LUT School of Business and Management

Analyzing Stock Market Returns: The Role of Investor Sentiment

Lappeenrannan–Lahden teknillinen yliopisto LUT
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ABSTRACT

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Investor Sentiment and Market Returns: An Analysis of Growth and Value Stocks

Bachelor's thesis

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32 pages, 5 figures and 5 tables

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Keywords: Investor Sentiment, Market Returns, Growth Stocks, Value Stocks, Behavioral Finance

In this thesis, we investigate the influence of investor sentiment on market returns, particularly examining how this impact varies across growth and value stocks. The study also explores the sensitivity of these effects during different economic periods, focusing on the 2008 financial crisis. This research utilizes daily returns data from the Russell 3000 Growth and Value indices over the period from 2002 to 2020 to measure market reactions. By applying multiple statistical techniques, including regression analysis, lag analysis, and correlation analysis, we evaluate the role of investor sentiment in shaping market dynamics.

The empirical analysis of the Russell 3000 Growth and Value indices offers nuanced insights into the effects of investor sentiment on market returns. Growth stocks react more markedly to changes in sentiment, especially during economic downturns, suggesting that investor mood plays a significant role in periods of market stress. This study indicates that sentiment's impact varies across different types of stocks and is not uniformly distributed, highlighting the complexities in the sentiment-return relationship. Findings not only deepen understanding of behavioral finance but also provide valuable perspectives for investors in managing market risks tied to emotional trading. These outcomes suggest that while investor sentiment can deviate market prices from fundamental values, its influence is tied to the type of stocks and might depend economic conditions.

TIIVISTELMÄ

Lappeenrannan–Lahden teknillinen yliopisto LUT

LUT-kauppakorkeakoulu

Kauppatieteet

Stepan Wirkkunen

Osakemarkkinoiden tuottojen analysointi: Sijoittajasentimentin rooli.

Kauppatieteiden kandidaatintutkielma

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Tässä kandidaattitutkielmassa tutkitaan sijoittajien tunnesentimentin vaikutusta markkinatuottoihin, erityisesti tutkien, kuinka tämä vaikutus vaihtelee kasvu- ja arvo-osakkeiden kesken. Soveltamalla useita tilastollisia tekniikoita, mukaan lukien regressioanalyysi, viiveanalyysi ja korrelaatioanalyysi, arvioidaan sijoittajasentimentin roolia markkinadynamiikan muokkaamisessa.

Russell 3000 Growth- ja Value -indeksien empiirinen analyysi tarjoaa tarkkanäköisiä oivalluksia sijoittajien tunnesentimentin vaikutuksesta markkinatuottoihin. Kasvuosakkeet reagoivat voimakkaammin tunnesentimentin muutoksiin, erityisesti taloudellisten taantumien aikana, mikä viittaa siihen, että sijoittajien mielialalla on merkittävä rooli markkinastressin aikana. Tutkimus osoittaa, että sentimentin vaikutus vaihtelee erityyppisten osakkeiden välillä eikä ole yhtenäisesti jakautunut, mikä korostaa monimutkaisuuksia tunnesentimentin ja tuoton suhteessa.

Löydökset eivät ainoastaan syvennä käyttäytymistaloustieteen ymmärrystä, vaan tarjoavat myös näkökulmia sijoittajille markkinariskien hallintaan liittyen tunnepohjaiseen kaupankäyntiin. Tulokset viittaavat siihen, että vaikka sijoittajien tunnesentimentti voi johtaa markkinahintojen poikkeamiseen perusarvoista, sen vaikutus on sidoksissa osaketyyppeihin ja saattaa riippua taloudellisista olosuhteista.

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1 Introduction

In the evolving landscape of financial markets, the classical theories of economics, based on the rationality of market participants, often fall short of explaining the complex behaviors observed in stock price movements. Traditional finance models have predominantly focused on rational, information-based trading as the main driver of market dynamics. However, empirical evidence increasingly supports a different narrative—one where investor sentiment, a mix of emotional and cognitive perceptions, plays a role in influencing stock prices and market returns. This thesis aims to dig into the complexities of investor sentiment and its impact on stock returns, particularly exploring how this effect varies among different types of stocks under different market conditions.

The theory that markets are perfectly efficient and always reflect all available information—known as the Efficient Market Hypothesis (EMH)—has been foundational in financial theory. Nonetheless, work by Baker and Wurgler (2007) has challenged this perspective by demonstrating that psychological factors can cause significant deviations from market fundamentals. These deviations suggest that investor sentiment can lead to systematic pricing errors, particularly in stocks that are difficult to value and hard to arbitrage.

Further, the rapid advancement of digital media has introduced new dynamics into the financial markets. The influence of news content and social media on market movements, as evidenced by Tetlock (2007) and Bollen, Mao, and Zeng (2011), indicates that investor sentiment is now more quickly and broadly disseminated, potentially leading to immediate and pronounced market reactions.

This thesis is motivated by the need to understand the underlying mechanisms, how much sentiment affects market returns and to explore how these impacts differ across the stock types. It particularly focuses on the nuances of investor sentiment's influence on growth versus value stocks and investigates whether certain periods, like economic crises-

1.1 Previous research & research questions

Analyzing the role of investor sentiment in stock market volatility is a complex topic that includes various theories, empirical findings, and methodologies across the finance literature. This review will highlight key works and results that have significantly contributed to the understanding of this process.

Traditional models assume rational behavior and often do not capture the complexities of investor decision-making. On the contrary, behavioral finance seeks to explain irrational choices made by market participants, at the heart of this area of study lies the concept of investor sentiment – an aspect that connects emotions, perceptions, and the cognitive side, shaping the financial landscape in ways that challenge classic economic theories. Numerous studies have examined the way investor feelings and expectations influence the financial markets, focusing on the way emotions can cause stock prices to drift away from their realistic worth (Baker & Wurgler, 2007). Yet, those studies usually consider all investors acting similarly, without paying enough attention to how various kinds of stocks react differently to those emotional changes.

The foundational theory in this area is the Efficient Market Hypothesis (EMH), which stands for that prices of different assets react to all available information; however, another research has challenged this view by demonstrating that investor sentiment, or investors' general mood and outlook, can cause significant deviations from market fundamentals. Baker and Wurgler (2007) provided a significant contribution by constructing an investor sentiment index and showing its predictive power for stock returns, particularly among stocks that are hard for the valuation process and arbitrage.

The role of social media and news in shaping investor sentiment has been another crucial area of study. Tetlock (2007) found that the content of news articles could predict stock market movements, indicating that the sentiment conveyed through news impacts investor behavior and market trends. Bollen, Mao, and Zeng (2011) extended this research by analyzing Twitter data to predict stock market movements, highlighting the growing importance of social media sentiment in financial markets.

Empirical studies have also focused on the mechanisms through which sentiment affects market volatility. For instance, Barberis, Shleifer, and Vishny (1998) developed a model showing how investor psychology can lead to predictable patterns in stock prices, such as overreaction and underreaction to news, which in turn affects market volatility. Moreover, the model created supported the view that psychological factors among investors play a significant role in the financial market, which once again highlighted the importance of understanding the psychological aspect driving market behavior and their impact on market dynamics.

Antweiler and Frank (2004) investigated the relationship between online stock message boards and market volatility, finding that the volume of messages and the sentiment expressed within them were significant predictors of next-day stock volatility. This research underscores the importance of investor communication and its sentiment content as drivers of market dynamics.

Considering the complex nature of investor sentiment and its potential to influence market volatility, this thesis is an attempt to spot the underlying mechanisms through which sentiment affects the market. Specifically, it seeks to explore how variations in investor sentiment translate into changes in stock price volatility, with a particular focus on different stock types. This inquiry is grounded in the hypothesis that the impact of investor sentiment on market volatility is not uniform across all stocks and certain stocks may be more easily influenced by sentiment-driven factors than others (Tetlock, 2007).

