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Research article

Measuring the effects of investor attention on China's stock returns

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Abstract: The increasing abundance of information leads to the scarcity of investor attention, which has become an important factor affecting the financial market. Search engines play the role of information retrieval and record the search behavior of investors, which is a direct and accurate measure of investor attention. This paper investigates the relationship between investor attention and China's stock market. Considering the relationship with stock returns as the mainline, we take the Baidu index as a substitute variable of investor attention to deeply study the correlation and the time-varying nature between investor attention and China's stock returns. To this end, we used quantile regression to examine the relationship over the period 2006–2021 to capture its evolution during calm and turbulent times. We thus investigated the effect of investor attention on the mean and other quantiles. Our findings show that the relationship between investor attention and China's stock returns exhibits time-variation as investor attention significantly impacts the dynamics of China's stock returns, but its sign and effect vary per quantile: investor attention is negatively correlated with stock returns at low quantiles, but it turns positive at high quantiles. In addition, to test the model's robustness, variable replacement method and model replacement method are used to conduct significance tests, respectively. The results are equally significant.

Keywords: investor attention; China's stock market; quantile regression; Baidu index; time heterogeneity

JEL Codes: G15, C22

1. Introduction

Since the 1980s, the research on the influence of investor attention on stock investment behavior and stock market performance has been increasing. From the behavioral finance theory, we learn that financial markets may be driven by news, rumors, uncertainty, irrational exuberance, animal spirits, investors' feelings, etc. (Shiller, 2015; Akerlof and Shiller, 2009). For example, high uncertainty can lead to more anxiety and panic for investors, subsequently creating more volatility in the financial markets (Jawadi et al., 2017). According to efficient market theory, attention (whether from investors or media) can reduce information asymmetry, improve information transparency, and thus reduce market volatility (Jin and Myers, 2006). Glosten and Milgrom (1985), Seyhun (1986), and Bank et al. (2011) also believe that the improvement of information transparency enhances stock liquidity.

The first problem to be solved in this field is the measurement of investor attention. At present, there is no unified criterion in the academic circles. Most scholars measure investor attention through various indirect indicators. For example, Fang and Peress (2007) measured the number of articles in the existing authoritative newspapers. Seasholes and Wu (2007) measured extreme returns. Although these indicators can describe investor attention to a certain extent, they are objective and not a direct measure of investors' psychology, so there are inevitable errors in accuracy. In recent years, with the booming development of Internet technology, people gradually use Internet search engine technology to collect the information they need. The relevant data provided by Internet search engines (such as Google Trend and Baidu Index) can grasp people's concerns about something and accurately reflect the psychological activities of investors. If the attention data provided by search engines are used as the measurement index of investor attention, the psychological activities of investors can be directly grasped, and the research accuracy can be guaranteed. In light of this, this paper uses the search index that can reflect investor attention provided by Baidu as the measure of investor attention to study the influence of investor attention on stock returns. Since the download function of daily data is not provided officially, relevant data is obtained by using Python. In particular, we use quantile regression model to study the dynamics of stock returns under different quantiles. This model has the advantage of capturing asymmetry and time-variation in the relationship between investor attention and China's stock returns. We study the time-varying characteristics of this effect by focusing on the impact of investor attention on stock returns in different special periods. This paper selects three crises that have shown great impacts on China's financial market, and analyzes the heterogeneous effects of investor attention on stock returns in these special periods through the data extracted from the crisis periods.

Finally, in order to further test whether the empirical analysis results are robust, we replace the measurement of investor attention, and using OLS to regression the model again, then find that the empirical results do not change with the alter of parameters or regression methods, so the evaluation method and index interpretation ability of this paper are robust.

2. Literature

With the development of information technology, the attention of economic individuals is becoming a scarce resource (Kahneman, 1973). Attention to one event comes at the expense of attention to others, which may make investors unable to obtain certain information in time, leading to wrong judgments and the volatility of asset prices. Simon (1995) suggested that too much information would cause a lack of attention. When faced with a large amount of information, subjects would pay less attention to one piece of information than others. Therefore, financial events that attract investor attention will inevitably cause changes in the financial market, and stocks with different degrees of attention will have different returns. Hence, more and more scholars began to include investors' psychological factors in stock returns. Barber and Odean (2007) showed that, unlike institutional investors, attention was an important reason for individual investors to buy stocks. Aouadi et al. (2013) found the influence of investor concern on the stock market and showed that investor attention is highly correlated with stock trading volume, which is an important factor affecting the liquidity and volatility of the stock market. Goddard et al. (2015) found that investor attention was positively correlated with stock fluctuations in the foreign exchange market during the same period and could predict the next volatility. Peltomaki et al. (2018) also found that investor attention had a better ability to explain the stock price fluctuations of emerging markets in their research.

For the measurement of investor attention, early scholars used financial market indicators as proxy variables for investors' attention. For example, Gervais et al. (2001) took trading volume or turnover rate as proxy variables for investor attention. Peng and Xiong (2006) used stock trading volume to study investor attention, found that market information and stock information compete for attention, and believed that investors would spend more energy in industry or market level. However, investors can rationally allocate a variety of uncertain investment portfolios with limited attention to reduce the uncertainty of the investment. Ng and Wu (2006) studied the attention preference of individual investors in China through their stock transaction records, and the results showed that the attention preference of individual investors varies with their wealth level. Wealthier individual investors prefer stocks with growth potential, a history of good returns, high liquidity, and high volatility, while the investors with relatively little wealth have the opposite preference. Aboody et al. (2010) took excess return as a proxy variable for investors' attention.

