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Noise Trading and Abnormal Return in Stock Market

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Abstract

This study analyzes the relationship between noise trading and abnormal returns on assets. This study first validates the positive correlation between noise trading and abnormal returns on assets. In markets with high noise trading, the higher the abnormal returns on its assets, and vice versa. In exploring the relationship between noise trading and asset yield, this study uses abnormal return as a new indicator proposed in recent years for analysis. When analyzing the impact of company fundamentals on return on assets, the variables of company fundamentals are integrated using clustering analysis and principal component analysis. This suggests that in the long run there is a mutual causal relationship between noise trading and abnormal returns on assets. The results of this study show that the deviation from the interaction of noise trades and abnormal returns can be corrected and reach the equilibrium in the long run.

Keywords: noise trade, abnormal return, long-term equilibrium relationship, causal relationship.

1. Introduction

Noise trading research is an important research in behavioral finance. Scholars have carried out research and discussion on the influence of noise trading and related problems such as noise trading measurement indicators.

In recent years, with the vigorous development of China's financial market, more and more scholars based on China's special policy restrictions on China's capital market noise trading related research and empirical analysis.

This study explores the relationship between noise trading and excess return on assets. This study not only uses new indicators developed in recent years, but also uses newer research methods. In the specific exploration of the relationship between noise trading and asset returns, this study uses excess yield, a new indicator proposed in recent years, for analysis.

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In analyzing the impact of the company's fundamentals on the return on assets, the financial indicators reflecting the fundamentals of the securities and applied with clustering analysis and principal component analysis.

2. Literature Review

Noise traders are defined as investors who do not have access to inside information, irrationality, use error messages or even information as correct information and trade on that basis (De Long et al, 1989, De Long et al, 1990). Therefore, the noise of the capital market also mainly refers to the above-mentioned investors as the basic role of transaction decision-making, but not related to the capital market-related products in the capital market relevance or incorrect information.

In fact, how to measure noise and how to select the measure of noise trading has always been an important topic in behavioral finance.

Some literatures categorize the investors into two types which are rational investors and noise traders. The rational investors have rational expectations about security returns and noise traders trades according to their sentiment. Both types of investors trade in the market depending on their own beliefs. Therefore, the trading behaviors may be very different. However, most of the investors are avoiding risks. Previous researches consider the individual investors are noise traders and the institutional investors are rational investors. Because institutional traders generally mine information and are relatively knowledgeable about the information; while individual investors cannot dig deep into effective information due to financial, material, and manpower constraints, and even trade based on gossip, so the researchers believe that noise trading Generally speaking, they are individual investors. However, practically it is difficult to ensure that all traders are completely rational. Some institutional investors may be irrational investors sometimes and trade with a strong noise (De Long et al, 1988, Hirshleifer and Luo, 2001).

Some researches use the quantitative methods to defined the noise trading. There is no consensus in academia on how to quantify noise trading. In general, the metrics are divided into two broad categories: cross-disciplinary psychological indicators and directly related financial transaction indicators. Among them, the psychological substitution index is mainly confidence index, business climate index, etc. Financial trading indicators, on the other hand, focus on liquidity-related indicators, including the rate of signature, the growth rate of new account openings, the turnover rate, etc. First, scholars proposed the use of liquidity, information and trading frequency to distinguish between informed traders, unsuspecting traders and market makers of the EKOP model, and built a framework for calculating the probability of informed trading (Easley,1996). Dynamic volatility index is another measurement of noise trader risk and proves that the turnover rate is currently a better standard for reflecting noise trading. (Ramiah, 2003).

The related research on noise trading focuses on the existence of noise trading and the influence of noise trading on the effectiveness of capital markets.

