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The Relationship between Investor's Attention and Stock Performance in Fashion Industry

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The Relationship between Investor's Attention and Stock Performance in Fashion Industry

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Abstract

The popularization of the Internet makes information dissemination extremely rapid. After obtaining relevant stock information, investors conduct relevant searches and make investment decisions. Google Trends records the number of keyword searches, which measured the investors' attention. Since fashion industry companies' performance is greatly affected by Internet public opinion, this study took the top 100 listed companies in the fashion industry by corporate assets as the research object. It established a multiple regression model by fixed effect and adding interaction terms. The results show that the changes in investor attention as measured by Google Trends have a positive relationship to changes in company stock prices using Robustness. This study used the VAR model and found out the exact lag period when investors' attention affected the stock performance and confirmed that there is indeed a causal relationship between them by Granger analysis. This research draws attention to helping investors provide important tips when forecasting the fashion industry stock market.

JEL Classification: G14, G12, G41

Keywords: Investor attention, stock returns, stock volatility, Google Trends

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1. Introduction

All the investors in the securities market are always focusing on the trend of stock prices because accurate price prediction is essential for implementing a stock market investment portfolio (Tuna, 2021). The real-time price of company stocks is related to supply and market demand. It is vital to find the relevant influencing factors to capture the change of stock price. The previous research has shown that investors' attention and social media sentiment are some main factors that can predict the stock market (Nti et al., 2020). The public's attention to a stock can reflect investor demand trends to a certain extent.

Moreover, this kind of attention may come from the company's potential profits, or it may be because of some social scandals related. Furthermore, social media sentiment can reflect the positive or negative impression of this kind of attention on the company's image. Therefore, if we quantify investor attention as a measurable indicator and prove that greater attention can contribute to positive stock performance, we can predict stock prices more accurately.

Since Google has disclosed the data and launched a function called google trend to record the weekly search volume of keywords, it can be used as an entry point to quantify public attention and launch projects on its correlation with stock prices (Bank, et al., 2011). Besides, Baidu's successively launched sections called Baidu Index also have the same functions and provide additional data sources. In the past, a few researchers have already carried out research based on the data from google trends. Da et al. (2011) tracked the impact of the google search volume of the Russell 3000 stock code on IPO returns. And they proposed that Google Trends is an intuitive measure to measure the attention of retail investors, and the increase in that data indicates the stock price will probably rise within the next two weeks.

Moreover, Bank et al. (2011) observed a positive short-term relationship between changes in Google search volume and future stock returns. This effect will be reversed over a more extended holding period. However, as a key influencing factor, social media sentiment has become an omitted variable in this research, which might interfere with the data results. For example, the long-term and short-term opposite phenomena mentioned above have not been found to prove whether this relationship is caused by a sudden increase in search volume for significant events or a steady increase in attention. In addition, there is no research to consider the influence of search volume on stock prices by connecting the positive and negative of social sentiment.

The stock price performance of the companies affected by the scandal matches the long-term performance of the controlling company's performance after the announcement (Jory et al. 2020). Some researchers have recently introduced emotions inherent in search terms when evaluating the predictive power of Internet search data to study its impact on overall stock market trends. This study replaces the stock names used for search in the early research with keywords of different topics to find the overall stock price trend of the stock market represented by its search volume and the S&P 500 index. For example, there is a lagging negative correlation between the number of searches on political and financial-related topics and the stock market trend (Huang et al., 2020). As the brand name is integrated into an important marketing tool in the fashion industry, social media activities have had a positive impact on the direct relationship between social media and consumer purchase intentions (Martín et al., 2018), the news sentiment spread by social media and the public's attention both have a significant impact on the fashion industry's asset value.

The fashion industry is a typical monopolistically competitive market, which amplified the correlation between public platform search volume and stock price changes. And this research started from the direction of the difference in the volume of individual company's

name and the volatility of the stock price in one month and took the leading listed companies by their market value of company assets in the fashion industry as the experimental subjects and found that investors' attention to fashion companies fluctuates significantly from year to year, while changes in their stock performance are relatively small. In addition, although there is indeed a strong causality between investor attention and stock performance, there is a long lag in response to changes in attention reflected in the stock performance of fashion companies.

