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Analysis of the Time-Varying Effect of News Sentiment on Asset Pricing Based on Text Mining

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Abstract: This study explores the dynamic impact mechanism of sentiment changes on asset prices based on text mining technology of news sentiment and Stata data analysis tools. By constructing a dynamic regression model and using rolling window estimation, the time-varying effect of sentiment fluctuations on asset prices is captured, revealing the short-term impact of sentiment on asset prices in different periods and its impact characteristics under different market conditions. The results show that extreme sentiment values are consistent with significant fluctuations in market prices. Changes in sentiment scores not only affect prices in the short term, but may also predict future market volatility trends. The case analysis of an unexpected interest rate hike further illustrates how sudden shifts in news sentiment can lead to immediate and pronounced market reactions, underscoring sentiment's role in amplifying short-term volatility. By introducing sentiment factors, the model better depicts the irrational dynamic behavior of the market, helps explain market anomalies that are difficult to capture in traditional asset pricing models, and provides new perspectives and empirical support for asset pricing and investment decisions.

Keywords: News Sentiment, Asset Prices, Time-Varying Effects, Dynamic Regression Models, Stata Analysis

1. Introduction

1.1 Research Background and Importance

In the ever-evolving terrain of financial markets, where the speed of information dissemination continues to accelerate, news sentiment has ascended to a prominent position, playing a pivotal role in the fluctuation of asset prices. The rise of diverse channels for obtaining market information has seen news media and social platforms emerge as key conduits for sentiment dissemination, shaping how market participants interpret and respond to the flood of information. While news sentiment is invariably laced with a wealth of non-financial data, including investor sentiment and market expectations, these often prove to be powerful drivers of short-term asset price movements, even inciting fluctuations and market bubbles. Whereas asset pricing models have traditionally been based on financial data and the principles of the rational expectation theory-the CAPM or the Fama-French three-factor model, among others-a number of studies recently point to irrational factors in financial markets and urge one not to underestimate those. Adding news sentiment quantitative analysis can better explain what impact could possibly be brought to market pricing by non-financial information for an integral understanding of financial and non-financial causes [1]. News sentiment is originally unstable, complicated; its effects are temporal in the market. It is these dynamic natures that introduce new challenges to conventional asset pricing models; the usual static analysis methods, for these reasons, turn out to be not good enough to explain such dynamic effects. Moving into modern financial times, the need arises for new and innovative dynamic analysis methods to interpret the multifaceted role of news sentiment with a view to understanding its impact on market dynamics [2]. Of the many methodologies utilized in sentiment research, text mining-based sentiment analysis is one of the major methods, where NLP and machine learning algorithms are able to extract and quantify emotional signals embedded in news content [3]. Such advanced technology allows researchers to obtain nuanced sentiment data from a lot of texts in a structured fashion, thereby giving far better insight into public opinion and its possible effects on the financial markets. Often, these emotional cues can be so fine or implicit as to be tough to detect through traditional analysis. Text mining does just that: it identifies and quantifies those sentiments with precision. The strength of this approach will lie not only in extraction but also in the ability to mark quantitative values for those emotional signals, showing the intensity level and hence the possible market influence. This reduces sentiment into numerical scores, providing researchers with a measurable indication of the likely effects of news sentiment on asset pricing-a key element for investors and financial analysts in trying to understand and anticipate market responses. This quantification allows for the inclusion of sentiment, as a dynamic variable in various asset pricing models, which could enable one to trace, with the requisite rigour, how changes in sentiment drive changes in market behavior.

In the last years, the development of both NLP techniques and machine learning methods has gained much acceleration. Subsequently, this development annulled unprecedented possibilities to analyze large-scale news data, most especially in sentiment. The use of sophisticated quantitative tool usage in news data analysis has gone beyond being the exception to being the rule. Such tools parse a mountain of textual data for underlying sentiment and, therefore, have been found useful in understanding the news' affective resonance, and further, its consequences for asset pricing. They provide invaluable data points for research with which to create more nuanced models that better capture the dynamics of news sentiment and its influence on financial decision-making. news sentiments integrated into the asset pricing models considerably enrich the predictive capabilities of such models. It captures information that is otherwise not taken into account and reflects a much broader perspective on what actually drives asset prices. News sentiment can be successfully described by its dynamic features; thus, it allows for the modeling of its shifting and changing process over time. Any better understanding of the changing role of news sentiment in asset pricing would therefore be important for the refinement of existing theories and the provision of new evidence to investors in their quests to make informed investment and risk management decisions. What is needed, instead, is deep research that can present a nuanced role of news sentiment in asset pricing-particularly its changing influence over time.The results of such research may come up with pathbreaking observations that can alter existing theories relating to asset pricing and give investors new insights for decision-making.

1.2 Research Objectives

The core objective of this research is to use text mining technology to quantify news sentiment and explore its mechanism of dynamic impact on asset pricing under different market conditions. Based on this process, construct the process of the establishment of an asset pricing model based on news sentiment, and then study how news sentiment affects the fluctuation of asset prices in different time periods and market environments. Specifically, it is expected that this study will reveal the characteristic of short-term and long-term impact brought by news sentiment to asset pricing, and analyze the fluctuation range of news sentiment and its driving effect to asset prices under different market scenarios. It will also be necessary to dynamically model the time-varying characteristics of news sentiment with large-scale news data in order to quantify its expressiveness with respect to asset pricing and with a view to informing the dynamic development of the latter.

This paper conducts an empirical analysis not only to verify whether news sentiment plays a role in asset pricing but also tries to show its time-varying effect in financial markets. It is expected that this study could provide a new perspective to enrich further developments of asset pricing models and, in particular, predict irrational factor-driven market fluctuations. It will provide a new idea for asset price prediction through profound analysis on dynamic variation of news sentiment and further enrich the current asset pricing theory, providing scientific decision-making grounds for investors and policymakers in the financial market.

2. Literature Review

2.1 Review of Asset Pricing Theory

Research

Asset pricing theory is often thought to be the cornerstone in finance, and it does inherently attempt to explain the rate of return on assets by systematically accounting for risk factors and the passage of time within a pricing model, usually done to arrive at a more complete understanding of asset valuation. This traces back to the classic capital asset pricing model, which was advanced in 1964 by finance expert William Sharpe and a year later by John Lintner. The CAPM was widely credited for pioneering the idea of risk-adjusted asset pricing, and it has served as a tool for academics and researchers alike in deciphering the relationship between risk and expected return. However, despite wide usage and popularity largely due to CAPM's simplicity and intuitively appealing method of measuring risk, empirical findings from various studies have often exposed serious limitations within the model's framework. These have undermined its effectiveness in predicting and explaining the risk-return performances observed in the complex realm of the stock market [4]. These limitations not only raised questions about the model's validity but also initiated a wave of research efforts toward developing substitute, more credible multi-factor models. One such popular model is the Fama-French three-factor model, which was presented in 1992 and was, at least in part, a reaction to the deficiencies of the traditional CAPM. These extended models are usually considered to be the developments in asset pricing theory and try to offset CAPM deficiencies by taking into consideration the influence of non-market factors [5]. Among those non-market primary factors included the book-to-market ratio and market value counted as two of the most significant valuation variables providing investors with pieces of information about assets' real value. By doing so, these models try to enhance the explanatory robustness of asset pricing theory, enabling a more comprehensive and precise view framework in expressing how assets are valued and perform within ever-changing financial landscapes.

