# FEEDBACK TRADING, DELAYED ARBITRAGE, AND ASSET PRICE BUBBLES: THEORETICAL AND EMPIRICAL STUDIES BASED ON DIFFERENT CYCLES

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**Abstract:** The 20th CPC National Congress emphasized that financial security is the cornerstone of national security, and preventing asset price bubbles is the core task of financial market risk prevention and control. China's stock market has developed rapidly, but it is characterized by frequent price fluctuations, and the deviation of prices caused by irrational investor behavior and arbitrage restrictions is prominent. Existing research mostly focuses on the theoretical level and lacks empirical analysis targeting the Chinese market. Moreover, the inverse relationship between investor sentiment and stock returns contradicts the reality of the weak presence of rational traders in China's market. This paper, from the perspective of behavioral finance, combines feedback trading and delayed arbitrage theory to construct an investor sentiment index based on principal component analysis and explores its dynamic relationship with the formation of stock price bubbles in China. Through empirical tests across multiple cycles, it reveals the mechanism by which arbitrage restrictions affect the persistence of bubbles and explains the "reverse induction puzzle," providing theoretical support and policy insights for improving China's stock market risk prevention and control system. **Keywords:** Investor sentiment; Feedback trading; Delayed arbitrage; Stock price bubbles; Arbitrage restrictions

# **1 INTRODUCTION**

# 1.1 Research Background

The 20th CPC National Congress elevated financial security to a national strategic level, emphasizing that "preventing and resolving financial risks is the fundamental task of financial work." Data shows that the total market value of China's A-shares has exceeded 80 trillion yuan, accounting for more than 12% of the global capital market. However, its price formation mechanism still has significant particularities: compared with mature Western markets, China's stock market, with a shorter development history and distinct characteristics of institutional transformation, exhibits more frequent asset price fluctuations and bubble accumulation phenomena.

Through a systematic review of the literature, two core issues were identified: first, the disconnection between theoretical mechanisms and empirical tests. Although Berger and Turtle conducted empirical tests on the investor sentiment index using U.S. sample data, no scholars have conducted empirical analyses using Chinese sample data [1]. Second, the theoretical paradox of investor sentiment indicators and the need for localization reconstruction. China has fewer investment institutions and weaker forces of rational traders, making it more prone to stock price bubbles. Therefore, this inverse indicator cannot match the current situation of China's stock market. This also necessitates the expansion through an investor sentiment index, studying the dynamic relationship between investor sentiment and stock returns to solve the reverse induction puzzle and better explain why China is more prone to stock price bubbles.

# **1.2 Research Significance**

This paper has three practical values: First, it systematically analyzes the internal mechanisms of stock market fluctuations. By revealing the dynamic characteristics of the interaction between investor sentiment and market cycles, it provides a theoretical basis for understanding the special operating laws of China's capital market. Second, it innovates the investor decision-making analysis framework. It constructs a multi-dimensional decision-making model based on the identification of behavioral biases, providing methodological support for individual investors to avoid cognitive traps and optimize asset allocation. Third, it strengthens the effectiveness of financial risk prevention and control. By identifying early signals of emotion-driven price deviations, it helps regulatory authorities establish a forward-looking early warning system and improve the response mechanism for market imbalances caused by irrational trading, effectively maintaining the stable operation of the capital market.

# 2 DOMESTIC AND INTERNATIONAL RESEARCH STATUS

# 2.1 Definition and Measurement of Investor Sentiment

Li Junpan et al. pointed out that investor sentiment originates from investors' minds and psychological states and is a subjective influencing factor in investors' decision-making and actions [2]. The definition of investor sentiment has not

(1)

(2)

yet been unified, and existing research mainly defines it from the perspective of investors' beliefs and preferences deviating from traditional rational theory. In terms of measurement, although principal component analysis is widely used, it has certain limitations, such as requiring investor sentiment components to account for the largest proportion in common factors. Some studies have attempted to construct an emotion index using partial least squares to make up for the shortcomings of principal component analysis.

#### 2.2 Feedback Trading

Chen Jian and Zeng Shiqiang studied the impact of optimistic and pessimistic emotions on the behavior of noise traders and rational traders from both theoretical and empirical perspectives [3]. They further analyzed how these emotions drive market feedback trading behavior and explored the reaction of returns to investor sentiment shocks. Chen Zijun argued that since arbitrageurs' understanding of mispricing is sequential [4], they generally do not act immediately when they discover mispricing but choose the right time to enter and arbitrage. This also indicates that the impact of behavior on prices has a short-term resistance to arbitrage.

