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Taxing Investor Emotions: An Analysis of Stamp Duty Policy and its Influence on the China Stock Market

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Master in Finance

Supervisor:
PhD, Luciana Salles Barbosa, Assistant Professor,
ISCTE-IUL

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BUSINESS SCHOOL

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Acknowledgment

As I complete this study on the policy of stamp duty and its impact on the Chinese market, my heart is filled with gratitude and reflection. This research not only is a milestone in my academic life but also reflects my profound interest to financial markets. Here, I would like to express my deep thanks to all supporters.

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The motivation of this paper stems from my curiosity about stock market fluctuations and my desire is to explore the effects of macroeconomic policy. I have always believed that through in-depth analysis and research, valuable insights can be quantified so that providing constructive suggestions to investors and policymakers. This belief has supported me through countless studies until midnight, it is a driving force that propels me forward

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Overall, thanks for your reading.

Resumo

Este estudo investiga a impressão imediata do ajuste do imposto de selo no mercado de ações chinês, com especial ênfase em como estas mudanças políticas influenciam o sentimento dos investidores e, subsequentemente, o desempenho do mercado a curto prazo. Reconhecemos que o sentimento dos investidores é um fator crítico na resposta do mercado de ações a anúncios de políticas importantes, como refletido nos retornos anormais observados durante estes períodos. Para quantificar esse sentimento, utilizamos *Principal Component Analysis (PCA)* para construir índices que encapsulam a psicologia coletiva dos traders. Além disso, aplicamos *Granger causality test* para explorar a potencial relação preditiva entre o sentimento dos investidores e os retornos do mercado. A nossa investigação também incorpora a análise de resposta ao impulso para examinar as ligações dinâmicas entre o sentimento dos investidores e as tendências dos índices, proporcionando uma compreensão mais profunda de como esses fatores interagem ao longo do tempo. Nossa análise está fundamentada na metodologia do estudo de eventos, que é implementada na avaliação do impacto dos anúncios de políticas sobre os retornos anormais, oferecendo assim uma visão abrangente das implicações estratégicas dessas mudanças políticas. O nosso estudo lança luz sobre a dinâmica complexa entre os retornos do mercado e o sentimento dos investidores, oferecendo aos formuladores de políticas e participantes do mercado insights valiosos sobre os efeitos a curto prazo, para que possam compreender o efeito das medidas fiscais no mercado de ações.

Palavras-chave: imposto de selo, sentimento dos investidores, *Principal Component Analysis*, *Granger causality test*, função de resposta a impulsos, estudo de eventos.

Abstract

This study investigates the immediate impression of stamp duty adjustment on the Chinese stock market, with a particular emphasis on how these policy changes influence investor sentiment and, subsequently, the short-term market performance. We recognize that investor sentiment is a critical factor in the stock market response to major policy announcements, as reflected in the abnormal returns experienced during these times. To quantify this sentiment, we employ Principal Component Analysis (PCA) to construct indices that encapsulate the collective trader psychology. Furthermore, we apply the Granger causality test to explore the potential predictive relation between investor sentiment and market returns. Our research also incorporates impulse response analysis to examine the dynamic linkages between investor sentiment and index trends, providing a deeper understanding of how these factors interact over time. We ground our analysis in the framework of event study methodology, which is implemented in assessing the impact of policy announcements on abnormal returns, thus offering a comprehensive view of the strategic implications of such policy shifts. Our study sheds light on the complex dynamics between market returns and investor sentiment, offering policymakers and market participants valuable insights into the short-term effects so as to comprehend the effect of fiscal measures on the stock market.

Keywords: stamp duty, Investor Sentiment, Principal Component Analysis, Granger causality, Impulse response function, Event study.

Contents

List of Abbreviations

PCA	Principal Component Analysis
IRF	Impulse Response Function
ADF	Augmented Dickey-Fuller
VAR	Vector Autoregression Model
OLS	Ordinary Least Squares
ETF	Exchange Traded Fund
CBOE	Chicago Board Options Exchange
CSI	China Securities Index
MSCI	Morgan Stanley Capital International
SHCOMP	Shanghai Composite Index
SZSE	Shenzhen Stock Exchange
RSI	Relative Strength Index
RSIDC	Overbought & Oversold Deviation Coefficient
PCR	Put-Call Ratio
OIV	Option Implied Volatility
PDR	Stock Index Futures Premium/Discount Rate
IRP	Implied Risk Premium
VR	Volatility Volume Ratio
ADR	Advance/Decline Ratio
ALU	Actual Number of Limit Up
IM	Stock Index Momentum
MPP	Margin Purchase Proportion
AR	Abnormal Return
CAR	Cumulative Abnormal Return
CAAR	Cumulative Average Abnormal Return

CHAPTER 1

Introduction

The macroeconomic landscape is shaped by two primary tools of government policy: fiscal and monetary policies. These are often employed in tandem or separately to steer the macroeconomy toward growth and stability and to address various economic challenges. However, the effectiveness of these policies is not immediate; they are subject to a lag period, which is the time it takes for the policy changes to be implemented and for their effects to be observed in the economy.

Martijn Boons (2015) has highlighted the consistency between macroeconomic activity and market risk premium through time series analysis of macroeconomic factors such as the three-month Treasury bond interest rate. This consistency indicates that capital markets are responsive to macroeconomic policies, albeit with a rapid and effective reaction.

The literature on the influence of stamp duty adjustments on the financial market is extensive, with scholars employing diverse research methods and considering a range of influencing factors. For instance, Marco, C., Antonio, G., & Andreas, U. (2022) explored the effects of the financial transaction tax (FIT) on different types of traders, noting its influence on aspects such as the spread of ask-bid prices and price volatility. In this paper, we will draw upon our extensive experience in securities trading to focus specifically on the China stock market. Our aim is to identify the factors that are susceptible to changes in China's stamp duty and to understand the implications of these changes on the stock market.

As a trader, it is crucial to select appropriate data as benchmarks during trading hours while the access is limited. This selection can be the key to maximizing profits or securing gains. Therefore, to ensure investors can obtain in a timely manner, all the data will be carefully selected from real-time market.

As a form of government tax, stamp duty can influence the liquidity of the stock market and can either stimulate or inhibit market activity. This paper employs an event study approach, focusing on the announcement made on August 28, 2023, that the stamp duty on China's securities transactions would be halved from 1‰ to 0.5‰, with a subsequent adjustment after 15 years.

The study examines whether this policy measure can stimulate the short-term stock market and what the primary objectives of the stamp duty adjustment are. The research provides a new perspective to help all market participants better understand the impact of stamp duty adjustments on stock market. By quantifying investor sentiment and analyzing market feedback on the first trading day of the event, we found that reducing stamp duty has a certain stimulating effect on the stock market, which is mainly reflected in enhancing market confidence and easing the downward trend of the market. However, this impact may only be temporary. It cannot fundamentally reverse the overall long-term market trend. Furthermore, the paper also revealed that the main purpose of stamp duty adjustment is to improve the pessimistic sentiment of investor, which prevent continuous selling caused by market panic so that avoiding the occurrence of stock market crashes. All in all, the reduction of stamp duty can boost the market in the short term while the long-term effect is required further observation and analysis

The structure of this paper is as follows: Section 2 retraces the related paper and outlines our contributions to the field. Section 3 detailed explains the data collection and variables used in the study. Section 4 introduces the methods for constructing the sentiment index as utilized in the paper. Section 5 conducts an empirical analysis of investor sentiment and stock returns. Based on event study methodology, Section 6 aims to identify significant abnormal returns. Finally, Section 7 presents the discussion and concluding remarks.

CHAPTER 2

Literature Review

2.1 Investor Sentiment & Market Return

Investors determine the willingness to buy or sell. When there is big news, investor sentiment dominates the willingness of traders to buy or sell, no matter who is on or off the exchange. Brown et al. (2005) explored how investor sentiment could affect both short-term and long-term markets, finding that short-term stock market returns could directly affect investor sentiment while the reverse relation is not apparent. In the long term, investor sentiment is negatively correlated with future market returns. However, Yanran Wu et al. (2007), based on the concept that investor sentiment is not entirely rational, empirically found that investor sentiment has a significant positive impact on short-term market returns while there is a reverse impact in the long term. Also, Malcolm Baker and Jeffrey Wurgler's (2006) conditional characterization model shows that in the context of the (1961) U.S. dot-com bubble market, investor sentiment has a clear cross-sectional effect on stock market return. High sentiment is more conducive to the rise of stocks of comprehensive growth and high dividend companies, and the opposite is true when sentiment is low. They all focused on analyzing the interactive relation between market and investor sentiment. However, the confirmation of these conclusions relies heavily on various company data or exchange data, such as dividend premiums, number of IPOs, etc. Most of the company information is disclosed in financial statements, typically with a quarterly lag while the data from the exchange is disclosed monthly.

Staring at tourism stock market investor sentiment, Peng et al. (2023) analyzed the time-series positive impact of investor sentiment on capital flows and observed market fluctuations caused by sentiment during the COVID-19. Hu & Sun (2024) push a salience theory as a reliable investor sentiment measure, finding that in the China stock market, the salience theory can significantly predict the market return as there is a pricing effect for the consensus of sentiment. Xiao et al. (2024) explored the effect of different types of policy uncertainty under a “good” or “bad” volatility in the Chinese market by assessing investor sentiment as the role between policy uncertainty and stock market volatility. They discovered that investor sentiment can mitigate a positive effect with policy uncertainty on "bad" volatility. Meanwhile, Chen et al. (2024) constructed a sentiment index with the perspective of margin trading business, exploring that its impact on the fluctuation of China stock market indices across several time scales. It concluded that investor sentiment has an asymmetric effect on market index fluctuations at multiple time scales.

The Chicago Board Options Exchange (CBOE) published the Put-Call Ratio, which is also used by academic researchers and market analysts to study and interpret market dynamics. Many studies recognized it as an indicator of investor sentiment; if the volume of put options traded exceeds that of call options, it can be inferred that investors anticipate a decrease in stock market returns. In addition, the Relative Strength Index (RSI) created by Welles Wilder in 1978, was initially used for futures trading and was later found by many investors to be quite effective for guiding stock investments as well.

2.2 Investor Sentiment & Market Behavior

In the opening of the secondary market, where investors have limited information in a short timeframe, and many are not researchers capable of data modeling and analysis, we take a versatile approach to select factors influencing investor sentiment. Academic research by Lucy F. Ackert and Richard (2009) in behavioral finance explored investor mindsets and behaviors linked to psychology. The disposition effect, where investors prefer selling profitable stocks while holding the losing stocks, indicates risk aversion in both profit and loss scenarios. The casino effect suggests that easy profits make investors more risk-taking. The anchoring effect shows that investors anticipating a bull market, especially in response to positive news like a reduction in stamp duty, are more likely to be confident and hold or increase investments, contributing to increased market trading volume.