To address this research gap, my thesis will formulate several research questions aimed at investigating the complexity of the sentiment-volatility relationship. The primary research question is: How does investor sentiment influence market returns, and does this reaction change by stock type? This question will be supported by sub-questions, including, how the effect of sentiment on returns differs between growth and value stocks.

1.2 Research Structure

After the introduction, the thesis continues in the following order:

Chapter 2: Theoretical Backgrounds

This chapter delves into the psychological and behavioral underpinnings of investor sentiment and market dynamics as part of the theoretical framework in behavioral finance. It examines the significant impacts of investor sentiment on stock prices, emphasizing the departure from traditional, purely rational financial models to include psychological influences and biases that affect financial behaviors and market outcomes.

Chapter 3: Data Sources and Selection Rationale

The rationale behind the selection of data is thoroughly articulated in this chapter, justifying the use of the Russell 3000 Growth and Value indices as primary indicators to analyze market responses to investor sentiment. This chapter introduces the sentiment index used in the thesis as a comprehensive measure to capture the prevailing mood in the market, instrumental in examining how different types of stocks react under varying sentiment conditions.

Chapter 4: Methodology

This chapter describes the methodological approaches employed in the thesis, including correlation and regression analyses to explore the relationships between investor sentiment and the performance of market indices. It also discusses the use of lag analysis to understand the temporal effects of sentiment on market reactions and the broader implications for predicting market dynamics.

Chapter 5: Results

Empirical findings are detailed, discussing the results from correlation, regression, and lag analyses. This chapter offers a nuanced discussion on the impact of varying levels of sentiment (segmented into four quartiles) on the performance of the Russell 3000 indices, each reflecting different market conditions from highly positive to deeply negative sentiment.

Chapter 6: Conclusion and Future Research

The concluding chapter synthesizes the findings, reflecting on their theoretical and practical implications. It acknowledges the complexities of market behaviors in response to investor sentiment and suggests further research avenues. Potential areas include comparative studies across global markets and different economic sectors, as well as exploring the influence of digital media on market sentiment.

2 Theoretical backgrounds

2.1 Investor Sentiment

Baker and Wurgler (2007) explore the concept of investor sentiment and its impact on the stock market. They focus on overall investor mood, independent of market fundamentals, can significantly influence stock prices and market dynamics. Switching the focus from traditional, purely rational models of financial markets to consider psychological and behavioral factors, this study is embedded in the broader context of behavioral finance, an area that examines how psychological influences and biases affect the financial behaviors of investors and the subsequent market outcomes.

As one of the most important studies about the topic Baker and Wurgler's 2007 study, "Investor Sentiment in the Stock Market," published in the Journal of Economic Perspectives, provides an in-depth analysis of how investor sentiment affects stock market volatility. According to their research, investor sentiment, defined as the overall attitude of investors towards the financial market or specific securities, plays a crucial role in influencing stock prices (Baker & Wurgler, 2007). The authors argue that certain types of stocks, particularly those that are hard to value and difficult to arbitrage, are less stable to the effects of investor sentiment. This typically includes younger, smaller, less profitable, and more volatile stocks, as well as those not issuing dividends whose speculative nature makes them more vulnerable to sentiment-driven price fluctuations (Baker & Wurgler, 2007).

According to Baker and Wurgler (2007), shifts in investor sentiment can lead to systematic pricing errors, causing stocks to move away from their fundamental values. An extra-optimistic sentiment can result in stock overvaluation, while a pessimistic view can lead to undervaluation. This effect is especially significant in speculative stocks, which lack clear, objective valuation measures. As well the study also discusses how investor sentiment-induced price deviations can alter risk premiums, for instance, high sentiment levels, associated with elevated stock prices, tend to lower future expected returns, reducing the risk premium. Conversely, low sentiment levels depress stock prices, increasing expected future returns and the associated risk premium (Baker & Wurgler, 2007).

Baker and Wurgler also explore the feedback loop between stock prices and corporate fundamentals, emphasizing that inflated stock prices, a result of positive investor sentiment, may encourage companies to issue new shares or undertake mergers and acquisitions, actions that can fundamentally alter a company's market value and contribute to market volatility (Baker & Wurgler, 2007). The research underlines the significant impact of investor sentiment on stock market dynamics, particularly on the volatility of speculative and hard-to-value stocks. The findings emphasize the importance of understanding sentiment trends in market analysis and investment strategy formulation, providing valuable insights for both investors and financial analysts (Baker & Wurgler, 2007).

In their work Baker and Wurgler employ various empirical methods to measure investor sentiment and its effects on stock returns, utilizing proxy variables for sentiment, such as IPO volume and closed-end fund discounts, to construct a sentiment index. This approach is innovative as it provides a quantifiable measure of sentiment, which is inherently abstract. Their methodology guides future research in behavioral finance, suggesting that the study of market sentiment requires creative approaches and indirect measures due to the subjective nature of investor mood. The authors identified limitations in existing models that fail to account for psychological factors, pointing out gaps in the literature where future studies could contribute, indicating that understanding market dynamics requires rational and irrational behaviors, thereby broadening the scope of financial research to include psychological and behavioral elements.

Newer articles, that investigate a similar topic, made by Sun, Najand, and Shen (2016) and Huang, D., Jiang, F., Tu, J. & Zhou, G (2015) look at the phenomenon itself quite similarly. Building on the broader context of behavioral finance, Huang, Jiang, Tu, and Zhou (2015) made significant strides with their research on "aligned investor sentiment." They proposed that when various sentiment indicators show a high level of agreement or alignment, this can serve as a predictor of stock returns. The concept presented above extends the analysis beyond individual sentiment measures to consider the collective mood of investors, providing a more nuanced understanding of how sentiment affects market dynamics, especially to speculative or riskier stocks.

The methodological approach adopted by Huang et al. (2015) demonstrates the importance of using multiple sentiment measures to assess the overall mood of the market. The construction of an aligned sentiment index offers a template for future research, implying that a composite approach may yield more reliable indicators of market sentiment. Sun, Najand, and Shen (2016) introduced a high-frequency perspective to sentiment analysis, employing minute-by-minute data to explore how rapid shifts in sentiment can predict short-term stock return variations. This high-frequency method highlights the significance of considering both macro-level sentiment trends and micro-level fluctuations in sentiment when analyzing stock market responses.

The insights from Huang et al. and Sun, Najand, and Shen help in setting clear guidelines for future inquiries into the relationship between investor sentiment and stock market behavior. They think that research should not only account for the overall level of sentiment but also consider the degree of consensus among different sentiment indicators and the speed at which sentiment changes occur. Identifying the differential impact of sentiment on various types of stocks, such as speculative versus fundamentally anchored stocks remains a crucial area for the research questions.

2.2 Understanding Market Volatility

Market volatility refers to the degree of variation in the prices of financial instruments over some period (Schwert, 1989). It is a concept in finance, reflecting the degree of uncertainty or risk present in the market. It is obvious that fully comprehending market volatility is essential for investors, as it impacts investment decisions, portfolio management strategies, and risk-related processes.

The relationship between investor sentiment and market volatility has been the subject of research. Studies have highlighted the influence of sentiment on market fluctuations, with heightened sentiment often associated with increased volatility (Baker & Wurgler, 2007; Tetlock, 2007). It was found that investor sentiment acts as a catalyst for market movements, amplifying price fluctuations and exacerbating volatility (Shiller, 2003).

Moreover, empirical evidence verifies that changes in sentiment can lead to abrupt shifts in market dynamics, causing periods of heightened volatility (Baker & Wurgler, 2007). Sentiment-driven factors, such as fear, optimism, and others, can dramatically increase market volatility, leading to price changes and increased uncertainty.

2.3 Market Efficiency

This section provides an understanding of the existing knowledge on market efficiency and investor behavior, guiding the foundational structure of this thesis. The overview of seminal works that have shaped the understanding of financial markets are presented, particularly focusing on the concepts introduced by Paul A. Samuelson and Eugene F. Fama.

