An Overconfident Market Environment - A Place for Irrational Noise Trading

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Abstract: Compared to developed foreign capital markets, the Chinese A-share market is not always efficient. In most cases, noise trading by investors using misinformation does not generate excess returns for them and can even lead to losses. However, in somewhat overconfident market environments such as the one studied in this paper, noise trading can lead to positive returns in a bull market that develops after the end of a bear market with persistent pessimistic market sentiment starting with a major short-term negative event. This paper selects the time period that fits the above description, combines the theoretical basis of behavioral finance, analyses and compares the performance of investment agents with different noise levels in general and specific market environments, and analyses the correlation between overall market noise trading risk and excess returns in different market environments through regressions, finally concluding that the additional noise trading risk borne by investors in an overconfident market environment risk can earn them excess returns.

Keywords: Overconfident market environments, Behavioral asset pricing model, Noise trading risk, Excess returns

1 Introduction

The continued downturn and economic downturn in China's capital markets in recent years has been evident to every investor. Broadly speaking, a series of major domestic and international negative events have followed each other since 2018 when the US and China started a trade war, which can cause persistent pessimism in the market under the constant impact of short-term negative events. According to Barberis, Shleifer and Vishny (2007)[1], when market sentiment is highly volatile, investors in the market are more likely to become irrational, which can lead to a series of behavioral biases and ultimately lead to market inefficiencies. When the market is inefficient, the market is more irrational and noise traders are more likely to capture excess returns and gain a foothold in the market due to the artificial risk they have created and the lack of arbitrage correction from rational investors. This phenomenon is particularly evident in times of overconfidence or over-optimism in the market. The nature of noise trading is to trade on information that is unrelated to value, so noise trading should not earn excess returns according to the efficient market hypothesis, but this conclusion does not necessarily hold true if the market is not perfectly rational.

This paper aims to look at the performance of noise traders with different levels of noise in an overly emotional market environment and to investigate the correlation between noise trading

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risk and excess returns in such a market environment. This will go some way to explaining the difference between an overly emotional market and a normally rational market, and may help to improve market efficiency in an overly emotional market. The novelty of this paper, compared to previous literature, is that it combines the risk of noisy trading with a specific but not uncommon market environment, rather than discussing the performance of noisy traders in general terms, and that it discusses the noise levels of different actors by further segmenting them rather than the market as a whole, in order to identify the main sources of noise in the market, and to trace the differences in the performance of these noisy groups in general terms and in specific market environments. The paper also discusses the performance of the different actors by further segmenting them rather than the market as a whole. The paper further divides the period from 2018 to 2022 into a bull cycle and a bear cycle, and focuses on the bull cycle using a multiple linear regression model with financial indicators as control variables to investigate the correlation between noise trading risk and excess returns, combined with t-tests to determine the relationship between the selected explanatory variables and excess returns.

2 Literature review

Noise was originally a concept in the realm of physics, referring to sounds that are unpleasant. In 1986 Black[2] introduced the concept of noise, defining it as information that has no effect on the underlying information of a security, and gave a definition of a noise trader, a market participant who uses noise as valid information on which to base a trade. With the discovery of financial anomalies, the concept of noise was also widely recognized. Many researchers later developed the behavioral finance theory based on noise and studied the impact of noise on the capital market, with empirical results showing that noise does cause fluctuations and deviations in the prices of securities in the capital market, with significant side effects on the allocation of market resources. The development of behavioral finance theory has been accompanied by the lack of explanatory power of many traditional financial models for financial anomalies, which has led to the development of behavioral finance models, such as the behavioral asset pricing model, which is important in analyzing the value and price of securities in markets with noisy trading compared to the capital asset pricing model.

2.1. Noise trading theory

Noise is one of the most important concepts in the field of behavioral finance. Black (1986)[2] was the first to break away from the original classical framework of financial analysis and coined the term 'noise', as opposed to 'information', as a pervasive phenomenon in capital markets. Black argued that as market participants, noise traders only provide a degree of liquidity to the market, but cannot survive in the market permanently. However, many traditional finance scholars argue that although there is a lot of noise in the market, the impact of noise trading can be ignored in the asset pricing process. On the one hand, arbitrageurs will play the relevant game with noise traders, thus gradually returning the asset price to value; on the other hand, noise has a great deal of randomness, and in the long run, noise traders will eventually tend to rational trading.

De Long et al. (1990)[3] further illustrate asset pricing on the premise of Black's noise theory, where they argue that noise plays a considerable role in pricing assets such that asset prices do not explain the value of the asset, which in turn allows noise traders to profit from it. On this basis, De Long et al. (1990)[4] developed a noise trading (DSSW) model by integrating information and noise traders. The DSSW model reveals that if the expectation of future excess returns on an asset is higher, then the demand for the risky asset is higher, but at the same time the demand for the risky asset is inversely proportional to the risk; in contrast to information traders, the demand for the risky asset by noise traders also depends on the misperception of expectations of the risky asset.

Froot et al. (1992)[5] suggest that if the capital market is very active during a short cycle, then market participants will focus more on noisy information that has nothing to do with the value of the security, leading to a large surge in the volume of noisy trading in the market, causing the price of the security to deviate significantly from its intrinsic value, which to some extent leads to inefficient allocation of resources in the market. Odean (1998)[6] introduces the concept of psychological overconfidence, arguing that traders are overconfident and believe that their own is the best when sifting through information and making judgments, thus allowing noise trading to persist throughout the capital markets. Hirshleifer (2001)[7] provides a further detailed comparative analysis of the investment behavior of rational and overconfident traders in the market, and conducts a static and dynamic analysis of investor behavior, pointing out that overconfident traders provide better liquidity to the market. Models that have been more influential in the analysis of the psychological aspects of investors include the BSV model[1], the DHS model[8] and the HS model[9].