This research has made the following significant contributions to the field. First, the paper supplemented the indicator of investor attention that has an impact on stock performance. Compared with the total monthly search volume, the monthly average weekly search volume has more reference value. Secondly, the thesis made the finding that investor attention has an impact on stock return is generally applicable to the field of the fashion industry. Finally, the paper estimated as accurately as possible the maximum lag period of investor attention to stock return.

The following part of this paper consists of the second part of the literature review and hypotheses, the third part of the data sources and method construction, the fourth part of the analysis of the model results, and the fifth part of the conclusions.

2. Literature Review and Hypotheses Development

The relationship between investor attention and company stock prices has always been the core issue of stock market return forecasting. Understanding how relevant variables cause stock price volatility helps investors determine asset allocation and risk management. For several years, attempts to simulate human behavior in the context of economic systems have become the essence of financial modeling and understanding of the stock market's goals (Huang et al., 2020). The emergence of social media is accompanied by the speed and quantity

of information sharing. The large amount of data recorded in the background can reflect people's views and reactions to the event (Morgan and Wilk, 2021). The launch of Google Trends and the Baidu Index has given us quantitative investor attention. And emotional abilities. Therefore, in the following sections, we will use the functions and principles of Google Trends to use empirical evidence to demonstrate the relevant concept of its correlation with stock prices and propose the most likely conjecture.

2.1. Investor's Attention based on Search Volume

Today's information circulation is developing rapidly, and the digital environment provides consumer behavior that was previously impossible to measure (Joseph et al., 2011). Investors, as the primary consumers of the stock market, often search for relevant information on the Internet, and their behavior research can also rely on Internet data. As the predictive value of data collected on digital platforms is gaining attention, more and more research and practical applications use social media data as an agent of complex social behavior (Bukovina, 2016). For example, online search on web pages can be used to measure the public's attention to emergencies and provide timely feedback on investment trends, thereby providing researchers with new research approaches (Liu et al., 2020) because investors use online search engines as tools to search for information on the Internet. When the Internet has become an indispensable part of modern daily life, keyword search instructions have become an essential indicator for everyone to achieve social and economic evolution (Fan et al., 2021).

Google is the world's leading search engine, and Google Trends analyses the keywords searched by Google search users. According to Liu et al. (2020), in 2018, 79% of US citizens with an IP address used Google to search for information, and Google Trends analyses the search volume of keywords searched by Google search users, while Baidu Index is a free and massive data analysis service like Google Trend in China. Based on the significant search

volume data provided by the platform, we can find out the corresponding intra-day or intra-week search volume according to the research object, such as stock name or company brand name, and link it with the dependent variable we need to predict and find the trend law. In recent studies, new data series constructed by Internet platforms such as Google have been widely used to analyze economic and financial indicators and proven effective in short-term forecasts (Li et al., 2015). For example, Trichilli et al. (2018) measure investor sentiment through Internet search behavior. In the research conducted by Wen et al. (2019), the attention of retail investors is measured by the search frequency of the Baidu Index. Besides, real-time ample data information from non-traditional sources, such as Google Trends or Baidu Index, can further help research investors' understanding of company performance and the ability to develop appropriate response measures (Lee, 2020).

We propose the following hypotheses based on the high correlation between investor attention and brand keyword search volume.

Hypothesis 1: The increase in the search volume of companies on Google will affect the investment behavior of investors.

2.2. Investor's Attention and Stock Returns

More and more empirical evidence shows that fluctuations in investor attention over time will affect asset prices. The expected growth rate can be estimated by focusing on changes in available information. Inspired by behavioral finance research, Hu et al. (2021) used qualitative analysis and empirical evidence to show that investor attention has an impact on the level of stock return linkage and market-level and found that jackpots are related to decreased concentration. Furthermore, Andrei and Hasler's (2015) experiments prove that stock return variance and risk premium increase with increased investor attention and uncertainty.