Paul A. Samuelson's landmark paper lays the mathematical groundwork for the theory of market efficiency. He argues that in an efficient market, price movements are entirely unpredictable and follow a 'random walk', meaning that past price information has no bearing on future price directions. Samuelson challenges conventional trading strategies based on historical data and emphasizes the role of new information in price determination with his theory underscoring the futility of attempting to predict short-term market movements based on past trends, thereby shaping the methodologies for studying financial markets and investor behavior. As a result, his work encourages researchers to consider models that accommodate the unpredictability of price movements, setting a precedent for subsequent financial theories (Samuelson, 1965).

Building on the foundation laid by Samuelson, Eugene F. Fama extends the concept of market efficiency through his comprehensive review, which categorizes market efficiency into three distinct forms: weak, semi-strong, and strong. Fama's analysis suggests that the extent to which market prices reflect all available information forms the basis of market efficiency. It has profound implications for the development of investment strategies and the interpretation of financial data since it argues that stock prices already incorporate all known information. Fama challenges the merit of active trading strategies aimed at outperforming the market. This paper further guides methodological choices by encouraging empirical research that tests market reactions to new information, thereby offering a clear direction for academic inquiry into financial market dynamics (Fama, 1970).

Insights provided by Samuelson and Fama are a huge theoretical base for this thesis. The methodologies and problem definitions derived from this literature underscore the importance of embracing complex models that account for the market's efficient response to new information. In this light, this thesis research aims to explore investor behavior within the context set by these foundational theories, examining how complex market dynamics align with or diverge from the principles of market efficiency.

3 Data Sources and Selection Rationale

3.1 The Russell 3000 Indexes

For the testing I decided to pick dataset, which would include a database that is relevant and wide enough to provide accurate results, my choice fell on the Russell 3000. The Russell 3000 Value Index is comprised of those Russell 3000 companies considered to have value characteristics. Value stocks are usually characterized by lower price-to-earnings ratios and are considered by investors to be underpriced relative to their fundamentals. According to the principles of behavioral finance, the type of stocks mentioned might react differently to changes in investor sentiment compared to growth stocks, when sentiment is high, investors might be less inclined towards value stocks, as they prefer the potentially higher returns from growth stocks despite their higher risk. Conversely, in times of low sentiment, investors might favor value stocks, perceived as safer investments due to their undervaluation (Baker and Wurgler, 2007).

In contrast, the Russell 3000 Growth Index comprises companies that manifest growth characteristics, such as significant growth rates in earnings or revenues. Typically, these stocks are priced higher relative to their current earnings and are associated with increased levels of volatility. Behavioral finance theories suggest that growth stocks are likely to be more influenced by investor sentiment due to their speculative nature and the greater uncertainty regarding their future earnings (Barberis, Shleifer, & Vishny, 1998).

3.2 Sent

The relationship between investor sentiment, as operationalized by the SENT index developed by Baker and Wurgler, and market performance. It specifically focuses on the differing stock types represented by the Russell 3000 Value and Russell 3000 Growth indexes, to examine how varying market conditions and investor sentiments affect these different segments.

The SENT index, as previously detailed, serves as a measure of market sentiment, derived from various market indicators. Its use in academic research provides valuable insights into the psychological underpinnings of market dynamics. Specifically, Baker and Wurgler's sentiment index has been instrumental in demonstrating how swings in investor mood can significantly impact the pricing and performance of stocks, independent of fundamental factors (Baker & Wurgler, 2007).

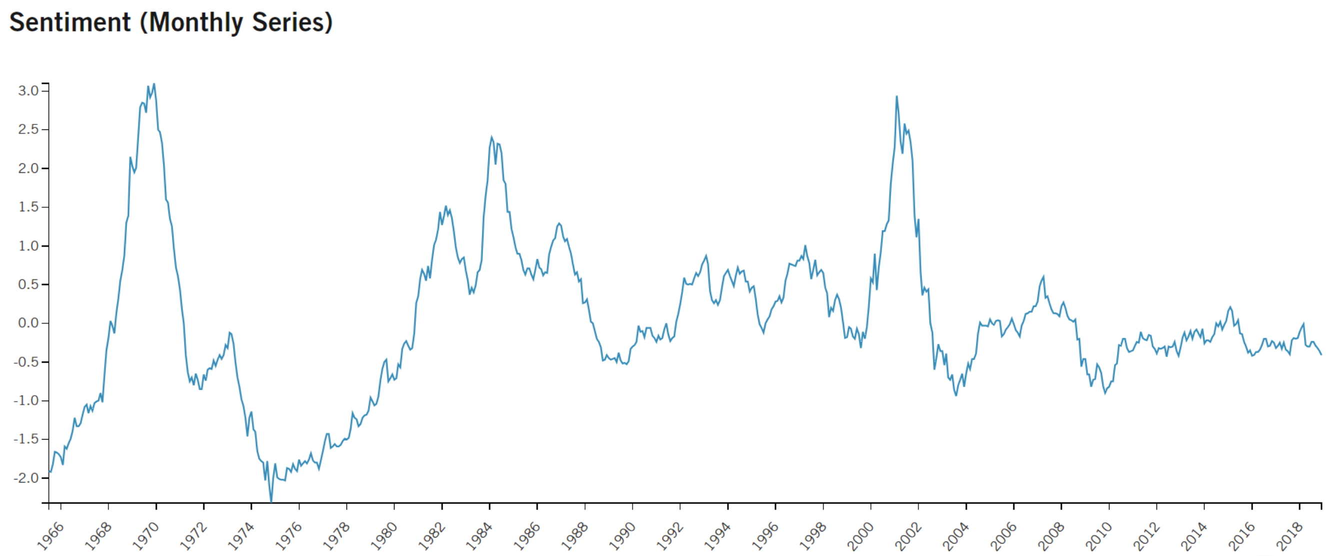

Figure 1: Harward Business School, Behavioral Finance and Sustainability, Sentiment Index

For this scholarly work, we presume that the impact of investor sentiment on stock prices, as reflected by the SENT index, varies between value and growth stocks. I propose that growth stocks, represented by the Russell 3000 Growth Index, are more sensitive to changes in investor sentiment than value stocks, represented by the Russell 3000 Value Index. The hypothesis is based on the speculative nature of growth stocks, which makes them more dependent on the effect of investor sentiment, while value stocks are going along more strongly with fundamental analysis, making them less sensitive to sentiment changes (Baker & Wurgler, 2007; Barberis et al., 1998).

To test this idea, the research will employ quantitative data analysis, examining historical performance data for the Russell 3000 Value and Growth indexes in conjunction with the SENT index. By applying regression analysis and event study methodology, this study aims to search patterns and show possible relationships between investor sentiment and market volatility, with a focus on the different impacts on value versus growth stocks.

3.3 Data for testing the impact of Market Sentiment on Index Returns

The analysis relies on a selected dataset that combines information on market indices, investor sentiment, and risk-free rates from October 2002 to October 2020. This period is particularly interesting because it includes major economic events, such as the global financial crisis and periods of rapid growth in technology markets, making it a suitable timeframe to study the effects of investor sentiment on market indices.

In this study, I use the Russell 3000 Growth and Russell 3000 Value indices as the main indicators of market performance. These indices, which I accessed via Yahoo Finance, represent a broad spectrum of U.S. equities and are ideal for examining different investment styles under various market conditions. The long study period from 2002 to 2020 allows us to see how these indices react during both good and bad economic times.

The sentiment data, a crucial part of this analysis, comes from the "SENT" index. This index helps us understand how feelings and behaviors might influence the stock market (Baker & Wurgler, 2007). By looking at this data alongside the index data, this study tries to show how changes in investor sentiment could signal upcoming changes in the market. As well, I include risk-free rate data from Kenneth French's Data Library to compare the performance of the market indices against a safe investment alternative, using 1-year U.S. Treasury bill rates. This comparison is important to assess how much better or worse investing in the stock market is compared to risk-free investments, especially during different economic conditions.

Data preparation is thorough, ensuring all information from different sources matches up correctly. It involves making sure all dates are in the same format and that all data points line up correctly across sources. The period chosen for this study, 2002-2020, helps fulfill the thesis's goal of understanding how investor sentiment can influence market performance during unstable and stable economic times.