Later, scholars began to use the relevant data provided by the Internet to measure investors' attention for analysis and research. Generally speaking, investors do not necessarily buy all the stocks they care about, but the stocks they buy must have been looked at before. In recent years, more and more research has emphasized investor attention, and scholars generally use excess returns, turnover rate, trading volume, media reports, and advertising expenditure as the proxies for investor attention. With the popularization and development of the network, search index began to receive attention. When investors search for a stock symbol or name in a search engine, there is no doubt that those investors are paying attention to the stock. The search index is based on the number of times a certain keyword is searched in the search engine. Only when attention has been paid first will there be corresponding search behavior. Therefore, compared with other indicators, the search index can more accurately reflect investor attention to the stock and improve the accuracy of research.

Da et al. (2011) proposed to use the Google search Volume Index (SVI) to measure investors' attention directly. Vlastakisa and Markellos (2012) extracted the weekly Internet search time series from the recently released Google Trends database to approximate the market information demand, and Bodo (2012) used Google data to determine the relationship between asset price and trading volume. Stephan and Nitzsch (2013) studied the information value of individual investors' suggestions published in online communities for investment strategies. Nguyen et al. (2019) investigated the impact of investor attention on the dynamics of stock returns for five emerging countries: Indonesia, Malaysia, Philippines, Thailand, and Vietnam over the period 2009–2016. Using the Google search index to proxy investor attention, the authors showed that investor attention has a negative and significant effect on stock returns for the Philippines, Thailand, and Vietnam, suggesting that investors are likely to react more quickly to bad rather than good news in their investment decisions. According to Calvo, investors in emerging markets are less rational and less informed, and their strong interest could thus generate lower stock returns as they may overreact to negative signals. Wang et al. (2017) used the Baidu index as a proxy for investor sentiment to study its impact on China's stock index futures market and found that computer search would affect trading volume and futures returns, while mobile search would only affect trading volume.

Based on the above research, to analyze the linkage between investor sentiment and the stock market, this paper investigates the impact of investor attention on stock return dynamics. In China's stock market, the proportion of individual investors in China's stock market is much larger than that of institutional investors, and the two groups of shareholders and netizens are highly coupled. Therefore, we focus on China's stock market and its interaction with investor attention in recent years. In order to capture its evolution during calm and turbulent times and to analyze the heterogeneity of these impacts, we selected three special periods: the Global finance crisis (GFC), China's stock market crash (CSMC), and the COVID-19 pandemic outbreak (CPB).

Existing researches mostly adopt the research method based on mean regression, which is suitable for discussing the influence of Internet sentiment on stock market returns in the central position or under a normal environment, but there are certain limitations. This study believes that there is indeed some connection between China's Internet sentiment and the stock market, but this connection is not necessarily in the central position and is more likely to exist in the tail extreme quantile range (Jawadi 2020). Therefore, our paper proposes a different method to model the dynamics of China's stock returns, taking into account the effects of investor attention. Different from the normal linear regression, we use a more robust quantile regression， quantile regression is a modeling method to estimate the linear relationship between a set of regression variables X and the quantile of the explained variable Y, it is a new estimation method proposed by Koenker and Bassett (1978) for the deficiency of least squares. Previous regression models actually studied conditional expectations of explained variables. People also care about the relationship between explanatory variables and the median and quantile of the distribution of explained variables. Quantile regression can more comprehensively describe the overall picture of the conditional distribution of the explained variable, rather than just analyzing the conditional expectation (mean value) of the explained variable, and also analyze how the explanatory variable affects the median and quantile of the explained variable. The estimators of regression coefficients under different quantiles are often different, that is, explanatory variables have different influences on explanatory variables at different levels. This method also has the advantage of capturing time-variation in the relationship between investor attention and China's stock returns. It enables us to further capture the effects of investor attention in China's stock returns for lower and higher quantiles (Koenker and Hallock 2001).

Although previous studies have used different methods to measure the impact of investor attention on stock market, few studies have studied the heterogeneity of this impact in different special periods. On the basis of studying the influence of investor attention on stock returns, this paper further focuses on the time-varying influence. We draw the conclusion that under the impact of different events, investor attention has different influences on China's stock returns.

3. Econometric methodology

We conjecture there is a correlation between investor attention and China's stock returns while taking into account that the effect of investor sentiment may vary from time to time. In order to find and explain it, we specify a quantile regression, enabling us to characterize this relationship more clearly through several quantiles. This specification presents the advantage of relating the quantile with investor attention, which could help explain the dynamics of China's stock returns.

However, investor attention is not the only factor affecting stock returns. According to portfolio theory, portfolio changes lead to exchange rate changes, and stock market rise will bring wealth effect, thus driving domestic currency demand and interest rate and then driving domestic currency appreciation. Therefore, we choose to increase the exchange rate as the control variable.

