Title

Empirical analysis of investor sentiment and stock return in China

A research thesis submitted by

Yi Chen

Student number: 1603858

for the degree Master of Management in Finance and Investment

Supervisor: Dr Euphemia Godspower-Akpomiemie

University of Witwatersrand

Wits Business School

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DECLARATION

I, Yi Chen declare that the work reported in this research is my own, except where otherwise indicated and acknowledged. It is submitted for the degree of Master of Management in Finance and Investment in the University of the Witwatersrand. This research paper has not, either in whole or in part, been submitted for a degree or diploma to any other universities.

Yi Chen

………………………...   …February 8, 2023…….

Signature of candidate   Date

DEDICATION

This work is dedicated to my teachers who help me, my family and friends who care about me.

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I would like to thank my supervisor Dr Euphemia Godspower-Akpomiemie. In the process of writing the thesis, every detail from the framework to the thesis has been carefully guided by her. Her rigorous, dedicated, and gentle patience has benefited me a lot, and it has also enabled me to complete my thesis smoothly. I offer my sincere gratitude.

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As my knowledge structure becomes more complete, combined with previous work experience, the combination of practice and theory can make me more competitive in the future workplace.

Table of Contents

LIST OF TABLES

LIST OF FIGURES

ABSTRACT

Behavioural finance believes that both investor sentiment and the intrinsic value of securities affect the price of financial assets, therefore investor sentiment is an essential component in determining the price of securities and the market's operation. Individual investors dominate most Chinese stock markets, with only a few institutional investors. The immaturity of capital leads to a more obvious influence between investor sentiment and the stock market, therefore it is of practical significance to study the relationship between investor sentiment and stock market returns. This thesis explored the relationship between investor sentiment and stock market returns, laying a foundation for South African investors to further understand and invest in the Chinese stock market.

This thesis used the number of IPOs, IPO first day return rate, market turnover rate, price-earnings ratio as objective indicators and consumer confidence index as subjective indicator and uses principal component analysis to construct a single investor sentiment indicator. Through the Granger causality test, it is found that there is no Granger causality between investor sentiment and the monthly return of the Shanghai Composite Index. Investor sentiment has a positive impact on the monthly return of the Shanghai Composite Index most of the time, according to the results of impulse response analysis, while the monthly return of the Shanghai Composite Index has a negative impact on investor sentiment. The variance decomposition analysis shows that the contribution of the monthly return of the Shanghai Composite Index to investor sentiment is 3.80% less than the contribution of investor sentiment to the monthly return of the Shanghai Composite Index, which is 4.60%. Thus, investor sentiment explains the monthly return of Shanghai Composite Index more than the monthly return of Shanghai Composite Index explains investor sentiment.

CHAPTER 1: INTRODUCTION

1.1 Overview

Investor sentiment research emerged in the 1980s to examine the impact of human factors on the stock market from a new perspective. As it breaks through the theoretical framework and economic paradigm of the traditional capital market and focuses on the analysis of human psychology, emotion, and behaviour (Szyszka, 2014), it has become one of the most important research fields in the financial field. This chapter mainly introduces the research background, research problems, research objectives, significance, and outline of the Research.

1.2 Background of the Study

Traditional financial theory holds that markets are efficient, that is, investors are completely rational, so stock prices are not affected by investor sentiment (Szyszka, 2014). The view in the efficient market hypothesis is that investors can make correct decisions through market analysis because investors' rationality can be guaranteed. However, with the development of financial markets, scholars have discovered more and more anomalies that cannot be explained by traditional financial theories, such as herd effect, overreaction and underreaction, and noise trading (Stambaugh, Yu, & Yuan 2012).

The findings of emotional psychology and social psychology research are frequently applied in many areas of behavioural finance, along with investor preferences. Behavioural finance has started to examine how emotions affect investor psychology and decision-making by using the findings of psychological study. Behavioural finance believes that financial asset prices are not only affected by fundamental values, but also constrained by factors such as investor sentiment. Baker (2007) pointed out that emotions often affect investors' decision-making. Simon (1955) believed that investors' bounded rationality affects decision-making. Other researchers argue that investors often make decisions based on their intuition (Chang, Faff & Hwang 2012).

Investor sentiment is one of the key elements that affects securities prices and market operations, according to the framework of behavioural finance, even if traditional finance is incapable of explain the impact of investor sentiment on the securities market. Considering this, research on investor sentiment has become crucial to the field of behavioural finance. At present, there is still no unified framework for research on investor sentiment. Compared with

Western stock market research, there are still not many English-language studies on investor sentiment in China's stock market. Affected by the global economic crisis, the Shanghai Composite Index fell by more than 70% between October 2007 and October 2008 (Areddy, 2015). In the process of the stock index plummeting, the role of investor sentiment in it is very intriguing. 2023 is the 25th anniversary of the establishment of diplomatic relations between China and South Africa. The friendship between China and South Africa is deepening day by day, and the unity and cooperation are getting closer. China and South Africa are major developing countries in the world. Both countries hold the same or similar views on development, security and international order. China's capital market has steadily grown its involvement in the South African and global financial markets in recent years. Research on the connection between Chinese investor sentiment and stock market returns can therefore not only assist investors in making prudent investment choices but also assist South African investors in gaining a thorough understanding of China's stock market and economic performance.

1.3 Research Problems

Individual investors account for more than 80% of Chinese stock market investors, with the rest being institutional investors (Chen, 2019). Individual investors lack professional theoretical knowledge and are easily affected by market fluctuations. Investor sentiment rose as the stock market continued to improve, leading to a surge in the stock market. Conversely, investor sentiment turned negative as the stock market continued to fall, causing the stock market to plummet. Behind the sharp rise and fall of the stock market, it must be inseparable from the role of investor sentiment. The relationship between investor sentiment and stock market performance is now a topic of debate in academic circles without a single, agreed-upon solution. The relationship between investor sentiment and stock market returns can generally be divided into three categories which are positive correlation, irrelevant correlation, and Granger causality.

The Chinese stock market has minority of institutional investors, and because immature capital makes the relationship between investor sentiment and stock price more visible, it can serve as a theoretical basis for practice. Institutional investors have many outstanding talents and funds to make more accurate predication on future stock market trends and can also bear relatively large losses. Therefore, institutional investors' investment philosophy is relatively rational. Individual investors are irrational because of their limited capital and knowledge structure, which makes them susceptible to being misled by false information in the market and causing significant losses. Investors can better understand market development laws, sharpen their forecasting skills, and grasp scientific investment concepts by studying this part of the group. Particularly for individual investors, it is important to develop a sound investment philosophy, comprehend all the risks, and make rational investment decisions.

Since investor decision-making behaviour affects stock returns in China's financial market, studying the relationship between investor sentiment and stock market returns is beneficial for improving relevant theoretical content of existing behavioural economics and enriching the theoretical system as well as providing an in-depth and thorough explanation of the main causes for the anomaly in China's stock market. On the other hand, the proportion of China's capital market in the international capital market has been increasing year by year in recent years, and behavioural finance used to mainly draw on Western theories and frameworks, which itself needs to be improved in many areas, so the study of Chinese behavioural finance also has Significance. Individual investors in China are Individual investors in China are deeply influenced by traditional culture, and often make decisions that are emotional. Studying the impact of their mood swings on capital markets can provide an oriental perspective on behavioural finance theory. It is also the improvement of the theoretical system of behavioural finance and makes corresponding contributions. In this research, investor sentiment is the explanatory variable, and the monthly rate of return of the Shanghai Composite Index is the explained variable. Therefore, other factors that affect the rate of return should be removed to make the results more objective and fairer.

1.4 Research Objectives

Based on the motivation on the study of a single investor sentiment, this research is set to achieve the following objectives:

1. To construct a single investor sentiment index using objective sentiment indicators and subjective sentiment indicators.
2. To analyse the relationship between the single investor sentiment (from objective 1) and the monthly yield of the Shanghai Composite Index.

1.5 Significance of the Study

This thesis is based on the research on investor sentiment in the Chinese market, so the research significance is divided into the reasons for studying investor sentiment and the purpose of choosing to study the Chinese market.

The immaturity of China's stock market capital leads to the obvious impact of investor sentiment on stock market returns. Therefore, studying the relationship between investor sentiment and stock market returns is conducive to improving the relevant theoretical content of existing behavioural finance, enriching its theoretical system, analysing the impact of investor behaviour on stock returns in financial markets. The results of this research can help investors establish a correct investment philosophy, have a full understanding of risks, and invest rationally.

This article will construct the corresponding investor sentiment index based on the SSE market and explore the relationship between itself and income. Considering that both China and South Africa belong to the BRICS countries and are increasingly connected with each other, China has gradually become a market pursued by South African investors. Research on investor sentiment in the Chinese market will help South African investors improve their cross-market portfolio returns and gain a deeper understanding of the Chinese market.