However, investors are decision-makers driven by sentiments. Since their psychological behaviors are challenging to quantify, researchers believed that there were limitations in measuring investor attention at first. The feasibility of investigating investor attention based on the search volume based on search engine back-end records discussed above made the recent studies use search volume as an indicator of consumer attention and discover the relationship with stock price trends. Smales (2021) used Google Trends to analyze the relationship between investor attention and global market returns during the COVID-19 pandemic and confirmed that the attention of investors during the crisis would hurt international stock returns. Besides, Da et al. (2015) also used Google to search sentiment-related terms, such as "unemployment," to develop a sentiment index and confirmed that it was negatively correlated with stock market returns over the same period, indicating that pessimism would reduce stock market returns. Furthermore, as daily data, Baidu Index contains multiple forms of classification Information can improve the accuracy of the volatility prediction of related factors (Zhang et al., 2021). They found that as investors' attention increases, price volatility increases, while stock returns decrease. Even Bijer et al. (2016) used Google Trends to develop a trading strategy, choosing to sell stocks when the search volume is high and buying stocks when the search is infrequent. At the same time, profit analysis shows that this strategy is profitable and worth using Google search as an investment tool.

The literature mentioned above mainly uses regression analysis as the primary research method. However, the complexity of the relationship between human behavior and the stock market makes it inevitable that omitted variables will appear in the correlation test to mislead the result. And That is the reason why different scholars hold different views on whether changes in investor attention will have a positive or negative impact on the stock market. For example, Moat et al. (2013) found that the indicators that investors pay attention to are usually negatively correlated with market trends, while Jin et al. (2016) found evidence that the rise in

search volume has led to an increase in trading volume in the Chinese stock market since then. According to Li et al. (2012), the research showed that the stock market underreacted to intermittent news, and its price often did not change significantly but overreacted to a series of social good or bad news. Besides, Mezghanib et al. (2021) showed that in the case of optimism or pessimism, there is a dual causal relationship between investor sentiment and financial market index, which means the positive or negative of financial market returns may be related to investor sentiment. Therefore, the following study needs to include the fluctuating frequency of its changes and the different emotionality of related events based on previously studied search volume trends.

Based on the above discussion, there must be a specific correlation between investor attention, brand keyword search volume, emotional impact of news events, and stock price changes. Therefore, we propose the following hypothesis.

Hypothesis 2: The increase of investors' attention to a company can improve the company's stock performance.

2.3. Search Volume and Stock Market in the Fashion Industry

We chose fashion industry companies as the relevant sample group for the following reasons. First, customers extensively use the Internet to learn about and purchase apparel and beauty and personal care products online. In contrast, groceries, such as "offline" purchases or pharmacy products, do not require Internet research (Kupfer and Zorn, 2019). Second, customers will frequently use social platforms to learn about fashion information. At the same time, fashion brand-related activities or negative news, such as labor disputes, will also receive the attention of the Internet public in the first place.

Besides, the rapid development of technology has provided consumers with almost unlimited space for self-expression on the Internet. The emergence of social media, such as Facebook and Twitter, has increased the influence of online viral marketing in fashion and luxury brands (Mohr, 2013). From the perspective of the financial market, the attention of investors has a certain degree of participation in the performance of the fashion industry. As consumers increasingly express their opinions about brands on social media (Tsimonis and Dimitriadis, 2014), companies are now vulnerable to the negative emotions spread through these channels, regardless of whether they choose to participate in these platforms (Cooper et al., 2019). In other words, the influence of word of mouth on the fashion industry has been expanded with the help of the Internet. If we lengthen the timeline of search terms, the volatility of stock prices in the fashion industry with a faster update speed can provide a significant reference. We conclude that the search volume of hot words can better reflect the market changes in the fashion industry, and the opposite influence of positive and negative sentiments spread by social media also has a significant degree of distinction.

Based on the support of the above research on the high correlation of news sentiment and social media to the fashion industry's performance, a final hypothesis is proposed as follows.

Hypothesis 3: The increased attention of investors has a certain lag in the performance of the company's stocks.