First of all, we specify the dynamics of China's stock returns, noted RCS_t, as follows:

$$RCS_t = \varphi_1 IA_t + \varphi_2 C_t + \varepsilon_t \tag{1}$$

where IA_t denotes investor attentions and ε_t is the error term. Considering that it is not only investor attention that will affect the stock price, we add a control variable C_t that includes the exchange rate. $\varphi_1 IA_t + \varphi_2 C_t$ is the conditional mean of the level of China's stock return and ε_t is the error term.

In practice, we estimate the quantile of the conditional distribution of China's stock returns and, for each quantile, we specify an equation for the conditional quantile of China's stock returns, denoted as $q_\alpha(RCS_t|I_t)$, where I_t contains information known at time t and defined as:

$$q_\alpha(RCS_t|I_t) = \varphi_{1,\alpha} IA_t + \varphi_{2,\alpha} C_t + u_t,\ \text{where}\ \alpha \in (0,1). \tag{2}$$

Equation (2) enables us to estimate a time-varying distribution of China's stock returns, which is less restrictive than the standard OLS approach as the slope coefficients $\varphi_{1,\alpha}$ and $\varphi_{2,\alpha}$ can vary by quantiles. In particular, if the effect of investor attention is time-varying and fluctuates with the tail of China's stock return distribution, this specification might have a different coefficient in the quantile regression tails from that in the median.

Then, we estimate the parameters $\varphi_{1,\alpha}$ and $\varphi_{2,\alpha}$ by the check function (Koenker and Orey 1994):

$$\rho_\alpha(e_t) = e_t(\alpha - I\{e_t < 0\}) \tag{3}$$

or

$$\rho_\alpha(e_t) = \begin{cases} \alpha e_t, \alpha \geq 0 \\ (\alpha - 1)e_t, \alpha < 0 \end{cases} \tag{4}$$

where $e_t = C_t \hat{\hat{q}}_{\alpha,t}$ is the forecast error, $\hat{\hat{q}}_{\alpha,t}$ refers to the conditional quantile forecast computed at time t, and $\mathbf{1}\{\cdot\}$ is the indicator function. It is easy to see that $\rho_\alpha(e_t)$ is an asymmetrical piecewise function consisting of two rays starting from the origin in the first and second quadrants in a ratio of $\alpha: (\alpha - 1)$. The function graph of $\rho_\alpha(e_t)$ is shown in Figure 1.

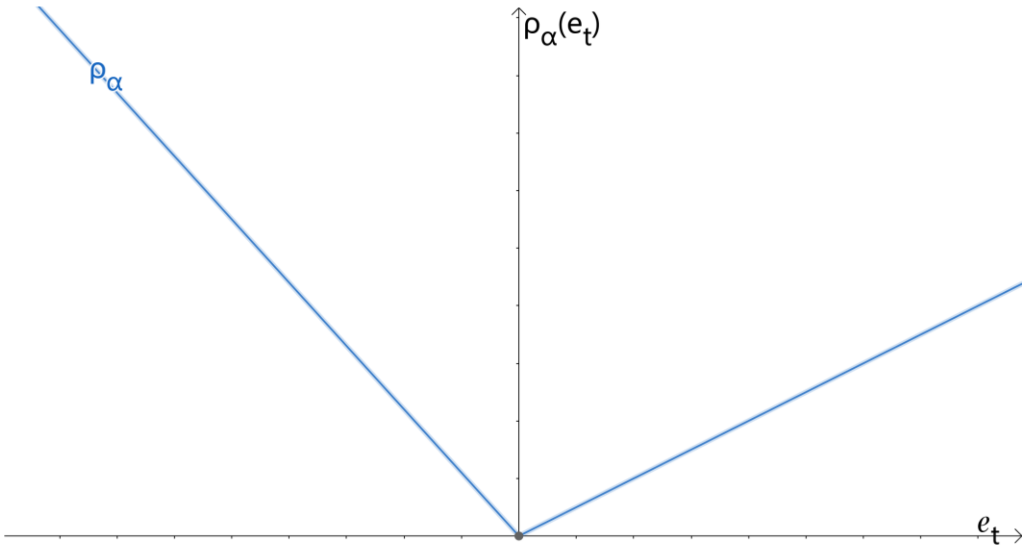


Figure 1. The check function diagram.

4. Empirical analysis

4.1. Preliminary results

Many A-share indices in China can be divided into four categories: sector, scale, industry, and concept theme. Chinese A-share market combines more than 1,000 stocks from the Shanghai Stock Exchange and more than 2,000 stocks from the Shenzhen Stock Exchange to form China's securities. As a scale index, the CSI 300 index ranks 3797 stocks according to size and liquidity of all the stocks in China's stock market, then takes the top 300 and makes these 300 stocks into a new index named CSI 300. It represents the middle and large stocks among more than 3,000 stocks in China's entire stock market, covering about 70% of the market value of the Shanghai and Shenzhen stock markets, with good market representativeness. Therefore, we use the CSI 300 stock index to represent China's stock index. The relevant data is obtained from Investing.com.

Since we chose to investigate China's stock market, and Baidu is much more used in China than Google. When people need to know something, they often say "Let me search it on Baidu" or "Ask Baidu". Therefore, the Baidu Index provided by Baidu can accurately measure investor attention to China's stocks. In order to further explore the value of Internet-based big data, based on Baidu's leading position in China's search engine, we select Baidu Index as an index to measure investor attention and studies the impact of investor attention on stock returns. Since the daily data of the search index cannot be downloaded directly from Baidu's official website, we used Python to obtain the required data.