In a favorable market, we observe the existence of hot-hand effect, which means the investor making a profitable trade will believe that the subsequent trades will also be profitable. Additionally, the casino effect also tends to display. Therefore, examining the ratio of market rises and falls will help grasp overall market profitability for the day, serving as an indicator of investor sentiment and reflecting optimism or confidence in the investment decisions.

2.3 Experience of Investor Sentiment Construction

2.3.1 Investor Sentiment Explicit Indicators

Explicit investor sentiment indicator is also named direct indicator. It stands for the process where researchers or institutions design survey questionnaires, then distribute them to the target group for collecting the answers. They use it for data analysis to get the targets' expectations on the future market. The statistical results of overall data can visually represent most of the investor sentiment in the market. Presently, the most common used of explicit indicators by worldwide researchers contains:

1. HADady Index. It is also well known as the Investor Sentiment Friendly Index. By directly consulting with large fund companies or institutional investors, it is constructed with their opinions to the future market trend. In addition, this index also incorporates the weekly trading viewpoint from financial media. Through the concordance of these professional views, it is able to form a comprehensive expectation of the future market movement.

2. American Individual Investors Association Index. The American Individual Investors Association will investigate the investment attitudes among its clients to yield result which is representative to their investment sentiment. Fishe (2000) defined the individual sentiment index as the proportion of individuals holding a bullish outlook. This index is useful to predict future returns of the S&P 500 index after statistical and econometric analysis. However, it was considered as a powerful contrarian indicator at that time. For instance, if 1% decrease in the individual sentiment index, there will be about 0.1% increase in the S&P 500 returns over the following month.

3. The Investors Intelligence Index is built by taking surveys through the media to calculate the difference of proportion of investors who are bullish while others are bearish. Most of the time, the target of this survey are often institutional investors or major players in the stock market. It is no doubt that this index can also on behalf of sentiment to a certain extent.

2.3.2 Investor Sentiment Implicit Indicators

Implicit investor sentiment indicator is also called indirect indicator. It bases on the directly trading data that can reflect investor sentiment in securities market. These indicators are often required the further processing of quantitative program to form the sentiment index. Indicators that could reflect the market's activity level as follow: the discount rate of closed-end funds (CEFD), trading volume, the number of new shares issued, market turnover rate, the put-call transaction ratio, etc.

The Chicago Board Options Exchange (CBOE) published the Put-Call Ratio, which is also used by academic researchers and market analysts to study and interpret market dynamics. Many studies recognized it as an indicator of investor sentiment; if the volume of put options traded exceeds that of call options, it can be inferred that investors anticipate a decrease in stock market returns. Furthermore, the Relative Strength Index (RSI) created by Welles Wilder in 1978, was initially used for futures trading and was later found by many investors to be quite effective for guiding stock investments as well.

In Smales's study written in 2016, an innovative methodology was introduced to seize the investor sentiment. With the help of news information related to major international banks, Smales (2016) examining the correlation between investor sentiment and the spreads of LIBOR-OIS and CDS. The principal of this approach is that the sentiment preference in news could reflect the psychological disposition of market participants. Proceeding to the next step, it will affect the evaluation of market interest rates and credit risk assessments.

Like what Smales did, Wang, Changyun, et al. (2015) also investigated the influence of investor sentiment on market actions. They quantified the number of positive and negative terms reported by mainstream media before an IPO (initial public offering) company goes public to be a proxy variable for investor sentiment. This study provided an IPO pricing strategy following the core of sentiment. It implicates that investor sentiment is of important to a company valuation as well as the initial performance of its stock price.

2.4 Abnormal Return

The literature on abnormal returns in stock markets offers a multifaceted perspective on the factors influencing financial performance. Mollet, von Arx, and Ilic (2013) delved into the nexus between strategic sustainability and financial success. They suggested that small and innovative firms with robust Corporate Social Responsibility (CSR) practices may cause a positive abnormal return due to the growing interest in Socially Responsible Investing (SRI). Meanwhile, there is a further exploration supported by Doryab and Salehi (2018), who employed the Nash nonlinear grey Bernoulli model to forecast the abnormal return, demonstrating its superiority in accuracy over the traditional grey model.

Cyree and DeGennaro (2001, 2002) proposed a generalized event study method with extending beyond conventional approaches. It allows for the detection of implicit changes in systematic risk and event periods that are tailored to the individual firm. Their work highlights the importance of considering the parameter shifts and the variance changes for a more accurate assessment of abnormal returns. In addition, Thuy et al. (2019) contributed to this discourse by examining the influence of microeconomic factors on the abnormal return with listed companies in Vietnam, revealing that profitability, capital structure, and growth rate are positively associated with abnormal returns, while firm size is inversely related. All in all, these studies provide ideas for us to understand the complex dynamics driving stock market returns. It offers an inside view of seeking to navigate market volatility for investors and policymakers.

This paper expands on the cross-sectional study of the relation between investor sentiment and market return did by (Malcolm et al., 2006), incorporating time series to conduct an event study for the main intention of this stamp duty adjustment. It is worth noting that in this paper, not only in terms of the type and frequency of factor but also in the process of establishing a comprehensive sentiment index is different. To identify the most intuitive factors affecting investor sentiment over short periods, we adopt the control variable concept. This involves fixing nonsensitive factors for sentiment while focusing on those that are representative in the Secondary Market Level.

Therefore, from the perspective of cross-section, we will base on several historical constructions of sentiment indicator. It selects direct market data that can reflect changes in sentiment, which investors can intuitively obtain over a short period of time, to establish a grading model for sentiment factors. Following this, PCA (Principal Component Analysis) is used for dimensionality reduction to identify and construct the sentiment index.

CHAPTER 3

Data & Variables

3.1 Data Source & Timeframe Selection

The data in this report are sourced from Bloomberg News, the world's largest financial information company, known for its unquestionable authority and reliability. We are tasked with gathering comprehensive daily sentiment decompositions over a specified period for subsequent analysis. The timeframe of interest spans from May 24, 2022, to November 28, 2023, with the considerations of the open & close price of two important China stock market indices: the Shanghai Composite Index, identified by 000001SS, and the Shenzhen Stock Exchange Index, identified by 399001SZ.

In addition to the Chinese indices, our research will also delve into the daily value of the MSCI Global Index, which serves as a broad measure of the international stock market performance. The inclusion of the MSCI Global Index in our data collection is crucial for our event study, as it will enable us to contextualize the findings within a global investment landscape. This index includes a diverse representation of companies across developed and emerging markets, making it a valuable benchmark for better understanding the impact of economic events on equity markets.

3.2 Relevant Variables

In traditional financial theory, it is assumed that all investors are rational, which means the efficient market is always existing. On this basis, investors can process information effectively and then make reasonable judgments about the value of securities. In this case, investor sentiment does not reflect in the prices of securities. However, in the real market, investors are often irrational and are usually driven by two emotions: fear and greed. Excessive fear can cause stock prices to fall significantly below their intrinsic value, while excessive greed can drive stock prices to rise sharply, well above their intrinsic value. Therefore, investor sentiment should be considered an important part of market characteristics. In this paper, drawing on the scoring method of the CNN Money sentiment index, this paper constructs a short-term market sentiment index by applying the principal component analysis (PCA) to the scored factors. The more panicked investors are, the smaller the index value.

This section describes the meaning and calculation methods of the decomposition indicators. We take sample from the construction of the well-known sentiment indices in U.S. stock market, such as the CNN Fear & Greed Index, with that of the CITIC

Securities Sentiment Index in China. A total of 10 decomposition indicators are utilized by the index to identify potential proxy indicators for investor sentiment, and overall, they all fall into the category of financial market trading performance indicators.

Investor Sentiment Decomposition Indicators:

a) Overbought & Oversold Deviation Coefficient "RSIDC"

The Overbought & Oversold coefficient is based on the RSI (Relative Strength Index) indicator, which is the sum of the market's price gains divided by the sum of the market's price advances. When signals of being overbought or oversold appear, it is common for the RSI index to reverse its trend, leading to an increase in volatility. Therefore, a sharp increase in the deviation coefficient implies that investors are optimistic about the future market direction, with correspondingly increased greed, and the indicator is positively correlated with the sentiment index. The calculation method involves using the standard deviation and mean of the RSI over the previous six trading days to create a ratio.

$$RSIDC = \frac{RSI_{\sigma_6}}{RSI_{mean_6}} \tag{3.1}$$

b) Put-Call Ratio in Options Trading "PCR"

If investors believe that the stock market will fall in the future, they will purchase more put options. Therefore, an increase in the trading volume of put options indicates that investors have a more bearish sentiment towards the future than a bullish one, and the indicator is negatively correlated with sentiment. The calculation method involves the ratio of puts to calls in the daily trading volume of the CSI 300 ETF.

$$PCR = \frac{Number\ of\ Puts_{daily}}{Number\ of\ \ Calls_{daily}} \tag{3.2}$$

c) Option Implied Volatility "OIV"

The implied volatility of options measures the market's expectation of future asset price volatility. An increase in implied volatility indicates that the market anticipates greater price fluctuations in the future, which can increase market uncertainty and lead to the emergence of investor panic sentiment. Therefore, the indicator is negatively correlated with the sentiment index. The calculation method involves multiplying the sum of the trading volumes of all the traded contracts of the CSI 300 ETF options by the implied volatility of the CSI 300 ETF to derive the implied volatility of the options.

$$OIV = IV_{CSI\ 300\ etf} * \sum CSI\ 300\ etf\ trading\ volumes \tag{3.3}$$

d) Stock Index Futures Premium/Discount Rate "PDR"

Reflecting investors' expectations to the market trends in future, the rise or fall of stock index futures prices relative to spot index prices is desirable. When the premium widens or the discount narrows, it indicates that investors have an optimistic attitude towards the future, which can easily lead to a surge in market sentiment. Therefore, this indicator shows a positive correlation with the sentiment index. The calculation method involves dividing the gap between CSI 300 futures price and the spot index price by the current price of the index.

$$PDR = \frac{Future\ price_{CSI\ 300} - Index_{CSI\ 300}}{Index_{CSI\ 300}} \tag{3.4}$$

e) Implied Risk Premium "IRP"

The implied risk premium reflects an overall attractiveness of stock market and bond market to investors, indirectly reflecting investors' risk preferences. When the implied risk premium rises, stocks become more attractive to investors, which is conducive to an increase in the sentiment index. Conversely, when the premium falls, investors prefer bonds with lower risk, indicating an increased risk of a stock market downturn. This indicator is positively correlated with sentiment. The calculation method involves taking the D-value between inverse of the price-to-earnings ratio with the All A-shares and the yield of two-year government bonds.