3. Data and Methodology

3.1. Data

The study uses two data sources: (1) Historical prices of fashion industry stock in Yahoo, (2) Google Trends.[1]

According to the report of the FashionUnited 200 Index and the report of Top Foreign Stock, we have brought together the world's largest fashion companies by market capitalization and screened out companies that have just gone public in the past two years.[2] Then we have obtained the monthly stock prices of 100 listed fashion industry companies from October 2016 to October 2021 from Yahoo Finance. Yahoo Finance reports the historical data of each stock about the opening price, high price, low price, closing price, and adjusted closing price.[3] Since the market may have a situation where the trading volume is enlarged and the stock price is adjusted during the intraday, the stock return rate cannot measure the intensity of market trading activities. Therefore, the trading volume of each stock as the evaluation index of demand, and its market capitalization as the evaluation index of liquidity, will be included. The sample period is from October 1, 2016, to October 1, 2021. Among all the kinds of stock prices, we will choose the weekly adjusted closing price as the standard data to embody the real-time

[1] The search volume data comes from http://www.google.com/insights/search/. "The search results are standardized to the time and location of the query through the following process: each data point is divided by the total search volume of the geographic and time range it represents to compare relative popularity." (Source: Trends Help)

[2] The company list comes from https://fashionunited.com/i/top200/ and https://topforeignstocks.com/stock-lists. "FashionUnited has created a unique benchmark for fashion companies that are only used to calculate the current market value of privately held companies." (Source: FashionUnited)

[3] Specifically, we use Yahoo as the data source for real-time stock price monitoring, and the historical data and daily updates of US stocks and global indexes displayed on the Yahoo Finance website are provided by Commodity Systems, Inc. (Source: Yahoo Finance)

stock price, thus calculating the stock return as a measurable indicator. And the market capitalization and volume are both directly extracted from Yahoo Finance.

And we obtain the investor attention data from Google Trends. This external website provides weekly search intensity indicators for any keyword starting from January 2004.[4] The recording interval is weekly, and the results are updated every Sunday. To minimize the noise in the data, this paper uses the Google Trend data of the aimed company name as the research variable that investors pay attention to, generating a time series containing monthly entries, since the searching volume data of the stocks' ticker are insignificant. The sample period is from October 1, 2016, to October 1, 2021. I will calculate the monthly total search intensity based on the weekly search intensity after normalization within Google Trends and calculate the average search volume by adding all the weekly data. In addition, to reduce the impact of the scale of the data and create a different smooth database, this study will take the normalization of the two kinds of search volume measurement to construct two indicators of investor attention as *AT* and *AT1*.

3.2. Methodology

First, we select the user search volume in Google Trends as an alternative change in investors' attention. To make the data smoother, we constructed the retail investor attention indicators by normalization:

$$AT_{i,t} = \frac{SV_{i,t} - \overline{SV}}{\delta_{SV}} \tag{1}$$

[4] As Trends help explain, "search results are normalized to the time and location of a query by the following process: Each data point is divided by the total searches of the geography and time range it represents to compare relative popularity." (Source: Trends Help)

We use the adjusted close price to obtain the monthly average stock price because the market may have enlarged trading volume and stock prices adjusted intraday. At the same time, we use the past five years' average stock market return of 11.96% to find the abnormal return *AR*.[5]

$$AR_{i,t} = Ret_{i,t} - Ret_{mt} \tag{2}$$

This research first uses investor attention proxy indicators to regress with various market indicators. It selects fixed effects models for research and analysis. Since the market may increase trading volume and the corresponding adjustment of the stock price, stock returns cannot measure the market's trading activity. For this reason, we also included market capitalization in the research variables.

In the process of stock selection, investors will continue to collect information to verify their decisions in the face of numerous stocks in the market and make corresponding investment behaviors. Because information processing takes a certain amount of time, the stock market performance caused by investors' attention and lagging investors' attention may differ. To this end, we built the following model:

$$Ret_{i,t} = m + \alpha_1 AT_{i,t} + \beta_1 Vol_{i,t} + \gamma_1 MC_{i,t} + \theta_1 EV_{i,t} + \eta_1 PeR_{i,t} + \lambda_1 PsR_{i,t} + \varepsilon_{i,t} \tag{3}$$

The dependent variable *Ret* refers to the monthly stock return, and the overall model uses investor attention (*AT*) market portfolio yield, trading volume (*Vol*), market capitalization (*MC*), Enterprise Value (*EV*), Trailing P/E (*PeR*), and Price/Sales (*PsR*) as explanatory variables. Since it is necessary to test whether investor attention will lead to the reversal of stock returns, we have selected the current and lag periods to study the attention variables.