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4 Methodology

The methodology section will outline the approach taken to investigate these questions, including the usage of quantitative data analysis to examine historical market data and sentiment indicators. The research will employ a combination of regression analysis and event study methodology to identify patterns and causal relationships between investor sentiment and market volatility across different stock types and periods. As for data collection, data for the years from 2002 to 2020 will be used and will include analysis of various stock indexes' performance, both growth and value. As for investor sentiment SENT index, by Baker and Wurgler. As for the qualitative side, it will contain a comparative analysis of the effects of sentiment on market volatility across different stock types (growth vs. value) and during different market conditions.

In the empirical section of this thesis, I plan to dive deeper into the complex relationship between investor sentiment and how different market segments perform. I would like to perform a several statistical tests and as well It will include a simulation of a trading strategy. This analysis specifically looks at the Russell 3000 Value and Russell 3000 Growth indexes over a period from 2003 to 2022. By making use of Python's tools for data handling and statistical analysis, such as the pandas library for data organization and manipulation and the statsmodels library for conducting statistical tests and models, we meticulously prepared and analyzed a dataset. This dataset includes monthly records of investor sentiment scores along with performance metrics of these indexes. This detailed examination helps us understand how changes in investor mood can influence stock market movements, providing insights into the broader market dynamics during the studied period.

4.1 Correlation Analysis

Correlation analysis is a foundational tool in finance research, enabling the examination of the relationship between two variables (Field, A. & Field, A. P, 2013). This approach suits the case discussed since it provides a measure of how closely two sets of data are related, which is crucial in finance where relationships between variables like sentiment and stock prices are often hypothesized but need empirical verification.

In this context, the assessment is based on the fact how investor sentiment (SENT) correlates with the performance of the Russell 3000 Value and Growth indices. Further studies by Baker and Wurgler (2006) highlight the importance of understanding the linkage between sentiment and stock returns, providing a basis for the expectation of significant correlations observed in this analysis. The timeframe of data in use is 2002-2005.

4.2 Regression Analysis

Regression analysis serves as a foundational tool in this research to search the predictive relationships between investor sentiment (the independent variable) and the closing prices of market indices (the dependent variable). This analytical method is crucial as it extends beyond mere correlation, offering deeper insights into how fluctuations in investor sentiment might forecast movements in stock market indices. For this purpose, the thesis employs Ordinary Least Squares (OLS) regression, a widely recognized statistical technique for modeling relationships between variables.

OLS regression is particularly effective in estimating the true parameters of a linear relationship under standard conditions. By applying this method I aim to quantify the impact of changes in investor sentiment on indices such as the Russell 3000 Value and Growth indexes.

4.3 Lag Analysis

To further our understanding of the dynamics between investor sentiment and market performance, I have created a lag analysis into the thesis. This analysis is important as it helps in determining the reaction speed of different stock indexes—specifically the Russell Value and Growth indexes—to changes in investor sentiment. Understanding this reaction speed is essential for identifying the speed with which investor sentiment influences stock prices, which can significantly inform investment strategies and risk assessment.

The lag analysis will be performed using time-series data of investor sentiment indices and stock market performance from 2005 to 2011. This period includes a variety of market conditions, providing a robust data set for analysis. By examining the correlation of investor sentiment at various time lags (ranging from one month to one year), the analysis will reveal how long after a change in sentiment the market typically responds. This approach not only sheds light on the persistence of sentiment effects over time but also helps in pinpointing periods when the market is responsive to sentiment changes.

4.4 Testing the impact of Market Sentiment on Index Returns

The period of analysis extends from October 2002 to October 2020, a timeframe that has various economic cycles, including expansions and recessions, making it suiteble for examining how market sentiment influences index performance across different market conditions.

The primary data sources for my analysis include Yahoo Finance, from which I will retrieve the daily and monthly returns of the Russell 3000 Growth and Value indices. Additionally, I will use risk-free rate data for one-year Treasury bills from the Kenneth French Data Library. The sentiment data, important to my analysis, will be sourced from the sentiment index ("SENT") developed by Baker and Wurgler. This index is widely recognized for its efficacy in capturing the prevailing market sentiment, which is believed to influence market behavior.

To analyze the impact of sentiment on index returns, I will separate the sentiment data into four quartiles, referred to as 'boxes'. Each box represents a range of sentiment, from the highest 25% of sentiment values (most positive) down to the lowest 25% (most negative). This separation allows for an analysis of how varying levels of investor sentiment correlate with changes in index returns.

As well analysis will include monthly volatility calculations and a Sharpe ratio for each of the “Boxes”. The Sharpe Ratio, developed by William F. Sharpe in 1966, is a critical financial metric used to assess the performance of an investment compared to a risk-free asset, after adjusting for its risk. This measure, named after its creator, provides a simple yet profound insight into the relative attractiveness of an investment by comparing its excess returns to the total variability of its returns, quantified as standard deviation (Sharpe, 1966).

Mathematically, the Sharpe Ratio is defined as: S=(Rp-Rf)/ σp where Rp is the return of the portfolio, Rf is the return of a risk-free asset, and σp is the standard deviation of the portfolio’s excess returns over the risk-free rate. This formula essentially divides the risk premium by the standard deviation of the portfolio returns, which is an indicator of the portfolio's total risk (Sharpe, 1966). By employing the Sharpe Ratio, analysis not only measures the returns but also adjusts these returns for the risk needed to achieve them, providing a better understanding of the indices' performances relative to their risk level.

After that I am planning to create a Regression analysis, looking into how investor sentiment, quantified through sentiment boxes, impacts the returns of the Russell 3000 Growth and Russell 3000 Value indices. By segmenting the sentiment data into quartiles, or "boxes," I can closely examine the relationship between varying degrees of market sentiment and index performance. This structured approach allows to identify if different sentiment levels typically result in returns that exceed or fall short of the market’s expected performance.

In this case, I will use Excel to organize the return data and sentiment scores, ensuring everything is aligned correctly for accurate analysis. Excel’s Data Analysis Toolpak is useful for carrying out the regression analyses, the feature provides a method to explore the complex relationships within the data, allowing me to assess the statistical significance of sentiment as a predictor of market returns.

5 Results

5.1 Results of the correlation analysis

The empirical results underscore the positive correlations between the SENT scores and the open prices of both Russell 3000 indices, consistent with Tetlock (2007), which highlighted the significant influence of public mood on market outcomes. Specifically, the analysis reveals that the Russell 3000 Value Index has a correlation coefficient of 0.652431 with the open prices. This strong coefficient suggests a robust linear relationship between investor sentiment and the performance of value stocks.