$$IPR = \frac{1}{\left(\frac{P}{E}\right)_{TTM}} - Two\ Year\ Treasury\ Yield \tag{3.5}$$

f) Volatility Volume Ratio "VR"

Volume can reflect the activity level of investors on a given day, but it does not necessarily indicate the direction of the market for that day. Therefore, this paper will utilize the volatility rate of the trading volume of the CSI 300 Index to represent the overall vigor of buying and selling in the market. When this indicator increases from a low base, it suggests that investors are predominantly engaged in buying, which corresponds to a positive investment sentiment. Consequently, It presents a positive correlation between this indicator and the investor sentiment.

g) Advance/Decline Ratio "ADR"

The Advance/Decline Ratio (ADR) is the ratio of the number of stocks that increased in price to the number of stocks that decreased in price in the market each day. It infers the balance of power between bulls and bears in the stock market, thereby reflecting the actual trends of investor behavior in the stock market for that day. An increase in the ADR indicates a high level of enthusiasm in investment sentiment, showing a positive correlation.

$$ADR = \frac{Up_{daily}}{Down_{daily}} \tag{3.6}$$

h) Actual Number of Limit Up "ALU"

In the Chinese stock market, certain stocks have daily price movement limits. For companies with stock codes starting with 60 and 00, the daily range limit is ±10%, and for those starting with 30, it is ±20%. The presence of a price limit up (i.e., a stock hitting its maximum allowed price increase for the day, known as a "trading limit" or "daily limit") indicates a high level of investor sentiment. Therefore, this indicator represents the actual direction of change in investor sentiment and shows a positive correlation.

$$ALU = Limit\ Up_{daily} - Limit\ Down_{daily} \tag{3.7}$$

i) Stock Index Momentum "IM"

The indicator primarily focuses on the general trend of significant market indices, measuring the overall direction of the index. If the indicator is high, it suggests that the stock index is accelerating upwards, reflecting a greedy investor sentiment. It shows a positive correlation with the indicator and investor emotion; significant changes in the Stock Index Momentum (IM) often imply a reversal in sentiment. This paper posits that the stock prices of companies ranked 300-500 by market value in the Chinese market are more representative of sentiment, as they have good liquidity and activity, and are evenly distributed across various sectors, allowing changes in investor sentiment to better react in the stock prices. The indicator is positively related to sentiment. The calculation method involves taking the difference between the closing price of the CSI 500 Index and its 125-day moving average.

$$IM = CSI\ 500 - CSI\ 500_{125-Day\ Moving\ Average} \tag{3.8}$$

j) Margin Purchase Proportion "MPP"

MPP (Margin Purchase Proportion) refers to the proportion of the amount of funds bought on margin to the total market transaction volume. A higher ratio indicates a higher level of investor leverage and stronger bullish sentiment in the market. In 2015, China's stock market experienced a sharp fluctuation, known as the "Leverage Bull Market." During this period, the market grew rapidly, and to pursue higher returns, many investors increased their market leverage through margin trading (i.e., borrowing money to buy stocks). This led to a surge in stock market turnover and an increase in speculative behavior. Shanghai Composite Index (SHCOMP) rose from around 3,000 points in 2014 to 5,178 points in June 2015, making the indicator positively correlated with sentiment.

$$MPP = \frac{Margin\ Purchase}{Market\ Transaction\ Volume} \tag{3.9}$$

The collection of these daily data will involve rigorous scrutiny of various financial metrics and market movements, ensuring that the information is accurate, up-to-date, and relevant to our study's objectives. In the following sections, we analyze the construction of the sentiment index and its predictive power separately, ultimately ensuring that fluctuations in investor sentiment will affect the performance of the stock market.

CHAPTER 4

Sentiment Index Construction

In this section, we first need to conduct factor detection and preprocessing of the data. Then, through dimensionality reduction methods, we need to select the factors that accumulated explain at least 80% of the sentiment. Geometric weighted of each factor matrix with its according proportions of sentiment that explains, ultimately resulting in the Chinese Investor Sentiment Index.

Therefore, it is significant to note that, unlike the setting model, we ought to conduct factor detection first to ensure the accuracy of the subsequent construction of the sentiment index.

4.1 Multicollinearity Test

From the correlation of the decomposed indicators in the Table 4.1 below, the implied risk premium has a higher correlation coefficient with the premium/discount rate and market momentum. At the same time, the ratio of the number of stocks that hit the daily limit up or down and the actual number of stocks that hit the daily limit up are also relatively high, but their values are only around 0.6, which means they cannot completely substitute for each other. Therefore, in general, the independence between the factors is relatively strong, and they can all be included separately in the construction of the sentiment index.

Table 4.1- Investor Sentiment Index Decomposition Indicator Correlation

	RSIDC	PCR	OIV	PDR	IRP	VR	ADR	ALU	IM	MPP
RSIDC	1.0000									
PCR	0.0767	1.0000								
OIV	0.0078	0.2576	1.0000							
PDR	0.1812	-0.1431	0.1077	1.0000						
IRP	0.3065	-0.1671	0.1608	0.6154	1.0000					
VR	-0.4104	0.0474	0.0337	-0.4822	-0.4764	1.0000				
ADR	0.0438	-0.1827	0.0312	-0.0633	-0.0496	0.1824	1.0000			
ALU	-0.0957	-0.0683	0.2195	-0.0105	0.0100	0.3124	0.5920	1.0000		
IM	-0.2504	0.1314	-0.0352	-0.1329	-0.5689	0.2434	0.1079	0.0306	1.0000	
MPP	-0.3825	-0.1416	-0.2073	-0.4153	-0.3656	0.1899	0.1229	-0.0062	0.2401	1.0000

Annotation: RSIDC- overbought & oversold deviation coefficient; PCR- put-call ratio in options trading; OIV- option implied volatility; PDR- stock index futures premium/discount rate; IRP - implied risk premium; VR- volatility volume ratio; ADR- advance/decline ratio; ALU- actual number of limits up; IM- stock index momentum; MPP- margin purchase proportion.

The research time series we are looking for is centered around the first trading day following the announcement date of August 27, 2023, which is August 28, 2023, with a span of 60 trading days before and after. Therefore, the first adjusted value of the factor will appear on June 1st. The method for adjusting the factor values and scoring them is as follows.

4.2 Grading Sentiment Factors

Firstly, standardize each measurement indicator by calculating the adjusted value against its historical mean and standard deviation. The higher the score of each decomposed indicator's adjusted value, the more it represents a greedy sentiment, while a lower score indicates greater investor panic. Specifically, the adjusted value is obtained by subtracting the mean of each decomposed data from the previous 250 trading days and then dividing by the standard deviation calculated by prior 250 trading days. If the decomposed indicator is negatively correlated with the sentiment indicator, it is necessary to process the sign of the indicator, that is, to multiply each value by -1. Subsequently, the cumulative normal distribution is used to find the cumulative function value of the adjusted indicator, which is the scoring value.

4.3 PCA Constructing Sentiment Index

Based on the scoring values of each decomposed indicator, principal component analysis (PCA) is used. It aims is to screen out the most influential factors.

The first step is to standardize the scoring values of each factor, followed by a feasibility test for factor analysis. Then, we look for the presence of factor outliers. The appearance of outliers indicates that a larger portion of the variable remains unexplained in the principal component and that the variable has a lower correlation with the principal component (i.e., factors with uniqueness greater than 0.6 are excluded). Next, calculate the characteristic values of each factor and their contribution rates in the regression. Here, the criteria for selecting factors as principal components are factors with all characteristic values approximately equal to 1 and a cumulative contribution rate greater than 80%. The factors screened out through the above process are the components that mainly make up the sentiment index. Second step involves conducting principal component forecasting for the factors that have been screened out. The sentiment index, which is the comprehensive indicator of sentiment, is then calculated by dividing the weighted average of the forecasted scores by the cumulative contribution rate.

The analysis results from Table 4.2 which examines all the factors, indicate that the p-value from the factor analysis is notably significant. This statistical significance suggests that the factor analysis model is meaningful for the data set in question. The KMO measure of sampling adequacy is calculated to be 0.561, which is above the acceptable threshold of 0.5, further supporting the suitability of conducting a principal component analysis (PCA) on the set of variables.

Table 4.2- Factor Characteristic Value and Elimination Analysis

```
. norm x1-x10, method(mmx)

. factortest mmx_x1-mmx_x10

Determinant of the correlation matrix
Det                  =     0.060


Bartlett test of sphericity

Chi-square           =          325.357
Degrees of freedom   =               45
p-value              =            0.000
H0: variables are not intercorrelated


Kaiser-Meyer-Olkin Measure of Sampling Adequacy
KMO                 =     0.561

. factor mmx_x1-mmx_x10 ,pcf
(obs=121)

Factor analysis/correlation                    Number of obs    =        121
    Method: principal-component factors        Retained factors =          4
    Rotation: (unrotated)                      Number of params =         34
```

Factor	Eigenvalue	Difference	Proportion	Cumulative
Factor1	2.62091	0.69886	0.2621	0.2621
Factor2	1.92205	0.58579	0.1922	0.4543
Factor3	1.33626	0.21478	0.1336	0.5879
Factor4	1.12147	0.19548	0.1121	0.7001
Factor5	0.92599	0.23071	0.0926	0.7927
Factor6	0.69528	0.22739	0.0695	0.8622
Factor7	0.46789	0.12177	0.0468	0.9090
Factor8	0.34613	0.00978	0.0346	0.9436
Factor9	0.33635	0.10868	0.0336	0.9772
Factor10	0.22767	.	0.0228	1.0000

```
    LR test: independent vs. saturated:  chi2(45) =  328.17 Prob>chi2 = 0.0000

Factor loadings (pattern matrix) and unique variances
```

Variable	Factor1	Factor2	Factor3	Factor4	Uniqueness
mmx_x1	-0.6042	0.3888	0.5238	-0.0706	0.2044
mmx_x2	0.4063	-0.1021	0.2254	0.0758	0.7680
mmx_x3	0.6201	-0.4662	0.3034	-0.1948	0.2682
mmx_x4	-0.3879	-0.1219	-0.4216	0.6301	0.2599
mmx_x5	-0.1239	0.5817	-0.3870	-0.5877	0.1510
mmx_x6	0.8236	0.0450	-0.0701	-0.2060	0.2722
mmx_x7	0.2146	0.7358	0.2362	0.3905	0.2042
mmx_x8	0.4061	0.7056	0.3024	0.1358	0.2273
mmx_x9	0.7089	-0.0541	-0.0504	0.3413	0.3754
mmx_x10	0.3854	0.3816	-0.6609	0.0201	0.2686

However, despite the characteristic value of the factor mmx_x2 exceeding the value of

1 - which typically would suggest that the factor carries significant variance - the uniqueness associated with mmx_x2, representing the "Put-Call Ratio in Options Trading" is found to be greater than 0.6 in the outlier detection process. The high uniqueness value implies that a substantial portion of the variance, specifically over 60%, within this variable remains unaccounted for by the principal components selected by the PCA model. This indicates that the variable mmx_x2 does not align well with the other factors and may introduce statistical issues that could distort the analysis.