From the efficient market hypothesis (EMH), the existence of noise trading noise trading does exist in a short period of time and later on the market will become rational (Fama, 1970). The EMH believes that the vast majority of traders in capital markets are rational. These people have all the information they have and can make accurate judgments about the value and price of assets based on the information. The revised efficient market hypothesis acknowledges that there are indeed a small number of irrational people in the market who trade in a way that causes a deviation in the instinct value of the asset. The modified efficient market hypothesis states that assuming arbitrage is risk-free, rational investors will quickly adjust their portfolios to the fair market values. Meanwhile, the return of rational investors comes from the losses of irrational investors. If the irrational traders continue to lose money, they will gradually exit the market or become rational investors. Therefore, under the efficient market hypothesis, irrational noise traders cannot be squeezed out of the trading market for long periods of time due to the natural selection of the market and the arbitrage behavior of rational and informed traders.

The efficient market hypothesis remains controversial after the amendment. Opponents have questioned the efficient market hypothesis from previous references to final conclusions. First of all, noise trading is widely present in the market and does not correspond to the small number of presences expressed in the hypothesis (Lee et al, 1991, Baker and Stein, 2004). Second, investors have a high probability of expected the same preference for choice, which is statistically significantly different from the objective probability in the expected utility (Tversky and Kahnemand, 1974). Third, in an environment of information asymmetry, investor sentiment interacts with each other, rather than as stated in the hypothesis that irrational investors' investment decisions are independent of each other. Finally, due to the mutual influence of investor sentiment, coupled with the problem of principal agent and the shortage of arbitrage assets, arbitrage does not have the ability to completely eliminate pricing errors caused by irrational behavior. Specifically: First, the issue of proxy, in the fund managers and other found that the capital market asset pricing errors and arbitrage activities, because the reverse forces in the market is more powerful, the fund managers manage the net asset value of the fund is likely to have a larger drawdown or even reach the warning line situation. Fund managers cannot reverse this mispricing, whether based on fund contract rules or under pressure from fund investors. Second, it is also likely that the average free-trader will be unable to prevent mispricing and generate large losses because the amount of assets cannot compete with the amount of assets of the reverse forces in the market. Based on these two considerations, most arbitrage traders choose to trade in the same way as noise traders in order to obtain positive returns. And since the arbitrage will operate later than the noise trader, the noise trader will not be squeezed out of the market. The other researches suggest that the return of assets to their instinct value is a long process. It is difficult for anyone who continuously lose money can still restrain the anxiety of the state of mind and maintain the original rational judgment. Therefore, rational investors cannot completely eliminate noise. In addition, Chinese and foreign scholars have tested the effectiveness of different markets, indicating that noise traders' behavior is not effectively controlled, such investors are likely to dominate the entire market, at which point it is rational traders who are squeezed out of the market.

3. Methodology

3.1 Cluster Analysis

Cluster analysis is a technique for grouping similar observations into clusters based on observations of multiple variables for each individual (Ketchen, and Shook, 1996). Clustering is conceptually similar to differential analysis. The group membership of the observation sample is known in advance in the latter, while any observation of the former is not known. Cluster analysis divides the subjects into different categories according to certain criteria or scales. In general, clustering is used to classify data into categories. Major clustering approaches include hierarchical clustering algorithms and partitioning clustering algorithms. Hierarchical clustering algorithms are dividend in two methods which are agglomerative method and divisive method. The clustering approaches are adapted differently due to the data selected. Currently, the hierarchical agglomerative clustering approach is broadly adopted in academic researches. However, no matter which clustering method is used, the core principle is to analyze the similarity between the investigated objects and then classify them. Therefore, the key to clustering is how to measure the similarity between two objects. In general, the distance function is used to d(x,y) represent the distance between x and y. Supposed there are two points $\mathrm{x} = (\mathrm{x}_1, \mathrm{x}_2, \mathrm{x}_3, \ldots, \mathrm{x}_\mathrm{k})$ and $\mathrm{y} = (\mathrm{y}_1, \mathrm{y}_2, \mathrm{y}_3, \ldots, \mathrm{y}_\mathrm{k})$. The block distance between x and y can expressed as $d(x,y) = \sum_{i=1}^{k} |y_i - x_i|$. Then in a general form $d(x,y) = \sqrt{\sum_{i=1}^{k} (y_i - x_i)^2}$. Minkowski distance can be expressed as $d(x,y) = \left(\sqrt{\sum_{i=1}^{k} (y_i - x_i)^{\lambda}}\right)^{\frac{1}{\lambda}}$ with λ>0.