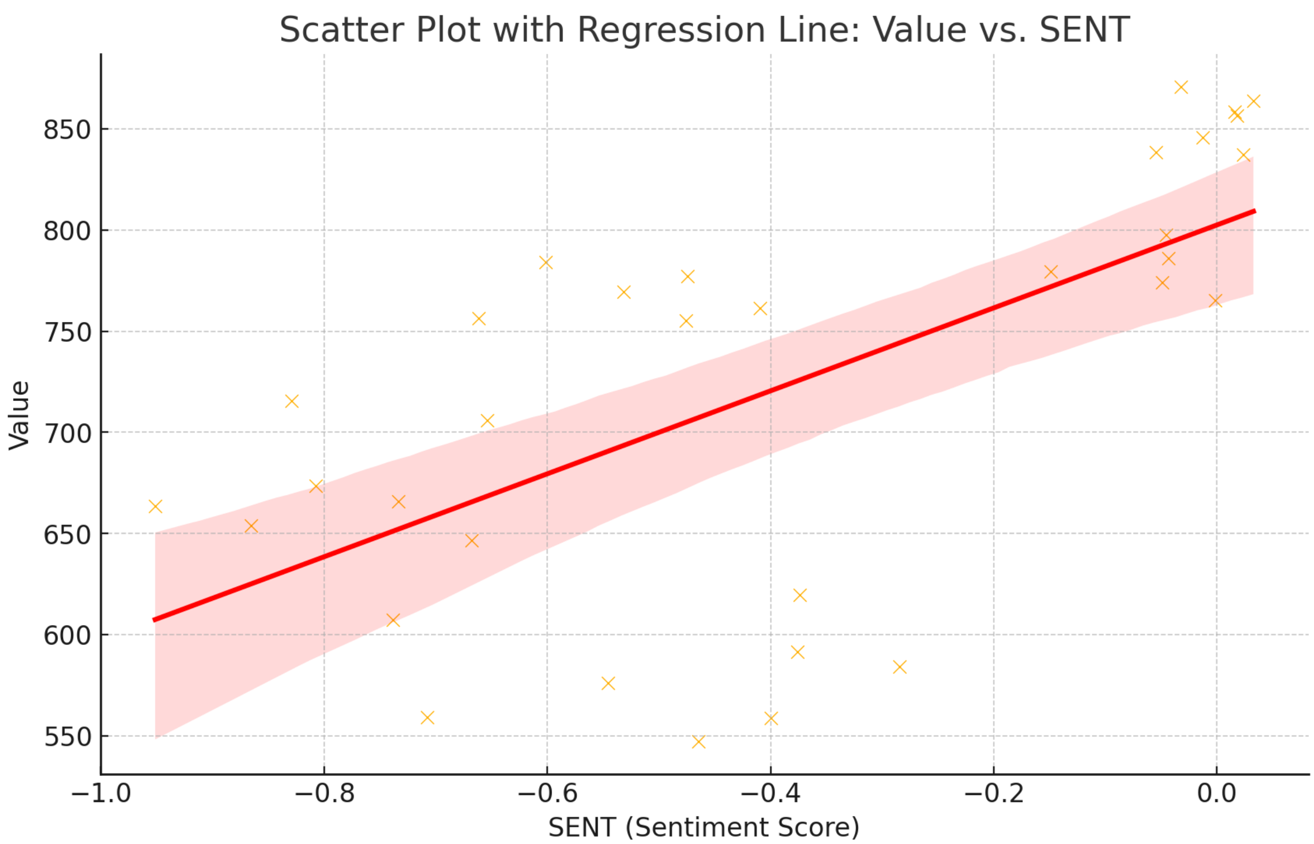

Figure 2: Scatter Plot with regression line: Russell 3000 value index & SENT

The scatter plot above is a visualization of the correlation between sentiment scores ('SENT'), SENT index and 'Value', Russell 3000 Value index in the timeframe of 2003-2005. Each dot represents a data point, with sentiment on the horizontal axis and value on the vertical axis. The upward-sloping red line, the regression line, indicates a positive linear relationship between sentiment and value, suggesting that higher sentiment generally correlates with higher values.

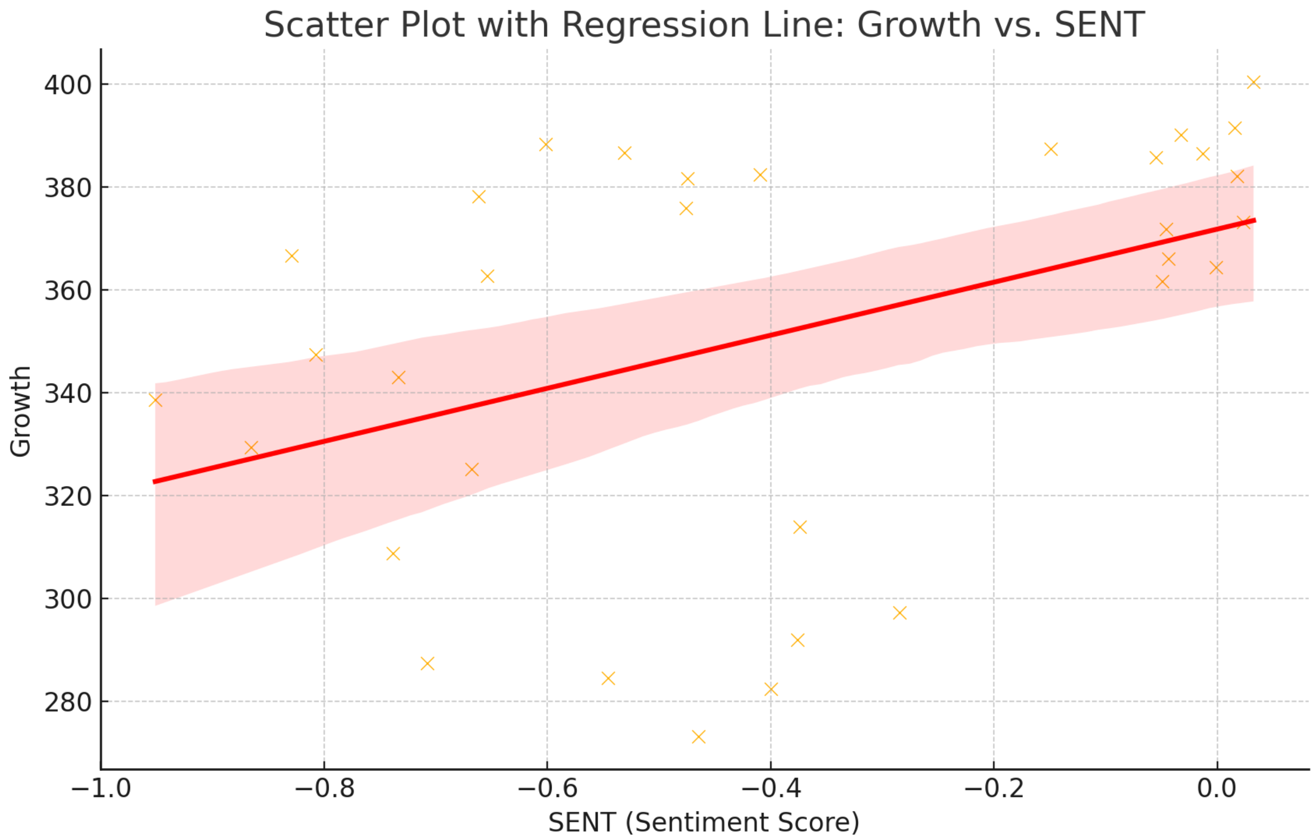

Figure 3: Scatter Plot with regression line: Russell 3000 growth index & SENT

For the Russell 3000 Growth Index, the correlation coefficient with open prices is 0.421. This indicates that growth stocks, while still positively influenced by changes in investor sentiment, show a less intense sensitivity compared to value stocks, which is not going in line with the theory that Growth stocks are more sensitive to the effects of investor sentiment, this could be the result of limitation of the data as for this particular testing, I picked the data for the period 2002-2005 years, as well, other macroeconomic factors not accounted for in the analysis could have impacted growth stocks differently from value stocks during the study period, thus affecting the observed correlation with sentiment.

5.2 Results of the regression analysis

In the case of Russell 3000 Growth Index indicates a minimal correlation between the independent variable, “SENT” and the index performance. The Multiple R value stands at 0.22239, suggesting a weak linear relationship. R Square value of 0.04945, which reveals that only 4.95% of the variability in the Russell 3000 Growth Index is explained by the independent variable, highlighting a significant portion of unexplained variance. The Adjusted R Square value of 0.04503 confirms the model's limited explanatory power, even after accounting for the number of predictors. However, the F-statistic, at 11.1866 with a p-value of 0.00097, establishes the model’s statistical significance. This paradox between the low explanatory power and statistical significance suggests that while the factors included do influence the index, they are far from being the dominant result drivers. The regression coefficient for X is 0.00018241, indicating a positive influence on the index.

Turning to the Russell 3000 Value Index, the results depict a more complete relationship. The Multiple R of 0.39046 suggests a moderate correlation, and the R Square value at 0.15245 means that about 15.25% of the index's variability is accounted for by the predictor. This is higher than what is observed with the Russell 3000 Growth index. The Adjusted R Square of 0.14851 closely follows, indicating robust model performance relative to the number of predictors. The model's relevance is further emphasized by an F-statistic of 38.6730, which is significant at a p-value of less than 0.00001, decisively confirming that the model fits the data significantly better than a model with no predictors. The coefficient of 0.00032971 for X (Russell 3000 Value index) showcases a more substantial positive effect on the Value index. This implies that changes in the predictor have a more considerable impact on value stocks, suggesting that investor sentiment plays a role in influencing their market performance.

