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The Calendar Effect of Investor Attention Based on Baidu Search Index

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Abstract. Within the framework of behavioral finance, investors' limited attention is a crucial factor influencing information transmission and asset pricing, and the Baidu Search Index(BSI) serves as an effective tool for directly measuring investor attention. The research sample of this study is the constituent stocks of the CSI 300 Index. It also employs the BSI based on individual stock codes as a proxy variable for investor attention. This study empirically examines the weekly and monthly calendar effects of investor attention and their impact on individual stock trading activity. The statistical results imply that there is a significant difference in investor attention among stocks, exhibiting a right-skewed distribution. Furthermore, it showed a significant positive correlation with the daily trading volume of individual stocks. Investor attention does not exhibit a significant intra-week calendar effect, but it shows a very strong calendar effect at the monthly level. The differences in attention and trading volume across different months are highly significant at the 1% level. The results suggest that investor attention distribution shows an obvious monthly cyclical pattern, which provides a new empirical basis for understanding the temporal characteristics of investor behavior in China's A-share market.

Keywords: Investor Attention, Calendar Effect, Baidu Search Index, Trading Activity

1. Introduction

In an efficient market framework, investor attention allocation is a key factor influencing information transmission and asset pricing. Limited attention can lead to insufficient market response and sustained anomalies [1]. As a critical tool to directly measure investors' attention, BSI has been proven to have a stable correlation with stock returns, volatility and liquidity [1, 2]. Published literature mostly revolves around the impact of attention on the market, but seldom examines whether attention itself exhibits a calendar effect [3, 4]. Based on BSI, this paper uses descriptive statistics, analysis of variance (ANOVA), and correlation analysis to empirically test the time law of investor attention. The study aims to systematically identify the weekly and monthly calendar effects of investor attention and examine their impact on trading activity. This study provides supplementary empirical evidence for the calendar effect of investor attention and offers a reference for understanding the temporal patterns of attention allocation in the A-share market.

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2. Theoretical basis and literature review

Investor attention is a key indicator in behavioral finance for measuring how much investors care about information. Search volume on search engines can be used as a direct proxy variable for investors' attention, which can accurately capture investors' active attention behavior. Bank et al. have used Google search volume to verify that it can effectively measure investor attention and reflect the attention of retail investors [5]. Yu and Zhang confirmed that Baidu Index is well-suited to the attention metrics of individual A-share investors in China and can significantly explain trading behavior [6]. Ding and Hou further proved that search volume can be independent of passive attention indicators such as media and advertising to capture incremental active attention information. Moreover, the search volume is significantly correlated with stock liquidity and shareholder breadth [7].

The calendar effect refers to the regular differences between returns and volatility over time, and is one of the typical market anomalies in the capital market. Investors' limited attention will lead to insufficient information response, resulting in differences in weekly calendar patterns [8]. The CSI 300 Index exhibits a significant Friday effect, meaning that returns are significantly positive and volatility is relatively stable on Fridays [9]. The frequency of investor attention fluctuates regularly with the week. Superimposed with the calendar effect, it will further strengthen the time distribution characteristics of returns and transactions [10].

The change in investor attention will directly drive trading behavior and market activity. The information overload resulting from search behavior significantly increases the frequency of individual stock trading [11]. Rising industry attention will form short-term buying pressure, boosting trading activity and returns. This effect is even more prominent in retail-dominated markets [12]. The distraction of investors' attention will reduce the intensity of their response to information about a target stock, resulting in a decline in trading activity and a weakening of abnormal returns. It is confirmed that attention distribution is a core factor affecting trading behavior [13].

3. Research design

3.1. Data sources and sample selection

This study selects the constituent stocks of the CSI 300 Index as the research object, with data sources including investor attention data based on BSI and trading behavior data from the CSMAR stock trading database. Among them, the investor attention data takes the stock code of individual stocks as the keyword to construct the SVI_code index as the independent variable. A total of 1,048,575 records of original data cover the daily search volumes of individual stocks during the sample period. The trading behavior data uses the number of daily trading stocks Dnshrtrd as the dependent variable to measure the trading activity of individual stocks in the market. In the process of data cleaning and merging, samples with wrong or missing date formats are excluded first, and a total of 5 invalid date records are eliminated. Then the search index and trading data are matched by stock code plus date, and mismatched samples are removed. The final effective sample size is 27,682, covering the daily data of the CSI 300 constituent stocks during the sample period.

3.2. Variable definition and model setup

The variable definitions are shown in Table 1.

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Table 1. Definition of the variables

Variable type	Variable name	Symbol	Definition and description
Dependent variable	Number of shares traded in individual stocks	Dnshrtrd	This represents the daily trading volume of individual stocks, which measures the trading activity in the stock market. The higher the value, the more active the trading.
Independent variable	Investor attention	SVI_code	This represents the BSI based on the stock code of an individual stock. A higher value indicates greater investor attention towards the stock.