[5] According to the S&P 500 Historical Annual Returns from https://www.macrotrends.net/2526/sp-500-historical-annual-returns, the past five years average market return has been 11.96%. (Source: Macrotrends)

4. Results and Discussions

4.1. Robustness Checks

The first multiple regression model is based on the simultaneous changes of all variables in the same period, which is represented by monthly *t*:

$$Ret_{i,t} = m + \alpha_1 AT_{i,t} + \beta_1 Vol_{i,t} + \gamma_1 MC_{i,t} + \theta_1 EV_{i,t} + \eta_1 PeR_{i,t} + \lambda_1 PsR_{i,t} + \varepsilon_{i,t} \quad (3)$$

This research first uses the investor attention index to analyze the correlation with each market index, and the results are shown in Table 2. As a control variable, there is a significant correlation between the market volume Vol and PER and the weekly average investor attention AT measured by Google trend search volume. At the same time, there are some weak positive correlations between MC and EV, and AT. In the above model regression, the most critical research variable: Weekly average monthly investor attention AT and the dependent variable stock return have a significant positive correlation, while the monthly total investor attention AT1 is not significantly correlated with the dependent variable stock return, so we take AT as the research independent variable.

The results of multivariate regression using Robustness are shown in Table 3. The first two columns of the table show the one-yuan linear relationship between the leading research independent variables Weekly average monthly investor attention AT and monthly total investor attention AT1 and the dependent variable stock return Ret. According to the comparison of the size of the coefficients, we will find that the influence of AT on Ret is much more significant than the influence of AT1 on Ret, which presents the same conclusion as the correlation of table 2. Among the two right columns, we mainly focus on the p-value between the independent variable and the dependent variable. The p-value mainly tests whether the linear relationship between the dependent variable and the independent variable is significant.

The linear model describes whether the relationship between them is appropriate. The smaller the data, the more accurate the description. In the case of this robust test, the p-value between AT and Ret is less than 0.1, which indicates that the dependent variable and the independent variable are significantly correlated. In the regression result table, R-squared is the focus of attention because it is used to test the significance of the regression equation coefficients. We found that when using the independent variable AT1, the value of R square is slightly larger than when using the independent variable AT1. The constant is the intercept of the entire model. The coefficient captures the trends of explanatory variables and explained variables in the model. In addition, the positive correlation between AT and Ret indicates that the increase in user attention can increase the return on stocks.

4.2. VAR Model

The VAR model implies that the current relationship is a random disturbance term, so it requires not only a lagging influence between the variables but also no contemporaneous influence relationship. If the maximum lag order p of the explanatory variable in the VAR model is too small, it will cause the residual to have autocorrelation so that the parameter estimates are inconsistent, so it is necessary to increase the p-value appropriately, that is, increase the number of lagging variables. However, the p-value cannot be too significant. When the p-value is too large, the number of parameters to be estimated will reduce the degree of freedom.

Based on the rule above, the research selected Top ten typical companies by market value to establish a time series and calculated their average lag period, which is about the fourth period, almost one season.

4.3. Granger Causality

The previous research can only prove that there is indeed a positive correlation between an investor's attention and stock return, but we need to prove that an investor's attention is the cause of stock return changes, so we use the Granger Causality analysis to test. The connotation of Granger causality: If the past information of variables X and Y are included, the predictive effect of variable Y is better than the predictive effect of Y alone based on the past information of Y. That is, variable X must help explain the future changes of variable Y; variable X is the Granger cause of variable Y.

This study selects the first two companies as experimental subjects, replaces X and Y for causality testing, observe the results of the F test between them according to the lag period established by the VAR model, and finds that when AT is the independent variable, Ret is the dependent variable Time is significant.

4.4. Additional Results

Table 4 uses the individual stock return of each company on the abnormal return of the market stock return as the dependent variable to perform multiple regression of the fixed effect. This is because the data used in this study is panel data, and each company can share the same variable correlation coefficient and then determine a different intercept. But the experimental results show that there is no significant correlation between AT and AR.