The comparison between the Growth and Value indices highlights distinct sensitivities to the predictor, which are likely reflective of the inherent differences in the nature of growth versus value stocks. While both indices show statistically significant models, the Value index not only shows a stronger response in terms of coefficient magnitude but also captures a larger portion of variability explained by the predictor.

5.3 Results of the lag analysis

The dynamics between sentiment shifts and market performance are examined through lag analyses, for the Russell 3000 Value Index, the correlation coefficients decrease gradually from 0.629950 at a one-month lag to 0.231180 at an eleven-month lag, indicating that the influence of past sentiment gets lower over time but remains notable up to nearly a year later.

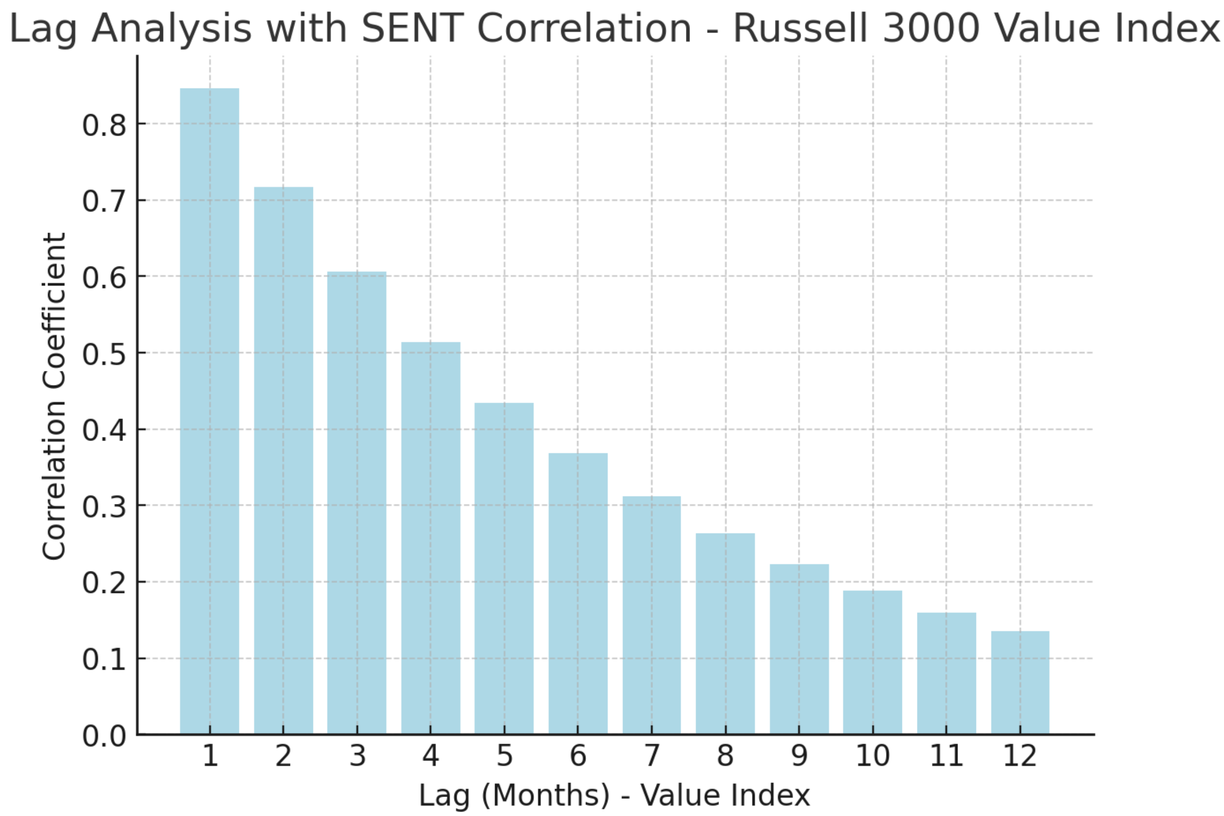

Figure 4: : Lag analysis with SENT correlation, Russell 3000 Value Index

Similarly, the Russell 3000 Growth Index experiences a diminishing yet sustained sentiment impact, with correlation coefficients decreasing from 0.634710 at a one-month lag to 0.229176 at an eleven-month lag. Consequently, the formed pattern underscores that while the immediate impact of sentiment is more pronounced, its effects can linger, affecting market performance over extended periods.

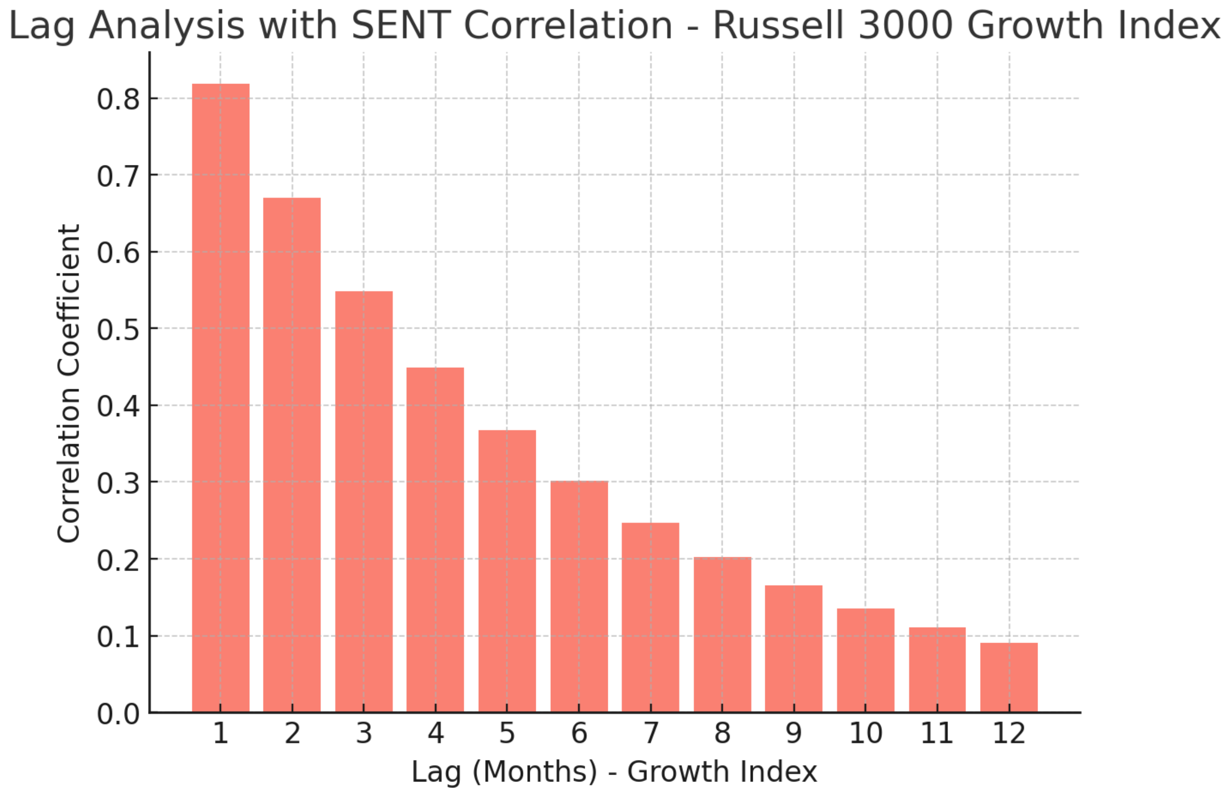

Figure 5: Lag analysis with SENT correlation, Russell 3000 Growth Index

5.4 Impact of the sentiment on the market returns

I explore the intricate relationship between market sentiment and the performance of the Russell 3000 Growth and Russell 3000 Value indices over different sentiment conditions. This exploration involves dividing sentiment into four quartiles, or 'boxes,' to assess how varying levels of sentiment — from highly positive to deeply negative — affect these indices' performance, particularly focusing on the Sharpe Ratios for risk-adjusted returns.