3.2 Principal Component Analysis

Primary Component Analysis (PCA) is a technique that reduces the size of such datasets, improves interpretability, and minimizes information loss. It does this by creating new uncorrelated variables to continuously maximize variance. The principal components of the actual p-space mid-point collection is the direction vector sequence, where the vector is the direction of the line that best fits the data and mates with the first vector. The core of PCA is to find out a number of "common information" hidden behind the variables among the many variables. In practical application, in order to understand the characteristics of data in all aspects, the value of multiple variables will be collected from multiple angles. More variables do reflect the characteristics of data more completely, but it also creates some difficulties for data analysis such as degrees of freedom reduced and a high degree of collinearity. Therefore, PCA can not only grasp the important information of the original data, but also reduce the number of variables and simplify the actual application.

3.3 Panel Regression

The parameters of a linear model with a fixed single effect can be estimated with the fewest squares in the ordinary. In panel data analysis, linear fixed and random effect models undoubtedly provide most of the ideas. Panel datasets are becoming increasingly popular because of the widespread use of computers, making it easy to organize and generate such data. Panel data is observational multi-dimensional data that is measured repeatedly over time. Considering the dataset of this study are cross-sectional, therefore, it would be more appropriate to use the panel regression to analyze the relationship between noise trading and abnormal returns .

3.4 Causality analysis

Granger first analyzed the causal relationship between variables from the perspective of probability theory and the statistical nature of the data. When the two variables have a lead-lag relationship, it can be statistically observed that the relationship is one-way causality relationship or mutual causality relationship. If the performance of the previous issue y of the series x helps explain the changes in the current period of y the sequence, the Granger cause for the series y. If the above help interpretation behavior is primarily one series to another sequence, the two sequences are one-way relationship. There is a two-way relationship between the two sequences if both parties have been acting in the past to help explain each other's current behavior

4. Empirical Analysis

4.1 Data and Model Setting

The stocks listed in SSE50 index are selected. The samples are from January 2012 to December 2018.

This study selects the liquidity-related indicators of stock turnover rate to describe the noise trading. The stock prices reflect four perspectives of information including the market, industry, characteristics of individual company and the investor sentiment. The abnormal return can be views as the reflection of investor sentiment. According to the CAPM model, there is a certain relationship between market yield and individual stock yield. Combined with the methodology of the APT model, it can be concluded that market information and industry information will affect the price of individual stocks at the same time. Considering that macroeconomic information will also affect the development of an industry in many cases, that is to say, macroeconomic information will enlarge or narrow the impact of industry information on the company's share price, then there should be some interaction between market factors and industry factors.

$$AR_i = r_i - F(R_{m,i}, R_{I,i,}, C_i, AP_i) \quad (1)$$

where r_i is the return of individual company *i*, *ARi* refers to the abnormal returns of individual company *i*, $R_{m,i}$ and $R_{I,i}$ are the market performance and the industry performance. C_i is the characteristics of individual company and AP_i is the analysts' prediction of the individual company. The abnormal returns should consider these four factors can affect the expected price of individual company.

Hang Seng SOE Index is used as the benchmark of the market performance which reflects the fundamental information of the Chinese market. Shen Wanhongyuan Security Industry Index of each industry are used as the benchmark of industry performance. The cluster analysis performs cluster validation for the above classification. The clustering tree is shown in Fig. 1. The relevant indicators under debt-paying ability, profitability, growth ability and operational capability are clustered into groups, and the results of clustering analysis are consistent with expectations.