1.6 Outline of the Research

This research is divided into six parts. The first chapter (namely this part) is an introduction, which introduces the research background of this thesis, puts forward the research question and objectives, and introduces the research significance of this thesis, to clarify the main direction of the research.

The second chapter is a literature review, which introduces the origin and development of behavioural finance, the definition of investor sentiment, the characteristics of investor sentiment including herd mentality, overreaction, risk preference, etc., the theoretical model of investor sentiment, review of research on investor sentiment measurement methods and empirical findings on investor sentiment.

Chapter 3 presents the research methodology and design used to analyse the data. This includes explanations of data collection methods and statistical techniques used in data analysis. In addition, the limitations of the study and any ethical considerations that may arise in this study is discussed.

The fourth chapter is an investor sentiment index construction. First, the reasons for the selection of objective sentiment indicators and subjective sentiment indicator are introduced; then, based on the results of principal component analysis, the investor sentiment index is objectively constructed.

The fifth chapter is to analyse the impact of investor sentiment on China's stock market returns. The investor sentiment constructed according to the principal component analysis process is the explanatory variable, and the monthly return of the Shanghai Composite Index is the explained variable. The relationship between investor sentiment and the monthly return of the Shanghai Composite Index is illustrated using the Granger causality test, impulse response function analysis, and variance decomposition analysis.

The sixth chapter is the research conclusions and recommendations. According to the empirical results, the deficiencies and suggestions of this study are pointed out from different aspects.

1.7 Research Limitations

The subjective sentiment index only selects the consumer confidence index due to data availability, which may not guarantee the sentiment index's comprehensiveness. As a result, follow-up research can choose from a variety of subjective sentiment indicators, resulting in investor sentiment indicators that are not only more representative, but also more objectively reflect investor sentiment fluctuations.

The monthly data employed in this study has a greater span than the daily data and so cannot accurately reflect the fluctuations and changes in investor sentiment. The relationship between investor sentiment and stock market returns can be precisely appreciated to an extent if daily data can be collected, arranged, and analysed.

CHAPTER 2: LITERATURE OVERVIEW

2.1 Introduction

Since the 1980s and 1990s, scholars have gradually shifted from the neoclassical framework-based research paradigm to the behavioural-based research paradigm (Shefrin, 2001). Since then, behavioural finance has been continuously paid attention and recognized by financial researchers. This chapter mainly contains the origins and evolution of behavioural finance, the characteristics and theoretical models of investor sentiment, a review of research on the definition of investor sentiment, a review of research on investor sentiment measurement methods, and a review of empirical research on investor sentiment conducted by scholars.

2.2 The Origin of Behavioural Finance

With the continuous growth and development of financial markets, anomalies such as herd effect, overreaction and underreaction, and noise trading that cannot be explained by traditional financial theories such as the efficient market hypothesis appear in the market. Traditional finance, which cannot explain financial market anomalies, was replaced by Herbert Simon's (1955) research hypothesis of bounded rationality, which stated that investors are not completely rational and are heavily influenced by factors such as psychology, emotion, cognitive level, social, and so on. Therefore, researchers explain various financial anomalies through the research experience and results of psychology, behaviour, and sociology, and finally form behavioural finance.

Early academic research on behavioural finance mainly includes Keynes's beauty pageant game, Graham's investment analysis, and psychological experiments conducted by psychologists such as Kahneman. In the 1980s and 1990s, Robert Shiller and Richard Taylor were only recognized by mainstream economists when they studied the causes and laws of the anomalies in financial markets that violated efficient markets. So far, behavioural finance has been continuously concerned and recognized by financial researchers and has gradually become an important part of modern finance together with traditional finance.

2.3 The Evolution of Behavioural Finance

Gustave Le Bon's (1895) 'The Crowd: A Study of the Popular Mind' was a pioneering behavioural finance concept that combined psychology and financial research. Keynes was the first to emphasize the importance of psychological factors in investment decisions. Emotion, cognition, and expectation were first introduced into economics by American scholar George Cardona in the 1930s. Herbert Simon's (1955) 'bounded rationality' hypothesis provided an important theoretical foundation for the birth of behavioural finance. It was widely questioned in the 1970s for inability of traditional financial theories to rationally explain market anomalies. Since the mid-to-late 1990s, behavioural finance theory has focused on the impact of investor psychology on portfolio and trading decisions. After the millennium, behavioural finance not only begins with the psychology, emotion, and attitude of individual investors, but also considers macro-behavioural factors and conducts deeper research on various anomalies in the financial market. The constant emergence of new fields of behavioural finance research enriches research methods and theoretical systems, and the rapid development of social media and big data has provided new opportunities for the study of investor sentiment. However, there are still many issues in behavioural finance that need to be addressed. For example, the theoretical framework lacks a unified theoretical foundation.

2.4 Definition of Investor Sentiment

At present, there is no standard definition of investor sentiment, but most scholars agree that investor sentiment is an expectation of investors.

De Long et al. (1990) refer to investors' false beliefs as investor sentiment. Baker & Stein (2004) believe that investor sentiment is the mispricing of assets and the tendency to speculate. Lee, Shleifer & Thaler (1991) pointed out that due to the influence of many aspects such as value evaluation and their own emotions, investors form an expectation on the price of financial products in the market, and there is a significant difference between the expectation and the actual situation. Investor sentiment, according to Brown & Cliff (2004), Baker & Wurgler (2006), is defined as investors' optimistic or pessimistic expectations and mentality about financial asset values and the entire market. Investor sentiment, according to Barberis, Shleifer et al. (1998), is a cognitive process based on expectations theory. According to Chang, Faff, and Hwang (2012), investor sentiment is investors' perception of future investment risk and cash flow. Wurgler (2012) proposed in the special topic of investor sentiment in the Journal of Financial Economics that investor sentiment is a non-Bayesian belief of investors about the returns and risks of financial assets. The existing consensus view is that investor sentiment is the investor's expectation that investors have deviations in the future price of risky assets.

2.5 Characteristics of Investor Sentiment

2.5.1 Herd Mentality

Herd mentality is when people change their behaviour to conform to the group (Le Bon, 1895). Asymmetric and incomplete investor information, lack of professional knowledge and investment experience, and attempts to reduce search costs by imitating others are all investment herd behaviours in the financial market. Individual investors dominate most Chinese stock markets, with institutional investors accounting for a small portion. Individual investors largely blindly follow the behaviour and decision-making of others because it is often extremely difficult for them to grasp timely and effective information. In the financial market, investors' herd behaviour may result in the 'herd effect' of stock investment, which occurs when individual investors are influenced by other investors, imitate others' decisions, or rely too heavily on media information while making investment decisions due to information asymmetry. As a result, the stock market is volatile, and there is a positive leverage effect.

2.5.2 Over- and Under-reaction

Overreaction occurs when investors place undue emphasis on new information about their price expectations for the future. Inadequate response primarily refers to the fact that, despite having a certain amount of public information in the market, investors are unable to evaluate the price within a specific time frame, which ultimately affects the stock price. Overconfidence manifests itself in both overreacting and underreacting trading behaviours. Overconfidence primarily refers to people who are overconfident in all aspects of their abilities, believing that they can be successful while also dividing success into their own abilities, ignoring the role of indicators such as external forces, luck, and opportunities.

Overconfidence usually manifests itself in two ways. The first is a perception of inaccuracy in likelihood estimates. The second is that the confidence intervals for the quantity estimates are excessively narrow. The direct impact of overconfidence cause investors to over-rely on information compiled by themselves, affecting their attention to financial market-related information; the indirect impact of overconfidence cause investors to pay close attention to information that improves self-confidence while automatically blocking some content that is not conducive to self-confidence during the information analysis process.

Investors forecast future prices because they believe that public company stock prices are regular and easy to control. Since the future price of listed company stocks changes randomly, it can lead to overreaction and underreaction, which can have a serious impact on the stock price and value. Overconfidence among investors has caused the stock market to fluctuate wildly and exhibit a positive leverage effect. Investors are not only prone to overconfidence as stock market yields rise, but they also pay full attention to good news while automatically shielding other information. Investors believe that the stock market's upward trend is not reversed anytime soon, and even if the stock market has experienced significant changes, they still believe that the stock market would soon resume its upward trend and that they would continue to increase their holdings.

2.5.3 Characteristics of Investors' Risk Preference

Investor sentiment is related to a person's psychological biases and preferences. Psychological bias is the psychological feeling that investors have different assumptions than rational people based on cognitive activities. The discrimination of value and utility for different scenarios or event states is referred to as preference. Investors are classified as risk-averse, risk-neutral, or risk-loving. Investor risk appetite can be classified into four categories which are loss aversion, regret aversion, disjunction effect, and certainty effect.