In the realm of finance and economics, academia has witnessed a plethora of advancements in the development of dynamic asset pricing models. These models, it must be emphasized, are meticulously designed to keep pace with the ever-changing market conditions and the ever-evolving investor preferences. These models combine three key components, namely, the no arbitrage principle, state price, and Markov chain. Building upon these, Duffie's dynamic asset pricing theory emerges as a significant theoretical contribution. It further developed an asset pricing framework, introducing a multi-period uncertainty element. This addition notably enhanced the theory's aptitude to capture the nuanced process of risk adjustment that occurs amidst the ups and downs of the market, colloquially known as market vicissitudes [6]. The theoretical landscape continued to evolve with Çelik (2012), who put forward a comprehensive review of both static and dynamic pricing models. The review aimed to ensure applicability in practical applications and to critically assess the performance of multi-factor asset pricing models when subjected to empirical tests [7]. Such theories, in the current academic landscape, could arguably act as a solid foundation for future research. They enable scholars to introduce nonlinear factors and delve deeper into investor behavior. The ultimate objective being, to provide a more comprehensive explanation of market anomalies that have, at times, remained inexplicable.

2.2 News Sentiment and Its Application in Financial Markets

News sentiment analysis has just become one of the hotter topics in the diverse financial markets, a topic seen by many as very important. Indeed, various detailed studies and comprehensive research results have all confirmed that news, due to its inherent potential to greatly influence and shape public opinion and discourses, may significantly and concretely affect investor decisions and prices in the market. Among the notable studies in this regard was one proposed by Uhl et al., which stated that a good calculation of news sentiments momentum would, in fact, help in constructing strategic asset allocation for the market, which would yield further or 'superfluous' returns. This proposal implied that news sentiment held significant value and could be efficiently used as an instrumental reference factor for the prediction of market trends [8]. The findings study were carefully analyzed and all variables accounting for a cumulative effect of news sentiment were taken into consideration. The same would, in turn, lead to the overreaction of the market price. Although this may perhaps sound counterintuitive at first, it actually serves a positive purpose for investors. It provides them with observable investment signals on which they can potentially act, giving insights that might not be available otherwise. An application and expansion of the proceedings concept further, Kelly and Ahmad applied news sentiment, in their 2018 study, to the domain of the foreign exchange market. They found that the news sentiment of this market had very strong predictive power for this exchange rate fluctuation. This result further supports the notion that the sentiment information has sizable explanatory power across markets and provides a practical application of sentiment analysis in foreign exchange. Therefore, sentiment information does bear enormous explanatory power, and entries about news sentiment find extremely broad applications in financial markets and have really robust evidence of its tangible impact on providing a predictive tool within various market scenarios [9]. This will help investors greatly become informed investors, while market analysts seek to understand the underlying dynamics that drive market behavior.

The conventional traditional financial modeling has been associated with prior-based models only, in this ever-changing financial world. These models have, however, increasingly come into question because of their possible inability to reflect real-time performance within the market. The various asset pricing methods incorporating news sentiment lately try to give an alternative view, reflecting the performance in a more dynamic and updated manner. An example in this area given by Chandra and Thenmozhi is the Behavioural asset pricing model. This model has been presented in their 2017 paper, which systematically reviewed the role of behavioural emotion in financial markets and explored the use of News Sentiment as an unconventional risk factor [10]. Their study has illustrated that it is the fluctuations in sentiment that bear crucial importance for the prediction of short-run market turmoil and long-term return changes. All these findings underline the importance of monitoring financial market sentiment and give a theoretical basis for monitoring.These documents have been able to illustrate that the integration of news sentiment into asset pricing models is bound to improve real-time performance and accuracy, hence cementing its place as a useful tool in improving financial market analysis.

2.3 Research Status of Text Mining in the Financial Field

In the last ten years, the technology of text mining, which means extracting information with great value from textual data, has been developing brilliantly and widely used in the niche area of finance. With advanced technology, it's increasingly recognized to play an important role in offering crucial technical support in a certain undertaking called news sentiment analysis. News sentiment analysis is one of the sub-disciplines of text mining used to find out the sentiment that is being plainly expressed in news articles, so as to understand the attitudes and sentiments of investors with regard to certain investments or their view about the market as a whole. This increased activity in the application of text mining technology to finance is further demonstrated in a 2012 work by Zhou and Fabozzi, who gave strong emphasis to the importance of text mining in uncovering nontraditional information enclosed in asset prices [11]. They applied sentiment dictionaries and natural language processing to study the effect of news sentiment on stock price movements. This research indicated that through extracting keywords from news texts, the investors' emotional preference may be identified; thus, it forms a theoretical basis for constructing the sentiment index. Big data and advanced artificial intelligence technology develop rapidly in the digital wave. Text mining technology has been proven to process large-scale unstructured data, handling analysis tasks remarkably well, especially under real-time data conditions. It is essential to indicate that the literature review of multi-factor asset pricing by Pitsillis in 2005 analyzed the application of text mining into the asset pricing models. They concluded that after incorporating these sentiment indicators, these models can explain the market fluctuations better. This research provides the theoretical basis for the introduction of text mining technology within the asset pricing model, showing how effective such an introduction would be and how important this technology is [12]. Against that multi-dimensional and many times complex backdrop of arbitrage pricing models, as one battlefield area of considerable interest and relevance within the broad expanse of financial world discussions, the seminal work of Rothschild in 1985 imposed itself. The paper by Ross draws on topics from his earlier work.

This pioneering work drew on text mining as a method of assessing the noises, thereby focusing on the quintessence of this field in finance. The research added immensely to knowledge through an extensive and intensive research investigation of textual data on how text information, with its complex network of language and semantics, deeply affects sentiments in the market [13]. This strong result, considered within the thoroughly dynamic context of the financial world, can only serve to reinforce the improbable significance of text mining technology very strongly [14]. It is not just a technique for technical support in news sentiment capture; rather, it has turned out to be an indispensable tool in the dynamic evolution of asset pricing models. The implications of this fact are enormous. In other words, text mining technology has become the cornerstone in the financial industry, able to extract meaning from the information hidden in textual data. Though its application can be traced to news sentiment analysis, it also filters through to asset pricing models, opening a wide avenue of possibilities for users of the technology [15]. Therefore, text mining technology plays more than its immediate role; it has been an agent of change in how we think of financial analysis by revolutionizing the way finance models have traditionally been conceptualized to be more inclusive and dynamic. Its various applications and impacts can be limitless, changing the historical mode of analyzing finance and providing a dynamic platform for the evolution of finance as a whole [16].

