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Research on Investor Sentiment in Different Periods

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Abstract: This paper reviews the evolution of the research methods and views of researchers on investor sentiment in different periods and emphasizes the transformation from the qualitative analysis of traditional financial theory to the technical quantitative economic analysis. Financial theories in the early 20th century ignore the huge influence of investor sentiment on markets, treating it as a noise, part of the error. With the development of behavioral finance, more and more people have realized the existence and importance of investor sentiment, especially when the market is extremely volatile. However, since sentiment is a very subjective concept, it is difficult to quantify according to the technical conditions at that time. With the progress of technology, the way to collect data has become simpler and creative; especially in the 21st century, the empirical analysis of investor sentiment has been gradually improved, including the creation of different sentiment models and index. In addition, this literature review also emphasizes the interdisciplinary nature of modern emotion research, involving computer science, physics and other fields. At the end, the limitations of current methods are mentioned, and possible future research directions are discussed.

Keywords: sentiment, methodology, market, asset price, quantitative.

1. Introduction

1.1. Research background

In the asset market under the study of behavioral economics, investor sentiment is considered one of the essential reasons for market price fluctuations. Conventional financial theory posits that all investors act rationally so that prices are fully reflected by all available information. However, empirical research shows that investor sentiment often affects market prices significantly, leading to extreme events such as market bubbles and crashes. Following the progress of behavioral finance, the study of investor sentiment has gradually moved from the fringe to the mainstream, becoming an essential factor in understanding market dynamics.

The research methods in different periods reflect the evolution of academic thought, technology, and the nature of the market. Early research was limited by technology, and it was difficult to quantify subjective parameters such as emotion, so people at that time mainly relied on qualitative analysis. With the development of statistical methods and computing techniques, research in the 21st century has gradually turned to complex quantitative analysis. Over the last few years, due to the evolution of artificial intelligence technology, sentiment analysis methods based on social media and the

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Internet have gradually emerged, providing new tools for studying the role of investor sentiment in market fluctuations.

1.2. Main content

This study will review different periods of investor sentiment research, state the research ideas of the time, and analyze the reasons for the evolution of these methods. By revealing the applicability of different methods in different market environments and exploring the direction and potential challenges of future research, our objective is to develop a methodological framework for investigating investor sentiment in financial markets and academic research

2. literature review

2.1. The early to mid-20th century

Throughout the early to middle decades of the 20th century, investor sentiment had not yet become a mainstream focus of financial market research, which at the time was mainly within the framework of traditional financial theories that assumed markets were efficient and rational. The Efficient Market Hypothesis (EMH), introduced by Eugene F. Fama in 1965 and further elaborated in 1970, asserts that market prices reflect entirely all available information [1][2]. Thus, all investors' decisions were thought to be based on rational judgment. In this theoretical context, investor sentiment is considered noise rather than a key factor driving market volatility. In fact, some early research noted the role of emotional and psychological factors in the market. For example, John Maynard Keynes mentioned the concept of “animal spirits” in his book, General Theory of Employment, Interest, and Money, which refers to the positive or negative emotions, intuitions, and confidence that drive investor behavior rather than entirely rational calculations [3]. Keynes' theory explained how investor sentiment could cause significant changes in asset prices. Still, the subject involved subjective factors such as sentiment, and the data analysis in those days was limited by technology, making quantitative analysis difficult. In addition, in Irving Fisher’s 1930 paper, The Stock Market Crash - And After, investors' excessive optimism drove the market bubble, and undue fear after the bubble burst exacerbated the market crash of 1929 [4].

In the 1986 paper Noise, published by Fisher Black, he mentioned the concept of information traders and noise traders [5]. As the name implies, an information trader is a rational investor who makes investment decisions based on market information; noise trading refers to trading based on noise as if it were information. Noise traders, while diverting the market price from its expected value, provide liquidity to the market and lead trades more frequently. Since market prices include the effects of noise, information traders have more arbitrage opportunities. When the noise trader dominates the market, while not necessarily harmful to other investors, it can cause extreme volatility in the market and even lead to bubbles and crashes. Based on this, the irrational investors and investor sentiment that bring noise to the market become essential subjects of study for analyzing bubbles and crashes.

2.2. The early 21st century

With the swift advancement of modern technology in the early 21st century, people can measure and predict the influence of investor sentiment on the market more accurately and reliably. This section includes the construction of investor sentiment indices, textual analysis, and sentiment analysis on social media platforms. These modern methods have significantly improved researchers’ ability to anticipate market trends according to investor sentiment, gaining valuable insights into problem-solving and risk management in a dynamic and complex financial market.