Loss aversion refers to the need for people to protect their own interests through decision-making when they are aiming for gains or losses, and the characteristics of this decision-making behaviour are asymmetric. Losses cause people's emotions to fluctuate if losses and gains are equal; that is, when losses and gains are equal, investors would pay more attention to losses. The agony of losing an asset outweighs the joy of acquiring it.

People with regret aversion regret bad decisions they made. To avoid regret, investors generally make decisions after gathering specific information, or they may choose to forego deciding in an important matter, resulting in some irrational decision-making behaviours. The theory of regret aversion is divided into three parts. The situation of having to act due to being threatened occurs first, followed by the situation of regret. The level of regret is lower when compared to when there is no threat. Second, the regret caused by the wrong behaviour is far more serious than the regret caused by the wrong behaviour itself. Third, the regret caused by accepting responsibility for wrongdoing is greater than the regret caused by not accepting responsibility.

The disjunction effect refers to the fact that investors simplify the decision during the implementation process, and for various types of options, the content adjacent to each other is eliminated, leaving different content. The effects of the various option combinations are also different, so the damage must be eliminated by separation, but this situation undoubtedly affect the accuracy of the risk assessment. Some scholars have proposed the phenomenon of 'mental accounting,' which states that people would treat these undervalued assets carelessly or arbitrarily. Investors generally classify funds according to factors such as the source and use of funds, allocate funds to different psychological accounts, and make decisions separately.

The certainty effect states that people prefer things they are familiar with and do not prefer unfamiliar things as much. People tend to avoid uncertainty, despise subjective or ambiguous uncertainty, and even despise objective uncertainty. Investors prefer certain outcomes when there are certain outcomes and probable outcomes in future returns. Behavioural economists believe that when deciding, investors change their perception of risk based on their knowledge of risk. When investors determine future returns, they usually have a high-risk aversion, whereas when they determine losses, they have a low-risk appetite.

2.6 Theoretical Model of Investor Sentiment

2.6.1 DSSW Model

The DSSW model was used by De Long, Shleifer, Summers, and Waldmann (1990) to investigate the impact of noise traders on asset pricing. The model is used to solve two major problems. The first is to investigate how noise traders affect expected asset values, and the second is to explain why noise traders can obtain higher expected returns. The model implies that both rational and noisy traders exist in the market. The DSSW model demonstrates that there is a lot of unrelated information that can have an impact, and that noise traders can create their own space because the risky assets traded are systematically mispriced. Rational investors arbitrage because noise traders create valuation biases that keep assets from reaching average levels.

2.6.2 BSV Model

The BSV model was first proposed by Barberis, Shleifer, and Vishny (1998). This model focuses on the factors that influence investor sentiment in the stock market, as well as the quantitative analysis method. According to the BSV model, the selection bias and the conservatism bias are two types of cognitive biases that affect investors' stock market decision-making. The case of selection bias occurs when investors pay too much attention to market movements in a short period of time, and only pay attention to a few indicators in the market, while seriously ignoring the observation of the overall characteristics of the market, resulting in investors making incorrect decisions, referred to as overreacting. Conservatism bias implies that investors are unable to timely revise the increased forecasting model in response to market changes, thus missing the opportunity to reflect market changes in a timely manner, and there is a significant lag, referred to as underreacting. These two types of deviations differ significantly in sensitivity to market share price fluctuations, which explains why the market deviates from the effective hypothesis. Investors often group data that have similar characteristics but are substantially different in the same category and some investors are stressed when processing data because of outdated information.

2.6.3 DHS Model

The DHS model was proposed by Daniel, Hirshleifer, and Subrahmanyam (1998). In the model, there are four trading ranges for two types of investors which are knowledgeable traders and uninformed traders. The model, which is based on behavioural finance, provides a plausible explanation for short-term momentum and long-term reversal issues. Investors attribute some of success to ability rather than luck. Investors have low expectations for publicly available information but are extremely concerned about private information. Investors may overreact to private information in this case. Partial self-evaluation implies that when the market's direction demonstrates that the investor's decision was correct, they believe that their decision was very wise. When the results were incorrect, they assumed it was due to outside noise. When private information is good news, the rational expectation value rises, and the stock price rises, according to the DHS model. When the information is bad, the rational expectation value drops, and so does the stock price. As a result, depending entirely on private information gathered by investors to execute market trades is risky and must be supplemented with public data.

2.6.4 Unified Theoretical Model

The HS model, also known as the unified theory model, was proposed by Hong and Stein (1999). This model is based on the BSV and DHS models, which are concerned with the effects of everyone. This model is based on the BSV and DHS models, which primarily focus on the effect of everyone by analysing and treating the causes of everyone differently. This model divides investors into two groups, those who make judgments based on future asset value information and those who make the decisions based on historical changes. Both types of investors make use of publicly available information. According to this model, the underreaction and overreaction in the BSV and DHS models are caused by the exchange of value information. Investors underreacted because of the influence of private information. Momentum traders can be encouraged to participate in the transaction by giving momentum traders arbitrage space, and arbitrage also cause this segment of the population to overreact. As a result, when an arbitrage opportunity arises in the market, a large amount of capital pours in, resulting in an excess. Short-term arbitrage opportunities fade quickly, but arbitrage is always existed in the market in the long run.

2.6.5 The Herd Effect Model

The herd effect model was proposed by Froot, Scharfstein, and Stein (1992). (FSS model). Its model should comprehensively measure the trading situation of informed and uninformed traders, and market makers with a competitive mechanism are used as intermediaries in the trading process. Market makers are primarily responsible for collecting the specific values of the relevant parties' transaction orders and, as a result, know the market price. The model is classified as sequential or non-sequential. Banerjee (1992) proposed a model of sequential herding. The model believes that investors should understand the decisions of previous investors before making decisions. Many investors believe that previous investors can gather a lot of unknown information, which can affect the information they have, leading to follow-up behaviour and eventually rendering the market invalid. The decision-making sequence of investors is clarified in this model, and the Bayesian process is used to obtain previous investor and market noise information to complete its own decision-making. The Bayesian process is also used to generate the non-sequential herd effect model, and its imitation of the investment subject is fixed. If the imitation is improved, the main body of the market would collapse. When the imitation tendency is low, the income distribution follows the Gaussian distribution. The FSS model demonstrates that, rather than aggregating disparate information in large quantities, the market is obsessed with a small set of non-value-related company attributes.

2.7 Investor Sentiment Measurement Method

Although the selection and measurement of investor sentiment indicators have not yet formed a unified view, the approaches are varied, and the outcomes are abundant. Trading volume, turnover, and bid-ask spreads, according to Baker & Stein (2004), can be used to measure investor sentiment. Pontiff et al. (1995) suggested that closed-end fund discount can be used as a proxy variable to measure investor sentiment. Ljungqvist, Nanda, Singh (2006) believe that the first-day yield of IPO can be used as a factor to measure investor sentiment, because initial public offering (IPO) behaviours are more likely to occur when stock market sentiment is high, and companies are more inclined to Issue stocks when they are high. Barber et al. (2009) proposed that trading volume can be used as a feedback indicator of investor sentiment. The consumer confidence indicator, according to Lemmon & Portniaguina (2006), can replace the investor sentiment index. Baker and Wurgler (2006) used principal component analysis to create a comprehensive index of investor sentiment based on the turnover rate, dividends, discount rate of closed-end funds, proportion of new shares issued, and number of IPOs. This approach is supported by Yu & Yuan (2012), Ben-Rephael, Kandel & Wohl (2012), etc. In order to achieve the first objective, there is no hypothesis testing required, rather a principal components analysis is conducted on the objective and subjective investor sentiment index to from a single investor sentiment index.Baker and Wurgler (2007) further claim that characteristics such retail investor trading, mutual fund flow, trading volume, option implied volatility, and insider trading can be used into the development of investor sentiment indicators. Trading volume or turnover is considered an effective indicator of investor sentiment by Brown and Cliff (2004) and Baker and Wurgler (2006).

The American Association of Individual Investors Index, according to Schmeling (2007), can be used to gauge and assess investor mood. Ho (2012) created a complete sentiment index by combining the Michigan Consumer Sentiment Index (MS), CCI, and II. Baker, Wurgler, and Yu (2012) integrated data from Japan, the United States, Canada, the United Kingdom, Germany, and France to construct a complex sentiment indicator based on the number of IPOs, volatility returns, first-day returns, and trading volumes. Da, Engelberg & Gao (2015) measure changes in investor sentiment through the daily Internet searches of millions of households. Dimpfl & Kleiman (2016) investigate and query household search volume with the help of aggregated Google, and for the first time, an indicator about the pessimism of German market investors was put forward, and it was used as the standard of German retail investor sentiment.

2.8 Empirical Research on Investor Sentiment

Western scholars' research on investor sentiment mainly focuses on the determinants, patterns, and mechanisms of investor sentiment on the market. In contrast, Chinese scholars have little research on the relationship between investor sentiment and the market, and most of them are based on the existing research of Western scholars.