Given these considerations, it is determined that the variable mmx_x2 should be removed from the PCA to maintain the integrity and reliability of the sentiment index construction. By excluding this variable, the PCA can proceed with a more coherent set of factors that exhibit stronger interrelations and are better suited to represent the underlying structure of the data in the context of the sentiment index. After excluding the outlier variable, a principal component analysis (PCA) was reconducted on the remaining factors. From the result of Table 4.3, KMO = 0.551 indicates that the remaining variables are still suitable for principal component factor analysis, and no outliers are present in any of the variables. Therefore, we can proceed to the next step. Despite the characteristic value of factor 5 being only about 0.73, it is obvious that the first five principal components account for a cumulative contribution rate of 0.844. Hence, to meet the primary requirement of cumulative contribution rate must larger than 0.8, we will select factors 1 through 5 as the principal components for forecasting. The final sentiment index will be:

$$Sentiment\ Index = \frac{0.2793 * \mathrm{f1} + 0.2128 * \mathrm{f2} + 0.1464 * \mathrm{f3} + 0.1245 * \mathrm{f4} + 0.081 * \mathrm{f5}}{0.8440}$$

where:

- f_i = the grading value of each factor (i=1,2,3,4,5)

Table 4.3- Sentiment Principal Component Construction Index

```
. factortest mmx_x1 mmx_x3 mmx_x4 mmx_x5 mmx_x6 mmx_x7 mmx_x8 mmx_x9 mmx_x10

Determinant of the correlation matrix
Det                 =     0.069


Bartlett test of sphericity

Chi-square          =           310.429
Degrees of freedom  =                36
p-value             =             0.000
H0: variables are not intercorrelated


Kaiser-Meyer-Olkin Measure of Sampling Adequacy
KMO               =     0.551
```

```
. factor mmx_x1 mmx_x3 mmx_x4 mmx_x5 mmx_x6 mmx_x7 mmx_x8 mmx_x9 mmx_x10 ,pcf
(obs=121)

Factor analysis/correlation                        Number of obs    =        121
    Method: principal-component factors            Retained factors =          4
    Rotation: (unrotated)                          Number of params =         30
```

Factor	Eigenvalue	Difference	Proportion	Cumulative
Factor1	2.51365	0.59805	0.2793	0.2793
Factor2	1.91560	0.59787	0.2128	0.4921
Factor3	1.31772	0.19759	0.1464	0.6386
Factor4	1.12014	0.39140	0.1245	0.7630
Factor5	0.72874	0.25791	0.0810	0.8440
Factor6	0.47083	0.10269	0.0523	0.8963
Factor7	0.36814	0.03174	0.0409	0.9372
Factor8	0.33639	0.10760	0.0374	0.9746
Factor9	0.22880	.	0.0254	1.0000

```
    LR test: independent vs. saturated:  chi2(36) =  313.10 Prob>chi2 = 0.0000

Factor loadings (pattern matrix) and unique variances
```

Variable	Factor1	Factor2	Factor3	Factor4	Uniqueness
mmx_x1	-0.6048	0.4222	-0.4987	-0.0632	0.2032
mmx_x3	0.5946	-0.4869	-0.3408	-0.1800	0.2608
mmx_x4	-0.3916	-0.1079	0.4662	0.6071	0.2491
mmx_x5	-0.0846	0.5780	0.3941	-0.6043	0.1383
mmx_x6	0.8276	0.0102	0.0398	-0.2032	0.2721
mmx_x7	0.2244	0.7361	-0.2066	0.3878	0.2148
mmx_x8	0.4324	0.6909	-0.3147	0.1503	0.2141
mmx_x9	0.7332	-0.0942	-0.0125	0.3684	0.3177
mmx_x10	0.4170	0.3556	0.6609	0.0036	0.2628

```
. pca mmx_x1 mmx_x3 mmx_x4 mmx_x5 mmx_x6 mmx_x7 mmx_x8 mmx_x9 mmx_x10

Principal components/correlation                 Number of obs    =        121
                                                 Number of comp.  =          9
                                                 Trace            =          9
    Rotation: (unrotated = principal)            Rho              =     1.0000
```

Component	Eigenvalue	Difference	Proportion	Cumulative
Comp1	2.51365	.598053	0.2793	0.2793
Comp2	1.9156	.597874	0.2128	0.4921
Comp3	1.31772	.197587	0.1464	0.6386
Comp4	1.12014	.391402	0.1245	0.7630
Comp5	.728735	.257908	0.0810	0.8440
Comp6	.470827	.102691	0.0523	0.8963
Comp7	.368135	.0317405	0.0409	0.9372
Comp8	.336395	.107596	0.0374	0.9746
Comp9	.228798	.	0.0254	1.0000

```
Principal components (eigenvectors)
```

Variable	Comp1	Comp2	Comp3	Comp4	Comp5	Comp6	Comp7	Comp8	Comp9	Unexplained
mmx_x1	-0.3815	0.3051	-0.4344	-0.0597	-0.1685	0.0673	0.0373	0.7313	0.0058	0
mmx_x3	0.3750	-0.3518	-0.2969	-0.1701	0.3398	0.4893	0.0248	0.1803	0.4801	0
mmx_x4	-0.2470	-0.0780	0.4061	0.5736	0.4965	0.1059	0.3206	0.2800	0.0092	0
mmx_x5	-0.0534	0.4176	0.3433	-0.5710	0.2117	-0.2002	0.3740	0.0003	0.3925	0
mmx_x6	0.5220	0.0074	0.0347	-0.1920	0.3728	-0.3298	-0.0990	0.3996	-0.5217	0
mmx_x7	0.1415	0.5318	-0.1800	0.3664	0.3047	-0.2031	-0.5055	-0.1132	0.3577	0
mmx_x8	0.2727	0.4992	-0.2742	0.1420	0.0303	0.4041	0.4891	-0.2698	-0.3238	0
mmx_x9	0.4625	-0.0680	-0.0109	0.3480	-0.4580	-0.3900	0.3850	0.1996	0.3322	0
mmx_x10	0.2630	0.2569	0.5757	0.0034	-0.3498	0.4892	-0.3201	0.2630	0.0068	0

```
. predict f1 f2 f3 f4 f5
(score assumed)
(4 components skipped)

Scoring coefficients
    sum of squares(column-loading) = 1
```

Variable	Comp1	Comp2	Comp3	Comp4	Comp5	Comp6	Comp7	Comp8	Comp9
mmx_x1	-0.3815	0.3051	-0.4344	-0.0597	-0.1685	0.0673	0.0373	0.7313	0.0058
mmx_x3	0.3750	-0.3518	-0.2969	-0.1701	0.3398	0.4893	0.0248	0.1803	0.4801
mmx_x4	-0.2470	-0.0780	0.4061	0.5736	0.4965	0.1059	0.3206	0.2800	0.0092
mmx_x5	-0.0534	0.4176	0.3433	-0.5710	0.2117	-0.2002	0.3740	0.0003	0.3925
mmx_x6	0.5220	0.0074	0.0347	-0.1920	0.3728	-0.3298	-0.0990	0.3996	-0.5217
mmx_x7	0.1415	0.5318	-0.1800	0.3664	0.3047	-0.2031	-0.5055	-0.1132	0.3577
mmx_x8	0.2727	0.4992	-0.2742	0.1420	0.0303	0.4041	0.4891	-0.2698	-0.3238
mmx_x9	0.4625	-0.0680	-0.0109	0.3480	-0.4580	-0.3900	0.3850	0.1996	0.3322
mmx_x10	0.2630	0.2569	0.5757	0.0034	-0.3498	0.4892	-0.3201	0.2630	0.0068

```
. gen x=(0.2793*f1+0.2128*f2+0.1464*f3+0.1245*f4+0.081*f5)/0.8440
(492 missing values generated)

. drop SenimentIndex

. gen SenimentIndex=x
(492 missing values generated)
```

CHAPTER 5

Empirical Analysis

In this section, we will base on the sentiment model above to explore the relation between the sentiment index and the "Shanghai Composite Index 000001.SS and SZSE Index 399001.SZ." This means that we need to confirm the predictive role of the investor sentiment index. Concurrently, we will employ impulse response analysis to further investigate the impact of a shock to one variable on the other.

5.1 Stationarity Test

Unit root testing is the most commonly used method for stationarity testing, which is utilized to check the appearance of one unit root in a variable's time series to test for the series' stationarity. In this paper, the Shanghai Composite Index (000001SS) and the Shenzhen Stock Exchange Component Index (SZSE Index, 399001SZ) are selected to represent stock market returns, and subsequent research is conducted on the impact of the investor sentiment index on stock market returns. Therefore, primarily using the Augmented Dickey-Fuller (ADF) unit root test, a stationarity test is conducted on the three variables: the investor sentiment indicator and the two stock market return indicators. Results are presented in the following table.

Table 5.1- ADF Tests

Test/Variables	Sentiment Index	Shanghai Return	Shenzhen Return
Dickey-Fuller Statistic	-5.230	-10.971	-10.166
1% Critical Value	-3.503	-3.503	-3.503
5% Critical Value	-2.889	-2.889	-2.889
10% Critical Value	-2.579	-2.579	-2.579
p-value	0.000	0.000	0.000
Result	Stationarity	Stationarity	Stationarity

From the data in the table above, it is obvious that both the investor sentiment index series and the market return series (Shanghai Return & Shenzhen Return) have passed the stationarity test.

5.2 Granger Causality Analysis

To further discuss the predictive power of investor sentiment on stock market returns, taking into account the influence of previous periods stock prices on the subsequent period as well as the lag effect of investor sentiment, we refer to the method in Vector

Autoregressive (VAR) model to determine that a lag of 2 periods is optimal. Subsequently, we conduct a Granger causality analysis between the sentiment index and the index returns to confirm whether the historical changes in the sentiment index can affect the market index returns. That is, to assess whether changes in sentiment have a certain predictive effect on future market returns.

H_0: sentiment index is not a Granger cause of index return.

Table 5.2- Granger Causality Tests

Null Hypothesis	Lags	F-statistic	P-value	Accept/Reject
Investor Sentiment Index is Granger Cause of Shanghai Composite Index	2	2.673	0.102	reject
Shanghai Composite Index is Granger Cause of Investor Sentiment Index	2	2.422	0.120	reject
Investor Sentiment Index is Granger Cause of SZSE Index	2	4.238	0.040	reject
SZSE Index is Granger Cause of Investor Sentiment Index	2	4.686	0.030	reject

The Granger causality test indicates that it has an apparent bidirectional causal condition between investor sentiment and the log returns of both the Shanghai Composite Index and the SZSE Index at around the 10% significance level. This suggests that changes in investor sentiment can provide short-term predictions for future market returns.