The US dollar is the main currency for international trade and financial market, the change of the US dollar to RMB exchange rate will affect the introduction of foreign investment, as well as domestic health care and education costs, etc., which in turn affects China's stock market. The weak dollar performance would further cement a small and slow RMB appreciation. According to the historical experience of currency appreciation and stock market surge in various countries around the world and the practice of RMB appreciation in China over the past year, it can be concluded that the weak dollar performance is conducive to the rise of China's stock market. Therefore, we choose to increase the US dollar to RMB exchange rate as the control variable. Daily data on the US dollar to RMB exchange rate is also downloaded from Investing.com.

Our data include daily China's stock returns (according to the CSI 300 index) and the investor attention indexes represented by the Baidu search index. Both data covers the period 2006.06.05–2021.06.05. We divide the data into three stages: the Global financial crisis, China's stock market crash, and the COVID-19 pandemic. We also use data on the US dollar to RMB exchange rate. This sample selection method is appropriate to analyze the interaction between investor attention and China's stock market before and after these specific stages. China's stock returns are calculated by subtracting today's closing price from the previous daily closing price in the CSI 300 index, while the investor attention indexes are set up using the number of Baidu searches carried out in China with the keywords "China's stock market". This Baidu search index thus captures the level and frequency of investors' attention with regard to China's stock market.

First, the modeling of the regression model is based on stationary variables. If non-stationary variables are directly used for regression modeling, the results are likely to appear pseudo-regression phenomenon. Therefore, it is the primary problem to determine whether the variable is stationary. The test method used in this paper is the commonly used ADF unit root test. The following are unit root tests for China's stock return (RCS), stock market Baidu search index (IA), and the US dollar to RMB exchange rate (ER).

Table 1. Unit root test for major variables.

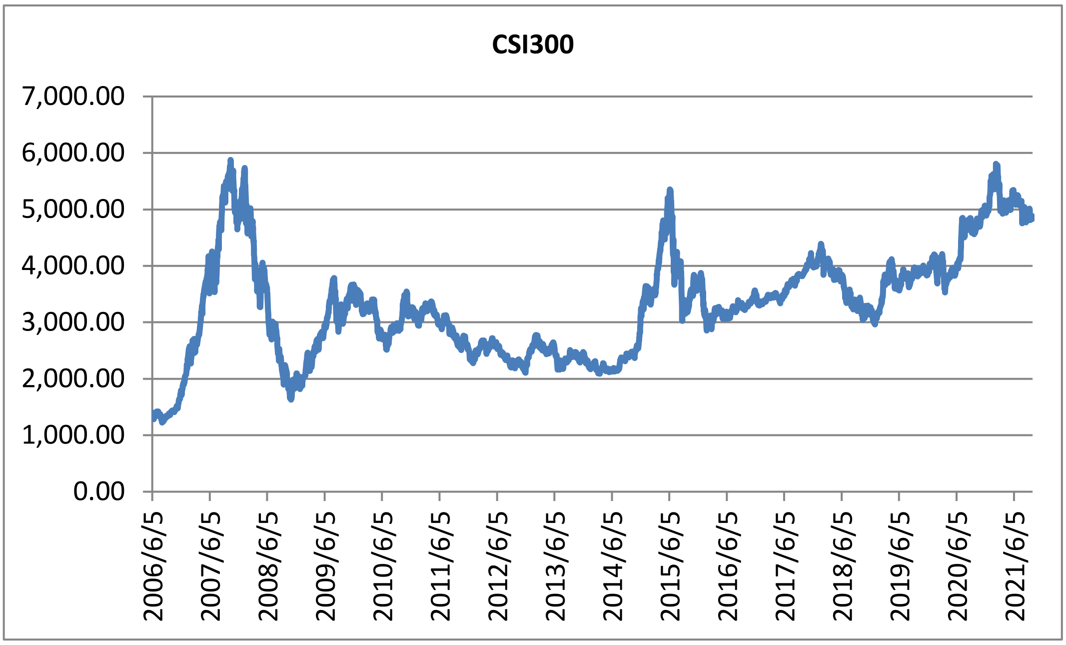
	RCS	IA	ER
Augmented Dickey-Fuller	−28.0397	−6.1562	−3.1974
MacKinnon (1996) one-sided p values.	0.00***	0.00***	0.0202**

Note: Signif. codes: 0.01'***' 0.05'**' 0.1'*'.

As shown in Table 1, the ADF test shows that the test results of the stock market Baidu search index and China's stock returns are significantly lower than the 1% level, and the exchange rate of US dollar to RMB is also significantly lower than the 5% level. These important indicators all significantly reject the null hypothesis of the existence of unit root, indicating that the time series variables selected in this paper are all stable and can be directly used for analysis and modeling.