3. Theoretical Basis And Analytical Framework

3.1 Theoretical Basis of Asset Pricing Model

The major concept in finance is the asset pricing model, which has an integrated central objective: to correctly estimate the anticipated returns of assets through the embedding of factors very important for understanding the dynamics of investment. These integral elements include risk exposure and time passage [17]. The pinnacle of this model is the famous Capital Asset Pricing Model or CAPM, believed to be the cornerstone of asset pricing theory. The fundamental principle of the CAPM model is the belief that there are rational investors whose investment decisions are based on the efficient market theory principles [18]. Furthermore, the model seeks to provide a comprehensive framework to explain asset returns, particularly through the lens of market systematic risk. To give a more detailed understanding, the basic structural form of the revered CAPM model can be illustrated as follows:

$$E(R_i) = R_f + \beta_i \cdot (E(R_m) - R_f) \tag{1}$$

Among them: $E(R_i)$ represents the expected return of asset i; R_f represents the risk-free rate; $E(R_m)$ represents the expected return of the market portfolio; β_i represents the sensitivity of asset i to market risk (i.e., the systematic risk coefficient).

The form of the three-factor model is as follows:

$$E(R_i) = R_f + \beta_i \cdot (E(R_m) - R_f) + s_i \cdot SMB + h_i \cdot HML \tag{2}$$

Among them: SMB (Small Minus Big) represents the return difference between small-cap stocks and large-cap stocks; HML (High Minus Low) represents the return difference between high book-to-market ratio and low book-to-market ratio stocks; s_i and h_i are the sensitivity coefficients of asset iii to SMB and HML factors respectively.

The classical models of asset pricing have provided a theoretical framework that is cornerstone for comprehending the influence of systemic risks inherent in the market and fundamental factors on the returns on assets. However, it must be acknowledged that these models predominantly depend on financial data and the presumption of rational expectations from investors [19]. This reliance leaves a gap in fully capturing the ramifications of irrational factors and emotional fluctuations that are inherent in the market. In the midst of this, the emergence of behavioral finance has been a significant contribution. It has done so by introducing emotional factors, which could be particularly non-financial aspects like the sentiment in the news, as supplementary variables. These are essential in explaining the fluctuations in market prices. This has not only enhanced our comprehension but has also expedited the development of emotion-driven models of asset pricing, which are more attuned to capturing the complexities of the market [20].

3.2 Theoretical Mechanism of the Impact of News Sentiment on Asset Prices

News sentiment is defined as a general attitude or feeling associated with a certain news story or topic. News sentiment is instrumental in shaping financial behavior among market participants and thus immediately affects asset prices. The two main psychological drives of investors are stressed by their emotional and expectational positions in the way this change comes about. The information picked up and conveyed-picked up by the news media, either through traditional media or through social media influencers-can have a strong and sometimes irrational effect on the emotions of investors. The good news leads to overestimation of asset values in the short term when investors perceive news as favorable. This overestimation is driven by their emotional reaction to the perceived good news, thereby driving up prices [21]. Whenever the news is perceived as negative or pessimistic, investors may underguesstimate the value of their assets. Again, such underestimation is one result of an influence of their emotional responses to the perceived negativity to delay or even to cause a fall in price reaction. This is not a rational estimate based on evidence but rather an emotional and often knee-jerk reaction. It is such irrational responses to news sentiment that create the observed short-term deviations in market prices [22]. To that end, the movement of the market will be accordingly set by sentiments, which are also themselves impacted by news and its purported impact on the assets. Consequently, this means that it's very critical to grasp investors' reaction psychology and the role of news sentiments at work in shaping emotions, so one can possibly predict and manage market behaviors [23].

The linkage among news sentiment, investor's emotions, and subsequent market price movements can be illustrated graphically-as in Figure 1, which displays a mechanism model with news sentiment as the main external input. On one side, the news sentiment in the model influences investor emotions and may result in traditional behavioral biases such as overreaction or herd effect. Overreaction refers to the phenomenon of new information overbidding up or down the price of a security, whereas the herding effect is one in which investors prefer to imitate other investors' choices and could result in a self-reinforcing cycle of buying or selling. These cognitive biases, when occurring en masse, lead to sharp, short-run asset price movements or supply and demand imbalances. On the other side of the model, sudden price movements create information feedback. This sets a feedback loop into market sentiment, amplifying positive or negative sentiment, or even causing a shift to the other side [24]. This forms a positive-negative cycle, which either results in continuous fluctuations in market sentiment, or gradually makes it stable. Thus, news sentiment, through an effect on investor emotions and expectations, plays a great, often invisible, role in prescribing the movements of the financial markets [25].

Various biases in investors' behavior, with their roots in psychology, may perhaps best explain the mechanics of how news sentiment influences asset prices. Selection biases also encompass overconfidence-a disproportionate belief in one's abilities or judgment in general; herding behavior-the tendency of individuals to acting like others; irrational emotive decisions compel investors to make certain financial decisions [26]. Under the subtle or not-so-subtle influence of these cognitive biases, a number of phenomena may show up in the financial market. The latter can exhibit pricing deviation, where the price of an asset is far away from its intrinsic value; or it might show irrational fluctuation-an asset's price rapidly ups and downs seemingly for no reason. Take, for example, the bull market, meaning a bullish and optimistic financial climate when prices of assets are on the rise. In such circumstances, positive news sentiment could amplify [27]. It can enhance the already elevated investor confidence, driving prices up even more. Conversely, in a bear market, which is a negative and bearish financial climate where asset prices are falling, negative news sentiment can act as a catalyst. It can intensify the already prevalent panic among investors, triggering a larger decline [28]. Therefore, the impact of news sentiment on asset prices is not uniform and static, but rather it often exhibits time-varying characteristics, changing and adapting to the ebb and flow of the market dynamics and the broader economic landscape [29].

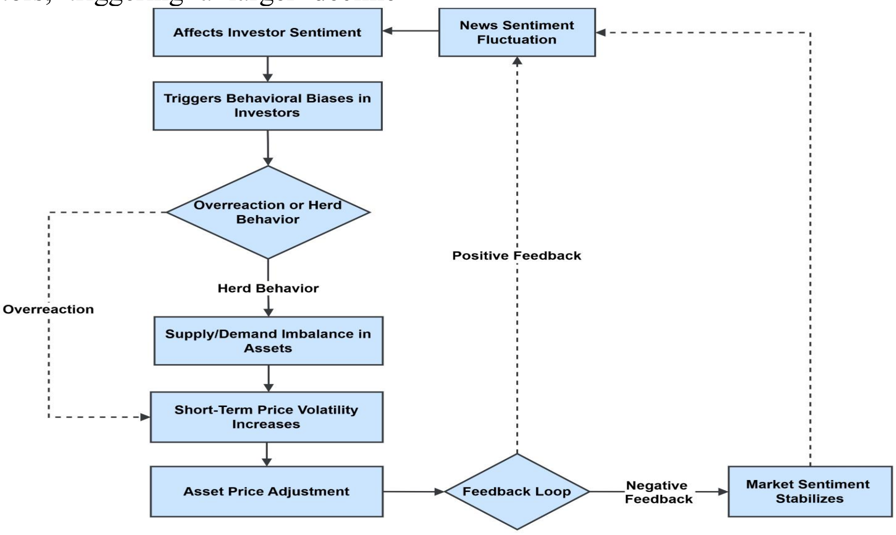

Figure 1. Theoretical Mechanism of News Sentiment Impact on Asset Prices

In addition, from a theoretical mechanism perspective, the volatility of news sentiment is often higher than that of traditional financial variables, which makes the impact of emotional factors on prices significant in the short term [30]. This emotional impact can be represented by quantitative indicators such as sentiment scores. Assuming the sentiment score is S_t, after controlling for market returns and other risk factors, it can be assumed that the impact of emotional factors on asset returns is:

$$R_{i,t} = \alpha + \beta_i \cdot (R_m - R_f) + \gamma \cdot S_t + \epsilon_t \quad (3)$$

Where: $R_{i,t}$ represents the return of the i-th asset in period t; γ represents the impact coefficient of the news sentiment factor; S_t is the sentiment score in period t; ϵ_t is the random error term.