In recent years, the prevalence of the existence of noise trading has been further corroborated with the development of heterogeneous investor belief theory. For example, Borovicka et al. (2016)[10] used Perron-Frobenius theory to extract the discount factor in a pricing model to further illustrate the problem of yield differences between different investors. Different investors trade according to different expectations, which provides better liquidity to the market and is of course a major source of capital market noise. Knyazeva et al. (2018)[11], by correlating the heterogeneity of different institutional investors, find that there are significant differences in their ability to collect information, which in turn leads to noisy trading.

2.2. Behavioral asset pricing model

With the discovery of a series of financial anomalies such as the equity premium puzzle and the herding effect, many of the cornerstones of related financial fields such as the efficient market hypothesis and traditional asset pricing theory were questioned and challenged to a great extent, and it was at this time that many models of behavioral finance were created and developed and have significantly better explanatory power than traditional financial theories and models for many of the anomalies.

Based on the traditional capital asset pricing model, Shefrin and Statman (1994)[12] established the Behavioral Asset Pricing Model (BAPM) based on theories related to noise trading, which laid a solid foundation for the development and improvement of behavioral finance theory. Under this model, market participants are divided into two categories, namely information traders and noise traders. Information traders are consistent with the "rational economic man" assumption of traditional financial theory, they do not have cognitive bias towards information and will constantly correct for bias in return expectations according to Bayes' Law. In contrast to information traders, noise traders do not have a good knowledge of information, do not have principles of information processing and analysis, and do not follow Bayes' rule of return estimation, and there is significant heterogeneity between market participants. The model analyses asset price fluctuations in markets where two types of traders interact, and whether markets are efficient depends on whether information traders have more power or noise traders. When the market is dominated by information traders, the market can be considered to be relatively efficient and the price of the security can effectively reflect its fair value; when noise traders are dominant, the market can be considered inefficient and the price of the security does not reflect the fair value of the security. On the basis of this theory, if all participants in the market are information traders, the BAPM model is transformed into a CAPM model.

To further develop and refine the theoretical basis of behavioral finance, Shefrin and Statman (2000)[13] proposed Behavioral Portfolio Theory (BPT) based on the previous work. The Behavioral Portfolio consists of two types of psychological accounts, a single psychological account and multiple psychological accounts. For a single mental account, participants are more concerned with the correlation of the assets of individual securities, while for multiple mental accounts investors split the portfolio into a number of different accounts, ignoring the correlation of assets between different accounts. The portfolio is built based on different investment objectives and risks and is a pyramidal portfolio structure. To further apply the model to empirical analysis of capital markets, two Australian financial economists, Ramiah and Davidson (2003)[14], conducted research and analysis on the pricing model in terms of empirical methodology. Xu et al. (2016)[15] conducted a quantitative noise analysis of the Chinese Shenzhen market through an adjusted behavioral asset pricing model, demonstrating that noisy trading is prevalence.

Of course, there are many other studies that have modelled behavioral financial noise, such as Vitale (2000)[16] who develops a two-period model and uses it to predict the likelihood of noisy speculation in the foreign exchange market. Tokic (2009)[17] further investigates the relationship between noise and market trading. Flynn (2012)[18] uses data related to US closed-end funds to analyze the relationship between noise trading, arbitrage, and asset prices.

3 Theoretical foundations related to noise trading risk

In the 1960s and 1970s, traditional financial theory, led by the Efficient Market Hypothesis (EMH), emerged and once dominated financial academia. However, with further empirical studies of capital markets, a large number of financial anomalies were discovered, which could not be explained by traditional financial theories. In 1986, Black introduced the concept of noise, and since then, behavioral finance has grown rapidly and become a major branch of finance, with strong explanatory power for many anomalies.

3.1. Theoretical foundations related to behavioral finance

In 1970 the economist Fama introduced the concept of efficient markets, which argues that in efficient capital markets, prices reflect all valuable information, that investors cannot consistently make excess returns based on information, and that investors cannot consistently make excess returns by analyzing historical prices. According to the definition of the efficient market hypothesis, a market is efficient if three conditions are met: 1. all investors are rational 2. the effects of irrational investors on the market cancel each other out 3. arbitrage is unrestricted.

However, in practice, markets are not always efficient and there is a large number of persistent excess returns. Behavioral finance challenges the efficient market hypothesis from two perspectives: 1. Investors are not fully rational. Investors can behave irrationally due to objective factors such as different levels of education and limited attention span, as well as subjective factors such as cognitive biases and subjective preferences. 2. Arbitrage is limited. In reality, arbitrage is limited by a number of factors, such as noise trading risk, as mentioned below, which prevent timely price corrections. The following section provides a brief introduction to the theoretical foundations of behavioral finance used in this paper.

3.1.1. Overreaction

Overreaction is the tendency of investors to value immediate information and discount past information when new information emerges in the market that is unexpected, resulting in excessive behavior compared to a perfectly rational state, causing the price of the underlying asset to trade at a different price to its actual value and ultimately causing market turmoil.

3.1.2. Underreaction

Underreaction, as opposed to overreaction, is the failure of investors in the market to react promptly and accurately to new information in the market, leaving the price of an asset at its previous level of inertia and failing to adjust the latest price of the asset to reflect its real value.