De Bondt's (1993) study found that there is a significant positive correlation between S&P500 returns and future changes in individual investor sentiment. According to Otoo (1999) & Fisher, Statman (2003), the return between the current stock market index and the confidence index has a positive impact, whereas the confidence index and the next return has a negative impact. Qiu & Welch (2004) research believes that investors' optimistic attitude would make small-cap stocks achieve better returns. Dorsaf, Ben & Aissia (2015) proposed that investor sentiment can reflect stock market returns and is a negative predictor.

Zhong (2015) proposed that stock prices are asymmetrically affected by investor sentiment. He, Zhu, Gu & Qian (2020) found that there is an asymmetry in the relationship between investor sentiment and stock market returns. Investor sentiment has a greater impact on the price of small-cap equities in the short run. Investor sentiment has a greater impact on the price of large-cap equities in the long run. Based on relevant research and analysis, Jiang et al. (2016) observed that there is negative impact between future stock market returns, and sentiment. According to Perez-Liston, Huerta, and Haq (2016), there is a positive correlation between changes in investor sentiment and changes in stock index returns. Seok, Cho & Ryu (2019) analysed and determined that the relationship between asset returns and investor sentiment in the Korean stock market is positive. The findings of Chue, Gul & Mian (2019) suggest that institutional investors can also be sentiment traders because beta returns are positive (negative) during bearish (bullish) periods. Only optimism can have a substantial non-linear effect on stock returns in the Chinese stock market, whether it is a balanced or bear market. Simultaneously, only pessimism has a non-linear effect on stock market volatility when the Chinese stock market is in a state of equilibrium. In this thesis, a hypothesis testing is required to analyse the relationship between investor sentiment and stock market returns. Refer to Timothy K. Chue，Ferdinand A. Gul & G. Mujtaba Mian（2019）, the null hypothesis of the study is there is no significant relationship between the single investor sentiment index and the yield of the Shanghai Composite Index. The alternative hypothesis is there is a significant interaction between the single investor sentiment index and the yield of the Shanghai Composite Index.

2.9 Conclusion

It is obvious that there are many problems that need to be solved in behavioural finance by introducing the origin and development of behavioural finance, the characteristics and theoretical models of investor sentiment, a review of research on the definition of investor sentiment, a review of research on investor sentiment measurement methods, and a review of scholars' empirical research on investor sentiment. For example, the theoretical framework lacks a unified theoretical foundation. Although the methods for selecting and measuring investor sentiment indicators are diverse, a unified view has not yet been formed. Chinese scholars have conducted little research on the relationship between investor sentiment and the market, and most of their findings are based on the work of Western scholars. The stock market in China is dominated by retail investors, with investment institutions accounting for only a small percentage of the market, making it prone to emotional volatility. As a result, the process of investigating the Chinese market must rely on Western scholars' research ideas and theoretical models to some extent, indicating that there are limitations.

CHAPTER 3: RESEARCH METHODOLOGY

3.1 Introduction

This chapter explains the research method to be deployed in this study. It presented the research paradigm, design, sampling technique, data collection method, as well as the hypothesis to be tested in this study.

3.2 Research Paradigm and Approach

This research use positivism to explore the relationship between investor sentiment and stock market returns. But the positivist approach is not a universal research model. Researchers can choose empirical research methods based on the specific circumstances of the problem.

The operating procedure of positivism in the study of the relationship between investor sentiment and stock market returns is as follows. First, transform the relationship between investor sentiment and stock market returns into actionable problems until the concepts involved in the problem can be accurately defined, manipulated, measured, and tested. Second, determine the possible link between the independent variable and the dependent variable. Finally, after the research questions and hypotheses are basically determined, a suitable research design is selected to test the hypotheses, which would become reliable knowledge.

3.3 Research Design

This is quantitative research that deploys the use of secondary data to establish the relationship between investor sentiment and stock market returns in the Chinese market, using the Shanghai Stock Exchange Composite Index. Quantitative research is preferred in the study compared to qualitative, as the study would empirically analyse the relationship between the two identified constructs (investor sentiments and stock returns). Subjective, objective, and comprehensive sentiment indicators were employed in this study to quantify investor sentiment; the subjective and objective sentiment indicators are parts of a single indication, and the comprehensive sentiment indicator is a composite of a single indicator. The measurement of a single indicator is not comprehensive, and it is often set only to solve a certain market anomaly. In order to address these issues and more precisely measure investor sentiment, comprehensive indicators typically employ principal component analysis to eliminate the influence of irrelevant factors (Baker & Wurgler, 2006).

Though a highly subjective approach of measuring sentiment, subjective sentiment indicators can acquire data by reflecting the emotional state of market participants. Although objective sentiment indicators can better capture changes in investor sentiment, all the data they use is post-event and cannot be used to predict an event ex ante. Most single indicators can only represent changes in a part of investor sentiment and are unable to measure investor sentiment completely. Therefore, it is possible to measure investor sentiment features more thoroughly by choosing two or more single indicators to extract sentiment factors.

3.4 Research Sampling

This research focuses on Chinese market, using the Shanghai Stock Exchange Composite Index to analyse the effect of investor sentiments on stock returns. Most Chinese stock markets are dominated by individual investors, who generally lack the necessary investment knowledge and skills and have obvious irrational trading behaviours. Severe fluctuations in investor sentiment would enhance the stock market's and even the financial market's uncertainty, as well as the possibility of systemic financial risks. Therefore, studying the relationship between investor sentiment and market returns is not only conducive to investors' rational stock investment, but also can maintain the stability of the national financial system and promote the healthy operation of the economy. Due to the obvious changes in the economic situation after the financial crisis in 2008 and before the Covid-19 epidemic, a total of 118 sample data from January 2010 to October 2019 were selected to objectively reflect the relationship between the two.

3.5 Data Collection Methods

This study primarily follows the approach of Baker and Wugler (2006) and Brown and Cliff (2004) as the ideological basis of the research, where the number of IPOs (IPON) and the first day return rate (IPOR), the market turnover rate (TURN), the price-earnings ratio (PE) as objective sentiment indicators and Consumer Confidence Index (CCI) as a subjective indicator.

IPO number, IPO first-day yield, market turnover, P/E ratio and Shanghai Composite Index Monthly Yield data is available on WIND database, Consumer Confidence Index is available on China Economic Database, which the researcher collected and downloaded into the Excel. Collecting data from WIND database and China Economic Database is the most appropriate forms of data collection. This is beneficial because large amounts of data can be collected quickly.

3.6 Data Analysis

To achieve the first research objective, this study used principal component analysis method to construct a single investor sentiment index using objective sentiment indicators and subjective sentiment indicators. This method is mostly used to tackle difficult issues that arise from the usage of too many indicators in the evaluation process. The fundamental concept is that if there are correlations between many indicators, a method can be utilized to combine them and create a new comprehensive indicator. Finally, these newly generated comprehensive indicators are used to replace the previous indicators. Researchers can only examine these comprehensive indicators if the original indicators to be investigated are all incorporated in a few main comprehensive indicators. While significant indicator information is not lost, the number of indicators is reduced, and the workload is greatly reduced.

To achieve the second research objective and test the research hypothesis, the Augmented Dickey Fuller (ADF) test; the Granger Causality test; Impulse Response Models and Variance Decomposition Analysis are used. The Augmented Dickey Fuller (ADF) test is the preliminary test to check the stationarity of the time series data. The Granger Causality test, Impulse Response Models and Variance Decomposition Analysis are used to analyse the correlation between the single investor sentiment and the monthly yield of the Shanghai Composite Index.

3.7 Ethical Consideration

This is quantitative research, which does not involve participation of human or animal during data collection and analysis. Therefore, the research does not pose any risk to humans or animals during the research process. However, the research must abide to the ethical policy of the University of Witwatersrand during this research process. Application for ethics approval has also been made, and permission obtained from the ethics committee of the university.

3.8 Conclusion

This chapter describes the data analysis research methods and design, including data collection methods and the interpretation of statistical techniques used in data analysis. Furthermore, the study’s limitations and any ethical considerations that may arise are listed, and ethics approval has been obtained. The research data is then constructed and analysed in this thesis.

CHAPTER 4: INVESTOR SENTIMENT INDICATOR CONSTRUCTION

4.1 Introduction

This thesis mainly adopts the practice of Baker and Wugler (2006); Brown and Cliff (2004) and uses the principal component analysis method to set up a composite indicator of investor sentiment. The following is an introduction to subjective, objective, and comprehensive sentiment indicators.

4.2 Measure of Investor Sentiment

Subjective, objective, and comprehensive sentiment indicators are indicators used to measure investor sentiment. The subjective and objective sentiment indicators belong to a single indicator, while the comprehensive sentiment indicator is a compound of a single indicator. A single indicator is set only to address one market anomaly and is therefore not comprehensive. To evaluate investor sentiment more accurately, the comprehensive index uses the principal component analysis method to eliminate the interference of irrelevant elements.