By adding sentiment scores, we can observe the marginal impact of sentiment fluctuations on asset prices, thereby revealing the role of news sentiment as an irrational driving factor in asset pricing models.

3.3 Analysis Framework of Time-Varying Effects

A proper analysis of the issue in question, which also includes a close examination of both theoretical and practical aspects of the subject matter, allows one to assume that the integration of news sentiment factors into the architecture of pricing models of assets contributes to a peculiar time-varying effect on the prices of assets. While most of the traditional static versions cannot capture the dynamic fluctuation and ephemeral shocks of market sentiments, this research shows that sentiment shocks are significantly impactful to the price of an asset and that it changes over time in different periods and conditions. In this perspective, this underlines the complexity by which news affects the market reaction and claims for flexibility in the model, which is capable of adjusting according to it all [31]. The proposed model also tries to catch up by adopting the rolling window estimation, incorporating sentiment scores derived from text mining analysis to provide a more accurate representation of financial markets that are so volatile and responsive to news sentiments.

This work underlines the vital role of sentimentdriven market behavior, when such sentiment reaches either pole of extreme optimism or deep pessimism. Using the case study of an unexpected interest rate hike, news sentiment emitted immediate market volatility, amplified short-term price swings, and created one of those cycling sentiment feedback loops. This framework of a dynamic model can seize those complex nonlinear responses and give predictive insight into the dynamics of such traits that were very difficult or impossible with traditional models [32]. It is closer to real market behaviors by considering the sentiment factors, while opening new avenues in the study of irrational elements moving changes in asset prices. These findings thus provide important empirical support in developing and refining asset pricing models by considering both rational and sentiment-based factors.

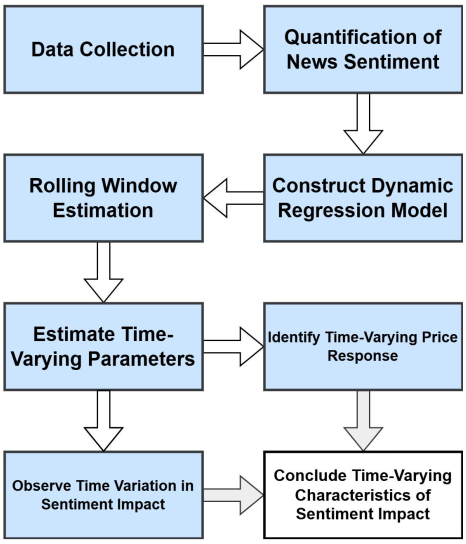

Figure2. Time-Varying Effect Analysis Framework

This framework-symbolized in Figure 2-starts with the systematic collection and quantification of news sentiment data in a way that the convictions are forceful, after which a dynamic regression model is provided to assess the linkage of changes in sentiment with the pricing of assets. Because of its evolving nature, the model will make rolling window estimation periodic readjustments to reflect the time-varying parameters accurately. It dynamically extracts the sentiment influence coefficients and analyzes the response of asset prices to change in the coefficients over time, thereby effectively revealing the transient characteristics of the impact of the sentiment and hence giving meaningful insights into the news-driven market behavior of sentiment in different periods.

To this end, either a state-space model or a time-varying parameter model is adopted to present the news sentiment impact that is of time-varying type at any instant. The intrinsic form of the state-space model is:

$$R_{i,t} = \alpha_t + \beta_t \cdot (R_m - R_f) + \gamma_t \cdot S_t + \epsilon_t \quad (4)$$

$$\beta_t = \beta_{t-1} + v_t \quad (5)$$

Among them: α_t , β_t and γ_t are all time-varying parameters, representing the degree of influence of news sentiment at different times; v_t is the state transition noise, which follows the white noise assumption.

Through the dynamic model, the volatility of news sentiment can be taken into account to observe the long-term trend and short-term impact of sentiment on asset prices. This time-varying analysis framework is not only suitable for explaining the dynamic effect of news sentiment on prices, but also provides methodological support for capturing market sentiment cycles and risk adjustments.

4. Data And Research Methods

4.1 Data Source and Processing

The data used in this study mainly consist of asset price data and news text data. The asset price data include daily returns from major financial market indices and individual stocks, covering more than five years in the sample period, with over 10,000 data points. This large dataset will ensure continuity in the time series and the robustness of the analysis. News text data are from various renowned news media and financial information platforms. Each news record captures critical information such as title, content, publish date, and other parameters. After a rigorous screening process, only news events that directly influence the financial market are kept, totaling about 500,000 records in this news sentiment dataset. During data preprocessing, text data is deduplicated to make the data standardized and to filter out noise, hence making the results of sentiment analysis more accurate and reliable. All these steps serve to improve consistency in the scoring of sentiments and enhance quality for better extraction of the sentiment signals and, thus, carrying out a more precisely meaningful analysis of the news sentiments and asset price movements.

4.2 Text Mining Method of News Sentiment

In this respect, to quantify the influence of news sentiment on asset prices, the current study will apply NLP techniques to news texts.

This approach ideates a structured way to extract and quantify sentiments for their measurable effects on market behavior. To mine texts, the entire process is divided into three critical stages: text preprocessing, sentiment classification, and calculation of sentiment scores, as depicted in Figure 3.

First, in the pre-processing of text data, cleaning and standardization for consistency, including tokenization or removal of stop words and language normalizations, take place. The next step involves sentiment classification that categorizes news texts into positive, negative, or neutral sentiments based on the underlying tone. Finally, sentiment scores are assigned quantitative values to these classifications, allowing for the generation of sentiment scores considering intensity and direction variably in the analyzed texts. In turn, this scoring system will allow the model to dynamically embed this variable-this thing known as sentiment that captures both the short-term and time-varying impacts it has on the prices of assets.