3.1.3. Financial bubble

A financial bubble is an economic phenomenon in which the market price of a financial asset or a series of financial assets is greater than its real value after a succession of price increases. And this paper deals with the overconfident market environment in which the market overreacts due to overconfidence, optimism, and herding effects, eventually generating a financial bubble.

3.1.4. Overconfidence

Overconfidence is when an investor demonstrates a high level of confidence in his or her own investment ideas and investment level when making specific investment choices, underreacts to information that contradicts his or her beliefs, and overly believes in his or her own personal investment return ability and risk aversion.

3.1.5. Optimism bias

Optimism bias is the belief that unfavorable events are less likely to happen to people than to others, but favorable events are more likely to happen to them than to others.

3.1.6. The sheep flock effect

The herd effect refers to the fact that investors in financial markets follow the market judgment and make similar investment decisions as other investors in the hope of reducing losses, which shows the irrational psychological characteristics of investors and forms the investment convergence in financial markets, which is likely to increase the volatility and price deviation from value in the stock market. Andrea Devenow and Ivo Welch (1996)[19] suggest that the herding effect is caused by the irrational behavior of investors who abandon their beliefs and blindly follow others.

The causes of the herding effect include both subjective and objective factors. Among them, the subjective factors are mainly reflected in the behavioral decisions of market participants, which are affected by behavioral biases such as overconfidence and blind optimism; while the objective factors are mainly manifested in the degree of availability and cost of information in the market, the degree of capital market effectiveness, and the adequacy of capital market development.

The sheep flock effect can be identified in the overconfident and inefficient market environment covered in this paper due to objective and subjective factors, and the sheep flock effect is one of the important drivers of abnormal excess returns by increasing the deviation of stock prices from value.

3.1.7. Noise and noise trading risks

Noise is information that is not related to the value of a security and the trades that result from this information are collectively referred to as noise trading. Noise trading arises when some market participants mistake noise information for useful information and trade on it. Due to the nature of noise trading, there is an additional noise trading risk associated with noise trading, mainly for rational investors who use information related to the value of securities. As mentioned earlier in the efficient market hypothesis, when the value of a security deviates from its price, rational investors will engage in arbitrage, which in turn serves to correct the price, a process that in theory should be risk-free. However, when the risk of noise trading is sufficiently high, it can cause rational investors to take on noise trading risk in their arbitrage behavior, which in turn can dissuade some rational investors from carrying out arbitrage operations, making it impossible for prices to correct in the short term, and thus noise traders may earn excess returns by taking on the additional risk they have created. The particular over-confident market environment chosen for this paper is also one in which the power of the noise trader community is more likely to be greater than that of the rational investor community, resulting in the particular phenomenon described above.

3.2. Behavioral asset pricing model

3.2.1. Capital asset pricing model (CAPM)

The capital asset pricing model, introduced by Sharpe in 1964, is well enough known to be covered in many textbooks and is only briefly described here:

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

where $\beta_i = \frac{Cov(R_i,R_m)}{Var(R_m)}$

If the $\beta$of a portfolio asset is greater than 1, it means that the risk-return of that asset is less than that of the market and vice versa. It is easy to see from the model that the return on a portfolio asset is related to the systematic risk of the capital market and that risk is directly proportional to return.

The assumptions of the capital asset pricing model are very stringent: investors are strictly risk averse; all investors in the market are perfectly rational and seek to maximize expected utility; investors are homogeneous in terms of expected returns on securities, variance and their correlation coefficients; there are risk-free assets in the market and investors can buy and sell them; assets in the capital market are tradable and unbounded and can be split; and securities markets are perfect and efficient, i.e. symmetric information, perfect competition, no transaction taxes, no price manipulation, etc.

However, in the real world of capital markets, where investors are in most cases limited in their ability to calculate and control their emotions, they are not as rational as the models assume, and information is not perfectly symmetrical in reality, which has led to limitations in the application of portfolio theory and capital asset pricing models in the real world. For example, these traditional theoretical models do not provide a strong explanation for the Friedman-Savage puzzle, that is why investors who buy low-risk insurance also buy high-risk lottery tickets, nor do they provide a strong explanation for many anomalies in finance.

3.2.2. Behavioral asset pricing model (BAPM)

Shefrin and Statman (1994) proposed a behavioral asset pricing model based on the CAPM model, which takes into account not only information as a determinant but also noise when pricing assets. Noise traders, like information traders, are important participants in the market and the behavioral asset pricing model takes both types of market participants into account. They do not follow Bayes' rule, have different cognitive biases, make different trading errors, have different risk preferences, etc. The involvement of noise traders leads to a reduction in market efficiency and a deviation of asset prices from value.

The expected return of security Z in the behavioral asset pricing model is:

$$E^* = E_\pi \rho(Z) - 1 = i_1 + \beta^*(Z)(E_\pi \rho^* - 1 - i_1) + A(Z) \tag{2}$$

Where $i_1$is the risk-free rate, $E_\pi \rho(Z)$denotes the expected return on asset Z according to objective information, ρ^* denotes the market factor, i.e. the portfolio return on the mean-variance portfolio boundary in an efficient market environment, $\beta^*(Z)$ is the βcoefficient for security Z and A(Z)denotes the abnormal return on the security.