Then, from Figure 2, we note that China's stock returns were negatively impacted by the GFC (2008), CSMC (2015), CPB (2020), which may be caused by a variety of reasons. For example, a crisis will cause a bad economic situation, banks, insurance companies, funds, and other investment institutions will be affected. These institutions are major investors in the stock market, when a crisis occurred they must want to withdraw the money. It is a vicious circle because people sell stocks to withdraw their money, which inevitably leads to a sharp drop in stock prices. In addition, consumers and investors will become less confident and sell stocks desperately to get cashback. We can see that each time we go through a crisis, it takes a hit to stock returns, causing them to fall sharply, but after these events, it will develop around positive trends. Otherwise, the investor attention index shows more excessive volatility during the pre-crisis, suggesting that investor attention in China's stocks rose during the most turbulent times but stabilized after these crises.

(a)



(b)

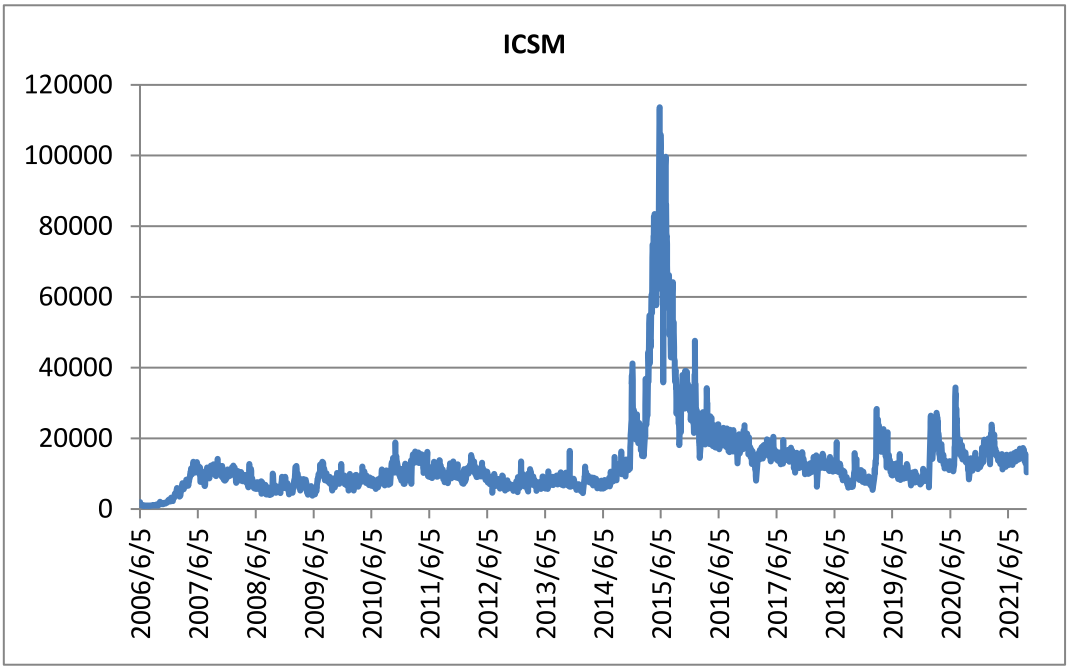


Figure 2. **(a)** The dynamics of China's stock index: CSI300. (**b**) The dynamics of investor attention: China's stock market Baidu index.

We focus hereafter on the specification of the relationship between investor attention and China's stock market returns. Thus, we compute the descriptive statistics for both series and note that while symmetry is rejected for both series, the investor attention series appears more volatile than China's stock return series. Further, the significant difference between the mean and the median for both variables suggests further evidence of asymmetry in the data. The descriptive statistical results are shown in Table 2.

Table 2. Descriptive statistical results of major variables.

	RCS	IA	ER
Mean	1.059	12346.25	6.713
Median	2.619	5548.000	6.687
Maximum	378.179	475955.0	8.023
Minimum	−391.866	1110.000	6.041

4.2. Results of the full sample

In order to characterize the effect of investor attention on China's stock returns, we investigate their relationship per quantile. The main results were reported in Table 3, and we note some interesting conclusions. First of all, investor attention has a negative and significant effect on the low quantiles of China's stock returns, suggesting that for lower quantiles, investors are more impacted by bad news than by good news, and bad news can make investors feel negative about stock prices. Second, from the perspective of the relationship between investor attention and the median return of Chinese stocks, there is no evidence that investor attention has always had a significant impact. Third, for higher quantiles of the stock return distribution, investor attention has a positive and significant impact. We think that this change from negative to positive is because investors will have different degrees of reaction to different news, which will also have different impacts on the stock market. With the development of technology, investors search the stocks they care about through search engines. This information advantage promotes investor attention on stocks, the increase of attention strengthens investors' confidence and enables them to make more rational judgments, which is conducive to the positive impact on China's stock returns. Moreover, the effect of the exchange rate is negative and significant on 5% quantile, then it switched to significant and positive on the high quantiles, however, and higher than that of market attention. The reason for this may be that the fluctuation of exchange rate will affect the value of RMB, and changes in the value of RMB will obviously affect the stock index when buying a large number of stocks. For example, the depreciation of RMB accelerates capital outflow, and many domestic assets including stocks and real estate are sold to cash and transferred abroad, which is bad for the stock market. The appreciation of RMB assets will increase the willingness of foreign investors to buy RMB assets, and A-shares will be boosted by foreign capital inflows.

However, the results obtained by the full sample cannot well reflect the changes in the relationship between investor attention and stock returns in different periods, so we will continue to study some special periods.