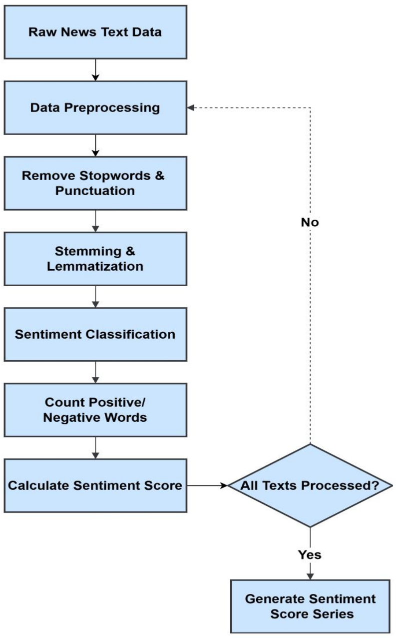

Figure 3. News Sentiment Text Mining Process

In order to more accurately quantify the intensity of news sentiment, this study uses the sentiment score StS_tSt to represent the dynamic changes of news sentiment. The calculation formula of the sentiment score is as follows:

$$S_t = \log\left(\frac{1+\mathrm{Pos}_t}{1+\mathrm{Neg}_t}\right) \tag{6}$$

Where: S_t represents the sentiment score of the t period; Pos_t and Neg_t represent the positive and negative sentiment word frequencies in the news during the t period, respectively.

This formula smoothes the data by logarithmically transforming the positive and negative word frequencies to ensure that the sentiment scores remain comparable under different intensity sentiments. The range of sentiment scores is usually $[-\infty,+\infty]$, with positive values indicating positive sentiment and negative values indicating negative sentiment. As an important variable for quantifying news sentiment, this indicator will be further analyzed in the model to analyze its dynamic impact on asset prices.

4.3 Model and Estimation Method of Time-Varying Effect

In order to capture the time-varying effect of news sentiment, a time-varying parameter model is used. Assume that the generation process of asset return rate $R_{i,t}$ is as follows:

$$R_{i,t} = \alpha_t + \theta_t \cdot S_t + \eta_t \cdot V_t + \epsilon_t \tag{7}$$

Rolling window regression and parameter smoothing techniques are used to dynamically estimate the coefficients θ_t and η_t to track the changes in the impact of sentiment in different periods.

4.4 Data Analysis

To examine the dynamic impact of news sentiment on asset prices, this study utilizes Stata for a comprehensive data analysis, which encompasses descriptive statistics, time series analysis, and regression model estimation. These analytical steps provide a structured approach to understanding the sentiment-driven fluctuations in asset prices. Descriptive statistics offer an initial overview of data characteristics, while time series analysis reveals patterns and trends within the sentiment and asset price variables over time. Finally, regression model estimation quantifies the relationships between sentiment shifts and asset price movements, highlighting the extent to which sentiment impacts market dynamics. The specific steps of this analysis process are outlined in Figure 4, ensuring a clear framework for replicable and systematic investigation.

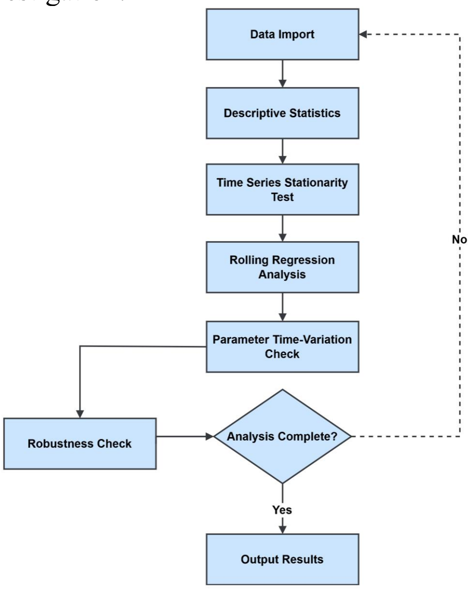

Figure4. Steps for Data Analysis in Stata

5. Experimental Results and Analysis

5.1 Descriptive Statistics and Data Feature Analysis

As depicted in Table 1, a comprehensive statistical analysis of both asset returns and sentiment scores has been meticulously carried out, aiming to distill the core characteristics of these financial indicators. The following data-driven study depicts a wide array of statistical features, such as mean or the average value; standard deviation or the dispersion/ spread of data-points from the mean, minimum value-hence the lowest point in the data range, and maximum value-the highest in the range. By closely examining the outcomes, it becomes obvious that the mean of asset returns is very close to zero-outstanding equilibrium in the market. However, it is important to note that the mean of asset returns is highly volatile, thus giving a clear indication of high-frequency volatility embedded in prices of markets. The very observation acts as a glaring reminder of the risks inherent in financial markets. In parallel, the average of the sentiment score has a slight negative bias, which can also mean that when the sentiment data is averaged out, it is generally biased toward negativity; this might reflect a pervasive sense of caution or pessimism among market participants. On the other hand, even the high standard deviation of the sentiment score in comparison with overall negativity denotes that the latter fluctuates a great deal. Of this nature, the characteristics would relate to high volatility in both asset prices and sentiments, acting like tales of good friendship. What this means is that market sentiment is somewhat fragile, making it change all of a sudden and unpredictably. This volatile sea of sentiments indeed can make for unstable shocks that hit asset prices directly. Therefore, investors and the market analysts need to understand and manage the inherent characteristics of financial indicators while attempting to navigate through the jungle of financial markets.

Table 1. Descriptive Statistics of Asset Returns and Sentiment Scores

Variable	Mean	Std Dev	Min	Max
Asset Return	0.002	0.015	-0.08	0.09
Sentiment Score	-0.001	0.1	-0.5	0.5

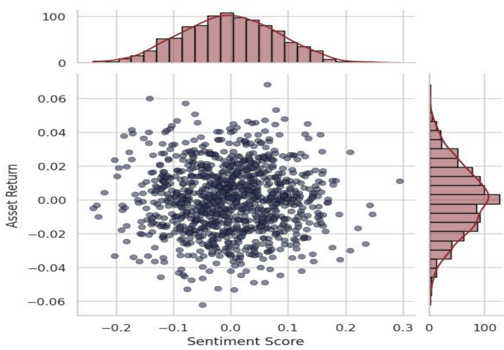

Figure 5. Distribution and Correlation of Sentiment Score and Asset Return

Figure 5 Scatter plot and marginal distribution of sentiment scores and asset returns to outline asymmetrical properties. It can be seen that the marginal distribution of the sentiment score is mildly skewed, possibly suggesting that when market sentiment becomes extreme, the volatility of asset prices also rises correspondingly. It follows that this type of skewness in distribution suggests that sentiments probably exercise an influence disproportionately on price dynamics.

The scatter plot further shows the general weak correlation of the sentiment scores and returns on assets, reinforcing the fact that sentiment alone cannot solely determine the price movements. However, it would hint that price volatility is in a position to increase during extreme conditions. It further points to the complex relationship between sentiment and market price behavior and supports further analysis on the time-varying impact of sentiments on the prices of assets over different market conditions.