If the market for the security is efficient, then A(Z) should be 0. However, if the market for the security is inefficient, then the transformation rate T_{ij} between the subjective and objective probabilities of the noise trader has a significant effect on the returns of market participants. If the market is perfectly efficient, then the conversion rate is 1. If there are noisy traders in the market, and assuming that the return on the market portfolio is ρ_{mv}, then the expression for the degree of risk of the security Z is:

$$\beta(Z) = \frac{Cov[\rho(Z), \rho_{mv}]}{Var(\rho_{mv})} \tag{3}$$

The β value at this point is the behavioral β value, i.e. the true β value.

Set up:

$$\beta(\rho^*) = \frac{Cov[\rho(\rho^*), \rho_{mv}]}{Var(\rho_{mv})} \tag{4}$$

Where $\beta(\rho^*)$is used to measure the degree of efficiency of ρ^*.It can be clearly seen that $\beta(\rho^*) \leq 1$, when it is equal to 1, the market is fully efficient at that point, while when the value is equal to 0, it is clear that the market is inefficient and the asset is unpriced.

As seen above, $\beta(\rho^*)$measures the risk associated with an efficient market ρ^*, but not all risk is priced.$\beta(Z)/\beta(\rho^*)$measures the risk premium of the security asset Z corresponding to ρ^*.The formula for the BAPM model created by Shefrin and Statman (1994) is shown in (5):

$$A(Z) = \left[\frac{\beta(Z)}{\beta(\rho^*)} - \beta^*(Z)\right][E_\pi(\rho^*) - 1 - i_1] \tag{5}$$

When the capital market is efficient, the excess return on the asset is then zero. equation (5) corrects for the risk factor β and reveals the link between the excess return on the asset and the return on the market portfolio. From the model, it can be seen that the excess return of a security is proportional to the mean−variance efficient frontier $\beta$of the asset and inversely proportional to the market coefficient β.

3.2.3. Noise trading risk (NTR)

In the BAPM model, the price of an asset is determined by behavioral $\beta$and not by the traditional β in the CAPM model. The presence of noise trading and hence the inclusion of noise traders within the pricing framework generates behavioral β, which essentially reflects only a lower risk β. In the CAPM model $\beta$is the sum of behavioral βin the BAPM model and the additional risk incurred by noise traders when participating in capital market transactions. Therefore, the traditional β is greater than the behavioral β.

Differentiating traditional β from behavioral β to create noise trading risk (NTR):

$$CAPM\beta = NTR + BAPM\beta \tag{6}$$

If the participants in the market are exclusively information traders (rational investors), then the noise trading risk (NTR) is zero, at which point the BAPM and CAPM are consistent. So that in a perfectly efficient capital market condition, the behavioral asset pricing model is of no practical relevance. However, if there is noisy trading, then the model can measure noise to some extent.

4. Analysis of the degree of risk of noise traders and its correlation with excess return

4.1. Program design

As the Shanghai A-share market is representative in China, this chapter focuses on the following steps to analyze noise trading in the Chinese capital market as a whole by using the Shanghai A-share market.

First, the data of Shanghai A-share market is collected, screened and processed, a reasonable market index is selected and a momentum index is constructed, relevant data processing is performed on the selected index, and then CAPM and BAPM are applied to calculate the noise trading risk (NTR).

Secondly, a comparative noise trading risk analysis is conducted on the long positions of different types of investors to identify the main sources of noise in the Chinese capital market. At the same time, by comparing the noise trader risk of different investors, it illustrates the heterogeneity of risk preferences and investment orientations among different types of investors.

Finally, the correlation analysis between noise trading risk and excess return is carried out by further dividing the selected time period into two scenarios: bull market period and bear market period, to illustrate the correlation between noise trading risk and equity excess return under different scenarios, and to make reasonable speculations on the causes.

4.1.1. Construction of momentum indices

For the application of behavioral asset pricing models, the most critical aspect is the construction of a market portfolio. In traditional financial empirical evidence, the return on the market composite index is generally used as a proxy for the return on the market portfolio. However, in behavioral asset pricing models, the empirical analysis requires the construction of a momentum index, which allows the effect of noise trading to be taken into account.

In the construction of the momentum index, the stocks selected are required to be relatively actively traded and traded above average volume levels so that they can be identified as preferred by market participants. Participants in the market are subjective and objective in their frequent trading of some stocks, resulting in increased and above-average trading volumes. In addition, the preferences of market participants change from time to time, so the corresponding momentum indices etc. also change from time to time.

Ramiah and Davidson (2003) argue that market traders' preferences can be captured by trading volume and therefore construct the momentum index by selecting stocks with trading volume at a high level in the market, as detailed in the following construction methodology:

In the first step, a trend filter is applied to market trading volumes.

$$V_t = \alpha + \beta_1 t + \beta_2 t^2 + \varepsilon_t \tag{7}$$

Where V_t is the trading volume, α、β_1、β_2 are the fitting coefficients, t and t^2 represent the linear and non-linear time trends respectively, and ε_t is the residual term.

In the second step,$V_t$is adjusted for autocorrelation. For the formation of the market portfolio, it is necessary to select the more active stocks in the market with the criterion that the expectation of the residuals is not 0.

In the third step, the calculation of the momentum index is carried out using equation (8).

$$DVI_t = \frac{\sum S_{it} P_{it}}{\sum S_{io} P_{io}} I_0 \tag{8}$$

Where DVI_t, S_{it}, S_{i0} are in turn the momentum index and the trading volume of the security at moment t and 0, P_{it}、P_{i0} are the closing prices at moment t and 0respectively, andI_0 is the adjustment factor.