The distribution of variables is shown in Figure 1. It can be observed that both SVI_code and Dnshrtrd exhibit right-skewed distributions, which is consistent with the typical characteristics of financial data. After Winsorization, the distribution becomes smoother, reducing the interference from extreme values.

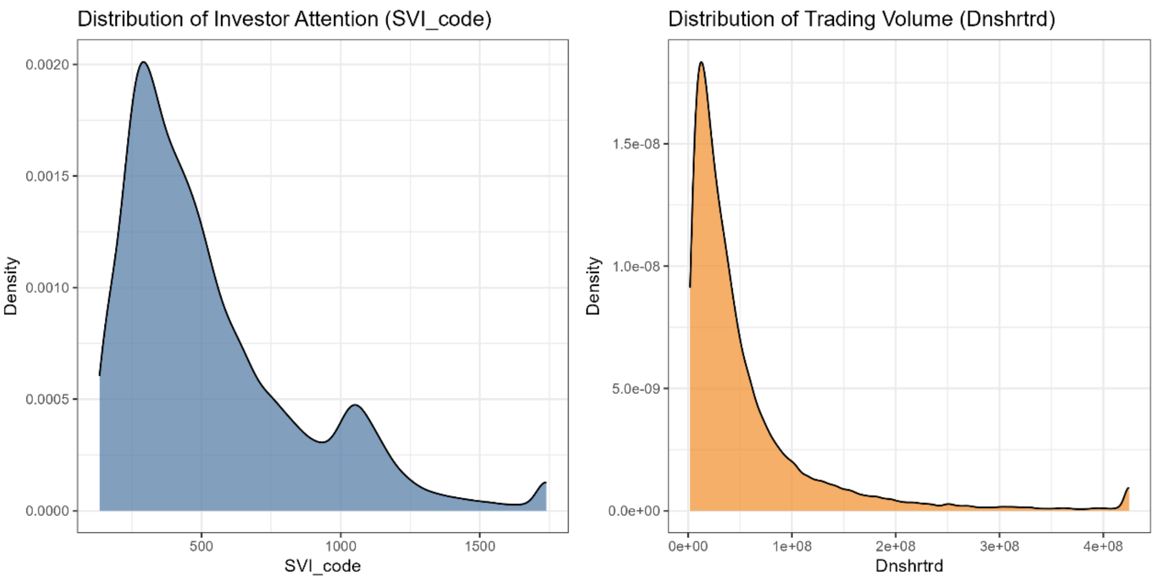

Figure 1. Density plot of core variables

To examine the calendar effect of investor attention and its impact on trading behavior, and to mitigate the right-skewed and heteroscedastic issues in the raw data, this study logarithmically processes investor attention (SVI_code) and individual stock trading volume (Dnshrtrd) as follows:

$$ln\_SVI = log(SVI\_code + 1) \tag{1}$$

$$ln\_Volume = log(Dnshrtrd + 1) \tag{2}$$

Based on this, a logarithmic benchmark model is constructed:

$$ln\_Volume_{it} = \beta_0 + \beta_1 ln\_SVI_{it} \tag{3}$$

$$+ \sum_{k=1}^{11} \beta_{3k} Month_{ik} + \varepsilon_{it}$$

where i represents an individual stock, t represents date. $Dnshrtrd_{it}$ (dependent variable) represents the exact number of shares traded by individual stock " i " on date " t ". SVI_code_{it}

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(independent variable) is the stock code based on BSI of individual stock " i " on date " t ". $\mathrm{Weekday}_{ij}$ is the virtual variable of weekly effect (based on Friday as the benchmark group, there are four virtual variables, corresponding to Monday to Thursday). Month_{ik} is the month effect virtual variable (based on December as the benchmark group, a total of 11 virtual variables, corresponding to January to November). ε_{it} is the random error term.

4. Research design

4.1. Descriptive statistics

After applying a logarithmic transformation, the descriptive statistical outcomes are summarized in Table 2.

Table 2. Descriptive statistical results of main variables after logarithmization

Variable	Obs	Mean	Std. Dev.	Min	Max
ln_SVI	24209	6.12	0.589	0	9.13
ln_Volumn	24209	17.3	1.13	13.5	21.5

For the logarithmized independent variable ln_SVI, there are significant differences in investor attention among different stocks. Some stocks have almost no investor attention, while some stocks have a very high level of attention, and the data distribution has obvious dispersion.

For the logarithmized dependent variable ln_Volumn, the standard deviation of trading volume is much greater than the mean. It shows that the individual difference in individual stock trading activity is very significant, which is in line with the liquidity difference between large-cap stocks and small-cap stocks, hot stocks and unpopular stocks in the A-share market.

4.2. Correlation analysis

This study conducted Pearson correlation analysis on the logarithmized core variables, and the results are shown in Table 3.

Table 3. Correlation matrix of variables

	ln_SVI	ln_Volumn
ln_SVI	1.0000	0.6723
ln_Volumn	0.6723	1.0000

The results shows that the correlation coefficient between ln_SVI and ln_Volumn is 0.6723. It is highly significant at the 1% statistical level ($p < 0.001$). It turns out that there is a strong positive correlation between the two.