Table 3. Quantile regression results of the full sample.

Quantile	IA_t	ER
5%	−0.002***	−63.751***
	(0.0002)	(7.987)
25%	−0.0008***	0.133
	(0.0001)	(2.332)
50%	−0.0002	4.476***
	(0.0001)	(1.489)
75%	0.001***	14.172***
	(0.0002)	(2.651)
95%	0.001***	32.363***
	(0.0002)	(5.459)
Slope equality test (p value)	0.00***	

Note: Signif. codes: 0.01‘***’ 0.05‘**’ 0.1‘*’.

4.3. Results of sub-samples

To study the impact of investor attention on China’s stock returns in turbulent times and to detect heterogeneity of the impact between investor attention and stock returns, we select three sub-samples for further research, namely, GFC, CSMC, and CPB periods. The main results were reported in Tables 4–6.

Under the influence of the financial crisis, the stock market plunged, which was a great blow to everyone who invested in the stock market, especially to some countries with relatively developed stock markets. The immediate impact of the global financial crisis on China’s stock market has been on bricks-and-mortar listed companies that rely heavily on exports and financial institutions with large investments overseas. The impact of these external events will lead to a change in investors’ psychological expectations. They may get emotional breakdowns in the huge market swings and make bad decisions resulting in losses at last.

When we analyze the results, it can be seen that the influence of investor attention on stock returns is significant in every quantile, which indicates that the global economic crisis has caused investors’ close attention. This scrutiny affects their trading behavior in the stock market because a bad economic environment will make investors feel desperate. They will be more inclined to keep cash in their own hands, which is disadvantageous for the stock market. Therefore, we can see that in the 5% quartile, investor attention has the greatest impact on stock returns, and it is negative. With the government’s self-rescue and economic regulation, the economic growth and the stock market gradually stabilized, so investors can calm down to analyze stock trends and find ways to profit again. The results in the table show that the impact goes from negative to positive from the 50% quantile.

Table 4. Quantile regression results during the GFC period.

Quantile (GFC)	IA_t	ER
5%	−0.034***	36.934***
	(0.003)	(7.017)
25%	−0.009***	23.609***
	(0.002)	(3.733)
50%	0.003**	1.771
	(0.001)	(2.684)
75%	0.010***	−11.730***
	(0.001)	(3.771)
95%	0.010***	−37.067***
	(0.003)	(4.264)
Slope equality test (p value)	0.00***	

Note: Quantile (GFC) shows the quantile regression results of the GFC period.
Signif. codes: 0.01‘***’ 0.05‘**’ 0.1‘*’.

The results change during the CSMC because the impact of investor attention at the 50% quantile is insignificant. It is not hard to explain why this situation happens. The bull market, which started in 2014, has been in full swing thanks to leverage, with stock prices accelerating and the average price Earnings ratio even rising to more than 140 times. This valuation has far exceeded the stock market bubble in most international markets, the market to the emerging growth stocks too high expectations. A severe valuation bubble is the root of the crisis. In June 2015, the stock index began to fall, and an occasional rebound could not save the stock market from falling. Major media began to focus on the huge fluctuations of the stock market, and investors were bound to become uneasy because of the volatile stock market. It can be seen that this stock disaster has dealt a huge blow to China’s investors’ confidence, so9 investors may be deterred by previous market turmoil although the crisis is fading away, afraid to make a rash move on the stock market. However, the effect is still significant in other quantiles. With the development of the economy and the regulation of various aspects, the stock market is gradually getting better, and the influence of investor attention on stock returns is also turning from negative to positive.

Finally, we take a look at the impact of investor attention on the stock market since the outbreak of COVID-19. At the beginning of 2020, the outbreak of COVID-19 cast a shadow on China’s economy and the world economy. This pandemic has affected many countries and regions, leading to declines in major stock markets worldwide and multiple circuit breakers in the US. Moreover, in 2020, the impact of COVID-19 was sustained, extensive, and long-term, becoming an economic background of the whole year. China’s stock market opened on February 3, 2020, despite the uncertainties that the COVID-19 outbreak may cause. The opening was not encouraging, with a total of 3,150 stocks in Shanghai and Shenzhen falling by their daily limit. This result is mainly affected by COVID-19, causing sharp fluctuations in oil prices and food prices, and the market is also a reasonable response to these factors. In the future, monetary policies, vaccine plans, fiscal policies, and changes in the epidemic will have a drastic impact on the stock market, which is also the focus of many investors.

Table 5. Quantile regression results during the CSMC period.

Quantile (CSMC)	IA_t	ER
5%	−0.002***	−50.369**
	(0.0004)	(23.681)
25%	−0.001***	−25.003**
	(0.0002)	(9.864)
50%	−0.0001	−4.443
	(0.0001)	(6.565)
75%	0.001***	1.313
	(0.0002)	(11.550)
95%	0.001***	4.587
	(0.0004)	(22.801)
Slope equality test (p value)	0.00***	

Note: Quantile (CSMC) shows the quantile regression results of the CSMC period.