As the process of constructing momentum indices is more complex and less feasible, scholars often adopt other methods of index construction when conducting relevant empirical analyses. For example, Ramia and Davidson (2003), the authors of a specific methodology for constructing momentum indices, did not use the methodology proposed in 2003 in their 2007 empirical analysis of the Australian market, but used the constituents of the MDI index to construct a momentum index, of which there were only 10 constituents of the MDI index, all of which were well-known companies.

In summary, this paper analyses the Chinese capital market with the help of the Shanghai A-share market and uses the SSE 50 constituents in the construction of the momentum index. Since the SSE 50 constituents have a pivotal position in the entire SSE market and their trading volume is more than 20% of the entire Shanghai market, and the constituents are adjusted every six months, with the proportion generally not exceeding 10% of the weight, they can be an effective substitute for the momentum index to a certain extent.

4.1.2. Noise trading risk calculation model

For the calculation of noise trading risk, the following steps are taken.

Regarding the calculation of the rate of return:

$$R_{it} = \ln\left(\frac{P_t}{P_{t-1}}\right) \tag{9}$$

$$R_{mt} = \ln\left(\frac{index_t}{index_{t-1}}\right) \tag{10}$$

$$R_{bt} = \ln\left(\frac{DVI_t}{DVI_{t-1}}\right) \tag{11}$$

Where R_{it} is the individual stock return and P is the daily (weekly, monthly, quarterly, etc.) closing price. R_{mt} is the capital asset portfolio return and $index$ is the daily (weekly, monthly, quarterly, etc.) SSE Composite Index. R_{bt} is the behavioral asset portfolio return and DVI is the daily (weekly, monthly, quarterly, etc.) SSE 50 Index.

Calculation of traditional β, according to the CAPM model：

$$R_{it} - R_f = \alpha + \beta_C\left(R_{mt} - R_f\right) \tag{12}$$

Calculation of behavioral β, according to the BAPM model:

$$R_{it} - R_f = \alpha + \beta_B(R_{bt} - R_f) \tag{13}$$

Calculation of noise trading risk：

$$NTR = \beta_C - \beta_B \tag{14}$$

The risk-free rate of return in this paper uses the regular lump sum one-year interest rate instead of the uncommon five-year Treasury bond yield as it takes into account that Treasury bond yields are artificially depressed due to tax and regulatory factors. The behavioral market portfolio in this paper uses the Shanghai Stock Exchange (SSE) 50 constituent stocks while the capital market portfolio is replaced by the SSE Composite Index. When performing the NTR calculation, if the value of NTR is greater than 0, then it can be assumed that there is noise trading, while a larger value of NTR indicates more serious noise trading. It is worth noting that the value of NTR is theoretically positive, but for the sake of operability, the momentum index uses the SSE 50 index for substitution, which will lead to some deviation from the actual result, and a negative NTR value can be negligible.

4.2. Data sources and processing

4.2.1. Data sources

All stock market data in this paper are sourced from the CSMAR database, and the research sample is all listed companies in China's Shanghai A-share market during the period from January 2018 to December 2022. As the research question in this paper is the correlation between noise trading in a bull market following a bear market rally caused by a major negative event and excess returns, the time period selected is the period of concentration of many short-term events that can cause market pessimism, such as the Sino-US trade war, the new crown epidemic, the Russia-Ukraine geopolitical conflict and the Fed's continued interest rate hike, and the continued downturn in China's capital markets and economic downturn in recent years is evident to all.

First, this paper analyzes quarterly data on shareholders of all stocks on the Shanghai A-share market from the first quarter of 2018 to the fourth quarter of 2022 to obtain the corresponding institutional shareholding ratio of each stock at the end of each quarter, and then takes the average value of the quarterly shareholding ratio to obtain the average value of the quarterly institutional shareholding ratio of each stock in the study interval x. According to the assumptions of this paper, investors are divided into institutional investors and individual investors According to the assumptions of this paper, investors are divided into institutional investors and individual investors, and the corresponding individual shareholding ratio is calculated as $1-x$.

The stocks in the whole market were then sorted and screened according to the investor shareholding ratios, and the top 30 stocks for each type of investor shareholding were selected for noise trading risk analysis, which in turn yielded noise information for different types of investors. For the screened stocks, stocks listed after 1 January 2018 were excluded, stocks in the ST, PT and *ST sectors were excluded, and returns were analyzed using daily frequency data. The final stocks selected for the different types of investors' long positions in this paper are shown in Table 1.

Since there are distinctly different risk preferences among different investors in the Chinese capital market, this paper divides investors in the Chinese capital market into individual investors and institutional investors. Further, as there are different behavioral characteristics, capital management teams, risk preferences, information acquisition and processing capabilities among different institutional investors, this paper conducts corresponding noise trading risks for public funds, brokerages, qualified foreign institutional investors (QFII), social security funds, insurance, trusts, finance companies, banks, non-financial listed companies and other institutions among institutional investors respectively Analysis.