Table 7 introduces the interaction term of AT*MC and the quadratic term of AT^2 to start a nonlinear regression discussion. The experimental results show that there is a nonlinear relationship between investors' attention and Stock Return.

5. Conclusions

According to the report of Top200 fashion industry companies estimated by asset market value in 2020, this experiment found 100 listed companies as the research sample and selected stock performance-related data in the past five years from 2016 to 2020 and the five-year company recorded by Google Trends Name search volume data. We found that in the monthly data, the contribution of investor attention measured by the average weekly search volume to stock return is more significant than that of the investor attention measured by the total monthly search volume. Under Robust check, we found that investor attention has a positive effect on stock return, but compared with variables such as market capitalization, the correlation coefficient in the regression model is not very large. This shows that investor attention has a particular influence on the stock price of fashion companies, but it has not played a decisive role. In addition, there is a significant lag period in the impact of investor attention on stock return, which is about the fourth period. This finding shows that investors in fashion companies have a keen observation of the degree of news attention, but they are slightly slower in acting on investment behavior. In addition, in the nonlinear follow-up regression, we found that introducing the square term of the investor attention degree measurement value will significantly increase the stability of the model, thus confirming that the relationship between investor attention degree and stock performance is nonlinear.

Since the launch of Google Trends, many scholars have previously devoted themselves to the study of the relationship between investor attention and stock performance. This study selects the rarely discussed fashion industry as the research object and makes the following significant supplementary contributions to this field. This article further explores the investor attention index that has an impact on stock performance and finds that compared with the total monthly search volume, the monthly average weekly search volume has a more excellent

reference value. This article also confirms that the findings that investor attention has an impact on stock returns are generally applicable to the fashion industry. Finally, this article estimates the maximum lag period for investors to pay attention to stock returns.

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Table 1: Sample Statistics of Inditex Stock

The table reports descriptive statistics for the sample of all corporate stocks covering from October 2016 to October 2021. Each *t* period refers to a month. *AT* is a monthly investor attention indicator, constructed based on weekly search intensity obtained from Google Trends; the *AT1* is all the volume in one month while the *AT* is the average volume for one week every month. *P* is the real-time stock price based on the adjusted closing price of the stock for each period *t*. *Vol* is the percent volume of the stock exchanged in each period t, while *MC* is the monthly market capitalization of stock. *Ret* refers to the stock's rate of return for each period *t*, which is calculated from the percentage change of the rate of return of period *t* to period *t – 1*.

Var	Obs.	Mean	Median	StdDev	Min	Max	Skewness	Kurtosis
Ret	3802	0.011	0.011	0.090	-0.200	0.239	0.068	-0.285
AT	3802	0.043	-0.003	1.132	-0.149	75.095	65.508	4344.612
AT1	3802	0.300	0.074	0.923	-1.066	3.928	0.899	0.159
Vol	3802	0.005	0.015	0.007	0.000	0.040	3.051	10.082
MC	3802	0.042	0.016	0.077	0.000	0.442	3.087	10.468
EV	3802	0.042	0.010	0.073	0.001	0.426	5.352	29.448
PeR	3802	0.022	0.007	0.049	0.001	0.328	2.640	8.004
PsR	3802	0.010	0.002	0.011	0.000	0.065	2.283	5.774

Table 2 Correlations

The table shows the correlation between monthly variables of fashion industry stocks. *Ret* is the stock return calculated by the real-time stock price for two consecutive periods, so we will have positive or negative digits for this dependent variable. To measure investor attention, I chose the Google Trends Search Volume Index of the company name that he actively searched as the research object and then used the logarithm method to construct a smooth attention indicator data set AT_t. For the processing of stock trading volume *Vol*, I use the maximum trading volume of each company in the year as the standard and take the ratio of each month's trading volume to it for normalization. As for the source of the market capitalization *MC*, I base my estimation on the outstanding shares provided by Yahoo Finance and multiplied by the real-time stock price of the month. ***, **, * are 1, 5, and 10 percent statistical significance respectively.