Table 1: Combined analysis of the SENT "boxes"

Category	Box 1 (Highest 25%)	Box 2 (Second Lowest)	Box 3 (Third Lowest)	Box 4 (Lowest 25%)
Sentiment Score	0.455	-0.001	-0.29	-0.666
Growth Index				
Average Return	0.01021732	0.006618942	0.00913	0.015456712
Volatility	0.0378	0.040115509	0.044606373	0.059747281
Sharpe Ratio	0.37132298	0.225847815	0.193470112	0.112641109
Value Index				
Average Return	0.007423245	0.001515904	0.0057	0.012060193
Volatility	0.03507657	0.03895312	0.04452917	0.030770204
Sharpe Ratio	0.301055661	0.101403944	0.117451099	0.145920385

The highest sentiment quartile, Box 1, has positive returns for both the Russell 3000 Growth and Value indices. This box, characterized by a sentiment score of 0.455, shows that both indices perform well, with Growth outpacing Value. The Sharpe Ratios are relatively high, indicating effective risk management alongside favorable returns. This suggests a positive correlation between investor optimism and superior performance in growth-focused stocks. In the case of the first box we should remember that on the timeline of 2002-2022 there were only 5 months that contain that certain level of SENT, so the statistical significance might be lower than in other cases.

Moving to Box 2, where sentiment approaches neutrality (-0.001), there is a noticeable decline in both performance and Sharpe Ratios for the indices. This decline underscores the sensitivity of both indices to diminishing sentiment, with the Growth index maintaining a lead in performance. This pattern implies that while both indices are affected by a drop in positive sentiment, the Growth index might possess greater resilience against such shifts, managing to keep better returns and risk adjustment.

In the third quartile, Box 3, where sentiment becomes more negative (-0.29), the indices again show reduced returns and Sharpe Ratios compared to the higher returns in Box 2. The continued poor performance in terms of risk-adjusted returns highlights the challenges faced by both indices under negative sentiment. The Growth index, despite these challenges, still manages to outperform the Value index, suggesting that growth stocks might be somewhat more robust in managing the impacts of negative investor sentiment.

The most intriguing results emerge from Box 4, the quartile with the lowest sentiment (-0.666), where both indices unexpectedly post the highest raw returns seen across all boxes. However, the Sharpe Ratios are the lowest, indicating that the higher returns come with disproportionately higher risks. In this scenario, the Value index exhibits a slightly better Sharpe Ratio than the Growth index, suggesting that value stocks may offer a marginal advantage in managing risk effectively during periods of extreme pessimism.

This analysis of sentiment impact across different market conditions reveals that while higher sentiment generally correlates with better risk-adjusted returns, the complexities of market dynamics under extreme sentiments can lead to unexpected outcomes. Specifically, the observation that the lowest sentiments correspond with the highest raw returns but the poorest risk-adjusted returns highlight the nuanced role sentiment plays in influencing market performance.

5.4.1 Regression analysis of the “boxes”

Table 2: BOX 1, the results of the regression analysis

Metric	Russell 3000 Growth Index	Russell 3000 Value Index
Multiple R	0.2343	0.2863
R Square	0.0549	0.0819
Adjusted R Square	-0.2602	-0.2241
Standard Error	0.0324	0.0305
SS (Regression)	0.00018044	0.00025032
SS (Residual)	0.00316766	0.00280444
MS (Regression)	0.00018044	0.00025032
MS (Residual)	0.00105589	0.00093481
F Statistic	0.1714	0.2678
Significance F	0.7044	0.6406
Intercept	-0.0151	-0.0221
Intercept Std. Error	0.0629	0.0587
Intercept t Stat	-0.2422	-0.3768
Intercept P-value	0.8240	0.7314
X Variable 1 Coefficient	0.0557	0.0649
X Variable 1 Std. Error	0.1334	0.1255
X Variable 1 t Stat	0.4174	0.5175
X Variable 1 P-value	0.7044	0.6406
Lower 95% CI (Intercept)	-0.2137	-0.2089
Upper 95% CI (Intercept)	0.1834	0.1647
Lower 95% CI (X Variable 1)	-0.3689	-0.3345
Upper 95% CI (X Variable 1)	0.4802	0.4644

Both the "Russell 3000 Growth Index" and the "Russell 3000 Value Index" reveals nuanced interactions between the indices and the sentiment (SENT) variable, but the correlations and statistical significances are not as robust as one might expect from a well-fitting model. The regression analyses for the Russell 3000 Growth and Value indices reveal only weak correlations with investor sentiment (SENT). The results for the Growth Index show a Multiple R of 0.2343 and an R Square of 0.0549, meaning just 5.49% of SENT's variability is explained by the index. This limited explanatory power is evidenced by a negative Adjusted R Square of

-0.2602 and a non-significant F-statistic of 0.1714 (p-value 0.7044), indicating no strong relationship between the Growth Index and SENT.

Similarly, the Value Index analysis showed a slightly higher Multiple R of 0.2863 and an R Square of 0.0819, suggesting it explains 8.19% of the variability in SENT. However, like the Growth Index, the Adjusted R Square is negative (-0.2241), and the F-statistic of 0.2678 with a p-value of 0.6406 also fails to reach statistical significance, showing a weak correlation.

In both models, the coefficients for the intercept and the indices are not statistically significant, underscoring the minimal impact of these indices on SENT. These findings highlight the need for additional research, potentially incorporating more variables or different modeling approaches, to better understand the relationship between market indices and investor sentiment.

Table 3: BOX 2, the results of the regression analysis

Metric	Russell 3000 Growth Index	Russell 3000 Value Index
Multiple R	0.0775	0.0949
R Square	0.0060	0.0090
Adjusted R Square	-0.0067	-0.0037
Standard Error	0.0357	0.0326
SS (Regression)	0.00060	0.00075
SS (Residual)	0.9967	0.9827
MS (Regression)	0.00060	0.00075
MS (Residual)	0.0128	0.0126
F Statistic	0.4717	0.7082
Significance F	0.4942	0.4026
Intercept	0.0066	0.0015
Intercept Std. Error	0.0040	0.0036
Intercept t Stat	1.6435	0.4134
Intercept P-value	0.1043	0.6898
X Variable 1 Coefficient	-0.0249	-0.0279
X Variable 1 Std. Error	0.0364	0.0331
X Variable 1 t Stat	-0.6870	-0.8415
X Variable 1 P-value	0.4942	0.4026
Lower 95% CI (Intercept)	-0.0014	-0.0058
Upper 95% CI (Intercept)	0.0145	0.0087
Lower 95% CI (X Variable 1)	-0.0974	-0.0938
Upper 95% CI (X Variable 1)	0.0474	0.0381

The regression analyses for the "Russell 3000 Growth Index" and the "Russell 3000 Value Index" exhibit weak correlations and limited explanatory power as evidenced by their R Square values.

The Growth Index displays a Multiple R of 0.0775, and an R Square of 0.0060, indicating that only about 0.6% of the variance in SENT is explained by changes in the index. The Adjusted R Square of -0.0067 further underscores the model's minimal explanatory power. The F-statistic of 0.4717 with a p-value of 0.4942 signifies that the model does not achieve statistical significance, indicating a very weak relationship between the Growth Index and SENT.

Similarly, the Value Index shows a Multiple R of 0.2863 and an R Square of 0.0819, suggesting that approximately 8.19% of the variability in SENT is captured by the model. The Adjusted R Square is -0.2241, reflecting the model's poor fit. The F-statistic is 0.2678 with a p-value of 0.6406, further confirming the lack of statistical significance and the weak connection between the Value Index and SENT. Both indices demonstrate very low correlations with SENT, highlighted by low R Square values and non-significant F-statistics.