4.2.1 Subjective Sentiment Indicators

Using surveys to properly comprehend the actual sentiments of investors is one technique to gather subjective sentiment indicators. However, as researchers must measure factors such as questionnaires and survey objects to compile subjective investor sentiment measures, overall objectivity is lacking. At present, the subjective sentiment indicators used in China include the Consumer Confidence Index, the Entrepreneur Confidence Index, the Business Prosperity Index, and the Economist Confidence Index issued by the National Bureau of Statistics.

4.2.2 Objective Sentiment Indicators

The public trading data in the securities market is used to generate objective sentiment indicators. The number of initial public offerings (IPON), the first-day IPO rate of return (IPOR), the number of newly opened accounts (NIAC), the market turnover ratio (TURN), the price-earnings ratio (PE), stock trading volume, and other objective sentiment indicators are the most used.

4.2.3 Comprehensive Sentiment Indicators

Single indicators are subjective and objective sentiment indicators, whereas comprehensive sentiment indicators are more complicated indicators. Although subjective sentiment indicators can obtain data by reflecting the emotional state of market investors, they are highly subjective; while objective sentiment indicators can accurately capture the changes in investor sentiment by arranging the data obtained, so they cannot be used for pre-forecasting. Most single indicators cannot accurately measure investor sentiment; instead, they can only reflect changes in the sentiments of a portion of investors. As a result, investors' sentiment characteristics can be measured more extensively by selecting two or more single indicators to extract sentiment factors.

4.3 Selection of Investor Sentiment Indicators

For the selection of sentiment indicators, comprehensively considering the availability and stability of data, the number of IPOs and the first-day yield, market turnover, and price-earnings ratio are selected as objective indicators and consumer confidence index as subjective indicators.

4.3.1 Number of IPOs and First-day Yield

Investor sentiment, according to Ljungqvist and Wilhelm (2003), Ljungqvist, Nanda and Singh (2006), Baker and Wurgler (2006), has a significant impact on IPOs and their pricing. As a result, the first-day yield can be used to measure investor confidence. The first-day yield of an IPO has a generally positive relationship with investor sentiment. When investor sentiment is high, for example, the company's first-day issue price and first-day yield on new shares are both high. On the other hand, if market sentiment is negative, the corporation would lower the price and yield on the first day of the stock offering.

4.3.2 Market Turnover Rate

Turnover refers to the frequency with which stocks change hands in the market during a certain period. It is regarded by many scholars as a proxy indicator of investor sentiment. Turnover is a measure of how high investor sentiment is. A high turnover rate indicates that market transactions are active and investor sentiment is high; a low turnover rate indicates that market transactions are sluggish and investor sentiment is low.

4.3.3 P/E Ratio

Generally, investors would use the price-earnings ratio as a leading indicator to measure market volatility. When the price-earnings ratio is relatively high, investors would be in high mood; if the price-earnings ratio is relatively low, the investor's mood is low. The price-earnings ratio has a positive correlation with investor sentiment. Therefore, investors' choice of price-earnings ratio can be used to reflect the degree of speculation in the market.

4.3.4 Consumer Confidence Index

The Consumer Confidence Index is a measure of consumer confidence in the current and future state of the economy. There is a positive correlation between the investor sentiment and consumer confidence index, according to numerous research. The improvement of consumer confidence shows that they are optimistic about the current economic situation, and investor sentiment would be very high; the downturn in consumer confidence means that investors have no confidence in the current economic situation, and investor sentiment would be very low.

4.4 Analysis of the Results of Investor Sentiment Indicators Construction

This research selects the number of IPOs, first-day yield, market turnover rate, and price-earnings ratio as objective indicators and consumer confidence index as subjective indicators and explores investor sentiment in the stock market from January 2010 to October 2019 through principal component analysis, and construct investor sentiment indicators based on comprehensive scores.

4.4.1 ADF Test

In this thesis, when the IPON sequence, IPOR sequence, TURN sequence, PE sequence and CCI sequence are tested, the stationarity test is implemented by the ADF unit root test method. The null hypothesis of the ADF unit root test is a non-stationary sequence, and the alternative hypothesis is that there is no unit root, which is a stationary sequence. The ADF test results of each sequence are shown in Table 4.1.

Table 4.1 Stationarity Test of Investor Sentiment Indicators

Variables	T-Statistic	Prob.*
IPON	—16.46206	0.0000
IPOR	—10.98902	0.0000
TURN	—11.21548	0.0000
PE	—3.200197	0.0224
CCI	—12.85385	0.0000

IPOR and PE are all zero-order single integers, and IPON, TURN and CCI are first-order single integers, and the stationarity assumption is accepted after the first-order difference, which is consistent with zero-order single integers. It can be seen from Table 4.1 that the ADF statistic P values of IPON, IPOR, TURN, PE and CCI are all less than 0.05, so the null hypothesis is rejected, that is, IPON, IPOR, TURN, PE and CCI are all stationary sequences. From this, it can be judged that the number of IPOs and the first-day yield, market turnover rate, price-earnings ratio, and consumer confidence index are all balanced sequences, and empirical analysis can be continued.

4.4.2 Principal Component Extraction

Principal component analysis is a statistical analytic method with a wide range of applications. Principal component analysis combines different indicators with correlation into a new comprehensive indicator, and these new indicators are not correlated with each other. Finally, use these newly generated comprehensive indicators to replace the previous indicators for analysis. These new comprehensive indicators are not only irrelevant, but they also have an obvious feature: the first comprehensive indicator comprises the largest number of previous indicators, followed by the second, and so on. If all the original indicators that need to be investigated are included in the first few major comprehensive indicators, this thesis can only focus on them. As a result, the number of indicators can be reduced without losing important indicator information, and the workload can be greatly reduced. This thesis uses the principal component analysis method to extract the principal components. Table 4.2 gives the value, proportion, and cumulative proportion.

Table 4.2 Principal Component Analysis for Constructing Sentiment

Number	Value	Difference	Proportion	Cumulative Value	Cumulative Proportion
1	1.332715	0.229580	0.2665	1.332715	0.2665
2	1.103135	0.084122	0.2206	2.435850	0.4872
3	1.019013	0.055637	0.2038	3.454862	0.6910
4	0.963376	0.381614	0.1927	4.418238	0.8836
5	0.581762	---	0.1164	5.000000	1.0000

This research extracts 4 principal components, the proportions of these 4 principal components are 26.65%, 22.06%, 20.38% and 19.27% respectively, and the cumulative contribution rate reaches 88.36%, that is, the 4 principal components can explain 88.36% of the variation information of the original indicator, a more comprehensive alternative to the original indicator. So, extract 4 principal components to construct investor sentiment.

Table 4.3 Component Matrix

Variable	PC 1	PC 2	PC 3	PC 4
IPON1	0.023258	0.841674	0.140044	0.323383
IPOR	0.712889	0.229037	0.037520	0.150385
TURN1	0.247923	-0.156949	-0.821499	0.410014
PE	0.108784	-0.438561	0.520931	0.706383
CCI1	0.646490	-0.148856	0.180969	-0.453563

From Table 4.3, the first principal component F1 has the largest load in IPOR, with a coefficient of 0.712889, followed by the consumer confidence index with a coefficient of 0.646490, and the market turnover rate with a coefficient of 0.247923. The first principal component is mainly affected by Impact of IPOR. The loading factor of the second principal component F2 in the number of IPOs is 0.841674, so the second principal component is most affected by the number of IPOs. The load factor of the third principal component F3 in the price-earnings ratio is 0.520931, so the third principal component is most affected by the price-earnings ratio. The load factor of the fourth principal component F4 in the price-earnings ratio is 0.706383, so the fourth principal component is also most affected by the price-earnings ratio. It can be seen from the load distribution of the component matrix that the investor sentiment in the stock market is mainly affected by three aspects, namely IPOR, number of IPOs and price-earnings ratio. The following formula can be used to determine the specific score of each principal component, as shown in Table 4.3.

$$F1= 0.023258IPON_t + 0.712889IPOR_t + 0.247923TURN_t + 0.108784PE_t + 0.646490CCI_t$$

$$F2= 0.841674IPON_t + 0.229037IPOR_t - 0.156949TURN_t - 0.438561PE_t - 0.148856CCI_t$$

$$F3= 0.140044IPON_t + 0.037520IPOR_t - 0.821499TURN_t + 0.520931PE_t + 0.180969CCI_t$$

$$F4= 0.323383IPON_t + 0.150385IPOR_t + 0.410014TURN_t + 0.706383PE_t - 0.453563CCI_t$$

4.5 Conclusion

This thesis determines the comprehensive score formula based on proportion and cumulative proportion as follows.

$$\text{Composite Score/IS} = (26.65\%F1 + 22.06\%F2 + 20.38\%F3 + 19.27\%F4)/ 88.36\%$$

The overall score of investor sentiment in the stock market from January 2010 to October 2019 may be determined by substituting the principal component score into the calculation, and is denoted by the symbol IS.