Constructing an index provides an effective method for quantifying investor sentiment so that people can forecast market trends and develop timely strategies to minimize risk. Baker and Wurgler explored the relationship between investor sentiment and the cross-sectional differences in stock returns [6]. Based on six sentiment proxies, they constructed a composite sentiment index. They found that when estimated investor sentiment is high, the subsequent returns for different unappealing stocks to arbitrageurs are relatively low, and vice versa. Their sentiment measurement and empirical findings lay a solid foundation for future research, promoting the study of the significance of sentiment in the market. Da, Engelberg, and Gao constructed the FEARS index to measure investor sentiment, discovering how sentiment changes lead to market fluctuations [7].

Meanwhile, sentiment analysis methods based on social media were gradually developed, providing compelling insights into investor sentiment research. Tetlock emphasized the crucial role of media in the stock market [8]. Through the examination of daily material from a Wall Street Journal column, he discovered that high levels of media pessimism can cause a downturn in market prices. Also, the abnormal value (high or low) will temporarily increase market trading volume. This article was the first paper to present evidence that media content can forecast changes in general stock market indicators.

In their 2011 study, Bollen, Mao, and Zeng utilized and examined content from Twitter with mood-tracking tools, Indicating that public sentiment expressed on social media may forecast market trends [9]. This paper is one of the earliest studies on using Twitter data in sentiment analysis. However, there are some limitations that geography and language factors should be considered due to Twitter's changing user base. Also, a short period of test set might be insufficient to demonstrate the accuracy and effectiveness of the method. Considering some deficiencies, Nguyen, Shirai, and Velcin proposed a new method to predict stock price movement [10]. The highlights are significant. Their novel 'topic-sentiment' feature considered the company's specific topics rather than overall mood, significantly increasing the accuracy of stock price prediction compared to previous traditional methods. They also pointed out some reasons why they did not choose Twitter as the mood information source due to the difficulty in collecting and screening relevant tweets.

In this period, textual analysis has become crucial in revealing investor sentiment. By extracting and analyzing the content and tone of the context, people can better understand the underlying sentiment that may affect market movements. Loughran and Mcdonald found a measurement problem of word misclassifications, implying that nearly seventy-five percent of the negative words listed in the Harvard Dictionary are considered non-harmful to finances [11]. To address this issue, they created a negative word list focusing on financial reports and a term weighting scheme that can reduce the noise caused by word misclassifications. They also acknowledged the significance of textual analysis in providing relevant information about stock returns.

Kearney and Liu reviewed the literature on textual sentiment by comparing their information sources and methods to analyze content and used empirical models [12]. They gathered and summarized key findings about textual sentiment, emphasizing the distinguished progress in this field. Also, they pointed out some blank areas and weaknesses, proposing potential directions for further future research.

In conclusion, while remarkable achievements in measuring and analyzing investor sentiment were made in the early 21st century, many ongoing limitations posed by technological problems still exist. Much research needs to be conducted to constantly refine the current methodologies and keep track of market trends in this promising area.

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2.3. Investor sentiment analysis in the information era

Since 2016, due to the impact of the data age brought by the advancement of computer science, scholastic research on investor sentiment has become more nitty-gritty. Progressed innovation has permitted scholastics to analyze investor sentiment and its effect more precisely in their research.

Frankie Chau, Rataporn Deesomsak, and Dimitrios Koutmos drew on sentiment survey information from person speculators, counting files such as the American Affiliation of Person Speculators Opinion Record [13]. They combined this sentiment survey information with stock market returns, volatility, and other advertise pointers through regression analysis and econometric models. The ponder found that studies of personal investor sentiment are a driving pointer of changes in advertise assumption. These overviews can capture changes in showcase assumptions and reflect them within the real exchanging behavior of speculators. This finding underscores the significance of sentiment survey information in foreseeing and recognizing potential exchanging openings, as unreasonable opinion swings by person speculators frequently cause costs to veer off from basics, making arbitrage opportunities.

Guofu Zhou specified that it is challenging to precisely the degree of investor sentiment due to its subjectivity, time-variability, differing qualities of estimation strategies, and complex relationship with principal esteem [14]. To fathom this problem, he recommends employing a combination of numerous temperament markers and machine learning strategies. The previous approach employs measurable procedures such as principal component analysis (PCA) to extricate central components from an assortment of opinion markers, counting advertise information (such as trading volume, volatility), study information (such as consumer confidence), and textual data, including analyses of social media opinions and news reports. This makes a difference in constructing a comprehensive assumption file that captures the variables that best reflect changes in advertising assumption. The last-mentioned approach employments natural language processing (NLP) innovation that permits analysts to analyze huge sums of content information, such as social media posts and news articles, to extricate watchwords and opinion scores that reflect advertise assumption.

Zhenyu Gao, Haohan Ren, and Bohui Zhang put forward the co-movement hypothesis of emotions, which holds that worldwide feelings may spread in different countries, thus influencing the neighborhood feelings in each nation [15]. The analysts accept that this co-movement may be encouraged through the exchanging exercises of universal financial specialists and information-sharing channels, such as the Web and the media. For illustration, when worldwide financial specialists hold offers in a country's advertisement, changes in their opinion can influence showcase estimation in that nation through exchanging movement. The spread of global sentiment over distinctive nations is impacted by the market integration level, which is confirmed by embracing International Financial Reporting Standards (IFRS) as a quasi-natural test. Research appears that advertising assumptions in nations that have embraced IFRS have a more grounded relationship with global sentiment, recommending that market integration makes a difference and encourages the spread and co-movement of assumptions over nations.