5.3 Predictive Analysis of Sentiment Index

The investor sentiment indicator, decomposed with five predictive variables, is depicted in the Figure 5.1. As it shows that rapid reversals in sentiment are always accompanied by reversals of the index trends, serving as an early warning signal for both the Shanghai Composite Index and the SZSE Index. When there is a divergence between investor sentiment and the index trend, it signals an impending reversal of the index trend. For instance, on August 13, the sentiment index moved in the opposite direction to the Shanghai Composite Index, after which the index trend was reversed downward. Similarly, on June 19, a divergence occurred between the sentiment index and the SZSE Index, followed by a downturn in the SZSE Index.

The reduction in stamp duty has a pivotal impact on enhancing short-term market confidence. On August 27, after a gap of 15 years, China's government announced a decrease in the stamp duty, an action that came at a time when investor sentiment had sunk into a state of deep pessimism. As shown in the graph, investor sentiment fluctuates below the zero value over a long period of time. It is obvious that the introduction of the policy catalyzed a swift turnaround in market sentiment, which in turn helped to arrest the declining tendency of the stock indices over a short period.

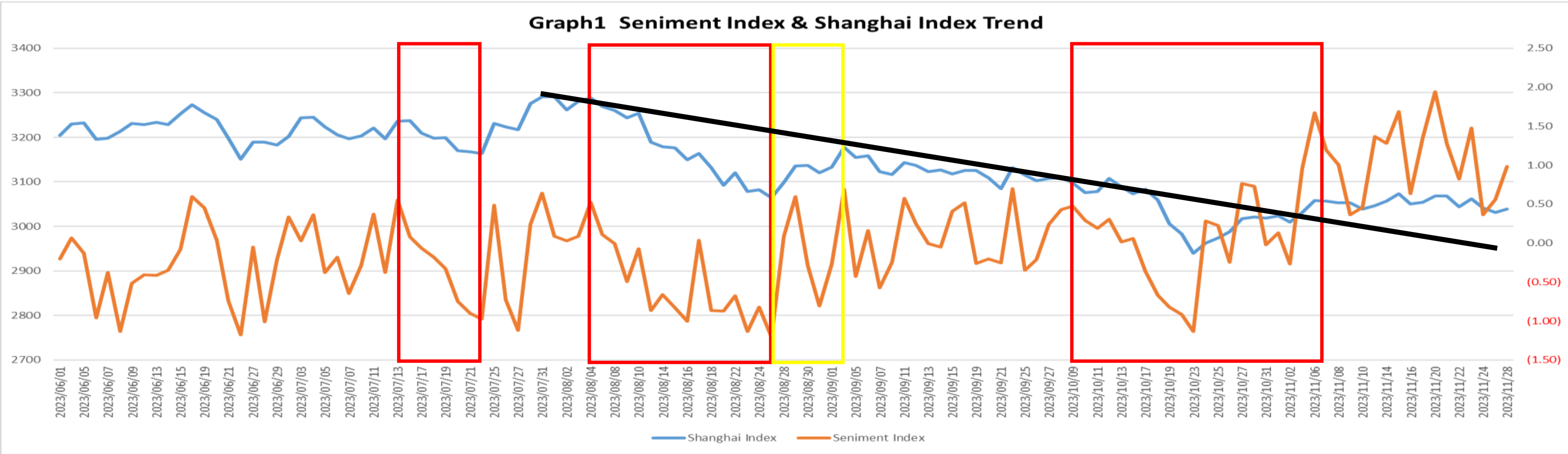
However, the overall long-term trend of market indices did not instantly reverse while there is a complex relationship between investor sentiment and market index returns. As shown in Figure 5.1, after the announcement of reducing stamp duty, investor sentiment rapidly rebounded in short-term. After, it experienced a significant recovery period while the movement of market indices also temporarily stopped the declining pace. This change not only reflects the fact that positive response of the market to the policy adjustment, but also implied that market confidence will gradual recover in the coming period of time. Besides, it is worth noting the recovery of emotions from below zero to above is not an overnight process. It takes a relatively long time to deal with it. The twists and turns of this process also evidenced a huge blow to investor sentiment due to the prolonged decline of the market index.

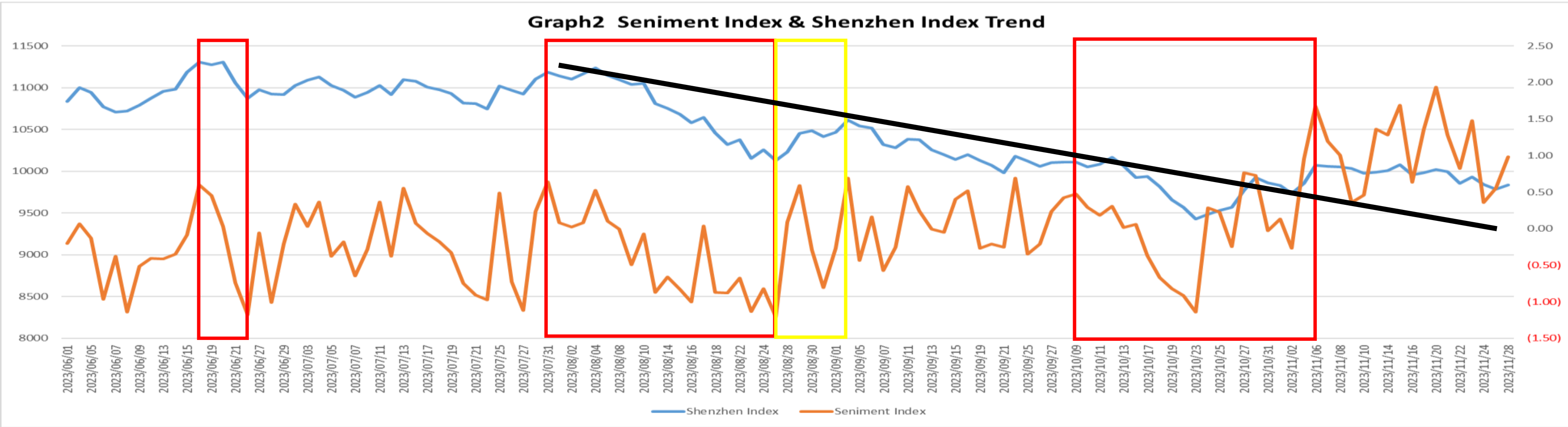
Specifically, market participants require time to digest information regarding policy changes for reassessing their expectations to the furture market. The transition of investors from pessimism to optimism is an emotional game. They swing between optimism and pessimism reflected in the market is volatility and repeatedly jump back of indices. Nevertheless, the trend of investor sentiment is upward over time, which means the adjustment is successful in raising market optimism to a certain degree.

Obviously, rather than stimulating the emergence of a bullish market, we can initially infer the aims of stamp duty policy is to afford investors confidence so that avoiding the occurrence of market crashes. Nonetheless, we still need a more rigorous discussion to ensure the influence of the policy announcement on market, which we will discuss further in the next chapter.

The forecasting analysis of investor sentiment index confirms despite of volatility and uncertainty, the recovery of market sentiment plays an important role in stability and growth of stock market. This finding emphasizes policymakers is necessary to take into account factors when formulating market interventions as financial stcok market is always full of uncertainty, external shocks, global economic fluctuations, geopolitical events and other negative news. It is invaluable for government to apply a variety of policy allocations to stimulate economic development so that aligning with the U.S. stock market over the past decade.

Figure 5.1- Sentiment Index & Market Index Trend





5.4 Impulse Response Analysis

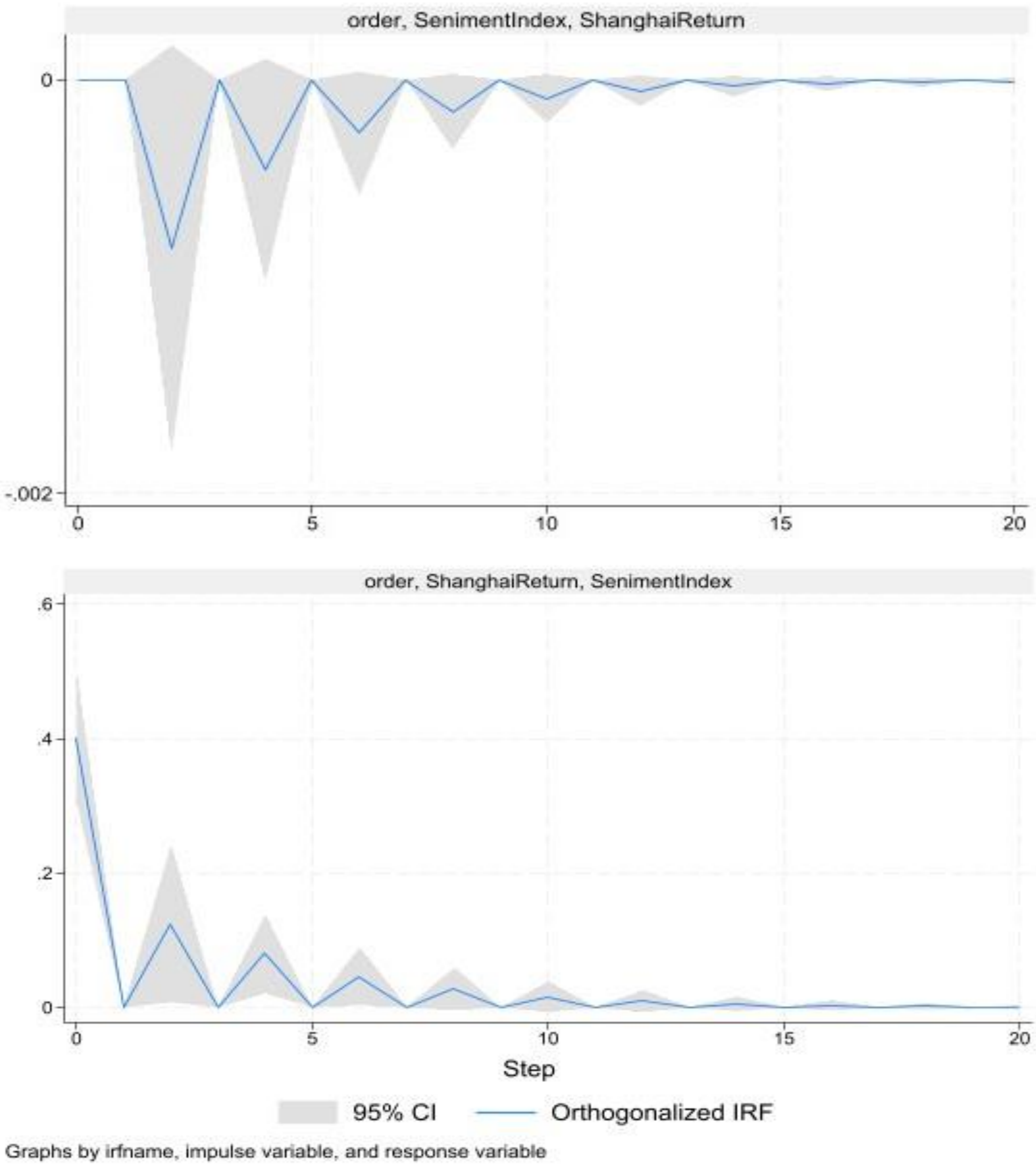
Using the sentiment index, impulse response models are established separately with the log returns of the Shanghai Composite Index and the SZSE Index. This model examines the dynamic impact of a change in an error term or when the model is subjected to a certain shock. This method is primarily used to observe the effects brought about by the endogenous variables of the system. It can reflect the impact of a shock to one variable on the current and future values of other variables, which helps us to observe the relationship more intuitively between sentiment and market returns. This will allow for a more systematic understanding of the main purpose of the stamp duty policy adjustment in the subsequent event study section. Before conducting the response analysis, a Vector Autoregression (VAR) model must be established. Based on the VAR model already constructed in the previous text, a 2nd-order lag is chosen as the optimal solution for both the Shanghai Composite Index Return and the SZSE Index Return. The unit roots of the model's data are all less than 1, indicating stable series, and thus analysis can be conducted.