4.3. Correlation analysis

To maintain consistency with the variable definitions used in the subsequent regression model, this section uses logarithmically transformed investor attention (ln_SVI) and individual stock trading volume (ln_Volume) to test for calendar effects. After logarithmic transformation, the test results are consistent with the original variables: the intra-week effect is not significant, while the monthly effect is highly significant.

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4.3.1. Weekly effect test

Through ANOVA to test whether there are significant differences in investor attention and trading behavior on different trading days in the week. The results are shown in Table 4 and Table 5. The p-value of the weekly effect of investor attention (ln_SVI) is 0.0955. It is only marginally significant at the 10% level. The p-value of the weekly effect of individual stock trading volume (ln_Volume) is 0.257, which is not statistically significant. Overall, there is no significant and stable weekly calendar effect among the CSI 300 constituent stocks during the sample period.

Table 4. Weekly effect of investor attention (ln_SVI)

Factor	Df	Sum Sq	Mean Sq	F-value	p-value (Pr (>F))
Weekday_Factor	4	3	0.6857	1.974	0.0955
Residuals	24204	8406	0.3473	-	-

Table 5. Weekly effect of trading behavior (ln_Volume)

Factor	Df	Sum Sq	Mean Sq	F-value	p-value (Pr (>F))
Weekday_Factor	4	7	1.685	1.326	0.257
Residuals	24204	30747	1.270	-	-

4.3.2. Monthly effect test

Further examination of the calendar effect at the monthly level yielded results shown in Table 6 and Table 7. The p-values for the month effects of both the logarithmic independent variable ln_SVI and the logarithmic dependent variable ln_Volumn are less than 0.001. The F-values are 41.07 and 39.81, respectively, and they are highly significant at the 1% statistical level. It suggests that there is a significant monthly effect on investor attention and trading volume during the sample period. There are obvious differences in market participation in different months.

Table 6. Monthly effect of investor attention (ln_SVI)

Factor	Df	Sum Sq	Mean Sq	F-value	p-value (Pr (>F))
Month_Factor	11	154	14.011	41.07	< 2e-16 ***
Residuals	24197	8255	0.341	-	-

Table 7. Monthly effect of trading behavior (ln_Volume)

Factor	Df	Sum Sq	Mean Sq	F-value	p-value (Pr (>F))
Month_Factor	11	547	49.69	39.81	< 2e-16 ***
Residuals	24197	30207	1.25	-	-

5. Conclusion

This study takes the constituent stocks of the CSI 300 Index as a sample and constructs an investor attention index based on the BSI. Empirical tests are conducted on the calendar effect and its impact on trading activity. The specific conclusions are as follows. First, there are significant differences in investor attention among individual stocks, and the overall distribution is right-skewed. A highly

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significant positive correlation exists between investor attention and daily trading volume of individual stocks. The correlation coefficient is 0.6723, $p < 0.001$, validating the driving effect of investor attention on trading behavior. Second, there is no significant weekday calendar effect in investor attention. There is no significant difference between attention and trading volume from Monday to Friday. The results of analysis of variance show that the p-value of the weekly effect of investor attention is 0.0955. It is only marginally significant at the 10% confidence level. The p-value of the weekly effect of individual stock trading volume is 0.257, which is not statistically significant. Third, there is a strong monthly calendar effect in investor attention. Analysis of variance shows that the p-values for the monthly effects of investor attention and trading volume are both less than 0.001. The F-values are 41.07 and 39.81, respectively, which are statistically significant at the 1% level. This serves to indicate that the allocation of investor attention exhibits a clear monthly cyclical pattern.

Based on the research findings, the following suggestions can be used as a reference for different groups. For investors, combining monthly patterns of attention can help optimize trading timing strategies and avoid the risk of trading congestion during months with close attention. For regulators, it is crucial to pay attention to market anomalies caused by monthly fluctuations. They should also strengthen information disclosure and investor behavior guidance to improve market pricing efficiency. Especially during peak periods such as quarter-end and annual report disclosure seasons, regulatory agencies should enhance oversight of the quality of listed companies' information disclosure to prevent abnormal trading behavior stemming from information asymmetry.

The following limitations should be taken into account when evaluating this study. Firstly, only the weekly and monthly effects are examined, and the calendar characteristics of longer cycles or specific time points such as quarterly effect, holiday effect and seasonal effect are not involved. Secondly, only the stock code search index is used as a proxy variable for investors' attention, and keywords such as securities abbreviation and company name are not included for robustness tests, which may have the problem of incomplete keyword coverage. Thirdly, the sample of this study is limited to the constituent stocks of the CSI 300 Index. Whether the conclusions apply to small and medium-sized stocks or ChiNext stocks still requires further verification. Future research can be expanded in the following directions. For instance, more keywords can be incorporated to construct a comprehensive attention index, and the sample time window can be extended to test the stability of the calendar effect. Additionally, moderating variables such as investor structure and market sentiment can be introduced to explore the formation mechanism of the calendar effect in depth.

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