Table 1 Top 30 heavy stocks of different types of investors

Institutional investors										Individual investors
Fund	QFII	Broker	Insurance	Security	Entrust	Finance	Bank	NonFIN	Other	
600610	603015	000166	601628	300395	600783	000551	000912	600829	601939	603768
000661	300620	603997	000001	002341	601928	600517	000792	002916	601398	601086

600399	603002	002856	600383	300357	002736	300084	600815	603823	600188	300028
600158	603663	603315	000402	002539	002676	600184	600423	600508	601998	603321
600763	002142	000932	000061	002884	000504	600710	600725	600270	601857	300135
300012	601328	600507	600620	600426	600243	002011	601005	000951	601988	002813
300207	300682	600745	600340	002126	000979	603889	000982	002080	601288	603726
300014	002472	600337	000012	002061	002387	600290	601128	000657	601811	002882
000504	601009	603778	300168	600486	002670	002169	002370	000905	600028	002613
300476	601169	601117	000601	000910	000793	002661	002716	600741	600025	002742
300037	300642	600299	600000	300035	600515	002686	601688	600511	600871	603421
300661	600761	601801	600016	002301	600106	600114	601777	000028	601633	002828
000860	000016	000988	600015	603599	603399	300304	002608	600268	000617	300539
300363	600132	603663	600085	600079	000767	601058	002647	601238	600917	002767
300285	002206	000719	600697	600858	002199	300252	000520	600845	002423	002360
601012	002314	000821	600712	300349	300038	000875	601601	600688	601158	002817
000568	300685	000670	600694	002250	002141	002666	600399	600841	001965	601218
600563	601012	600536	600751	603520	000673	600586	601258	600573	601991	002846
603096	300166	002532	601166	002583	600811	000582	600330	600754	601808	002526
300226	603520	002199	002638	600057	002442	300388	600900	000877	601898	002830
002821	300487	603008	002202	600872	000761	002026	300146	600835	002911	300099
600170	002410	600179	600578	300003	600782	000563	300116	600449	601088	603165
600660	300203	600273	600376	600138	600482	603377	600886	002800	002287	002566
600529	300481	002623	600050	300113	000728	600335	002169	000078	603103	002406
603179	603855	002701	002052	603811	600160	603338	300302	600961	601881	002177
002025	002173	002210	600036	300709	002042	002501	000031	600316	600403	002535
002475	300041	002435	600926	002039	000040	000546	600157	600281	601800	002702
300253	002186	002424	600872	300577	300061	002745	600395	603916	002461	603458
603345	002008	000623	600577	300083	000686	002180	601038	000776	002032	002763
002332	300660	603578	600628	000661	601900	000700	002210	600372	601326	002790

4.2.2. Data processing

This paper first performs normality and stationarity tests on the market index returns and momentum index returns, the results of which are shown in Table 2 and Table 3 respectively, and performs statistical analysis on the NTR of different investors, as shown in Table 4.

Table 2 Shapiro-Wilk normality test for yields

Variable	Obs	W	Prob>z
Rm	1,215	0.951	0.000
Rb	1,215	0.973	0.000

Table 3 Augmented Dickey-Fuller smoothness test for yields

	Test statistic	critical value			P value
		1%	5%	10%	
Rm	-35.046	-3.43	-2.86	-2.57	0.000
Rb	-34.05	-3.43	-2.86	-2.57	0.000

Table 4 Investor NTR calculation results

	VARIABLES	mean	sd	min	p50	max
Fund	β_m	1.137	0.214	0.736	1.149	1.59
	β_b	0.843	0.233	0.401	0.852	1.428
	NTR	0.294	0.138	-0.047	0.271	0.537
Security	β_m	1.121	0.182	0.779	1.118	1.49
	β_b	0.776	0.162	0.478	0.777	1.13
	NTR	0.345	0.119	0.079	0.343	0.574
QFII	β_m	1.097	0.202	0.507	1.15	1.401
	β_b	0.749	0.152	0.489	0.749	1.103
	NTR	0.348	0.173	-0.066	0.38	0.552
Broker	β_m	1.05	0.181	0.694	1.07	1.421
	β_b	0.678	0.153	0.283	0.661	0.974
	NTR	0.372	0.094	0.25	0.335	0.572
Insurance	β_m	0.976	0.193	0.6	0.958	1.315
	β_b	0.756	0.227	0.45	0.695	1.245
	NTR	0.22	0.174	-0.116	0.24	0.538
Entrust	β_m	1.066	0.194	0.736	1.054	1.395
	β_b	0.681	0.18	0.448	0.622	1.054
	NTR	0.385	0.089	0.263	0.356	0.554
Finance	β_m	1.115	0.177	0.759	1.177	1.347
	β_b	0.69	0.115	0.457	0.689	0.917
	NTR	0.426	0.1	0.202	0.434	0.595
NonFIN	β_m	1.123	0.196	0.736	1.109	1.486
	β_b	0.768	0.183	0.464	0.769	1.168
	NTR	0.355	0.106	0.124	0.331	0.531
Bank	β_m	0.973	0.256	0.338	0.974	1.494
	β_b	0.633	0.223	0.337	0.627	1.241
	NTR	0.34	0.152	-0.031	0.347	0.639
Other	β_m	0.908	0.248	0.453	0.888	1.516
	β_b	0.668	0.175	0.414	0.647	1.202
	NTR	0.241	0.129	-0.005	0.284	0.419
Individual	β_m	1.038	0.165	0.719	1.05	1.432
	β_b	0.607	0.117	0.237	0.603	0.865
	NTR	0.431	0.072	0.32	0.411	0.593

As can be seen from Table 2, the corresponding p-values for both the momentum and market index returns are less than 1%, so the original assumption of normality is rejected, which means mentum and market index returns are non-normally distributed.

As can be seen from Table 3, the p-values of the smoothness tests for both the momentum index and the market index returns are less than 1%, indicating that both are smooth series.