The relevant indicators under debt-paying ability, profitability, growth ability and operational capability are analyzed separately, and after these four major categorized factors are obtained, the principal component analysis are used to capture the characteristics of the corporate fundamental information.

$$CP = 0.98 \times (0.88CR + 0.91QR + 0.69DA) + 0.86 \times (0.90GPM + 0.45ROE) + 0.54 \times (0.64\Delta OI + 0.58\Delta TA) - 0.62 \times (0.31RT + 0.52IT) \quad (2)$$

This study will first collect all the analysis reports (including Internet articles) for the last 3 months of all the months of each individual companies, and give standardized weights on the numbers of reports in the range from 0 to 1.

This study uses the panel regression to understand the relationship between noise trading and abnormal returns .

$$\boldsymbol{AR_{i,t} = \alpha_{0,i} + \beta_{1,it} TR_{i,t} + \sum_{k_1=1}^{3} W_{k_1 t} D_{k_1 t} + \sum_{k_2=1}^{30} U_{k_2 t} F_{k_2 t} + \sum_{k_3=1}^{83} V_{k_3 t} T_{k_3 t} + u_{i.t}} \quad (3)$$

where *TR* represents the turnover rate of the individual company, the dummy variable *F* captures the panel differences and the dummy variable *T* captures the time differences.

$$r_{it} = \boldsymbol{\alpha_{0,i}} + \beta_{1,it} TR_{it} + \beta_{2,it} R_{m,t} + \beta_{3,it} R_{I,it} + \beta_{4,it} (CP \times AS)_{it} + \sum_{k_1=1}^{3} W_{k_1 t} D_{k_1 t} + \sum_{k_2=1}^{30} U_{k_2 t} F_{k_2 t} + \sum_{k_3=1}^{83} V_{k_3 t} T_{k_3 t} + u_{it} \quad (4)$$

Fig.2 shows the turnover rate of each individual company. The Chinese stock market is in a bull market due to lots of companies listed in ChiNext and lots of hot money invested in the stock market during September 2014 to June 2015. Therefore, this study divided the whole sample period into three time periods to distinguish whether if there is any difference between the bull market and the bear market.