The impulse response model, as illustrated in the figure below, uses the Shanghai Composite Index Return as an example (with the SZSE Index Return showing consistent results). The shaded area delineates the range of variation that is permissible for the variable under impact at a 95% confidence level. When the sentiment index receives a shock, the index returns experience a rapid decline in the subsequent period, after which the influence progressively stabilizes and trends towards zero. This dynamic indicates that shocks originating from sentiment typically result in a reduction of returns within the timeframe of this study, which indirectly corroborates the observation that investor sentiment was not favorable but rather characterized by a sense of panic during the period under review.

On the flip side, when the index return is subjected to a shock, there is an immediate and discernible uptick in investor sentiment. This sentiment rapidly rises on the first trading day following the shock and then gradually declines, reaching the baseline around 0 at the sixth trading day. This pattern stresses the positive impact that index returns could have on investor sentiment, especially during the time of painful market. In here, positive returns on the index can play an important role in reviving investor confidence, which aligns with the findings of Brown et al. (2005) that there is a direct effect of short-term stock market returns on investor sentiment.

In conclusion, these insights from the impulse response analysis contribute to a more particular understanding of the interplay between investor sentiment and the change of return. We highlight that the complex dynamics at work, where investor psychology is not only a reflection of market performance but also a contributing factor that can influence the market track. This feedback loop underscores the importance of considering investor sentiment as a critical variable in financial analysis and policy formulation, especially in times of market volatility or when significant policy changes, such as the adjustment of stamp duty.

Figure 5.2- The Interplay between Shanghai Composite Index Log Returns and Investor Sentiment



CHAPTER 6

Event Study

In this section, we will conduct an event study analysis on the market index. Ken B. Cyree and Ramon P. Degennaro (2002) used the event study methodology to explore the abnormal returns as the changes in systemic risk. Here, we will draw on their approach, adopting the core method of the event study, to focus on the stamp duty adjustment event on August 27, 2023, and study the index returns.

Following the market model equation, the expected return is given by:

$$R_{ij} = \alpha_i + \beta_i R_{mj} + \varepsilon_{ij} \tag{6.1}$$

where:

- j = the day is evaluated in comparison to the event
- R_{ij} = index i return on day j
- R_{mj} = MSCI World Index (A basket of market indices from various countries) return on day j
- α_i = estimated intercept of index i
- β_i = OLS estimated relationship between index i and MSCI World Index
- ε_{ij} = the error term of index i on day j

The abnormal returns (AR) are acquired as follow:

$$AR_{ij} = R_{ij} - \left(\alpha_i - \beta_i R_{mj}\right) \tag{6.2}$$

where:

- AR_{ij} = index i excess return on day j

Then, the daily average abnormal return with N sample is as follow:

$$AR_j = \sum_{i=1}^{N} \frac{AR_{ij}}{N} \tag{6.3}$$

During the event window, cumulative abnormal return (CAR) calculated by adding up the daily abnormal return:

$$CAR_{F,L} = \sum_{j=F}^{L} AR_j \tag{6.4}$$

where:

- F = the first trading day of the event window while L is the last day

The cumulative average abnormal return (CAAR) during the event window with n days, which ultimately reflects whether an event has an impact, is calculated by:

$$CAAR_{F,L} = \frac{1}{n}\sum CAR_{F,L} \tag{6.5}$$

Since the event occurred on a weekend, we designate the first trading day following the weekend, August 28th, as the event date. To study how the policy announcement will stimulate the short-term market returns, we select a window of one trading day before and after the event date as the event window, that is, -1 ≤ di ≤ 1. We also choose a period from 60 trading days before the event date to two trading days before as the estimation window, -60 ≤ di ≤ -2. By calculating the predicted return of the index through the estimation window, we ultimately derive the index's abnormal return (AR), which is the actual return minus the predicted return.

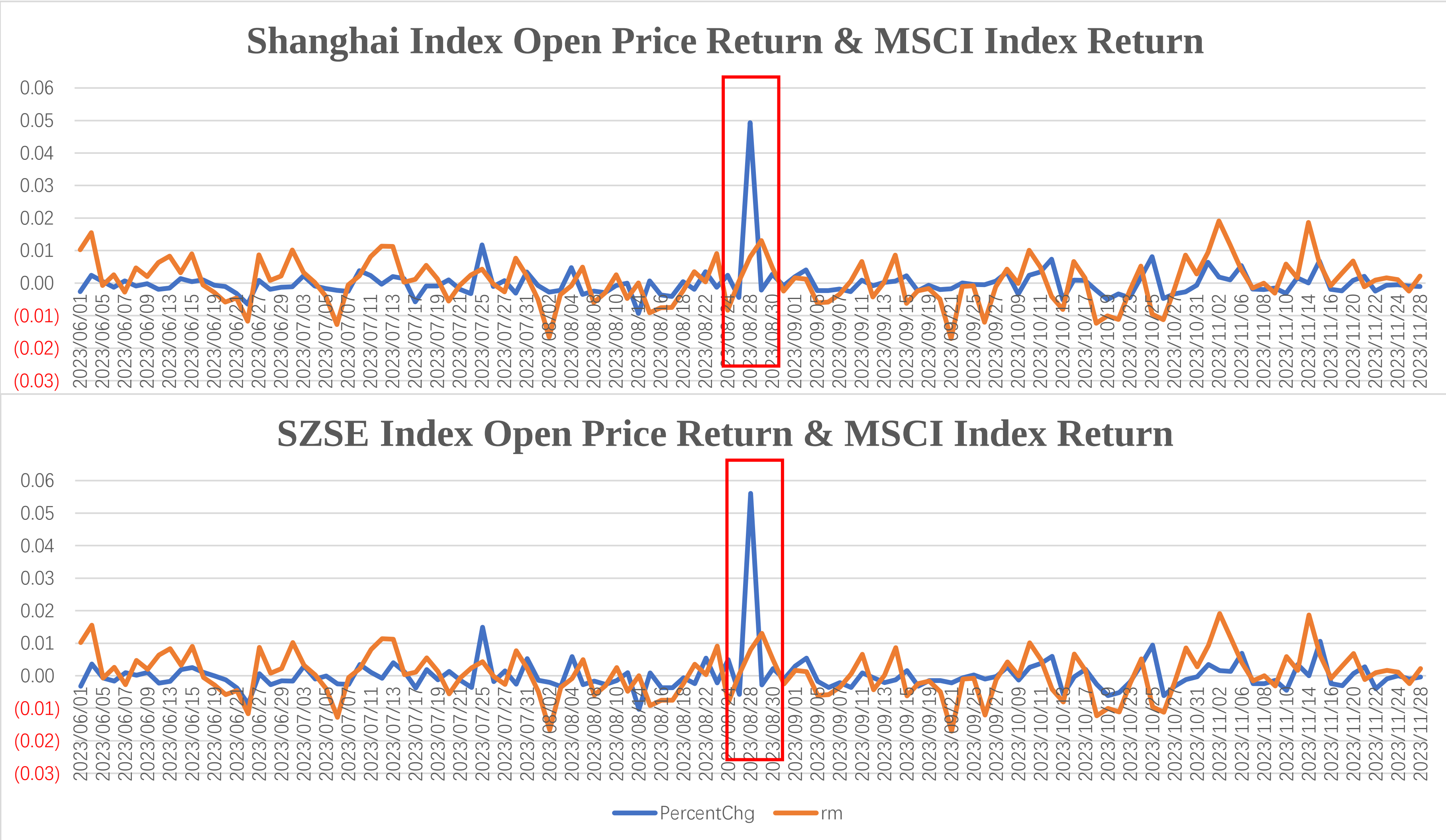
In addition, we note that event study methods are typically applied at the individual stock level, where numerous market indices are used as benchmarks to calculate the expected return. However, both the Shanghai Composite Index and the SZSE Index are market indices themselves, and we require a broader market return as the standard for the expected returns of these two market indices. Therefore, we will use the MSCI Global Index and perform data preprocessing on it. "Due to the existence of public holidays in China, there may be instances where the Chinese market is closed while foreign markets are open." If the Chinese stock market is on holiday, adjustments will be made to the time series of the MSCI Global Index to select data from the same dates as the Chinese market.

In order to delve deeper in the occurrence of abnormal returns to ensure the event influence, we will calculate the cumulative average abnormal returns (CAAR) with both open and close price of Shanghai Composite Index and SZSE Index. What’s more, by adjusting the estimation window to "−60 ≤ di ≤ −1", we will observe whether the abnormal returns AR on the event date are significantly different from those within the estimation window. Following this change could provide a more comprehensive understanding for the impact of the introduction that policy has on the market.

A series of studies have shown that for both open and close price, the p-values of the cumulative average abnormal returns (CAAR) are less than 0.01, which indicates that the event of the stamp duty policy adjustment has a significant impact on the index returns. As we control the estimation window and examine the open and close price on the event date, we find that for both indices, the abnormal returns (AR) significantly deviate from the abnormal returns within the estimation window. The results shows that all the statistics values are significant while the deviation with open price is much larger than that with close price.