	Ret	*AT*	*AT1*	*Vol*	*MC*	*EV*	*PeR*	*PsR*
Ret	1.000							
AT	0.018*	1.000						
AT1	0.001	0.108***	1.000					
Vol	-0.018	0.070***	0.005	1.000				
MC	0.035**	-0.009	0.008	0.021	1.000			
EV	0.038**	-0.009	0.006	0.045**	0.994***	1.000		
PeR	-0.030	0.146***	0.150***	0.063***	-0.040**	-0.047**	1.000	
PsR	0.007	0.000	0.137***	-0.138***	0.360***	0.332***	0.355***	1.000

Table 3 Main Regression Results using Robustness

The table demonstrates the results of our first regression model to measure the relationship between Independent variable $AT_{t,1}$, which has a better significance of correlation with dependent variable *Ret*.

$$Ret_{i,t} = m + \alpha_1 AT_{i,t} + \beta_1 Vol_{i,t} + \gamma_1 MC_{i,t} + \theta_1 EV_{i,t} + \eta_1 PeR_{i,t} + \lambda_1 PsR_{i,t} + \varepsilon_{i,t} \quad (2)$$

where all variables are taken from the relative situation of the current month for synchronization detection. In the above correlation analysis table, we found that the correlation coefficient between the independent and dependent variables is as high as 0.686, which is a strong correlation. The figure below shows the analysis of variance of the regression equation and the significance results of the coefficients of the regression equation. The P-value indicates that the result is statistically significant. ***, **, * are 1, 5 and 10 percent statistical significance respectively.

VARIABLES	ILLIQ	ILLIQ	ILLIQ	ILLIQ
AT	0.174		0.020*	
	(0.89)		(1.65)	
AT1		0.009		0.001
		(0.34)		(0.38)
Vol			-0.256	-0.263
			(-1.07)	(-1.10)
MC			-0.376**	-0.384**
			(-2.04)	(-2.07)
EV			0.440**	0.446**
			(2.28)	(2.30)
PeR			-0.060	-0.056
			(-1.55)	(-1.45)
PsR			0.076	0.099
			(0.48)	(0.63)
Constant	-4.864***	-4.860***	0.009***	0.009***
	(-196.71)	(-188.63)	(3.53)	(3.58)
Observations	3,503	3,503	3,503	3,503
R-squared			0.005	0.004

Table 4 Fixed Effect Regression Results with AR

We use panel data. It can be assumed that each group (Stock) has the same variable correlation coefficient， and different routes have different intercepts. The research method used is LSDV. ***, **, * are 1, 5 and 10 percent statistical significance respectively.

VARIABLES	FIXED	OLS	Robust
AT	-0.026	0.017	0.017
	(-0.66)	(1.33)	(1.30)
Vol	-3.114**	-0.300	-0.299
	(-2.38)	(-1.21)	(-1.05)
MC	-0.859**	-0.540**	-0.536*
	(-2.18)	(-1.96)	(-1.77)
EV	0.553	0.561**	0.558*
	(1.47)	(2.08)	(1.86)
PeR	0.376	-0.056	-0.056
	(1.45)	(-1.60)	(-1.43)
PsR	1.573	0.061	0.063
	(1.39)	(0.32)	(0.33)
g1		0.000	0.002
		(0.01)	(0.13)
g2		0.025	0.025
		(1.31)	(1.50)
g3		0.019	0.019
		(0.93)	(1.12)
g4		-0.001	-0.001
		(-0.05)	(-0.08)
g5		-0.012	-0.012
		(-0.93)	(-1.00)
g6		0.020	0.020*
		(1.35)	(1.69)
g7		0.016	0.016
		(1.11)	(1.04)
g8		0.007	0.007
		(0.54)	(0.57)
g9		0.015	0.015
		(0.97)	(1.15)
g10		0.010	0.010
		(0.80)	(0.92)
Constant	0.065***	0.010***	0.010***
	(4.26)	(3.75)	(3.61)
Observations	561	3,503	3,503
R-squared	0.035	0.007	0.007

Table 5 VAR Model with Selection-Order Criteria

The VAR method is to avoid the requirement for a structured model, so each endogenous variable in the system is used as a function of the lag value of all endogenous variables in the system to construct the model. To determine the maximum lag order p, the Akaike information criterion AIC, BIC or HQIC should be minimized in the process of increasing the p-value. The following table lists the maximum lag period of each company and its corresponding test data. ***, **, * are 1, 5 and 10 percent statistical significance respectively.