CHAPTER 5: AN EMPIRICAL ANALYSIS OF THE IMPACT OF INVESTOR SENTIMENT ON CHINA’S STOCK MARKET RETURNS

5.1 Introduction

This chapter firstly introduces the market environment of the investor sentiment studied in this thesis—the Shanghai stock market. Second, use Granger’s (1969) causality test to study the relationship between investor sentiment and stock market returns. At the same time, impulse response analysis is used to comprehensively examine the dynamic relationship between the monthly returns of the Shanghai Composite Index and investor sentiment. Finally, variance decomposition is used to measure the degree of reaction of investor sentiment and Shanghai Composite Index monthly yield to each other’s shocks.

To empirically analyse the link between the two variables, the monthly return of the Shanghai Composite Index is utilized as the explained variable, while the investor sentiment/IS obtained through principal component analysis is used as the explanatory variable. This empirical study covers the period from January 2010 to October 2019, with a total of 118 sample data sets.

5.2 Overview of Shanghai Stock Exchange

The Shanghai Stock Exchange, referred to as the SSE, was established on November 26, 1990, and opened on December 19 of the same year. By the end of 2020, there were 1,800 companies listed on the Shanghai Stock Exchange, with a total market value of RMB45.5 trillion. In 2020, the cumulative turnover of stocks was RMB84.0 trillion, with an average daily turnover of RMB345.6 billion. The number of listed stocks in the fund market reached 373, with a cumulative turnover of RMB10.8 trillion; the cumulative turnover of the derivatives market for the year was RMB716.7 billion. The number of investors in the Shanghai Stock Exchange has reached 275.5 million (Shanghai Stock Exchange, 2022).

5.3 Empirical Analysis of the Relationship between Investor Sentiment and Shanghai Composite Index Monthly Yield

5.3.1 Granger Causality Test

This research uses Granger’s (1969) causality test to test the causal relationship between the two variables, that is, to investigate whether the monthly return of the Shanghai Composite

Index is caused by investor sentiment or whether the monthly return of the Shanghai Composite Index is the cause of investor sentiment.

Table 5.1 Stationarity Test

Variables	T-Statistic	Prob.*
IS	-11.56157	0.0000
R	-9.292023	0.0000

As in the previous section, this research conducts the ADF stationarity test on the investor sentiment index (IS) and the Shanghai Composite Index return (R). Both series clearly reject the null hypothesis, as evidenced by the test findings in Table 5.1. That is, neither series has a unit root, and both series are significantly stationary.

Table 5.2 Granger Causality Test

Dependent variables: IS

Excluded	Chi-sq	df	Prob.
R	4.764086	2	0.0924
All	4.764086	2	0.0924

Dependent variables: R

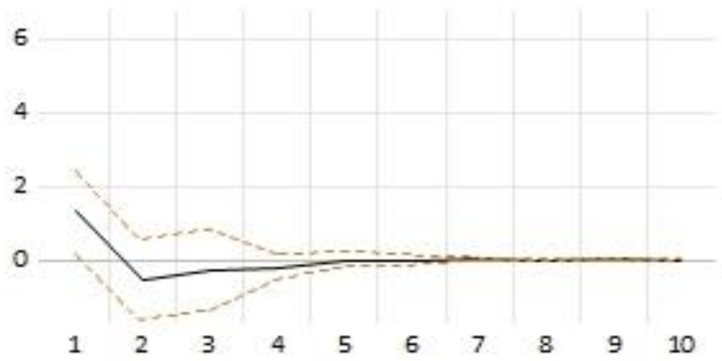
Excluded	Chi-sq	df	Prob.
IS	2.109950	2	0.3482
All	2.109950	2	0.3482

Table 5.2 shows that at the 5% level of significance, it can be inferred that there is no Granger causality between investor sentiment and the monthly return of the Shanghai Composite Index. As the Granger causality test can neither indicate the dynamic characteristics of a system, nor can it reflect the degree of influence between investor sentiment and the return of the Shanghai Composite Index. Therefore, this thesis uses impulse response function analysis and variance decomposition to analyse the influence degree of each variable in the system.

5.3.2 Impulse Response Function Analysis

This thesis uses the impulse response function to analyse the direction, magnitude, and duration of the dynamic impact of changes in investor sentiment on the returns of the Shanghai Composite Index.

Figure 5.1 Response of R to IS



From Figure 5.1, in the period 1-10, the reaction of investor sentiment to one unit of information on the monthly return of the Shanghai Composite Index changed from positive to negative, that is, there was a certain underreaction to overreaction. From the first period, investor sentiment reacted positively to the impact of one unit of information on the monthly yield of the Shanghai Composite Index, and then gradually attenuated. In the second period, the negative reaction of investor sentiment to the one-unit information shock of the Shanghai Composite monthly yield peaked, and then the degree of negative impact weakened. When the fifth period is reached, the reaction of investor sentiment to the shock of one unit of the monthly return of the Shanghai Composite Index gradually tends to balance.

Investor sentiment has a positive impact on the monthly return of the Shanghai Composite Index most of the time, according to the results of the impulse response analysis, while the monthly return of the Shanghai Composite Index has a negative impact on investor sentiment. This lays the groundwork for the next step in the variance decomposition to measure the degree of mutual explanation between investor sentiment and the Shanghai Composite's monthly returns.

5.3.3 Variance Decomposition Analysis

The principle of variance decomposition is to measure the contribution of each shock to the change of a variable by variance. It can be used to measure the degree to which investor sentiment is affected by the impact of the Shanghai Composite Index's monthly yield, and the degree to which the Shanghai Composite Index's monthly return is affected by the impact of investor sentiment, to measure the degree to which two variables respond to each other's shocks.

Table 5.3 Variance Decomposition of Investor Sentiment

Variance Decomposition of IS:			
Period	S.E.	IS	R
1	1.344591	100.0000	0.000000
2	1.374689	96.09483	3.905168
3	1.421227	96.30484	3.695160
4	1.424372	96.19074	3.809257
5	1.427803	96.20471	3.795292
6	1.428254	96.19837	3.801633
7	1.428565	96.19945	3.800548

8	1.428624	96.19895	3.801048
9	1.428654	96.19901	3.800991
10	1.428661	96.19898	3.801022

Table 5.3 shows that the fluctuation of investor sentiment in the first period is only affected by its own fluctuation. At the beginning of the second period, the impact of the monthly yield of the Shanghai Composite Index on investor sentiment began to show. At the same time, under the influence of the shock, investor sentiment began to develop towards a strengthening trend, but the overall impact is far less than the impact of investor sentiment fluctuations on their own. The shock response tends to be stable as the shock length increases, in the 10th period, the contribution of investor sentiment to itself was stable at 96.20%, and the contribution of the monthly return of the Shanghai Composite Index to investor sentiment was stable at 3.80%, with a limited contribution. It shows that the volatility of investor sentiment is mostly endogenous.

Table 5.4 Variance Decomposition of the Monthly Returns of the Shanghai Composite Index

Variance Decomposition of R:			
Period	S.E.	IS	R
1	6.196607	4.595637	95.40436
2	6.335132	5.170268	94.82973
3	6.361558	5.369295	94.63071
4	6.370327	5.474259	94.52574
5	6.370447	5.474069	94.52593
6	6.370548	5.476449	94.52355
7	6.370550	5.476491	94.52351
8	6.370559	5.476766	94.52323
9	6.370560	5.476775	94.52322

10	6.370560	5.476795	94.52321

From Table 5.4, the fluctuation of the monthly return of the Shanghai Composite Index in the first period is only affected by its own fluctuations to a degree of 95.40%. At the beginning of the second period, the impact of investor sentiment on the monthly return of the Shanghai Composite Index began to appear, and the impact of this impact on the monthly return of the Shanghai Composite Index showed a gradually increasing trend. The overall impact, however, is far less than the monthly rate of return on the Shanghai Composite Index. Investor sentiment’s contribution to the variation of the Shanghai Composite Index’s monthly yield increased from 5.17 percent in the second period to 5.48 percent in the tenth period.

As a result, the contribution of the Shanghai Composite Index’s monthly return to investor sentiment is 3.80 percent lower than the contribution of investor sentiment to the Shanghai Composite Index’s monthly return of 4.60 percent. That is, the extent to which investor sentiment explains the monthly return of the Shanghai Composite Index is greater than that of the monthly return of the Shanghai Composite Index for investor sentiment. That is, changes in investor sentiment would largely cause changes in the monthly return of the Shanghai Composite Index, while changes in the monthly return of the Shanghai Composite Index would cause less changes in investor sentiment.