In their study, M. Ángeles López-Cabarcos, Ada M. Pérez-Pico, Paula Vázquez-Rodríguez, and M. Luisa López-Pérez emphasized that advancements in the consideration of investor sentiment depend not as it were on fund and psychology, but to benefits from intrigue integration in areas such as computer engineering and physic [16].

In computer science, artificial intelligence and data mining procedures are broadly utilized in estimation examination. They permit vast amounts of unstructured information to be handled in real-time to assist in developing markers that reflect showcase estimation. Natural language processing (NLP) innovation is additionally being utilized to analyze investor sentiment on online stages, giving modern instruments for showcase estimation.

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In physics, statistical mechanics models are utilized to analyze the influence of investor sentiment on market dynamics, clarifying how personal activities can lead to systemic risk and market volatility. In expansion, quantum-mechanical models offer assistance to get investors' choices beneath instability.

These multidisciplinary approaches progress the profundity and accuracy of investor sentiment research, give researchers unused viewpoints, and give solid bolsters for market analysis and decision-making.

Jiangshan Hu, Yunyun Sui, and Tooth Ma utilized the Markov-Switching Vector Autoregressive model and impulse reaction investigation to uncover the non-symmetrical effect of investor sentiment on equity markets showcasing beneath distinctive advertise conditions [17]. The consideration found that positive stuns to investor sentiment have an essentially more prominent effect on stock market returns in bull markets compared to bear markets. This proposes that estimation drives stock costs more when the advertisement is hopeful, whereas assumption generally has little negative effect when the showcase is critical.

Wang, Wenzhao, Su, C., and Duxberry, D. examined fifty equity markets from various countries, counting 24 advanced markets and 26 developing markets, and found that the effect of investor sentiment on equity market returns is altogether distinctive between developed markets and emerging markets [18]. In emerging markets, value returns typically respond quickly to shifts in investor sentiment over the short term. Conversely, in developed markets, the influence of investor sentiment is more persistent and can endure for as long as 36 months.

3. Limitations and prospects

3.1. Limitations

The existing research methods still have some limitations.

Current research methods may face challenges in obtaining high-quality, large-scale data while dealing with the unstructured and timeliness of the data. There may also be limitations in the investor sentiment index creation method. For example, certain researchers apply principal component analysis to create sentiment indexes, but this method may not fully reveal the complex association between investor sentiment and market performance.

Research models, perhaps, are based on certain idealized assumptions that may deviate from actual market behavior, affecting the model's predictive accuracy. Thus, these theories and models need a lot of empirical tests to confirm.

There may be significant differences in investor behavior under different cultural backgrounds, and existing research methods may be complicated to fully capture these differences, resulting in limitations of research results. For instance, because of the differences between the A-share market and the US stock market, as well as the differences in the cultural environment between the US and China, many words that are identified in one context as a measure of investor negativity do not reflect very biased negativity in the other context.

3.2. Prospects

By summarizing the existing research and development, we can propose and predict the future research direction.

The current study leveraged various data sources, including big data, social media, and news reports, alongside advanced data analysis techniques like deep learning and natural language processing to enhance the scope and depth of the research. In the future, multiple data sources can be used for text analysis and cross-verification. For example, a more relevant financial sentiment

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dictionary is constructed and cross-verified through the intersection and combination of high-frequency emotional words in the company's annual report and related policy reports.

Scholars in finance, psychology, computer science, physics, and other fields are encouraged to collaborate and innovate theoretical frameworks and research methods.

Existing studies have used historical data to validate theories and models. Future research may be able to develop models that can monitor investor sentiment in real-time and respond quickly, improving the ability to predict market dynamics.

Different research methods have advantages and disadvantages and different applicability in different market environments and time scales. This applicability requires further clarification and demarcation. For example, different data sources determine the scope and field of application of the model, index, or dictionary constructed. Compared with the investor sentiment measurement index constructed according to the company's annual report, the index constructed according to policy reports and news reports is applicable to a more macro level, such as the broad market index, a certain industry sector, etc., but the accuracy of the company level will be reduced.

4. Conclusion

To replicate, with the continuous progress of theory and technology, the research methods of investor sentiment have also been improved. By combining theories and technologies such as psychology and computers, The quantification of investor sentiment and its influence on the market are becoming more and more accurate and predictive. Research on the future encourages more interdisciplinary research and methodological innovation to address the increasingly complex market challenges. Emphasize the importance of real-time data and the development of models that can quickly adapt to market changes. Considering the impact of cultural differences on investor sentiment, future studies should pay more attention to cross-cultural perspectives.

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