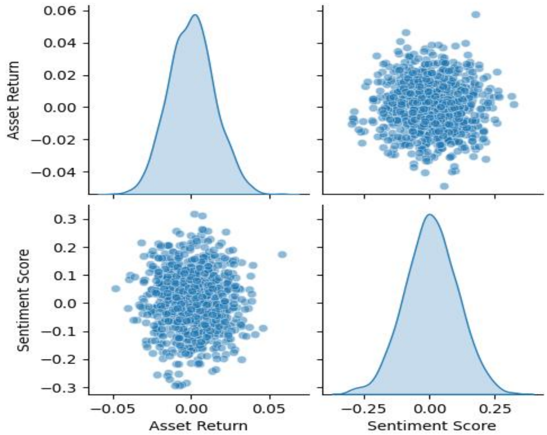

Figure 6. Distribution and Correlation Analysis of Sentiment Scores and Asset Returns

Figure 6 depicts a scatter plot of the sentiment scores versus asset returns along with their marginal distribution characteristics. A scatter plot is perhaps the most instructive data visualization technique. From the scatter plot, one immediately observes that the correlation between sentiment scores and asset returns is low. This result suggests that the relationship between these two variables is nonlinear, and the influence of sentiment on the prices of assets is correspondingly more mundane and less straightforward than was perhaps initially thought. To provide further detail regarding these data, the marginal histogram provides added insight. More specifically, the marginal histogram shows that the distribution of the sentiment score is somewhat skewed. Additional to this fact, though fewer such points exist, but still there are some outlier data points occurring around the extreme values of sentiments. This finding suggests that even though market sentiment is generally distributed around the mean, sometimes it shows a tendency to be extreme. In contrast to distribution in sentiment scores, asset return distribution is centered around zero. This central tendency reflects as a small peak, and the long tail of the distribution reflects the asymmetry and sporadic nature that exists in the market price fluctuations. These certain distributional characteristics capture the idiosyncratic nature of financial data; the fact that the market does not move en bloc but is characterized by everything from slight, easily forecasted movements to more extreme and less predictable movements.

5.2 Time Series Analysis and Stationarity Test

In order to ensure that the data were ready for expansive time series analysis, this study did an extensive stationarity test for two major data variables: asset return rate and sentiment score. This critical step of validation applied a well-accepted ADF test, which tests for unit roots that would make the data unstable or unreliable. The rationale for this test, therefore, is to guide that both series are stationary; only then would the time series analysis be possible and the model results be meaningful.

This revealed that asset return rate and sentiment score series were stationary through the ADF test results; that is, the information was consistent and stable. This is a quintessential result in ensuring the soundness of further analysis, as it might provide reasonable grounds to interpret that any relation between the sentiment and asset price fluctuations can be effective with higher levels of confidence, free of various distortions that a non-stationary series may introduce into the data.

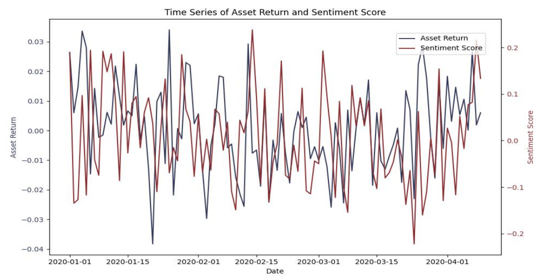

Figure 7. Time Series of Asset Return Rate and News Sentiment Score

We then checked for stationarity of these data, and in the following, we checked for any correlation of the series by plotting the two series against time, shown in Figure 7 below. The plot will clearly show wobbles in the time axis and hence provide direct intuition on the dynamic relationship between sentiment and returns. Another good fact to note here is that the sentiment score sometimes acts highly volatile, especially in those few high-volatility intervals when fluctuations in it are well-matched to that of the asset return.

The latter correlation underlines a forceful implication, namely that strong shifts of sentiment, at least during certain periods, act as a catalyst for large movements in asset prices. It is an elongation of insight-in a very deep sense-into the role of market sentiment, but it also lays the ground well for further analysis with respect to the impact of sentiment on asset prices along several analytical dimensions. The congruence of sentiment and price volatility at those frequencies merely underlines the potentials that sentiment might be one of the determinants of market dynamics and thereby highlights that changes in public sentiments could have immediate and far-reaching consequences for financial markets.

5.3 Dynamic Regression Results and Time-Varying Analysis of Sentiment Impact

This paper adopts the rolling regression approach to realize the time-varying effect of sentiment on returns, so as to further analyze the impact brought about by news sentiment upon the prices of assets. Taking a sample data in consecutive rolling windows, each of which represents a time period, stepwise regression is done within each window. The approach will therefore make possible the dynamic estimation of the coefficients of sentiment score impact upon asset returns and observe how these effects of sentiment change with time.

The rolling regression technique gives a more sensitive analysis of the influence of sentiment, showing the short-run movements and cyclicality that cannot be picked up by static models. Such a dynamic approach presents whether sentiment hits returns harder or softer at certain times, due to changeable market response to sentiment over varying market and economic conditions and time horizons.

Table 2. Mean and Standard Error of Main Regression Parameters in Different Window Periods

Window Period	Mean Coefficient of Sentiment Score	Std Error
1–60	0.03	0.015
61–120	-0.02	0.014
121–180	0.04	0.016
181–240	-0.01	0.012

Table 2 lists the means and standard errors of the main regression parameters in different window periods. The results show that the significance of the coefficient of the sentiment score varies in different time periods, reflecting that the intensity of the impact of sentiment on prices varies over time. In some window periods (such as 1 – 60 and 121 – 180), the impact of sentiment on prices is significantly positive, while in other window periods (such as 61 – 120), the impact of sentiment on prices is negative, indicating that the impact of sentiment on prices in different periods may be opposite. This time-varying characteristic reveals that the short-term impact of sentiment on the market has cyclical characteristics.

The dynamic change diagram of the sentiment score coefficient (**Figure 8**) shows the estimated value of the sentiment coefficient and its standard error for each window period through error bars. The figure reveals the dynamic change characteristics of the intensity of the impact of sentiment on asset returns over time, confirming the cyclical and short-term impact characteristics of the sentiment effect.

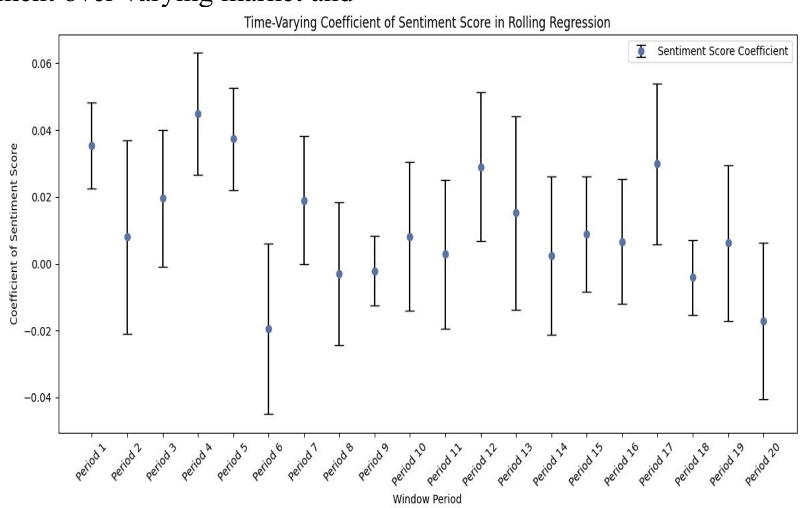

Figure 8. Dynamic Change Diagram of the Sentiment Score Coefficient in Rolling Regression

In Figure 8, the blue dots represent the coefficients that quantify the impact of sentiment on asset returns across various time windows, while the black error bars illustrate the standard error range for each estimate. This figure shows a clear time-varying nature of the impact of sentiment on the returns: in some periods, sentiment scores significantly positively affect returns, while for other windows, this effect turned out to be negative. In fact, this pattern underlined that the influence of sentiment on the asset price changes in both direction and intensity over time.