#### 2.3 Delayed Arbitrage

He Chengying et al. pointed out in their theoretical and empirical research that limited arbitrage is one of the main reasons for investor sentiment anomalies in the market [5]. In stock portfolios with more severe arbitrage restrictions, the phenomenon of negative correlation between investor sentiment and stock returns is more evident. At the same time, investor sentiment and stock price anomalies are more pronounced under extreme market emotions and extreme optimism.

#### 2.4 Asset Price Bubbles

Numerous studies have defined and interpreted asset price bubbles from different perspectives and used various methods to identify and test the existence, cycle, frequency, and degree of bubbles.

#### **2.5 Research Review**

Existing research has achieved certain results in the impact of investor sentiment on the stock market but still has shortcomings. There is a lack of theoretical and empirical research combining feedback trading and delayed arbitrage, and the explanation for the reverse induction puzzle is not deep enough, without fully considering the characteristics of China's stock market. This study will address these deficiencies and conduct in-depth analysis of the related issues.

#### 2.6 Theoretical Research

We assume that there is a stock D in the market and divide the market into positive feedback traders and fundamental traders. We construct a model using a sentiment index to explain the specific situation of positive feedback traders and fundamental traders considering the impact of favorable information. Through the mutual game of the two types of market traders and based on market clearing to solve the equilibrium price of the stock in different periods, we discuss the stock price mechanism from a theoretical level. For the basic price of the stock, we divide this model into four trading periods. Period 0: There is no trading in the market. Period 1: Positive feedback traders do not react to the current price, and the demand is 0. Fundamental traders buy low and sell high, and their demand function is:

$$D1 = \alpha 1 - \beta 1P$$

When the stock price becomes basic public information, the demand of positive feedback traders in Period 2 is:

$$D_2^e = \alpha(\varphi - P_2)$$

The demand of fundamental traders in Period 2 is negatively correlated with the price of the security relative to its fundamental value, and the demand is:

$$D_2^f = \beta(P_1 - P_0) \tag{3}$$

The demand of fundamental traders in Period 2 is negatively correlated with the price of the security relative to its fundamental value, and the demand is:

$$D_2^e = \alpha(\phi - P_2) \tag{4}$$

After a favorable signal for stock D appears in the stock market, this project studies the game process of positive feedback traders and fundamental traders and combines the supply and demand theory to obtain the fundamental value and price sequence at different times. Through numerical simulation, the changes in variables are obtained, and the price time series change chart is drawn.

#### **3** EMPIRICAL RESEARCH

#### 3.1 Constructing Daily, Weekly, and Monthly Investor Sentiment Indexes

First, several original investor sentiment indicators are determined. Principal component analysis is used to construct investor sentiment, which can effectively remove noise factors in the original data and retain the collinear components of these data.

#### 3.1.1 Selection of investor sentiment proxy indicators

Turnover Rate (ATR): Reflects market liquidity and can be used to distinguish between optimistic and pessimistic emotions.

Closed-End Fund Discount Rate (CEFD): The change in the discount rate of closed-end funds reflects the impact of investor sentiment changes.

Initial Public Offering Return (IPOR): The return on the first day of listing can well reflect the degree of investor enthusiasm and is a positive indicator of sentiment.

Consumer Confidence Index (CCI): It reflects consumers' satisfaction with the current economic situation and their expectations for future economic development. This indicator is monthly data and reflects consumers' confidence in the market this month. When studying daily and weekly data, the data will be adjusted. CCI is the only subjective indicator. To construct the daily, weekly, and monthly composite sentiment indexes, we first take the first-order difference of the sentiment proxy indicators and then perform principal component extraction on the processed variables. When conducting principal component analysis, we extract the first five principal components based on the method of eigenvalues greater than 1. These five principal components are then weighted averaged according to their respective eigenvalues to obtain the preliminary composite investor sentiment index (INSI1). The calculation method is as follows:

$$INSI_1 = P * \frac{VEL}{EVEL}$$
(5)

#### 3.1.2 Constructing the daily investor sentiment change index

To address the timeliness issue of the classic BW monthly frequency index, this paper constructs a daily sentiment change index using principal component analysis. A 1% winsorization is applied to this index to exclude the influence of outliers. Subsequently, the continuous positive parts are accumulated and summed up. It should be noted that the original data are all positive values. However, after standardization by mean and standard deviation, negative values may appear, which represent low sentiment scenarios.

# 3.1.3 Constructing the weekly investor sentiment change index

For the weekly index, after taking the first-order difference of the sentiment indicators, we apply the Partial Least Squares (PLS) method to effectively extract the sentiment S (sentiment change index). This process filters out irrelevant components and captures the consistent relationship between investor sentiment and expected stock returns across periods.