Therefore, it is not difficult to conclude that after the policy announcement, investors' bullish sentiment was strong. Through the whole night of information fermentation, the value of this sentiment was greatly reflected on the market index open price. At the same time, through the simple t-test, the abnormal return with open price is more significant than that with close price. This means our conclusion drawn in the previous chapter “the purpose of this stamp duty adjustment is to inspire confidence of investors” is also matched here.

Figure 6.1- Market Log Returns with open price & MSCI Index Log Returns



CHAPTER 7

Conclusion & Implication

This study intends to thoroughly explore the impact of investor sentiment on the short-term fluctuations of the China stock market as well as an intensive study the goal of stamp duty adjustment. In China's history, the adjustment of stamp duty is not common, and the decline of stamp duty benefits the whole market. Historical back testing has shown that each reduction in stamp duty has been accompanied by a short-term rise in the market index and even the start of a bull market. This indicates that each reduction in the stamp duty has been able to stimulate investors' desire to buy stocks. However, through our study, we found that the main purpose of this stamp duty adjustment is to stimulate the desire to invest, encourage investors to step out of pessimistic sentiments, ease the downward trend in the stock market so that preventing the occurrence of a stock market crash.

Despite the historical performance, this does not necessarily mean that the current reduction in stamp duty will have the same effect. The purpose of such government macro-control measures still requires further exploration. In this paper, through a series of econometric analysis methods, including Principal Component Analysis (PCA), Granger causality testing, impulse response analysis, and event study, we have drawn the following comprehensive conclusions:

7.1 Conclusions

1. **Stamp Duty Policy and Market Sentiment**: The study found that adjustments to the stamp duty are a key factor affecting investor sentiment. On August 27, 2023, the Chinese government announced a reduction in the stamp duty, a policy change that amplified the short-term market's abnormal positive returns, leading to a significant recovery in investor sentiment and thus having a positive impact on the market in the short term. However, a comprehensive recovery in long-term sentiment requires time to take effect. It is not difficult to observe that at the time of the policy announcement, investor sentiment was at its most panicked stage. When sentiment returns to this level, it indicates that market sentiment will gradually improve. This shows that the reduction in stamp duty not only reduces transaction costs but also conveys a positive signal to both the short-term and long-term markets, enhancing investor confidence.

2. **Construction and Application of the Sentiment Index**: Using the PCA method, we have constructed a comprehensive index that reflects market sentiment.

This index includes several decomposed indicators, such as the deviation coefficient of the RSI, option implied volatility, and the premium/discount rate of stock index futures. The selection of these indicators is based on data that investors can intuitively obtain in a short period of time. This not only ensures the timeliness and relevance of the sentiment index but also largely reflects investors' views on the future expected trends of the market.

3. **Granger Causality Test**: Through the Granger causality test, we have confirmed that there is a significant bidirectional causal relation between the investor sentiment index and the stock market index returns. The stock index returns can lead to a change in investor sentiment, and changes in sentiment can also predict the short-term market index returns, providing a new perspective for market analysis and investment decision-making.

4. **Impulse Response Analysis**: Impulse response analysis further reveals the dynamic power of sentiment change could have on the market index returns. When stock index returns are impacted by a shock in investor sentiment, they exhibit a responsive reaction in the opposite direction. The analysis indicates that during periods when sentiment has been in a state of panic for an extended time, a positive shock to investor sentiment will lead to a decrease in market index returns in the short term. Conversely, a positive shock to market index returns can quickly lift investor sentiment, demonstrating the presence of a reverse feedback loop between the two.

5. **Event Study**: The readjustment of the stamp duty plays a significant role in boosting market confidence and preventing stock market crashes caused by overly pessimistic market sentiment. Excessively panicked investor sentiment can lead to continuous selling of stocks, which in turn can cause the market to fall into a vicious cycle of decline. Through the study of the stamp duty adjustment event on August 27, 2023, we found that this policy change had a significant short-term impact on the market index. The results of the event study show that after the policy announcement, the abnormal return of the market index increased significantly, especially the abnormal return of the opening price, indicating that investors' response to the policy was extremely rapid. It is not difficult to observe that abnormal returns rapidly increased at the market open on the first trading day following the event and then continued to decrease. Also, the closing price returns of the index were also significantly lower than the opening price returns, indicating that investor sentiment does not easily undergo a direct reversal after a long period of panic. Subsequently, the index, after experiencing a period of fluctuation, continued to decline, and even hit new lows, which also indicates that the policy of reducing stamp duty only alleviated the market's downward trend for a certain time and could not completely reverse it. Therefore, in summary, we

conclude that the main purpose of this policy change was to improve investors' overly pessimistic sentiment while stimulating market returns, rather than to induce the onset of a bull market.

7.2 Main implications from the study

1. **Market Trend Forecasting**: The research findings indicate that when investor sentiment diverges from the trend of the stock index, it often signals a reversal in the market trend. By observing the changes and direction of the sentiment index, investors and analysts can make more accurate predictions about market trends.

2. **Limitations of Policy Intervention**: Stock market is a highly complex entity that cannot be boosted by just one policy. Although the reduction in stamp duty has boosted market sentiment and improved market liquidity in the short term, the reversal of the long-term downward market trend is not immediately apparent. This suggests that the market's response to policy changes is complex and influenced by a variety of factors. Therefore, a combination of policies needs to be implemented to enhance the government's guidance of the market.

3. **Improvement of the Investor Sentiment Indicator System**: The impact of the psychological level of investors on the market is often difficult to gauge and it is necessary to continue optimizing meso-indicators, selecting macro-indicators, and establishing a more comprehensive investor sentiment system. This study focuses on using market trading indicators and lacks macro-indicators that represent the impact on the market. There should be an active exploration of the establishment methods for macro-indicators to enhance the effectiveness of the sentiment index.

4. **Future Research Directions**: This study provides empirical evidence on how changes in transaction tax policies can affect stock market returns and subsequently improve investor sentiment. Future research can further explore the effectiveness of policy interventions under different macroeconomic conditions, as well as how to combine various policies to enhance the accuracy of sentiment index predictions.

In summary, this study reveals the significant impact of stamp duty policy adjustments on short-term stock market fluctuations and provides a new tool for market analysis through the construction of a sentiment index. The findings are of important reference value for policymakers, market regulators, and investors.

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Annexes

Annex A – General solutions of the methods used

CNN Fear & Greed Index is well known in US stock market, it is always used to observe the overall emotions of investor so that providing a direction during trading. Even though the process of calculations in the model are not complex; to avoid a heavy reading, we will place them in Annex A.1. Principal Component Analysis (PCA) is popular in data dimensionality reduction area. It can transform the data in a lower-dimensional for representing while retaining the characteristics. This will be plotted in Annex A.2.

Annex A.1 CNN Fear & Greed Index (4.2)

Beginning with data collection, the index must be constructed with a variety of market indicators that are believed to influence investor sentiment. These may include the variables such as market volatility, trading volume, price momentum, put/call ratio and so on. Then, Standardization must be taken before index construction to ensure all raw data have a mean of 0 and a standard deviation of 1. The formula is as follows:

$$\mathrm{Z} = (\mathrm{X} - \mathrm{\mu}) * \mathrm{\sigma} \tag{A.1.1}$$

where Z is the standardized value, X is the raw data value, μ is the mean of previous 250 trading days, and σ is the standard deviation of previous trading days.

By figuring each standardized variable weight, it is assigned a proportion based on its relative importance in reflecting investor sentiment. The weights are normalized so that they sum up to 1. The weighted formula is:

$$W_i = \frac{w_i}{\sum_{j=1}^{n} w_j} \tag{A.1.2}$$

where Wi is the weight of the $\mathrm{i_{th}}$ variable, and wi is the original weight of the $\mathrm{i_{th}}$ variable.

After calculating the weight of each variable, the single sentiment index of each day using a weighted average sum:

$$Sentiment\ index_i = \sum_{i=1}^{n} W_i * Z_i \tag{A.1.3}$$

where Zi is the standardized value of $\mathrm{i_{th}}$ variable.

It should be noted that after taking the normal values of each variable, we have to sign an adjustment based on the relationship between the variable and sentiment. Therefore, the total sentiment value derived from this summation will not exactly fall between (-1, 1). What's more, in the construction of the CNN sentiment index, they simply do an arithmetic mean of each factor, which means that we need to find the different proportions of variables through the following PCA dimension reduction method.

Annex A.2 Principal Component Analysis "PCA" (4.3)

Principal Component Analysis (PCA) is used to transform the original data into a set of linearly independent representations. The core of PCA is to identify the direction of maximum variance within the data and plot the data with this direction so that reaching the goal of dimensionality reduction. For example, if we have a dataset with n sample and p variables:

$$\mathrm{x} = \begin{bmatrix} \mathrm{x}_{11} & \cdots & \mathrm{x}_{1\mathrm{p}} \\ \vdots & \ddots & \vdots \\ \mathrm{x}_{\mathrm{n}1} & \cdots & \mathrm{x}_{\mathrm{np}} \end{bmatrix} = (\mathrm{x1}, \mathrm{x2}, \cdots\cdots, \mathrm{xp}) \tag{A.2.1}$$

After the process of normalization, the matrix:

$$\mathrm{X} = \begin{bmatrix} \mathrm{X}_{11} & \cdots & \mathrm{X}_{1\mathrm{p}} \\ \vdots & \ddots & \vdots \\ \mathrm{X}_{\mathrm{n}1} & \cdots & \mathrm{X}_{\mathrm{np}} \end{bmatrix} = (\mathrm{X1}, \mathrm{X2}, \cdots\cdots, \mathrm{Xp}) \tag{A.2.2}$$

Then, we need to figure out the covariance matrix:

$$\mathrm{Cov} = \begin{bmatrix} \mathrm{cov}_{11} & \cdots & \mathrm{cov}_{1\mathrm{p}} \\ \vdots & \ddots & \vdots \\ \mathrm{cov}_{\mathrm{n}1} & \cdots & \mathrm{cov}_{\mathrm{np}} \end{bmatrix} \tag{A.2.3}$$

Where: $cov_{ij} = \frac{1}{n-1}\sum_{k=1}^{n}(X_{ki} - \bar{X}_i)\left(X_{kj} - \bar{X}_j\right) = \frac{1}{n-1}\sum_{k=1}^{n} X_{ki}X_{kj}$