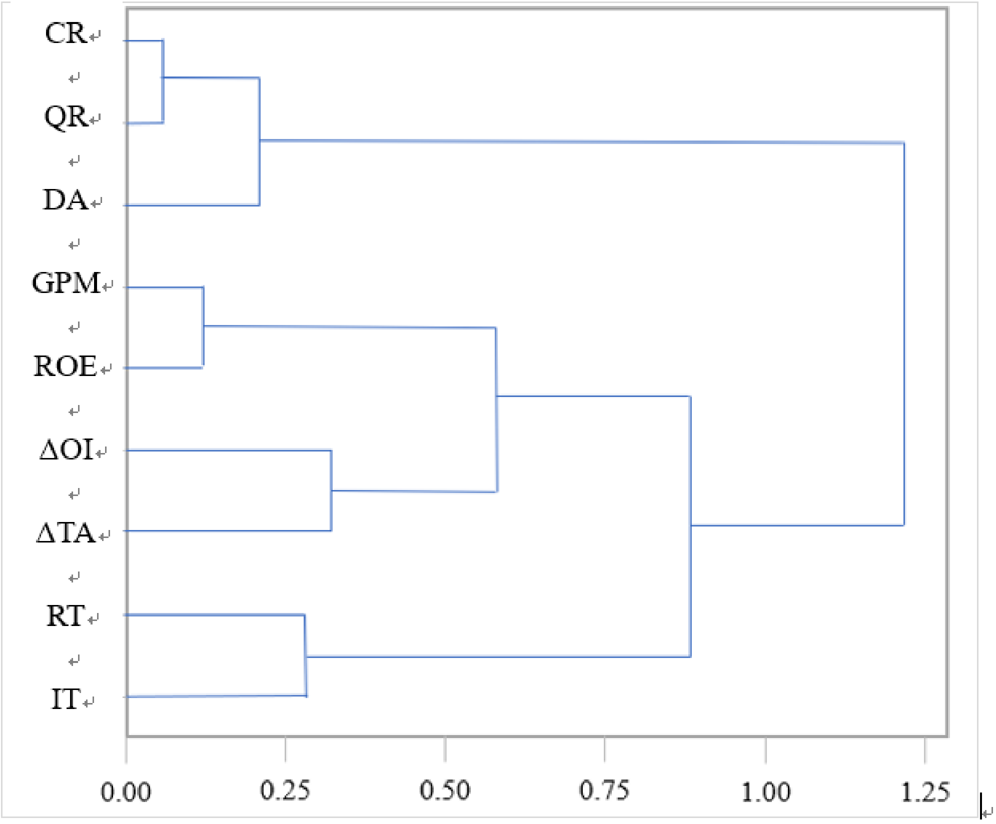

Fig.1 Cluster Analysis of the characteristics of companies

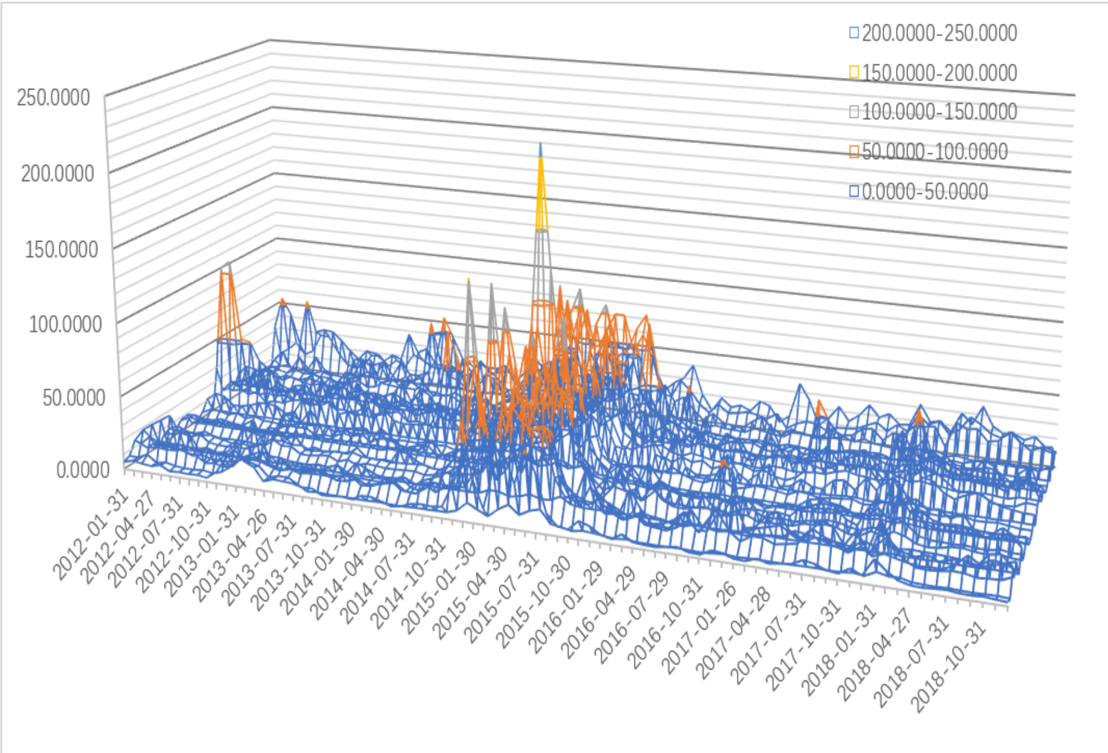

Fig.2 Turnover rate of individual companies

4.2 Empirical Results

Using the Hausman test, panel data exhibits a fixed effect on time and cross-section in the first period (January 2012 to August 2014) and the third period (July 2015 to December 2018), and the data of the second period (September 2014 to June 2015) shows the random effect. Table 2 shows the results of panel regression. The stock returns significantly positively affected by the market performance (R_m). Compared with the coefficient of R_m, in bull market (the second period) the marginal effect of the market performance on stock returns is 0.782 which is five times larger than the marginal effect in bear market. The stock returns also significantly positively affected by the industry performance (R_I). Compared with the coefficient of R_I, the marginal effects are very close with the values of 0.826, 0.840 and 0.817. The cross product of characteristics of individual company and the analyst's reports ($CP \times AS$) all significantly positively affect the stock return. The results indicate that the fundamental performance and market analyst sentiment all positively related with the stock return. The turnover rate (TR) all significantly positively affect the stock return which indicate that the noise trading affects the stock return.

To understand the relationship between the abnormal return and the noise trading, the Granger causality test is applied. The correlation coefficient between the abnormal return and the turnover rate is 0.8254 significantly. The Granger causality test is reported in Table 3. With the Granger causality test, the mutual causal interactions with noise trading and abnormal returns are detected. The results indicate that the higher the noise trading, the higher the abnormal return. The noise trading positively affects the abnormal return of the company.

Table 1 Financial Performance Indicators

Financial Performance	Variable
debt-paying ability	Current ratio(*CR)* Quick Ratio (*QR*) Debt Asset ratio (*DA*)
Profitability	Gross Profit Margin (*GPM*) Return on Equity (*ROE*)
Growth ability	Operating income growth rate (*ΔOI*) Total Assets Growth Rate (*ΔTA)*
