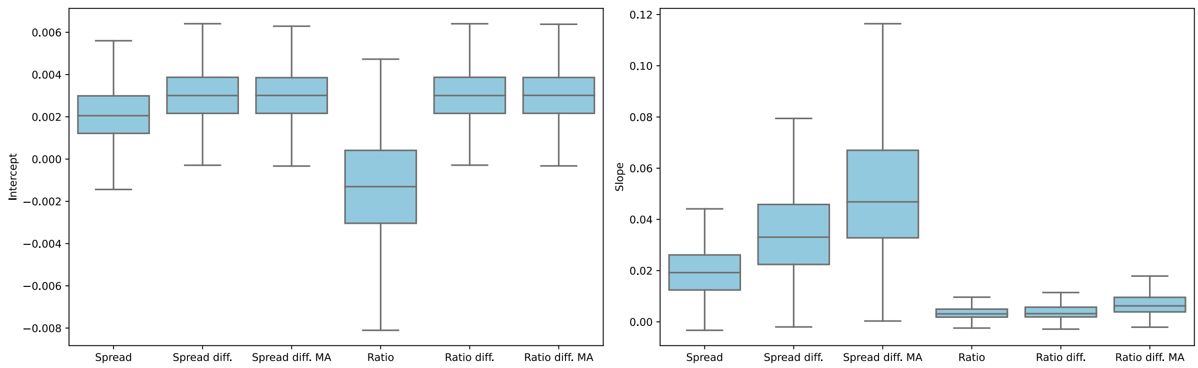
The same conclusions can be drawn when analysing the premiums, that is when we subtract the risk-free rate from the returns; see Table 2 and Figure 3. The median value of the intercept is 15.66% p.a. and the median value of the slope is 2.44% p.a. for every 1 bps of the difference between the sentiment value and its average in the previous four weeks. We can see that the slope has not changed while the intercept has changed by 1.3 % p.a., roughly equalling the risk-free return during the analysed period.

Table 2
Quantities of Statistically Significant Parameters of Regression of Premium on Sentiment

Independent variable	10% significance level		5% significance level		1% significance level	
	Intercept	Slope	Intercept	Slope	Intercept	Slope
Spread	206	373	142	338	43	238
Spread diff.	371	443	300	420	160	348
Spread diff. MA	374	447	302	439	161	390
Ratio	54	286	27	216	6	103
Ratio diff.	369	289	300	225	160	129
Ratio diff. MA	370	369	300	333	160	225

Source: Authors' work

Figure 3
Parameter Values of Premium Regressions



Note: Outliers positioned significantly far from the median have been excluded for the sake of clarity. Source: Authors' work

Third, we turn our attention to the association between sentiment and volatility. Given that volatility is not directly observable in the market, we opt for the GARCH(1,1) model for ex-post estimation. For each stock, we apply the GARCH(1,1) model; see equations (3) and (4), extracting weekly estimated volatilities, which are then utilized as the dependent variable in regression (1).

The results are presented in Table 3 and Figure 4. The intercept consistently exhibits statistical significance and a positive value for all stocks in each model. On the other hand, the slope is statistically significant only for the spread and ratio, i.e., the volatility depends on the value of the sentiment index and not on its change. The sentiment indexes calculated as both the spread and the ratio show similar results. There exists a statistically significant linear relationship between the sentiment index value and the next week's return volatility for 377 (347, respectively) stocks out of 480. Even when factoring in the potential for Type I errors (4.8 at 1%), we confirm a significant relationship between sentiment and volatilities. The predominant direction of this relationship is negative, as seen in Figure 4, which is observed in more than 75% of stocks, indicating that a higher sentiment index value is associated with lower volatility. However, a smaller fraction of stocks (less than 25%) exhibits a positive relationship, where higher sentiment aligns with higher volatility.

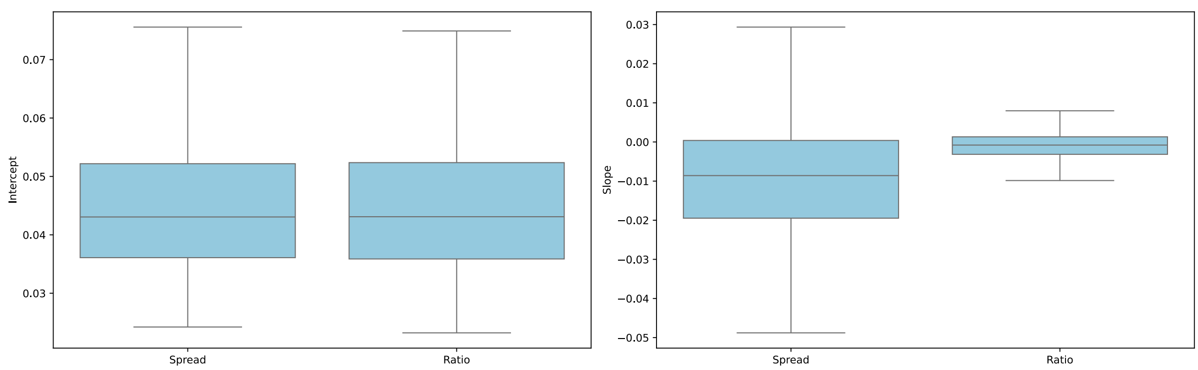
Concerning the median values, we can interpret the intercept and slope for the spread sentiment index as follows. The expected value of the next week's standard deviation of the return is 4.3% minus 0.86% for every 100 bps in the index value or, when annualized, 31% p.a. minus 0.62% p.a. for every 10 bps in the sentiment index value.