5.4 Conclusion

Based on empirical analysis, there is no Granger causality between investor sentiment and the monthly return of the Shanghai Composite Index. Investor sentiment has a positive impact on the monthly return of the Shanghai Composite Index most of the time, according to impulse response analysis, while the monthly return of the Shanghai Composite Index has a negative impact on investor sentiment. The variance decomposition analysis indicates that investor sentiment explains the Shanghai Composite Index monthly return to a higher extent than the Shanghai Composite Index monthly return explains the investor sentiment.

CHAPTER 6: CONCLUSION AND RECOMMENDATIONS

6.1 Introduction

This thesis takes investor sentiment as the explanatory variable, and the monthly return of the Shanghai Composite Index as the explained variable. Through the Granger causality test, impulse response function analysis and variance decomposition analysis, this thesis illustrates the relationship between investor sentiment and the monthly return of the Shanghai Composite Index. The sample interval is 118 samples from January 2010 to October 2019.

6.2 Summary of Findings

Through principal component analysis, this study effectively constructs the comprehensive investor sentiment index, or IS, and the cumulative contribution rate of extracted information reaches 88.36%, making it a more comprehensive substitute for the original index. Through the load distribution of the component matrix, it is found that the investor sentiment in the stock market is mainly affected by four aspects. According to the degree of influence, the first principal component is composed of the first-day yield of IPO, consumer confidence index, and market turnover rate. The second principal component consisting of the number of IPOs and the first-day yield of IPOs. The third principal component is composed of price-earnings ratio, consumer confidence index, and the number of IPOs, and the fourth principal component is composed of price-earnings ratio, market turnover, and the number of IPOs. Since investor sentiment is influenced by subjective sentiment indicators and objective sentiment indicators, which can more fully reflect investor sentiment, this thesis suggests that investor sentiment can be employed as a tool for market analysis.

There is no Granger causality between investor sentiment and the Shanghai Composite Index's monthly return. That is, the monthly return of the Shanghai Composite Index is not the cause of the Granger of investor sentiment, and the monthly return of the Shanghai Composite Index is not the cause of the Granger of investor sentiment. Investor sentiment has a positive impact on the monthly return of the Shanghai Composite Index most of the time, according to the results of the impulse response analysis, while the monthly return of the Shanghai Composite Index has a negative impact on investor sentiment. According to the variance decomposition analysis, the monthly return of the Shanghai Composite Index contributes 3.80 percent less to investor sentiment than the contribution of investor sentiment to the monthly return of the

Shanghai Composite Index, which is 4.60 percent. That is, the proportion of the Shanghai Composite Index's monthly return explained by investor sentiment is greater than the proportion of the Shanghai Composite Index's monthly return explained by investor sentiment.

6.3. Policy Implications and Recommendation

Based on the empirical results of this thesis, the researcher believes that the Chinese government, the China Securities Regulatory Commission, and other relevant departments should actively carry out the exploration and construction of China's securities market system, regulate and guide securities market transactions, to create a securities market system transaction mechanism with Chinese characteristics. At the same time, the government should also strengthen the supervision of the market, improve the punishment and supervision system, disclose false information in a timely manner, and prevent and severely punish acts of maliciously spreading false information to disrupt the securities market.

The empirical findings of this thesis demonstrate that investor sentiment has a positive impact on the Shanghai Composite Index's monthly return, suggesting that the two are related. Therefore, incorporating the investor sentiment index as an important reference index into the early warning index system of the securities market can capture the dynamic changes of the investor sentiment index and provide an important reference value for market early warning analysis and judgment. In addition, to better reflect the relationship between investor sentiment and stock market returns, future research needs to enhance the reliability and rationality of indicators and data to enhance the validity of empirical results.

6.4 Recommendation for Further Research

Although this thesis has carried out empirical research on the relationship between investor sentiment and stock market returns, there are still many aspects of this research that need to be further explored. In the future research, further research can be done on the reasons and process of investor sentiment formation and the complete measurement method of investor sentiment.

In addition, the construction of sentiment index in this research mainly focuses on the relationship between it and the time series of returns. Less attention has been paid to the cross-sectional aspect and the use of sentiment index to explain the existence of financial anomalies in the Shanghai market, and further discussion and research are needed.

6.5 Conclusion

This thesis takes the research of investor sentiment and stock market returns as the starting point, using the practice of Baker and Wugler (2006); Brown and Cliff (2004). Four objective sentiment indicators and one subjective sentiment indicator are selected, and principal component analysis method is used to construct a single investor sentiment indicator. Using investor sentiment as the explanatory variable and the monthly return of the Shanghai Composite Index as the explained variable, it is shown that investor sentiment has a positive impact on the monthly return of the Shanghai Composite Index, and investor sentiment has a higher degree of explanation for the monthly return of the Shanghai Composite Index, as determined by impulse response function analysis and variance decomposition.

The following recommendations are provided based on the empirical findings: Improve the investor sentiment index and stock market return index; accelerate the construction of China's securities capitalistic system to explore and improve the trading mechanism for the advancement of the securities market; strengthen financial market supervision and improve the supervision system; and establish an early warning system for investor sentiment risk.

The study of the relationship between investor sentiment and stock market results is already complete. However, due to a lack of research capability, the thesis still has several deficiencies and problems that would require further investigation and exploration in the future.

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APPENDICES

Stationarity Test

Null Hypothesis: D(IPON) has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 0 (Automatic - based on SIC, maxlag=12)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-16.46206	0.0000
Test critical values:	1% level	-4.039075	
	5% level	-3.449020	
	10% level	-3.149720	

*MacKinnon (1996) one-sided p-values.

Sample (adjusted): 2010M03 2019M10
Included observations: 116 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(IPON(-1))	-1.414372	0.085917	-16.46206	0.0000
C	0.136427	0.665980	0.204852	0.8381
@TREND("2010M01")	-0.002473	0.009756	-0.253495	0.8003

R-squared	0.705743	Mean dependent var	0.025862
Adjusted R-squared	0.700535	S.D. dependent var	6.427470
S.E. of regression	3.517328	Akaike info criterion	5.378802
Sum squared resid	1397.991	Schwarz criterion	5.450016
Log likelihood	-308.9705	Hannan-Quinn criter.	5.407711
F-statistic	135.5092	Durbin-Watson stat	2.064677
Prob(F-statistic)	0.000000		

Null Hypothesis: IPOR has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 0 (Automatic - based on SIC, maxlag=12)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-10.98902	0.0000
Test critical values:	1% level	-4.038365	
	5% level	-3.448681	
	10% level	-3.149521	

*MacKinnon (1996) one-sided p-values.

Sample (adjusted): 2010M02 2019M10
Included observations: 117 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
IPOR(-1)	-1.029037	0.093642	-10.98902	0.0000
C	0.151836	0.052464	2.894106	0.0046
@TREND("2010M01")	0.002848	0.000790	3.606203	0.0005

R-squared	0.514396	Mean dependent var	0.001813
Adjusted R-squared	0.505876	S.D. dependent var	0.387429
S.E. of regression	0.272339	Akaike info criterion	0.261769
Sum squared resid	8.455218	Schwarz criterion	0.332594
Log likelihood	-12.31348	Hannan-Quinn criter.	0.290523
F-statistic	60.37954	Durbin-Watson stat	1.985661
Prob(F-statistic)	0.000000		

Null Hypothesis: D(TURN) has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 1 (Automatic - based on SIC, maxlag=12)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-11.21548	0.0000
Test critical values:	1% level	-4.039797	
	5% level	-3.449365	
	10% level	-3.149922	

*MacKinnon (1996) one-sided p-values.

Sample (adjusted): 2010M04 2019M10
Included observations: 115 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(TURN(-1))	-1.313031	0.117073	-11.21548	0.0000
D(TURN(-1),2)	0.417183	0.085576	4.875013	0.0000
C	-0.001105	0.039950	-0.027664	0.9780
@TREND("2010M01")	-6.35E-05	0.000583	-0.108952	0.9134

R-squared	0.557167	Mean dependent var	-0.002139
Adjusted R-squared	0.545198	S.D. dependent var	0.307504
S.E. of regression	0.207378	Akaike info criterion	-0.274387
Sum squared resid	4.773611	Schwarz criterion	-0.178911
Log likelihood	19.77725	Hannan-Quinn criter.	-0.235634
F-statistic	46.55293	Durbin-Watson stat	1.881296
Prob(F-statistic)	0.000000		

Null Hypothesis: PE has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on SIC, maxlag=12)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-3.200197	0.0224
Test critical values:	1% level	-3.487046	
	5% level	-2.886290	
	10% level	-2.580046	

*MacKinnon (1996) one-sided p-values.