Operational capability	Accounts receivable turnover rate (*RT)* Inventory Turnover Rate (*IT*)

Table 2 Panel Regression Results

	January 2012 to August 2014 (Bear Market)	September 2014 to June 2015 (Bull Market)	July 2015 to December 2018 (Bear Market)
Intercept	-0.010 ***	0.005	-0.005
R_m	0.071 ***	0.782 ***	0.141 ***
R_I	0.826 ***	0.840 ***	0.817 ***
$CP \times AS$	0.008 ***	0.008 ***	0.008***
TR	0.092***	0.097 ***	0.066 ***
D_1	-0.005 ***	-0.031**	0.017 ***
D_2	0.002 ***	0.029*	0.001
D_3	0.009	-0.051 *	0.012 ***

Notes: ***, **, * represent the significance level at 1%, 5% and 10%, respectively.

Table 3 Granger Causality Test

Null Hypothesis:	***Obs***	***F-Statistic***	***p-value***
EXCESS does not Granger Cause *TR*	2602	53.2952	2×10^{-23}
TR does not Granger Cause *EXCESS*		12.4703	4×10^{-6}

5. Conclusions

This study applies the cluster analysis to categorize the financial condition of the company. After using the cluster analysis, this study uses the principal component analysis to compose the factor which reflects the characteristics of each individual company.

Then, this study applies the panel data regression to analyze relationship of noise trading and abnormal returns . This study collects the analysts' reports to represent the institutional investors' sentiment and uses the turnover rate to capture the noise trading of the stock market. To investigate if there is any difference between the bear market and the bull market, the samples are divided into three periods. The results show that the market performance affects the stock returns significantly positively, especially in the bull market, the market performance affects the stock returns larger than in the bear market. The fundamental performance and the institutional investors' sentiments positively affect the stock returns. The noise trading also affects the stock returns.

To understand the relationship between the abnormal returns and the noise trading, the Granger causality test is applied. The results show that the abnormal returns and the noise trading are mutual causal interacted with each other. The results of this study can be beneficial for the investors to make asset allocation.

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