Table 4: BOX 3, the results of the regression analysis

Metric	Russell 3000 Growth Index	Russell 3000 Value Index
Multiple R	0.0381	0.0319
R Square	0.0014	0.0010
Adjusted R Square	-0.0097	-0.0107
Standard Error	0.0508	0.0490
SS (Regression)	0.00033	0.00022
SS (Residual)	0.2329	0.2156
MS (Regression)	0.00033	0.00022
MS (Residual)	0.0026	0.0024
F Statistic	0.1302	0.0919
Significance F	0.7190	0.7624
Intercept	0.0172	0.0006
Intercept Std. Error	0.0242	0.0207
Intercept t Stat	0.8008	0.0298
Intercept P-value	0.4266	0.9763
X Variable 1 Coefficient	0.0259	-0.0209
X Variable 1 Std. Error	0.0762	0.0690
X Variable 1 t Stat	0.3609	-0.3031
X Variable 1 P-value	0.7190	0.7624
Lower 95% CI (Intercept)	-0.0255	-0.0404
Upper 95% CI (Intercept)	0.0599	0.0417
Lower 95% CI (X Variable 1)	-0.1166	-0.1581
Upper 95% CI (X Variable 1)	0.1683	0.1163

The regression analysis for the Russell 3000 Growth Index shows an extremely weak correlation with SENT, as reflected by a very low Multiple R of 0.0381 and an R Square of 0.0014, suggesting that only about 0.14% of the variability in the index is explained by SENT. The negative Adjusted R Square and the non-significant F statistic (p-value: 0.7190) show the model's lack of explanatory power and statistical significance. The coefficients indicate an almost negligible positive influence of SENT on the index, but this is statistically insignificant.

Similarly, the Russell 3000 Value Index shows a minimal correlation with SENT, with a Multiple R of 0.0319 and an R Square of just 0.0010. Like the Growth Index, the model for the Value Index shows a negative Adjusted R Square and an F statistic that does not achieve statistical significance (p-value: 0.7624), indicating a very weak model fit. The coefficient suggests a slight negative effect of SENT on the index, though this too lacks statistical significance.

Both indices exhibit very minimal relationships with SENT, highlighted by their low R Square values and non-significant F statistics. This analysis demonstrates that SENT has an insignificant predictive ability on the movements of the Russell 3000 Growth and Value indices, suggesting the need for more comprehensive models to understand the dynamics affecting these indices.

Table 5: BOX 4, the results of the regression analysis

Metric	Russell 3000 Growth Index	Russell 3000 Value Index
Multiple R	0.2494	0.2455
R Square	0.0622	0.0647
Adjusted R Square	0.0368	0.0395
Standard Error	0.0449	0.0545
SS (Regression)	0.00496	0.00796
SS (Residual)	0.0749	0.1091
MS (Regression)	0.00496	0.00796
MS (Residual)	0.0020	0.0029
F Statistic	2.4536	2.5630
Significance F	0.1258	0.1179
Intercept	-0.0339	-0.0491
Intercept Std. Error	0.0323	0.0391
Intercept t Stat	-1.049	-1.253
Intercept P-value	0.3007	0.2181
X Variable 1 Coefficient	-0.0742	-0.0918
X Variable 1 Std. Error	0.0473	0.0573
X Variable 1 t Stat	-1.566	-1.601
X Variable 1 P-value	0.1258	0.1180
Lower 95% CI (Intercept)	-0.0995	-0.1284
Upper 95% CI (Intercept)	0.0316	0.0303
Lower 95% CI (X Variable 1)	-0.1701	-0.2079
Upper 95% CI (X Variable 1)	0.0218	0.0244

The regression output for the Russell 3000 Growth Index shows a modest correlation with SENT, with a Multiple R of 0.2494. However, the R Square value of 0.0622 indicates that only about 6.22% of the variance in the Growth Index can be explained by changes in SENT. The low F-statistic of 2.4536 and a p-value of 0.1258 suggest that the model is not statistically significant. The coefficient for SENT is -0.0742, which indicates a slight negative impact on the Growth Index, though this impact is not statistically significant.

Similarly, the Russell 3000 Value Index also shows a modest relationship with SENT, reflected by a Multiple R of 0.2455 and an R Square of 0.0647. This implies that SENT explains approximately 6.47% of the variability in the Value Index. The F-statistic of 2.5630 and a p-value of 0.1179 also do not reach statistical significance. The coefficient of -0.0918 for SENT suggests a minor negative effect, although like the Growth Index, it is not statistically significant.

Both the Russell 3000 Growth and Value indices demonstrate a weak correlation with SENT, with both models showing low R Square values and F-statistics that do not indicate significant relationships. The negative coefficients in both indices suggest a slight inverse relationship with SENT, but the lack of statistical significance in these results means that SENT does not substantially influence the movements of these indices.

6 Conclusion

6.1 Testing summary

The empirical investigation of the Russell 3000 Value and Growth indices presents a picture that both corroborates and challenges the financial theories, particularly in relation to the impact of investor sentiment on market dynamics, as presented by earlier scholars like Tetlock (2007). The moderate correlation observed in the Russell 3000 Value Index aligns with this perspective, supporting the hypothesis that investor sentiment can significantly affect stock performance (Baker & Wurgler, 2007). Additionally, the lag analysis results support the notion that the effects of sentiment are not fleeting but have extended impacts on stock prices. This influence is in line with behavioral finance theories suggesting that investor mood can exert sustained effects due to cognitive factors and the diffusion of information. (Shleifer, 2000).

However, not all the study's findings are not in line with some theoretical expectations. Behavioral finance theories typically argue that growth stocks, which are characterized by their speculative nature and volatility, should be more sensitive to changes in sentiment. Yet, this is only partially supported by this data; the Growth Index displayed a low correlation with sentiment, an unexpected result suggesting that these stocks might respond differently to sentiment than traditionally expected. This difference could be from the factor, that growth stocks are being more influenced by long-term growth expectations rather than transient sentiment shifts (Frazzini & Lamont, 2008).

Similar to Tetlock's (2007) findings, negative sentiment predicts downturns in market prices and increases volatility, impacting both Growth and Value indices.The thesis also aligns with behavioral finance theories, such as those proposed by Barberis, Shleifer, and Vishny (1998), which suggest that investor psychology can cause stock prices to deviate from their fundamental values under extreme conditions. This is observed in the highest raw returns during the lowest sentiment periods, albeit with increased risk. This response under extreme sentiment conditions presents a more complex market behavior than traditional models might suggest.

A comparison between the Russell 3000 Growth and Value indices shows that while the Growth index is more sensitive to positive sentiment and maintains performance even when sentiment is low, the Value index demonstrates steadier performance across different sentiment conditions, suggesting it relies more on fundamental metrics than sentiment. As the minimal correlation observed in the Growth Index—where only 4.95% of the variability in stock returns was explained by sentiment— there might be a suggest that other factors, perhaps market trends, sector-specific developments, or broader macroeconomic conditions, may overshadow sentiment effects in driving the performance of these stocks.

6.1 Further research

Future research could extend the findings of this thesis to involve comparative analyses of stock markets in Europe, Asia, and emerging economies, potentially uncovering unique behaviors and challenges in implementing these strategies globally.

Additionally, exploring the impact of investor sentiment across different economic sectors would deepen our understanding of market dynamics, potentially leading to tailored investment strategies that enhance portfolio diversification. Sectors such as technology and healthcare, which have distinct characteristics and investor expectations, may exhibit different reactions to general market sentiment. The growing impact of digital media on financial markets also presents a fertile area for research, particularly in assessing how information from digital platforms like Twitter, blogs, and online financial news influences market sentiment. This could involve developing algorithms to quantitatively analyze sentiment from textual data and correlate it with market movements, building on the foundational work by Tetlock (2007) and Bollen, Mao, and Zeng (2011).

As well, tracking investor sentiment over more extended periods could provide insights into how prolonged sentiment trends influence market volatility across different market cycles, such as bull and bear phases, it would offer valuable perspectives on sentiment behavior during varying economic conditions.

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