From the data in Table 4, it can be seen that the noise trading risk of individual investors, finance companies and trusts is at a high level, with individual investors having the highest noise risk, which shows that irrational investment is particularly prominent in the group of individual investors. This also leads to a weaker ability to filter information when making decisions, which makes them susceptible to misinformation and blind investment, and because individual investors are more irrational, the probability of behavioral deviations increases, ultimately making the individual investor group the most exposed to noise trading and one of the main sources of noise in the Shanghai A-share market. Finance companies and trust companies take on a large amount of risk, including credit risk, and have a higher level of risk appetite, the pursuit of short-term interests, resulting in large fluctuations in the capital market, and this type of more noisy investors do not have a fine study of stock selection, so this part of the traders have a higher rate of turnover, there is a higher risk of noise trading. Therefore, under normal circumstances, where the market is more efficient, these noise traders are unable to use misinformation to beat the market, that is noise trading risk should be negatively or uncorrelated with excess return.

4.3. Correlation analysis of noise trading risk and excess return

So how does noise trading risk correlate with excess returns in the bull market that has been ushered in at the end of a sustained downturn in China's capital markets? Will investors earn more due to the additional noise trading risk they take in the particular market environment? With this in mind, this paper first conducts a statistical analysis of the correlation between noise trading risk (NTR) and excess return for each type of investor's long positions over the selected full period, as shown in Table 5.

Table 5 Investor Excess Return Statistics

Excess return	Fund	QFII	Broker	Insurance	Security	Entrust
mean	0.03802%	-0.00582%	-0.03345%	-0.03659%	-0.02493%	-0.07987%
sd	3.18841%	2.98089%	3.01999%	2.38489%	3.04847%	3.07534%
Excess return	Finance	Bank	NonFIN	Other	Individual	
mean	-0.03787%	-0.03782%	-0.01661%	-0.02306%	-0.06229%	
sd	2.91312%	2.91889%	2.76509%	2.27729%	3.00571%	

The statistics in Table 5 show that individual investors, finance companies and trusts have higher noise trading risks than banks, brokerages and QFIIs, yet the average returns are at the lowest level of the investment entities counted, lower than those of banks, brokerages and QFIIs. So overall the time period chosen is in line with the general perception mentioned earlier that trading with irrational noise information in a more efficient market cannot generate more returns for investors.

In order to further investigate the issues in this paper, a simple division of the market types for the selected time period is made. The selected time period was split into bull and bear markets by plotting and observing the chart of the SSE Composite Index, as shown in Figure 1.

Bull Market：2019.01.03-2019.04.19

2020.03.23-2021.09.13

Bear Market：2018.01.01-2019.01.03

2019.04.19-2020.03.23

2021.09.13-2022.12.31

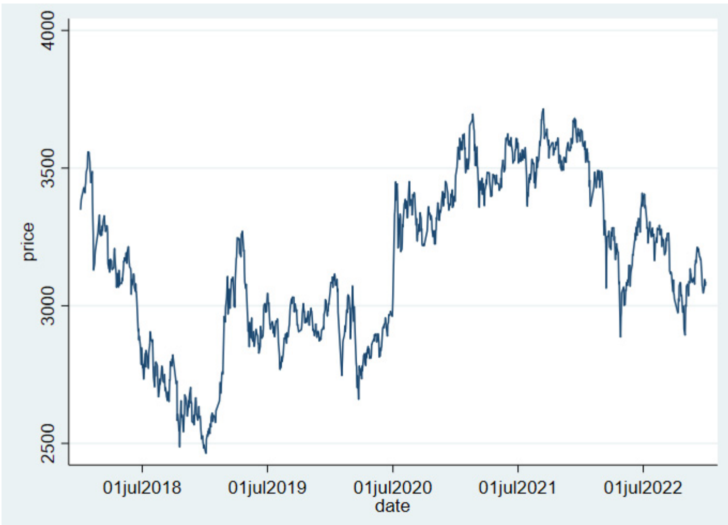

Figure 1: SSE Composite Index Chart

Next, a statistical analysis of the correlation between noise trading risk (NTR) and excess returns for each type of investor's heavy positions over the delineated bull market period was conducted, as shown in Table 6. By looking at the statistical results comparing Table 6 with Table 5, it can be seen that originally individual investors, finance companies and trusts had lower average returns than investment entities such as banks, brokerages and QFIIs due to the higher noise trading risk they bore, however, during the bull market period arising from the end of the persistently low bear market, the results reversed, with the investment entities bearing the highest noise trading risk, trusts, and Individuals and finance companies, however, had excess returns at a higher level than investment entities with lower levels of noise trading, such as banks, brokerages and QFIIs. Social security funds, public funds and the insurance industry take into account their industry attributes, social security funds are non-profit nature, not open to individual investors, income into the state treasury; public funds are subject to more stringent regulation, there are information disclosure, profit distribution, operating restrictions, etc.; insurance industry's main source of income through the probability of actuarial earning premiums, and the insurance industry's capital management is generally achieved through investment bonds. From this point of view, social security funds, public funds and the insurance industry are more strictly risk averse, more rational in the level of position selection and biased towards medium and long-term investment holdings and seldom carry out short-term frequent change of hands trading operations. Therefore, these three investment entities have certain specificities that are inconsistent with the hypothesis of this paper.