# 3.1.4 Constructing the monthly investor sentiment change index

When constructing the monthly index, after obtaining the preliminary composite investor sentiment indicator using the aforementioned methods, we need to take the first-order difference again. In the second construction of the sentiment composite index, only the first and second principal components are extracted, and then the coefficients of their linear combination are calculated.

#### 3.2 Establishing the Relevant Linear Regression Model

In this empirical study, we need to test two hypotheses related to the accumulation of sentiment changes. We create a new indicator, Sumt-1,pos , to represent the accumulation of high sentiment. For these values, if the sentiment change in a period is positive, then the value of Sumt-1,pos is accumulated with the sentiment of that period; otherwise, it is reset to zero. The purpose of this treatment is to ensure that this indicator measures sentiment that has been continuously accumulating. In this way, we can derive the investor sentiment accumulation index at different frequencies and levels. As the bubble persists and sentiment increases, we predict that the relationship between positive sentiment and subsequent regression will weaken. The growth rate of the bubble will slow down when fundamental traders engage in arbitrage, and the bubble will burst when it inflates to a certain extent. We test this through the construction of a linear regression equation:

$$R_{i:t} - R_f = \alpha_i + \theta_i SUM_{t-1,pos} + \varphi_i SUM_{t-1,pos}^2 + e_{i,t}$$
(6)

t represents the period. Depending on the sentiment index of different cycles, the length of each period will vary. Rj,t denotes the excess return of asset j in period t, Sumt-1, pos is the accumulation of high sentiment, and Sumt-1,pos2 is the square of this accumulation. According to Baker et al. [1], we do not include risk factors that may weaken the

empirical results.

We predict that the  $\theta$  coefficient will be positive because, in the short term, a surge in sentiment will lead to an increase in future stock returns. We also predict that the  $\phi$  coefficient will be negative because, as the bubble expands, the selling pressure from rational arbitrageurs increases, thereby suppressing the growth rate of the bubble. Ultimately, we can verify that as the accumulation of high sentiment has a diminishing marginal effect on future excess returns, the growth rate of excess returns gradually slows down. When the accumulation of high sentiment reaches a sufficiently high level, a price correction will occur.

# **3.3** The Accumulation of Investor Sentiment and the Behavior of Positive Feedback Traders and Fundamental Traders

The diminishing marginal effect of high sentiment accumulation on future excess returns leads to a gradual slowdown in the growth rate of excess returns. When the accumulation of high sentiment reaches a sufficiently high level, a price correction occurs. Through the fitted quadratic relationship, we obtain a graph that intuitively shows the process of mutual game between positive feedback traders and fundamental traders in the market[6-7].

# 4 RESULTS

# 4.1 Validation of Sentiment Index Effectiveness

The daily sentiment volatility (standard deviation of 0.38) is significantly higher than the monthly sentiment volatility (standard deviation of 0.21). Moreover, the correlation coefficient between daily sentiment and turnover rate reaches 0.67 (p<0.01), indicating that short-term market sentiment has a significant driving effect[8].

# 4.2 Bubble Formation and Bursting Thresholds

The regression results show coefficients of 0.15 (p<0.05) and 0.12 (p<0.01), confirming the nonlinear impact of sentiment accumulation on returns. When the sentiment accumulation SUM<sub>t,pos</sub>>4.7, the probability of price correction increases to 68% (95% Confidence Interval: 63%-73%), and the bubble cycle is shortened to 12-15 trading days.

# **5** DISSCUSION AND CONCLUSION

By measuring investor sentiment across different cycles (daily, weekly, and monthly), this paper captures the rapid changes in investor sentiment, which can better prevent asset price bubbles caused by investor sentiment. Analyzing the impact of investor sentiment fluctuations on stock market volatility can assess the potential impact of sentiment volatility on economic growth and market stability. It also helps us to further clarify the patterns of stock market fluctuations in China, providing guidance for policy-making and risk management to some extent. This enables financial regulators to promptly detect the formation of "irrational bubbles" in the market, thereby preventing them and maintaining normal stock price fluctuations. It also aids in making correct macroeconomic decisions in a timely manner to stabilize the stock market. Analyzing the impact of investor sentiment fluctuations on market trading behavior can assess the degree of impact of sentiment volatility on market efficiency. It also provides a new perspective for investors and financial institutions to make decisions, enhancing investors' risk management capabilities and contributing to the stability of the financial market.

# **COMPETING INTERESTS**

The authors have no relevant financial or non-financial interests to disclose.

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