Table 3
Quantities of Statistically Significant Parameters of Regression of Volatility on Sentiment

Independent variable	10% significance level		5% significance level		1% significance level	
	Intercept	Slope	Intercept	Slope	Intercept	Slope
Spread	480	413	480	404	480	377
Spread diff.	480	4	480	1	480	1
Spread diff. MA	480	63	480	27	480	3
Ratio	480	412	480	387	480	347
Ratio diff.	480	1	480	0	480	1
Ratio diff. MA	480	10	480	2	480	0

Source: Authors' work

Figure 4
Parameter Values of Volatility Regressions



Note: Outliers positioned significantly far from the median have been excluded for the sake of clarity. Source: Authors' work

Fourth, our focus shifts to the trading volume, the dependent variable in regression equation (1) being the trading volume in one week in US dollars. The results, illustrated in Table 4 and Figure 5, closely resemble those of the volatility regression, that is, the intercept consistently proves statistically significant and positive for all regressions, while the slope generally exhibits statistical significance and negativity only for the values of the sentiment index and not their differences. Specifically, we affirm the statistically significant relationship between the AAII sentiment index and trading volume in 378 (383, respectively) stocks out of the 480 considered at a 1% significance level. Even when factoring in the potential for Type I errors (4.8 at 1%), we confirm a significant relationship between sentiment and volatilities.

Concerning the median values, we can interpret the intercept and slope for the spread sentiment index as follows: the expected value of the next week's trading volume is $12,866,011 minus $55,129 for every 1 bps in the sentiment index value. In the sentiment case of the ratio index, the expected value of the next week's trading volume is $13,852,933 minus $11,002 for every 1 bps in the sentiment index value.

Table 4

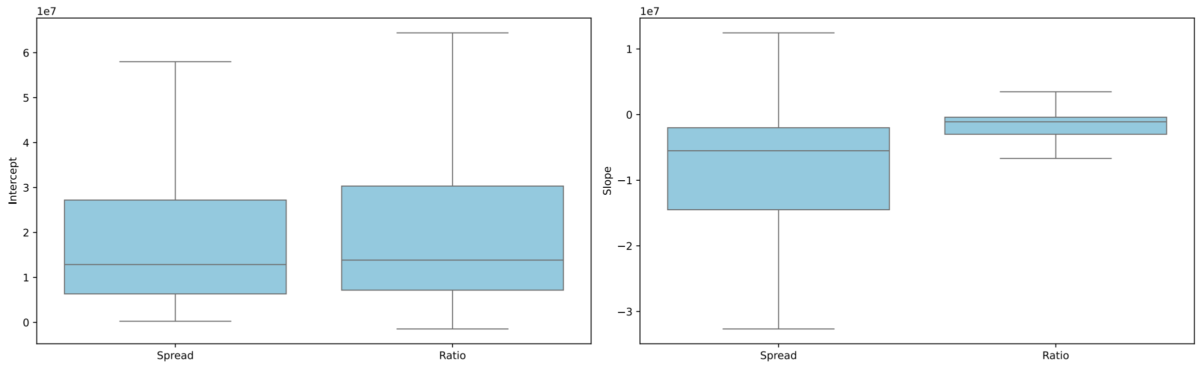
Quantities of Statistically Significant Parameters of Regression of Volume on Sentiment

Independent variable	10% significance level		5% significance level		1% significance level	
	Intercept	Slope	Intercept	Slope	Intercept	Slope
Spread	480	419	480	412	480	**378**
Spread diff.	480	23	480	14	480	**2**
Spread diff. MA	480	117	480	65	480	**20**
Ratio	479	420	479	410	479	**383**
Ratio diff.	480	8	480	3	480	**1**
Ratio diff. MA	**480**	**49**	**480**	**32**	**480**	**9**

Source: Authors' work

Figure 5

Parameter Values of Volume Regressions



Note: Outliers positioned significantly far from the median have been excluded for the sake of clarity. Source: Authors' work

Discussion

Our investigation uncovers evidence of a discernible linear relationship between individual investors' sentiments and returns, volatilities, and trading volumes. Specifically, our findings indicate a general positive relationship between sentiment changes and stock returns. Furthermore, we found general negative associations between sentiment and volatility and sentiment and trading volume. However, these relationships are not valid for all analysed stocks, as approximately 25% of stocks show the opposite relationship for volatility and trading volume and are not always statistically significant. In general, statistically significant relationships are discovered for 390 (returns), 377 (volatility), and 378 (trading volume) stocks out of 480 at a 1% significance level. It is important to account for Type I errors, which would cause 4.8 false relationships out of 480 at a 1% significance level. However, the quantities of statistically significant relationships are still relatively high.