Table 6 Results of investor excess return statistics during the bull market

Excess return	Fund	QFII	Broker	Insurance	Security	Entrust
mean	0.12009%	-0.02637%	-0.02893%	0.01211%	0.09393%	-0.02156%
sd	3.8336%	2.77796%	1.8032%	2.29867%	3.18561%	3.01636%
Excess return	Finance	Bank	NonFIN	Other	Individual	
mean	-0.00126%	-0.02284%	-0.0521%	-0.03085%	-0.02142%	
sd	2.83683%	2.82345%	2.60218%	1.38577%	2.35316%	

So, is there a strong positive correlation between noise trading risk (NTR) and the excess return of a stock in a particular capital market environment? In this paper, a regression analysis of the excess return on stocks and NTR was conducted for the selected 240 investor long positions, the regression model is shown in equation (15) and the correlation definitions of the control variables used in this paper are shown in Table 7.

$$R_i - R_f = \alpha + \beta_0 NTR_i + \beta_C ControlVariables_i + \varepsilon_i \qquad (15)$$

Table 7 Definitions relating to control variables

Variable	Description
Size	Logarithmic value of total assets ($ billion) in the balance sheet
Debt Asset ratio (leverage)	Total liabilities / total assets
Book to market ratio (BM)	Book value / total market value
Return on Assets (ROA)	EBIT x 2 / (Opening total assets + Closing total assets) x 100%
Turnover rate (turnover)	Operating income / (Opening total assets + Closing total assets)/2

The regression method for Equation (15) uses mean least squares and the regression results are shown in Table 8, where it is clear that there is a significant positive correlation between excess return and noise trading risk. The dependent variable of the regression equation is the average daily return of individual stocks during the bull market interval in the selected time frame and the explanatory variable is noise trading risk. The regression results are obtained with the inclusion of control variables for company financials, including company size, book-to-market ratio, gearing, return on total assets and asset turnover, as there is a more significant correlation between these company financial indicators and noise trading and excess returns. It can be seen that apart from a significant positive correlation between noise trading risk and excess returns, rational financial indicators such as firm size and excess returns show a significant positive correlation and book-to-market ratio and excess returns show a significant negative correlation, indicating that the bull market ushered in by the end of a long period of pessimism in the capital market presents a paradoxical but irrational dominant state, in line with behavioral finance's overreaction, overconfidence and other The concept is consistent with behavioral finance.

Table 8 Bull market returns and NTR regression results

	Ri-Rf
NTR	0.0035***(4.63)
turnover	0.0002*(1.71)
lev	0.0005(1.43)
BM	-0.0021***(-6.64)
ROA	0.0002(0.67)
size	0.0003***(4.00)
_cons	-0.0047***(-3.14)
R^2	0.0004

Note: *, ** and *** indicate significant at the 10%, 5% and 1% levels respectively, as in the following tables.

Further multiple linear regression analysis for the rest of the selected time horizon (bear market), as shown in Table 9, reveals that the correlation between noise trading risk and excess returns in a pessimistic bear market caused by a major short-term negative event is not significant, probably due to the phenomenon of under-reaction caused by the grip of pessimism, where investors' continued lack of optimism about the future market may make Investors may be more cautious in their approach to information, reducing the frequency of trading turnover to a certain extent, i.e. noise trading decreases in a pessimistic bear market.

Table 9 Bear market returns and NTR regression results

	Ri-Rf
NTR	0.0004(0.57)
turnover	0.0001(0.61)
leverage	-0.0010***(-3.01)
BM	-0.0032***(-10.43)
ROA	0.0006**(2.28)
size	0.0003***(5.95)
_cons	-0.0067***(-4.96)
R^2	0.0009

4.4. Summary of this chapter

Using the noise correlation theory in Part 3, this chapter presents an empirical analysis of the correlation between noise trading risk and return for different types of investors. The results show that different investors have significantly different risk preferences and investment levels, and that the main sources of noise risk in the Chinese capital market are individual investors, trusts, and finance companies. In the particular environment defined - a bull market arising from the end of a bear market under sustained pessimism brought about by a major short-term negative event - which is not sufficiently efficient due to the overall overconfidence of the market, a special phenomenon emerges in which investment agents with high noise trading risk are able to take on additional noise trading risk and more returns.

5. Conclusion

This paper is to explore the correlation between noise trading risk and excess returns in an over-emotional market, based on the traditional capital asset pricing model (CAPM) and behavioral asset pricing model (BAPM), with noise trader risk (NTR) theory as the basis for calculation, using the returns of all listed companies in the Shanghai stock market from January 2018 to December 2022 and listed financial data, etc., as samples, comparing and quantifying noise trader risk between individual investors and various different types of institutional investors, and conducting correlation analysis between noise trading risk and returns in the selected overconfident market environment, the following main conclusions were obtained:

1. The analysis of the level of noise trader risk shows that all traders are exposed to varying degrees of noise risk. Individual investors are not the only noise traders in the market, but institutional investors such as trusts and finance companies are also exposed to significant noise trader risk, and they are also the main sources of noise in the capital markets.

2. The correlation between noise trading risk and return during the selected bull market period, combined with the t-test, shows that noise trading risk is positively correlated with excess return in overly emotional markets as opposed to being negatively correlated with excess return in normally efficient markets.

In this light, China's capital markets are not sufficiently effective, especially in overly optimistic or overly pessimistic emotional markets caused by major short-term events. When the market as a whole tends to be less than rational in its frenetic state, rational investors are limited in their price correcting arbitrage behavior and will be less likely to arbitrage; noise traders will earn excess returns as they take on additional noise trading risk that they have artificially created. According to the relevant theories in behavioral finance, this particular phenomenon is likely to persist. However, as barriers to entry to capital markets are raised, investors involved in them become better educated and governments strengthen regulation, the phenomenon of markets becoming emotional rather than rational at particular times may gradually ease and eventually become more effective.

In future, this paper could be improved in by 1. introducing an index of investor sentiment as an evidential support to increase credibility and persuasiveness in particular market environments 2. introducing a longer period in the data to observe normal market performance under normal circumstances.

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