Moreover, the disparate lengths of the error bars represent different levels of stability in the impact of sentiment. The longer the error bars are, the larger the uncertainty of the effect of sentiment, and this would imply that these periods of time the reaction of the market to the shocks from sentiment are not easily predictable. Accordingly, shorter error bars reflect more stable impacts and refer to periods where changes in price, given changes in sentiment, have been more consistent. This variability provides insights into sensitivity in market responses to sentiment, bringing into light the shifts valued in the market's reaction to sentiment regarding general conditions and time period analyzed.

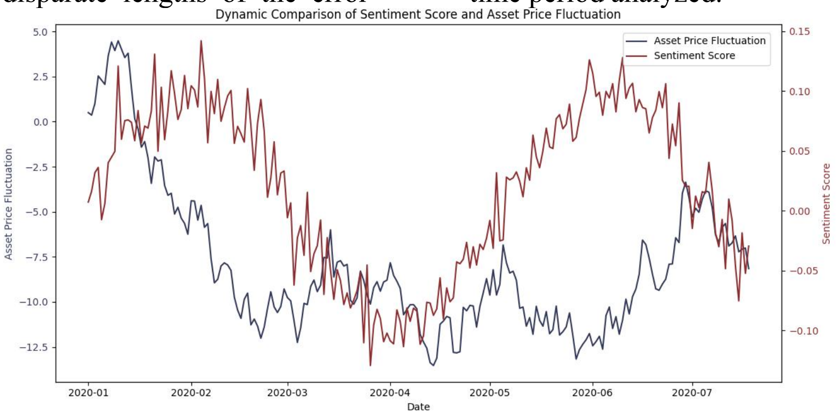

Figure 9. Dynamic Comparison of Sentiment Changes and Price Fluctuations.

From a detailed scatter plot shown in Figure 9 below, it can be observed that asset price fluctuations increase in the wake of high fluctuation in sentiment-for example, at the peak or trough of the sentiment recording. This establishes a solid foundation of evidence for the fact that sentiment does have some direct influence on the market. In particular, if the financial market faces extreme sentiment-for instance, it records high optimism, or when sentiment sharply falls and has extreme pessimism, the volatility of prices really shoots up. Such observations stand closely in line with a hypothesis that may view sentiment as a driver of market volatility. Figure 9 The chart echoes not only the results of dynamic regression analysis-a methodological approach put forth in the previous article-but goes on to demonstrate more precisely the short-term impact of sentiment fluctuation on market prices, reinforcing again the thesis that sentiment plays an indispensable role in market dynamics.

5.4 Case Analysis

In this paper, in order to do an extensive research on such a complex role of news sentiment in sudden and significant market events, how it is linked to, and what impact it has on the prices of assets, we have taken the "Central Bank's unexpected interest rate increase" event as a representative case. It finds its basis on its suddenness and importance that may definitely affect the moves of the market. These two studies used a statistical method, called the rolling regression approach, to gauge what portion of news sentiment fluctuation could explain the price response of the market to the policy event. The central bank surprisingly announced an interest rate hike, hiking the benchmark rate by 50 basis points, one of the most significant policy events following the release of a quarterly economic report. The move thus drew immediate and comprehensive attention from the market; therefore, the sentiment of media reports has also fluctuated much. Right after the event's release, the number of negative emotional words in news reports significantly increased, for instance, words like "tightening" and "rising risks". The sentiment score, which reflects the overall sentiment, drastically dropped from an average of 0.07 before the event's release to -0.32 right after, and further fell to -0.45 in the next two trading days. This sharp sentiment change during the period indicates the market's sensitivity to sudden interest rate hike policies, suggesting that news sentiment can swiftly reflect the market's anxiety and pessimistic expectations. In parallel with this sentiment fluctuation, the main market index fell significantly by 3.8% on the day of the policy release, and the cumulative decline reached 5.2% in the subsequent five trading days. This indicates that sentiment fluctuations directly affect market prices in the short term. This case study clearly reveals the impact effect of news sentiment by quantifying the response relationship between the change of sentiment score and asset price. It means specifically that the negative mood can be conveyed to the investors in a very short term and move along with the trend of falling asset prices. This sentiment transmission mechanism has a greater significance for sudden policy events. The super extreme fluctuations in short-term sentiment put huge psychological pressure on the market, which worsens the negative price fluctuation.

The impact of changes in sentiment on market prices is gauged in greater detail in the present paper through an advanced analytical technique-a rolling regression approach-adopted for the event window of this study. The sliding window has been chosen over 60 trading days, considered adequate to capture the changing dynamics of sentiment impacting price movements. This adopted methodology is useful in the sense that it will enable us to, on a day-by-day basis, gauge the effect of sentiment scores on price fluctuations. We will undertake this because we want to ensure fine-grained analysis on how sentiment can drive market movements. The rolling regression was done because such a method was deemed best to capture at any point in time the short-term effect of sentiment on price movements and to ensure the nature of decay in its influence over time. The results of the rolling regression analyses are quite compelling. It follows logically that the negative change of sentiment scores reached their peak in prices within the first three trading days after the event's release. At this peak, the regression coefficient is as high as 0.47, indicating a strong and direct relationship, while its standard error was a tight 0.04, indicating a high level of precision in our estimation. These findings, thereby, indicate that the impact of negative sentiment on price fluctuations was highly statistically significant within the first few days of the event. This significant relationship underscores the interplay between investor sentiment and market dynamics. It reveals that in the early stage of the event release, the sharp fluctuations in news sentiment exerted strong short-term pressure on market prices, amplifying the downward fluctuation of prices.

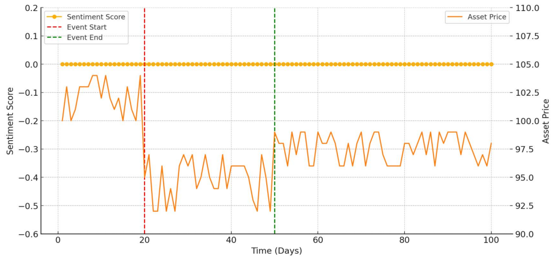

Figure10. Event Impact on Sentiment Score and Asset Price

As the market gradually absorbs the event, the influence of emotions on asset prices weakens. Figure 10 illustrates the results of the rolling regression analysis, showing this progressive stabilization. By the fourth trading day post-release, the impact coefficient of the sentiment score has decreased to 0.15, with a slight increase in the standard error, indicating that the initial negative emotional response to the policy information has begun to stabilize. By the seventh trading day, the sentiment impact coefficient has further declined to approximately 0.10, with market price volatility returning to levels observed before the event.