lag	**LL**	**LR**	**p**	**FPE**	**AIC**	**HQIC**	**SBIC**
Panel A-1: IDEXF							
4	3293.93	16.496	1.000		-492.759*	-493.572*	-488.804*
Panel A-2: NKE							
4	2571.38	61.122	0.115		-500.276*	-502.599*	-498.158*
Panel A-3: LVMUY							
9	1565.86	0			-435.388*	-439.399*	-435.713*
Panel A-4: TJX							
4	3293.93	16.496	1.000		-492.759*	-493.572*	-488.804*
Panel A-5: HNNMY							
5	2762.91	64.704	0.066		-488.347*	-490.103*	-485.562*
Panel A-6: HESAY							
10	6498.66	54.047	0.288		-485.897*	-483.361*	-477.090*
Panel A-7: FRCOY							
8	4484.15	28.512	0.992		-484.238*	-483.379*	-478.006*
Panel A-8: ADDYY							
10	5030.96	49.295	0.461		-489.096*	-487.735*	-482.126*
Panel A-9: CHDRF							
3	2058.81	86.586*	0.001		-500.703*	-504.453*	-500.147*
Panel A-10: CFRUY							
8	4042.63	64.268	0.071		-491.328*	-491.051*	-485.920*

Table 6 Granger Casualty

The goal is to predict the change of Y, plus the prediction result of X is better than the prediction result of only Y, then it can be said that there is Granger causality between X and Y. In other words, the change in X can explain the change in Y. In the case of controlling the lag term (past value) of y, if the lag term of x still helps explain the change in the current value of y, then it is considered that x has a causal effect on y. This can be tested by constructing F statistics. If the Prob>F is less enough, it is considered that there is a causal relationship; that is, investors' attention is the Granger cause of stock return. ***, **, * are 1, 5 and 10 percent statistical significance respectively.

lag	**Prob>F**	**LL(null)**	**LL(Model)**	**df**	**AIC**	**BIC**
Panel A-1: IDEXF						
1	0.0016*	-70.14	-43.05	3	92.10	97.72
2	0.0059	-63.81	-38.27	5	86.53	95.34
3	0.0017	-59.41	-31.45	7	76.91	88.56
Panel A-2: NKE						
1	0.2101	-69.62	-68.23	3	142.46	148.01
2	0.3715	-61.15	-57.31	5	124.63	133.19
3	0.2044	-56.41	-50.90	7	115.81	127.09
4	0.2150	-51.07	-45.17	9	108.35	121.82
5	0.1340	-46.27	-37.94	11	97.89	112.93

Table 7 Regression with Interaction

In the previous test, we have found that AT, which represents the total search volume per month, has a better correlation with stock return than AT1, which represents the average weekly search volume for each month. To explore the nonlinear relationship between variables, we choose to take a square of AT to add multiple regression to enhance the fitting of the model curve; in addition, we also need to exclude the interactivity of the independent variables in the model, so we set AT Multiply the term with Vol to study another nonlinear relationship. ***, **, * are 1, 5 and 10 percent statistical significance respectively.

VARIABLES			Nonlinear	Interaction
AT	-0.036	-0.032	-0.048	0.010
	(-1.31)	(-1.14)	(-1.57)	(0.87)
AT^2	7.517	6.872	9.732**	
	(1.63)	(1.47)	(1.99)	
AT×MC				-0.001
				(-0.25)
Vol		-0.168	-0.098	-0.182
		(-0.83)	(-0.44)	(-0.83)
MC			-0.158	-0.166
			(-0.95)	(-0.99)
EV			0.193	0.205
			(1.13)	(1.20)
PeR			-0.051	-0.052
			(-1.51)	(-1.53)
PsR			0.058	0.042
			(0.36)	(0.26)
Constant	0.111*	0.103*	0.139**	0.012***
	(1.84)	(1.69)	(2.18)	(4.93)
Observations	5,054	5,054	4,192	4,192
R-squared	0.001	0.001	0.003	0.002