Perform the eigenvalue decomposition on covariance matrix and calculate the eigenvectors (eigenvalue: $\lambda_1 \geqslant \lambda_2 \geqslant \lambda_3 \geqslant \ldots \geqslant \lambda_p \geqslant 0$; Cov is a semi-definite positive matrix and $\mathrm{tcovCov} = \sum_{k=1}^{p} \lambda_k = p$)

$$\text{Eigenvector: } a_1 = \begin{bmatrix} a_{11} \\ \cdots \\ a_{n1} \end{bmatrix}, a_2 = \begin{bmatrix} a_{12} \\ \cdots \\ a_{n2} \end{bmatrix}, \cdots\cdots, a_p = \begin{bmatrix} a_{1p} \\ \cdots \\ a_{np} \end{bmatrix} \tag{A.2.4}$$

Identify the principal components based on the contribution rate:

$$Contribution\ rate = \frac{\lambda_i}{\sum_{k=1}^{p} \lambda_k} (\mathrm{i} = 1,2,\cdots\cdots,\mathrm{p}) \tag{A.2.5}$$

$$Cumulative\ contribution\ rate = \frac{\sum_{k=1}^{i} \lambda_k}{\sum_{k=1}^{p} \lambda_k} (\mathrm{i} = 1,2,\cdots\cdots,\mathrm{p}) \tag{A.2.6}$$

Generally, the first, second, ⋯⋯, m[th] principal components corresponding to the eigenvalues with a cumulative contribution exceeding 80% are selected. Then, each grading factor can be calculated by:

$$F_i = a_{1i}X_1 + a_{2i}X_2 + \cdots + a_{ni}X_n (\mathrm{i} = 1,2,\cdots\cdots,\mathrm{m}) \tag{A.2.7}$$

Finally, we are ready to solve out the sentiment index value of each day:

$$Sentiment\ index = \frac{(\sum_{i=1}^{m} Contribution\ rate_i * F_i)}{Cumulative\ contribution\ rate} \tag{A.2.8}$$

Annex B – Complementary Tables

Descriptive statistics

VARIABLES	(1) N	(2) mean	(3) sd	(4) min	(5) max
Shanghai Composite Index	371	3,190	104.3	2,893	3,409
RSIDC	371	0.222	0.120	0.0398	0.653
PCR	371	0.999	0.153	0.667	2.092
OIV	371	255,030	128,810	86,350	1.020e+06
PDR	371	-0.0122	0.00546	-0.0281	-0.00123
IRP	371	0.0605	0.00202	0.0565	0.0671
VR	371	109.2	67.24	42.24	426.3
ADR	371	1.537	1.831	0.0623	12.73
ALU	371	38.92	30.28	-61	137
IM	371	-107.0	224.1	-894.7	326.7
MPP	371	0.0764	0.00800	0.0508	0.109

Note： RSIDC- overbought & oversold deviation coefficient; PCR- put-call ratio in options trading; OIV- option implied volatility; PDR- stock index futures premium/discount rate; IRP - implied risk premium; VR- volatility volume ratio; ADR- advance/decline ratio; ALU- actual number of limit up; IM- stock index momentum; MPP- margin purchase proportion.

Annex C – Stata Codes

Figure C.1

Sentiment construction & analysis Stata code

```
import excel "C:\Users\Simon\Desktop\thesis\data.xlsx", sheet("Sheet1") firstrow
*PCA method to find out the main fatcors to construct Seniment Index
norm x1-x10, method(mmx)
factortest mmx_x1-mmx_x10
pca mmx_x1-mmx_x10
factor mmx_x1-mmx_x10 ,pcf
factortest mmx_x1 mmx_x3 mmx_x4 mmx_x5 mmx_x6 mmx_x7 mmx_x8 mmx_x9 mmx_x10
pca mmx_x1 mmx_x3 mmx_x4 mmx_x5 mmx_x6 mmx_x7 mmx_x8 mmx_x9 mmx_x10
factor mmx_x1 mmx_x3 mmx_x4 mmx_x5 mmx_x6 mmx_x7 mmx_x8 mmx_x9 mmx_x10 ,pcf
pca mmx_x1 mmx_x3 mmx_x4 mmx_x5 mmx_x6 mmx_x7 mmx_x8 mmx_x9 mmx_x10
predict f1 f2 f3 f4 f5
gen x=(0.2793*f1+0.2128*f2+0.1464*f3+0.1245*f4+0.081*f5)/0.8440
drop SenimentIndex
gen SenimentIndex=x
drop x

*Set the panel data
encode Index,gen(leIndex)
encode Date,gen(leDate)
xtset leIndex leDate

*Stationarity Test
dfuller SenimentIndex
dfuller ShanghaiReturn
dfuller ShenzhenReturn

*Granger Causality Test
varsoc ShanghaiReturn SenimentIndex ,maxlag(2)
varsoc ShenzhenReturn SenimentIndex ,maxlag(2)
var ShenzhenReturn SenimentIndex,lags(2)
vargranger
var ShanghaiReturn SenimentIndex ,lags(2)
vargranger

*Impulse Response Analaysis
varstable,graph
irf create order1,step(20) set(myirf) replace
irf graph oirf,irf(order1) impulse( SenimentIndex ) response( ShanghaiReturn )
irf graph oirf,irf(order1) impulse( ShanghaiReturn ) response( SenimentIndex )

```

Figure C.2

Event study with close price Stata code

```
import excel "C:\Users\Simon\Desktop\thesis\Event study\Event study close price.xlsx", sheet(
"Sheet1") firstrow clear
reshape long rm Date Instrument PriceClose PercentChg,i(di) j(id)
rename Date date
rename PercentChg ri
drop PriceClose
order Instrument id di date rm ri

sor id di
by id: g estimation_window=1 if(di>=-60 & di<=-2)
by id: g event_window=1 if (di>=-1 & di<=1)
replace event_window=0 if event_window==.
replace estimation_window=0 if estimation_window==.

gen predicted_return=.
qui tabulate id

forvalues i=0/1 {
reg ri rm if id== `i' & estimation_window==1
predict temp if id==`i'
replace predicted_return=temp if id==`i' & event_window==1
drop temp
}

keep if event_window==1
gen ar=ri-predicted_return
sor id date

sort id di

by id: egen car_1=sum(ar) if di>=-1 & di<=1

collapse (mean) car_1 , by(id)

egen caar_1=mean(car_1)

egen sd_1=sd(car_1)

gen t_1=caar_1/(sd_1/sqrt(_N))

gen p_1=ttail(_N, abs(t_1))*2

keep caar_* t_* p_*
keep if _n==1

gen i=1
reshape long caar_ t_ p_, i(i) j(j)

gen interval="[-1,1]" if j==1

order interval caar t p
drop i j

gen star="***" if p<0.01
replace star="**" if p<0.05 & star==""
replace star="*" if p<0.1 & star==""

rename caar_ caar
rename t_ t
rename p_ p
```

Figure C.3

Event study with open price Stata code

```
import excel "C:\Users\Simon\Desktop\thesis\Event study\Event study open price.xlsx", sheet("Sheet1") firstrow clear
reshape long rm Date Instrument PriceOpen PercentChg,i(di) j(id)
rename Date date
rename PercentChg ri
drop PriceOpen
order Instrument id di date rm ri

sor id di
by id: g estimation_window=1 if(di>=-60 & di<=-2)
by id: g event_window=1 if (di>=-1 & di<=1)
replace event_window=0 if event_window==.
replace estimation_window=0 if estimation_window==.

gen predicted_return=.
qui tabulate id

forvalues i=0/1 {
reg ri rm if id== `i' & estimation_window==1
predict temp if id==`i'
replace predicted_return=temp if id==`i' & event_window==1
drop temp
}

keep if event_window==1
gen ar=ri-predicted_return
sor id date

sort id di

by id: egen car_1=sum(ar) if di>=-1 & di<=1

collapse (mean) car_1 , by(id)

egen caar_1=mean(car_1)

egen sd_1=sd(car_1)

gen t_1=caar_1/(sd_1/sqrt(_N))

gen p_1=ttail(_N, abs(t_1))*2

keep caar_* t_* p_*
keep if _n==1

gen i=1
reshape long caar_ t_ p_, i(i) j(j)

gen interval="[-1,1]" if j==1

order interval caar t p
drop i j

gen star="***" if p<0.01
replace star="**" if p<0.05 & star==""
replace star="*" if p<0.1 & star==""

rename caar_ caar
rename t_ t
rename p_ p
```

Figure C.4

Abnormal return of Shanghai Compsite Index close price Stata Code

```
import excel "C:\Users\Simon\Desktop\thesis\Event study\AR Event study\Shanghai Close.xlsx", sheet
("Sheet1") firstrow
rename PercentChg ri
drop PriceClose
g estimation_window=1 if(di>=-60 & di<=-1)
g event_window=1 if (di>=0 & di<=1)
replace event_window=0 if event_window==.
replace estimation_window=0 if estimation_window==.
gen predicted_return=.
reg ri rm if estimation_window==1
predict temp
replace predicted_return=temp if di>=-60 & di<=0
drop temp
drop ar
gen ar=ri-predicted_return
```

Figure C.5

Abnormal return of Shanghai Compsite Index open price Stata Code

```
import excel "C:\Users\Simon\Desktop\thesis\Event study\AR Event study\Shanghai Open.xlsx", sheet(
"Sheet1") firstrow
rename PercentChg ri
drop PriceOpen
g estimation_window=1 if(di>=-60 & di<=-1)
g event_window=1 if (di>=0 & di<=1)
replace event_window=0 if event_window==.
replace estimation_window=0 if estimation_window==.
gen predicted_return=.
reg ri rm if estimation_window==1
predict temp
replace predicted_return=temp if di>=-60 & di<=0
drop temp
drop ar
gen ar=ri-predicted_return
```

Figure C.6

Abnormal return of SZSE Index close price Stata Code

```
import excel "C:\Users\Simon\Desktop\thesis\Event study\AR Event study\Shenzhen Close.xlsx", sheet
("Sheet1") firstrow
rename PercentChg ri
drop PriceClose
g estimation_window=1 if(di>=-60 & di<=-1)
g event_window=1 if (di>=0 & di<=1)
replace event_window=0 if event_window==.
replace estimation_window=0 if estimation_window==.
gen predicted_return=.
reg ri rm if estimation_window==1
predict temp
replace predicted_return=temp if di>=-60 & di<=0
drop temp
drop ar
gen ar=ri-predicted_return
```

Figure C.7

Abnormal return of SZSE Index open price Stata Code

```
import excel "C:\Users\Simon\Desktop\thesis\Event study\AR Event study\Shenzhen Open.xlsx", sheet(
"Sheet1") firstrow
rename PercentChg ri
drop PriceOpen
g estimation_window=1 if(di>=-60 & di<=-1)
g event_window=1 if (di>=0 & di<=1)
replace event_window=0 if event_window==.
replace estimation_window=0 if estimation_window==.
gen predicted_return=.
reg ri rm if estimation_window==1
predict temp
replace predicted_return=temp if di>=-60 & di<=0
drop temp
drop ar
gen ar=ri-predicted_return
```