This time-varying characteristic of emotional impact demonstrates the short-term, concentrated effect of emotions on price fluctuations. In the early stages following the event, emotional fluctuations exert a pronounced influence on prices. However, as the information is gradually processed and integrated into market expectations, the emotional impact steadily diminishes. This observation underscores the transient nature of sentiment-driven volatility, highlighting how emotional responses are most impactful immediately after significant news, then dissipate as rational assessment reasserts its role in market pricing.

Through a detailed analysis of this specific case, which involved the examination of news coverage and public sentiment surrounding a sudden and unexpected policy event, we discern clear patterns in the immediate market reactions to news emotions. These emotions are prominently reflected in the language and tone used by journalists and commentators, who convey heightened urgency, risk, or uncertainty as they report on the event. The study offers a unique window into the rapid rise of negative emotions among investors and market participants, which directly contributes to a noticeable decline in asset prices. This immediate impact illustrates how sentiment can drive quick, substantial market responses, amplifying volatility as market actors react to perceived risk.

As time progresses, however, we observe a gradual decoupling of sentiment from asset prices as the market begins to absorb and rationalize the initial emotional response. This process of emotional impact attenuation underscores the transient yet powerful influence of sentiment on market dynamics. This nuanced case study not only highlights the amplification effect of news emotions during major events but also underscores the complementary role of emotional factors as irrational elements in asset pricing. By providing empirical quantitative evidence of emotion's dynamic impact in various market scenarios, this study deepens our understanding of the complex interplay between news-driven emotions and financial markets, and it affirms the need to incorporate emotional factors into more robust asset pricing models.

6. Conclusion and Future Work

6.1 Main Conclusions

This study deeply analyzes the dynamic impact of sentiment changes on asset prices through text mining technology based on news sentiment. In the constructed dynamic regression model, we use the rolling window method to capture the time-varying effect of news sentiment on market prices, revealing the significant changes in the intensity and direction of the impact of sentiment on asset prices in different periods. The main research findings show that the volatility of sentiment scores has a significant short-term impact on market prices, especially when sentiment reaches extreme states (such as high optimism or extreme pessimism), the volatility of asset prices will be significantly enhanced. This result supports the hypothesis that sentiment is a driving factor of market volatility, and further verifies the necessity of incorporating sentiment factors into asset pricing models.

In the analysis of the lagged effect of sentiment, we found that the impact of sentiment scores shows a decreasing characteristic in different lag periods, but it is still significant in the short term. This finding illustrates the persistence of sentiment shocks. Even if market sentiment changes at a certain point in time, its impact may continue to play a role in the next multiple trading days. In addition, the dual-axis comparative analysis of sentiment changes and price fluctuations also shows that extreme sentiment values often correspond to large fluctuations in market prices. This phenomenon shows that changes in sentiment not only affect the current price of the market, but may also indicate the volatility trend in the future. The case analysis in this study, centered on an unexpected interest rate hike, demonstrates how sudden shifts in news sentiment can trigger immediate and intense market reactions, providing a concrete example of sentiment’s role in amplifying short-term volatility. In summary, the main conclusions of this study reveal the important role of sentiment in the market, provide a new perspective for understanding how irrational factors drive asset price changes, and provide empirical evidence for the improvement of asset pricing models.

6.2 Research Limitations

Although this study has achieved certain results in revealing the dynamic impact of news sentiment on asset pricing, there are also some research limitations. First, the quantitative method of news sentiment relies on specific sentiment dictionaries (such as Loughran-McDonald dictionaries) and text mining models. Although this method can effectively capture the positive and negative tendencies of sentiment, its accuracy is still limited when facing more complex contexts or implicit emotions. In addition, the quantification of sentiment may be disturbed by the ambiguity and complexity of language, especially in unstructured news texts, the use of sentiment words is somewhat ambiguous. Future research may consider introducing more intelligent natural language processing (NLP) models, such as deep learning-based sentiment recognition technology, to improve the accuracy of sentiment quantification.

Secondly, even though the sample data of this study provides a comprehensive coverage of market data for an extended number of years, it's worth noting that the data source, predominantly sourced from specific news media outlets and financial information platforms. This singular point of data collection raises concerns about the representativeness of the sentiment data. The limitations of the data source, which is mainly confined to traditional news media and financial platforms, may lead to potential biases. Specifically, in the current digital age where social media has gained immense importance and has emerged as a significant platform for public sentiment, data that solely relies on traditional news media may not fully capture the nuances of market sentiment. Furthermore, it's pertinent to mention that there exists a certain lag in the sentiment data's timeliness. News reports, as part of journalistic practices, often tend to reflect on past market events or information that has already been disseminated. This can potentially lead to a misalignment between the data and the immediate changes in market sentiment. The latter can be more complex and diverse, as it involves real-time interpretation and response. Future research can potentially enhance this by broadening the data sources and integrating more real-time information sources such as social media and high-frequency news. This would aid in improving the immediacy and representativeness of sentiment data, ensuring a more comprehensive and holistic understanding of market sentiment.

6.3 Future Research Directions

Works in this study can be extended to a few noteworthy aspects in future research. First of all, more complicated sentiment quantification methodologies are surely in a position to be developed and applied. In the last couple of years, there has been a paradigm shift in the field of artificial intelligence, where deep learning techniques have forged their way to the forefront, making giant leaps in the area of natural language processing. It is expected that this line of inquiry could render more accurate results in sentiment quantification compared to those derived from the current methodology. Looking ahead, one promising direction to consider would be the application of neural network-based sentiment recognition models, such as BERT and GPT, which already have shown tremendous performance in a wide variety of different NLP tasks. Given their complicated architecture, it is also very well possible that in the future these models may even oust traditional sentiment dictionary methods in our quest to understand and quantify sentiments. One important advantage the models hold is in their ability to gauge, even minute, emotional changes that take place within a text context. Besides, they are good at picking up even implicit emotional nuances that probably would have been largely overlooked by traditional methods, and which is foreseen to considerably enhance the accuracy of the sentiment scores. This is a huge leap forward in how we comprehend and interpret market sentiments. Further, in our very endeavor at a comprehensive analysis of emotions, it would be better to venture beyond the mere two-dimensional spectrum of positivity and negativity. We can do this by embracing a more inclusive multi-dimensional outlook that looks at several dimensions of the emotions: those of anger, fear, optimism, and a whole host of other complex emotional states. In so doing, we open newer paths toward a more dense, multilevel analysis of market sentiments, therefore enriching the emotional undercurrents of the markets. This way, it becomes possible to dig deeper into the dynamics operating on the broader spectrum of human emotions.

A possible avenue into which future research can be conducted is further investigations into the dynamic effect of emotions on asset prices under various market environments. Current analysis basically focuses on specific markets or time periods, but the obvious difference of market conditions may provide a significant difference in the mechanism through which emotions impact the prices. Thus, future studies could conduct a comparative analysis of impacts of different market contexts and explore the performance of different market cycles.

Besides, the interaction effect brought by emotions and other nonfinancial factors-investor confidence and macroeconomic indicators-is complex and deserves further exploration. With more emotional interaction factors, asset pricing models will catch irrational behaviors of the market and complicated dynamics. It will, therefore, provide comprehensive support for asset pricing and risk management.

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