When comparing independent variables, we confirm that returns and premiums are influenced by the change in the sentiment index more than by the value of the index itself. However, volatility and trading volume depend on the sentiment index's value and are independent of changes in its values. We also found that the original construction of the sentiment index as the spread between the bullish and bearish percentages of votes performs better than its ratio as an alternative specification.

Our findings in terms of the influence of sentiment on returns contradict the existing body of research, which emphasises a predominantly negative relationship between returns and sentiment indices. Works such as (Baker & Wurgler, 2006; Baker et al., 2012; Jiang et al., 2019; Białkowski et al., 2023; Aissia & Neffati, 2023) have consistently reported this trend. Additionally, a meta-analysis conducted by (Gric et al., 2023) supports this observation, suggesting that the true effect is negative, although in some specifications it is not significant, and in the majority of specifications, researchers tend to report this effect as being much stronger than it actually is.

The explanation for our findings can be found in (Wang et al., 2022), who found that the relationship differs based on the market regime. In bull regimes, optimistic (pessimistic) shifts in investor sentiment increase (decrease) stock returns, whereas in bear regimes, optimistic (pessimistic) shifts decrease (increase) stock returns. Our period under investigation, i.e., the years 2000-2023, although containing recent crises and bear periods such as a burst of a dot-com bubble, global financial crisis, COVID-19 pandemic, and the Russian invasion of Ukraine, also contains a strong bull market in the period from 2009 to 2023. The positive relationship can, therefore, be caused by this long bull market period present in our data. In the study of Haritha and Rishad (2020), it was also discovered that when investors' sentiment is positive, their return expectations tend to be positive as well. This positive sentiment may prompt investors to capitalise on the situation for speculative activities, encouraging increased investment, which increases the prices.

Our study confirms the negative relationship between sentiment and volatility. The sentiment level exhibits a significant relationship with volatility, revealing a pronounced negative correlation trend. More than 75% of the stocks in our study demonstrated a connection between higher sentiment and lower volatility. The minority of stocks (less than 25%) that show a positive relationship between sentiment and volatility can be attributed to specific market conditions or idiosyncratic factors that affect these particular securities. Interestingly, our findings contrast with previous research by Brown (1999), who reported a positive correlation between sentiment and volatility. However, there also exists a related body of literature that yields findings consistent with ours. For instance, Sayim et al. (2013) observed that an unforeseen rise in the emotional rationality component among individual investors has a notably adverse effect on industry volatility, particularly in the US automotive and financial sectors.

The realm of sentiment's impact on trading volume remains largely unexplored in the existing literature, presenting a gap in the understanding of market dynamics. In particular, most studies investigating trading volume have traditionally focused on proxies for investor attention, exemplified by the use of indicators like Google searches

(Joseph et al., 2011). Our findings reveal a compelling negative relationship between individual investor sentiment and trading volume. This suggests a distinctive pattern of investor response, characterised by increased reactions to negative sentiment. As the market sentiment is positive, fewer individual investors are willing to sell stocks, reducing the trading volume. On the other hand, when the market sentiment is negative, individual investors sell the stocks, which increases the trading volumes.

However, it is essential to acknowledge several limitations of our study. First, we assume the one-directional causality is from the sentiment to stock characteristics; however, the causality can be bidirectional. Second, we use the sentiment index as the only independent variable, neglecting other factors that can influence stock characteristics. There are certainly other independent variables that can be used to predict future stock characteristics. Furthermore, our study focuses on a single period, from 2000 to 2023. The choice of a different period could influence the results. Future research efforts could address these limitations, providing a more comprehensive understanding of the intricate dynamics at play in financial markets.

Conclusion

In summary, our study provides comprehensive information on the intricate relationship between individual investor sentiment and various characteristics of the stock market, including returns, volatility, and trading volumes. Through rigorous analysis, we have discovered several key findings that contribute to our understanding of market dynamics.

First, our results reveal a positive relationship between the change in individual investor sentiment and future stock returns. This suggests that sentiment can serve as a valuable predictor of market performance, with higher changes in sentiment levels generally being associated with higher future returns. This finding underscores the importance of considering investor sentiment in investment decision-making processes.

Second, we find a negative association between sentiment and both the volatility and the trading volume. Specifically, higher levels of sentiment tend to coincide with lower levels of volatility and trading volume. For institutional and individual investors, understanding the impact of sentiment on trading volume can provide more appropriate strategies for trade execution, and understanding the relationship between sentiment and market volatility can be helpful in developing risk management tools and trading strategies that are more profitable and less risky.

However, it is important to approach these results with caution. Although our findings indicate a relationship between sentiment and stock returns, the sentiment variable used in our study does not capture the full spectrum of influencing factors. Thus, relying solely on sentiment indicators for investment decisions may not consistently yield an improved performance and investors should consider sentiment as one of many factors in their decision-making process.

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