Signif. codes: 0.01‘***’ 0.05‘**’ 0.1‘*’

Hence, when we analyze the results, we can see that the influence of investor attention on stock returns is significant in every quantile, and the impact goes from negative to positive from 50% quantile. We believe that the uncertainty caused by the sudden outbreak of COVID-19 may have triggered the change in investor sentiment because this uncertainty has a negative impact on the stock market. According to the herd effect, many investors will blindly follow the stock market volatility. Therefore, when the epidemic is severe, investors’ confidence will also be hit, which will have a negative impact on stock returns. However, as the epidemic is gradually brought under control, the uncertainty decreases, and investor sentiment becomes stable. These factors enable investors to rationally view the impact of the epidemic. Besides, during the pandemic, people have to work at home, so investors have more time to watch what happens in the stock market, which affects the daily trading volume of the stock market, which in turn affects stock returns.

In addition, we find that in the three special periods, investor attention around the 5% quartile during the CPB period has the greatest impact on stock returns, which may be due to the fact that after experiencing multiple crises, investors become more cautious and will stop their losses as soon as possible.

The above analysis can conclude that although investor attention has a significant impact on stock returns in general, the impact is heterogeneous in different periods. The impact of external events on the financial and stock markets is different, and the influence of investor attention on stock returns is also different. In addition, with the development of information technology, investors can use more and more channels to realize crises in time and take corresponding actions.

Table 6. Quantile regression results during the CPB period.

Quantile (CPB)	IA_t	ER
5%	−0.004***	29.948***
	(0.0004)	(10.077)
25%	−0.002***	20.024***
	(0.0003)	(7.102)
50%	−0.001***	4.430
	(0.0003)	(5.835)
75%	0.001**	−7.738
	(0.0004)	(8.025)
95%	0.003***	−29.873**
	(0.0003)	(11.942)
Slope equality test (p value)	0.00***	

Note: Quantile (CPB) shows the quantile regression results of the CPB period.

Signif. codes: 0.01'***' 0.05'**' 0.1'*'

5. Robustness test

To check our results' robustness, we first used Koenker and Bassett's test (1982) and show that the slope coefficients vary across quantiles, which shows that investor attention has different influences on stock prices in different quantiles. Second, we use ordinary least squares (OLS) to regress the total and the three crisis periods. The results obtained are shown in Table 7, which also shows that the effect was significant both in the general period and the crisis period.

Table 7. Ordinary least squares method results.

Variable constant	IA_t	ER
OLS (1)	−2.467e−04***	1.716
	(3.536e−05)	(2.164)
OLS (2)	−0.002***	15.360***
	(0.001)	(5.603)
OLS (3)	−2.031e−04***	−20.390***
	(3.425e−05)	(11.530)
OLS (4)	−9.034e−04***	9.199
	(1.235e−04)	(6.329)

Note: OLS (·) corresponds to the Equation (1) estimated by the OLS results of the whole period, the GFC period, the CSMC period, and the CPB period, respectively.

Signif. codes: 0.01'***' 0.05'**' 0.1'*'

Next, to further verify the credibility of the results, we consider using the substitution of variables method to change the indicator that investors lay emphasis on to see if the results are still significant. According to the popularity of related words of stock in the Baidu search index, we find that the popularity of stock quotation is similar to the stock market. Therefore, we think the stock quotation can also represent the investor attention. The dynamics of China's stock quotation Baidu search index are shown in Figure 3. We note that this new investor attention index shows volatility excess during the pre-crisis and then stabilized after these crises. We also conducted unit root tests for the variables after replacement, and the results are shown in Table 8. It can be seen from the table that all variables reject the random walk hypothesis, and all variables are stationary sequences. Therefore, we can directly use this data for regression.

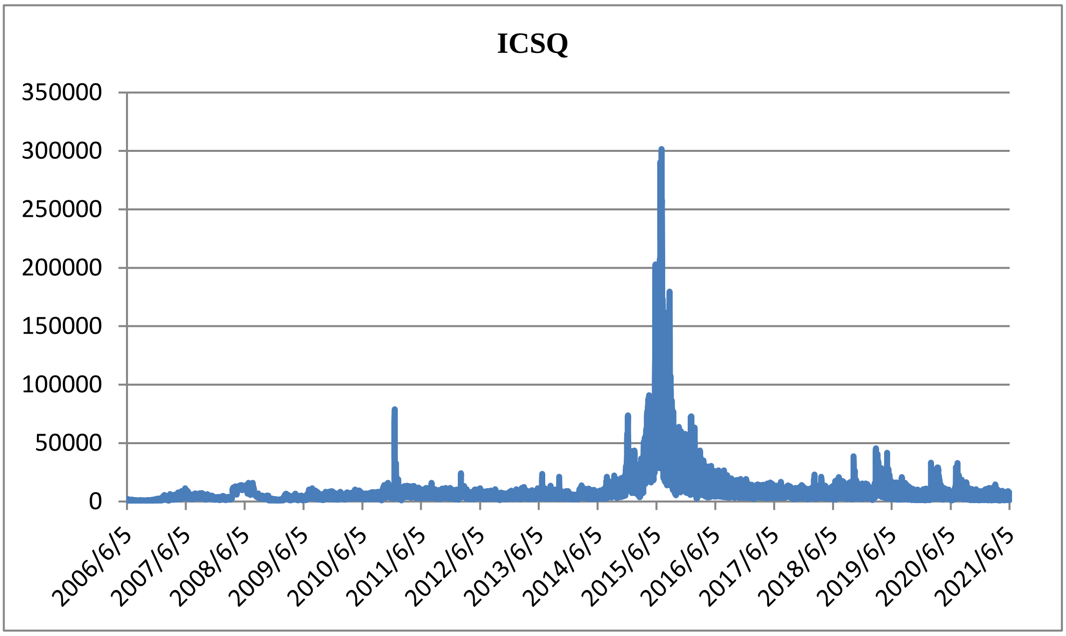


Figure 3. The dynamics of investor attention: China's stock quotation Baidu index.