Sample (adjusted): 2010M02 2019M10
Included observations: 117 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
PE(-1)	-0.094297	0.029466	-3.200197	0.0018
C	1.353593	0.474066	2.855283	0.0051

R-squared	0.081772	Mean dependent var	-0.116844
Adjusted R-squared	0.073788	S.D. dependent var	1.311375
S.E. of regression	1.262067	Akaike info criterion	3.320324
Sum squared resid	183.1734	Schwarz criterion	3.367541
Log likelihood	-192.2390	Hannan-Quinn criter.	3.339494
F-statistic	10.24126	Durbin-Watson stat	1.729477
Prob(F-statistic)	0.001775		

Null Hypothesis: D(CCI) has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 0 (Automatic - based on SIC, maxlag=12)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-12.85385	0.0000
Test critical values:	1% level	-4.039075	
	5% level	-3.449020	
	10% level	-3.149720	

*MacKinnon (1996) one-sided p-values.

Sample (adjusted): 2010M03 2019M10
Included observations: 116 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(CCI(-1))	-1.187655	0.092397	-12.85385	0.0000
C	-0.158401	0.459752	-0.344536	0.7311
@TREND("2010M01")	0.006102	0.006749	0.904119	0.3679

R-squared	0.593851	Mean dependent var	0.006034
Adjusted R-squared	0.586663	S.D. dependent var	3.775583
S.E. of regression	2.427371	Akaike info criterion	4.637017
Sum squared resid	665.8108	Schwarz criterion	4.708230
Log likelihood	-265.9470	Hannan-Quinn criter.	4.665925
F-statistic	82.61165	Durbin-Watson stat	2.013393
Prob(F-statistic)	0.000000		

Principal Component Analysis

Included observations: 117 after adjustments
Balanced sample (listwise missing value deletion)
Computed using: Ordinary correlations
Extracting 5 of 5 possible components

Eigenvalues: (Sum = 5, Average = 1)

Number	Value	Difference	Proportion	Cumulative Value	Cumulative Proportion
1	1.332715	0.229580	0.2665	1.332715	0.2665
2	1.103135	0.084122	0.2206	2.435850	0.4872
3	1.019013	0.055637	0.2038	3.454862	0.6910
4	0.963376	0.381614	0.1927	4.418238	0.8836
5	0.581762	---	0.1164	5.000000	1.0000

Eigenvectors (loadings):

Variable	PC 1	PC 2	PC 3	PC 4	PC 5
IPON1	0.023258	0.841674	0.140044	0.323383	0.408479
IPOR	0.712889	0.229037	0.037520	0.150385	-0.644444
TURN1	0.247923	-0.156949	-0.821499	0.410014	0.266324
PE	0.108784	-0.438561	0.520931	0.706383	0.159640
CCI1	0.646490	-0.148856	0.180969	-0.453563	0.566942

Ordinary correlations:

	IPON1	IPOR	TURN1	PE	CCI1
IPON1	1.000000				
IPOR	0.133815	1.000000			
TURN1	-0.064248	0.124036	1.000000		
PE	-0.071480	0.054952	-0.020453	1.000000	
CCI1	-0.098922	0.305260	-0.003429	0.005805	1.000000

Stationarity Test

Null Hypothesis: IS has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 0 (Automatic - based on SIC, maxlag=12)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-11.56157	0.0000
Test critical values:	1% level	-4.038365	
	5% level	-3.448681	
	10% level	-3.149521	

*MacKinnon (1996) one-sided p-values.

Sample (adjusted): 2010M02 2019M10
Included observations: 117 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
IS(-1)	-1.072033	0.092724	-11.56157	0.0000
C	3.653246	0.417265	8.755216	0.0000
@TREND("2010M01")	-0.004272	0.003897	-1.096369	0.2752

R-squared	0.539935	Mean dependent var	-0.014051
Adjusted R-squared	0.531863	S.D. dependent var	2.064463
S.E. of regression	1.412516	Akaike info criterion	3.553929
Sum squared resid	227.4529	Schwarz criterion	3.624753
Log likelihood	-204.9048	Hannan-Quinn criter.	3.582683
F-statistic	66.89543	Durbin-Watson stat	1.979359
Prob(F-statistic)	0.000000		

Null Hypothesis: R has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 0 (Automatic - based on SIC, maxlag=12)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-9.292023	0.0000
Test critical values:	1% level	-4.038365	
	5% level	-3.448681	
	10% level	-3.149521	

*MacKinnon (1996) one-sided p-values.

Sample (adjusted): 2010M02 2019M10
Included observations: 117 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
R(-1)	-0.853780	0.091883	-9.292023	0.0000
C	-0.157915	1.157874	-0.136384	0.8918
@TREND("2010M01")	0.005371	0.017044	0.315142	0.7532

R-squared	0.431105	Mean dependent var	0.084157
Adjusted R-squared	0.421124	S.D. dependent var	8.170445
S.E. of regression	6.216392	Akaike info criterion	6.517563
Sum squared resid	4405.362	Schwarz criterion	6.588388
Log likelihood	-378.2774	Hannan-Quinn criter.	6.546317
F-statistic	43.19421	Durbin-Watson stat	1.949424
Prob(F-statistic)	0.000000		

Granger Causality Test

Sample: 2010M01 2019M10
Included observations: 116

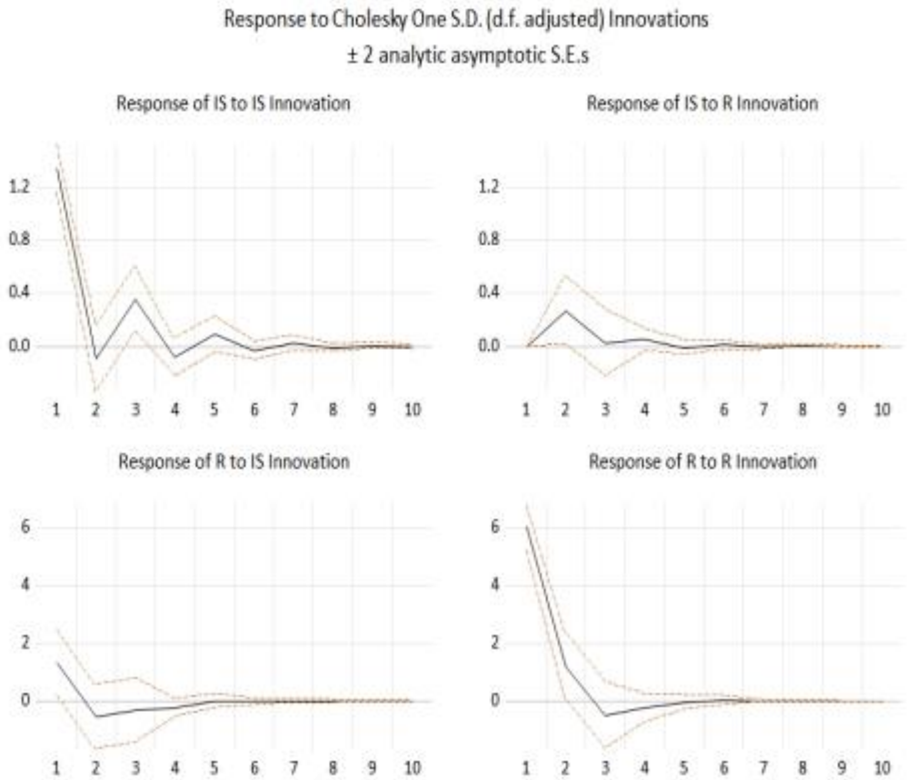
Dependent variable: IS

Excluded	Chi-sq	df	Prob.
R	4.764086	2	0.0924
All	4.764086	2	0.0924

Dependent variable: R

Excluded	Chi-sq	df	Prob.
IS	2.109950	2	0.3482
All	2.109950	2	0.3482

Impulse Response Function Analysis



Variance Decomposition Analysis

Variance Decomposition of IS:

Period	S.E.	IS	R
1	1.344591	100.0000	0.000000
2	1.374689	96.09483	3.905168
3	1.421227	96.30484	3.695160
4	1.424372	96.19074	3.809257
5	1.427803	96.20471	3.795292
6	1.428254	96.19837	3.801633
7	1.428565	96.19945	3.800548
8	1.428624	96.19895	3.801048
9	1.428654	96.19901	3.800991
10	1.428661	96.19898	3.801022

Variance Decomposition of R:

Period	S.E.	IS	R
1	6.196607	4.595637	95.40436
2	6.335132	5.170268	94.82973
3	6.361558	5.369295	94.63071
4	6.370327	5.474259	94.52574
5	6.370447	5.474069	94.52593
6	6.370548	5.476449	94.52355
7	6.370550	5.476491	94.52351
8	6.370559	5.476766	94.52323
9	6.370560	5.476775	94.52322
10	6.370560	5.476795	94.52321

Cholesky One S.D. (d.f. adjusted)
Cholesky ordering: IS R