Table 8. Unit root test for major variables.

	RCS	IA	ER
Augmented Dickey−Fuller	−28.0397	−3.4352	−3.1974
MacKinnon (1996) one−sided p values.	0.00***	0.0099***	0.0202**

Note: Signif. codes: 0.01'***' 0.05'**' 0.1'*'

We get the analogical conclusion when we take the stock quotation Baidu index as the measure of investor attention and run quantile regression on the model again for the total time period and the three crisis periods. The regression results across the full sample show that except for the median quantile, the other quantiles are significant and have different performances. The sample regression results for the three turbulent crisis periods were similar to those of the previous experiment.

Except for the median quantile during the whole time and the CSMC period, the symbols of all the quantiles are the same, and the significance test results are the same as well, though the absolute values of some coefficients are not equal. In addition, we test the coefficient equality of the model and also draw the conclusion that the coefficients of different quantiles are not equal. The main results are reported in Tables 9–12.

Although there are some differences in the values of the variables obtained from the robustness tests, the final results are consistent with the research conclusions obtained in this paper, which reflects the rationality of the model established in this paper from the side.

Table 9. Quantile regression results of the full sample.

Quantile	IA_t	ER
5%	−0.002***	−70.997***
	(0.0002)	(8.379)
25%	−0.001***	−2.085
	(0.0001)	(2.448)
50%	0.00001	5.127***
	(0.00007)	(1.560)
75%	0.001***	17.674***
	(0.0001)	(2.698)
95%	0.001***	43.840***
	(0.0001)	(5.609)
Slope equality test (p value)	0.00***	

Note: Signif. codes: 0.01‘***’ 0.05‘**’ 0.1‘*’.

Table 10. Quantile regression results during the GFC period.

Quantile (GFC)	IA_t	ER
5%	−0.014***	−33.682
	(0.002)	(22.434)
25%	−0.003**	12.320*
	(0.001)	(6.677)
50%	0.002**	9.695**
	(0.001)	(3.874)
75%	0.005***	11.036*
	(0.001)	(6.343)
95%	0.007***	13.199
	(0.002)	(9.809)
Slope equality test (p value)	0.00***	

Table 11. Quantile regression results during the CSMC period.

Quantile (CSMC)	IA_t	ER
5%	−0.002***	−49.201**
	(0.0002)	(21.167)
25%	−0.001***	−22.280**
	(0.0001)	(9.823)
50%	0.00003	−4.352
	(0.0001)	(6.331)
75%	0.001***	−5.876
	(0.0001)	(10.958)
95%	0.001***	9.904
	(0.0002)	(25.608)
Slope equality test (p value)	0.00***	

Table 12. Quantile regression results during the CPB period.

Quantile (CPB)	IA_t	ER
5%	−0.005***	52.512***
	(0.001)	(15.102)
25%	−0.002***	17.397***
	(0.001)	(6.495)
50%	−0.001***	0.021
	(0.0003)	(5.422)
75%	0.0002	−7.976
	(0.0005)	(8.299)
95%	0.003**	−22.136
	(0.001)	(20.821)
Slope equality test (p value)	0.00***	

Quantile (•) shows the quantile regression results of the whole period, the GFC period, the CSMC period, and the CPB period, respectively.
Signif. codes: 0.01‘***’ 0.05‘**’ 0.1‘*’

6. Conclusions

This paper investigates the relationship between investor attention and the Chinese stock market during calm and turbulent periods. Our results show that the quantile regression specification exhibits a significant effect of investor attention on the dynamics of China's stock returns.

Interestingly, we show that the attention effect has a time-varying impact on China's stock returns. Indeed, while investor attention might reduce the increase in China's stock returns around the low quantile, its effect is significantly more simulative around the high quantile. This phenomenon suggests that for higher China's stock returns, the investors tend to be more informed, and therefore the returns become more active driven by investor attention, as investors seek for highest benefits.

Further, through the simulation of the data in some special periods, we find that the influence of investor attention varies at different times and events. In times of crisis, a sluggish economy and volatile changes can affect investors' confidence. After that, the ever-changing and unpredictable market makes investors look at stocks more frequently. Although the impact of investor attention on China's stock returns is significant, the impact can be positive or negative, large or small, and plays a different role in different situations.

The above research conclusions have a certain reference value for individual investors when making investment decisions. However, this paper still has some limitations: First, the search index based on Baidu Index generally only reflects the attention of individual investors and does not reflect the attention degree of institutional investors to stocks, while this paper only studies the attention degree of individual investors. Secondly, some stocks are frequently searched because of the company's business, which interferes with our research. Whether such search volume can be used as a proxy variable is worth discussing.

Conflict of interest

All authors declare no conflicts of interest in this paper.

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