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Research Article

Weibo Attention and Stock Market Performance: Some Empirical Evidence

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In this paper, we employ Weibo Index as the proxy for investor attention and analyze the relationships between investor attention and stock market performance, i.e., trading volume, return, and volatility. The empirical results firstly show that Weibo attention is positively related to trading volume, intraday volatility, and return. Secondly, there exist bidirectional causal relationships between Weibo attention and stock market performance. Thirdly, we generally find that higher Weibo attention indicates higher correlation coefficients with the quantile regression analysis.

1. Introduction

The development of the Internet offers investors more channels to obtain information, discuss market performance, and communicate their forecasting. Also, the change of information environment has made the information network between investors and markets more complex and harder to analyze. Various websites have their own functions and user structures so that different websites have distinct degrees of influence on investors, e.g., Twitter, Facebook, Google, Baidu Index, and Sina Weibo. As the largest social media website in China, Sina Weibo has 340 million active registered users until the first quarter of 2017. It has exceeded Twitter and become the social platform which has most active registered users in the world. Almost all Chinese listed companies and government agencies have their own official Weibo accounts to publish information and discuss the influence by major policy changes. At the same time, many investors who are regarded as more technical and specialized than most of individual investors also use Sina Weibo to share their opinions and forecast stock market performance. In that sense, the use of Sina Weibo helps individual investors to obtain news and it also can be used to measure the change of investor attention. Therefore, the focus of this paper is on the relationships between Sina Weibo attention and stock market performance, i.e., trading volume, volatility, and return.

In recent empirical studies, many scholars investigated the relationships between investor attention measured by open-source information and stock market performance [1–3]. Some studies have shown that investor attention measured from Twitter [4, 5], Google [6], Facebook [7], Baidu Index [8, 9], and other channels [2, 10] can be used to analyze the stock performance. In particular, Chen [11] used Google search volume to measure investor attention to analyze global stock markets. Vozlyublennaia [12] used Google search frequency to measure investor attention and found that there was a significant short-term change in index returns following an increased attention but a shock to returns leads to a long-term change in attention. Bank et al. [13] explored the relationship between Google search volume and German stock performance, and the results show that increasing search queries lead to a rise in trading activity and stock liquidity. Zhang et al. [8] used search frequency of stock name in Baidu Index as the proxy variable for investor attention to explain abnormal return as well as trading volume. Shen et al. [9] regarded Baidu news as the proxy for information flow to study the relationship between information flow and return volatility, and the empirical findings contradicted the prediction of MDH but supported the SIAH. Other scholars used different categories of indirect proxies to measure investor attention. Sicherman et al. [14] used daily investor online account logins as the financial attention to explain the relationship between investors' personal portfolios and how attention affects trading activities. Lou [15] revealed how firm advertising attracts investor attention and influenced short-term stock returns. Fang and Peress [16] studied the relations between media coverage and expected stock returns and found that firms with more media coverage had a higher return and such influence maintains larger for small company. Ben-Rephael et al. [17] found that institutional attention responds more quickly to major news events rather than earnings announcements or analyst recommendation changes through using news searching and news reading activity for specific stocks on Bloomberg terminals and Google search activity to measure abnormal institutional investor attention.

Some scholars studied investor attention in China through different social media channels for information, such as Baidu [18, 19], Guba [20–22], and Sina Weibo [23]. But previous research on Sina Weibo often focuses on specific stock performance, particular time of duration, or account information. However, there is few research using the entire microblogs on Sina Weibo because it is hard to confirm the number of keywords in entire Sina Weibo. This paper is also in line with the abovementioned studies, but we consider Weibo attention through all appearing frequency of key words in entire Sina Weibo to reveal the relation between Weibo attention and stock performance. And we use quantile regression to analyze whether there is a difference between impacts of higher and lower attention from Sina Weibo on the stock market. At the same time, we use the performance of five major indices including Shanghai Stock 50 Index (SH50), CSI 300 Index (CSI 300), Shenzhen Index (SZ), Small and Medium-Sized Enterprise Index (SME), and China Growth Enterprise Market Index (ChiNext) to represent different stock markets rather than only focusing on a single market. We firstly consider the relations between Weibo attention and stock market performance through three contemporaneous correlations containing one linear and two nonlinear methods. In order to discriminate the bidirectional relationships, we use Granger causality test to further investigate the above relationships. Finally, we use quantile regression to analyze how different levels of attention may influence the stock markets. According to above methods, we find that there are positive relations between Weibo attention and trading volume or intraday volatility; however, the coefficients between Weibo attention and returns are different across markets. Moreover, the trading volume of SZ, SME, and ChiNext can Granger-cause Weibo attention but there is no Granger causality in other situations. Through quantile regression analysis, we also find that high attention actually indicates accurate market performance.

This paper is organized as follows. Section 2 describes the data. Section 3 introduces the methodology of empirical analysis. Section 4 performs the contemporaneous correlation, the Granger causality, and the quantile regression test. Section 5 concludes this paper.

2. Data Description

Sina Weibo as the largest Chinese microblogging website has more influence than other social media platforms, and many investors use their Sina Weibo account to share their opinion on specialized stock market performance [23]. So, the high frequency of the keywords appearing in Sina Weibo means that more investors discuss the performance of specialized stock market and they pay more attention on the stock market. So, we regard Weibo Index which represents the number of the keywords appearing in Sina Weibo as the proxy to measure Weibo attention and obtain the data from the official website (http://www.weizhishu.com/).

On the other hand, we use returns, trading volume, and intraday volatility to measure stock market performance. We choose Shanghai Stock 50 Index (SH50), CSI 300 Index (CSI 300), Shenzhen Index (SZ), Small and Medium-Sized Enterprise Index (SME), and China Growth Enterprise Market Index (ChiNext) as the keywords and obtain relevant Weibo Index in this paper. The market index data including returns, closing prices, opening prices, the highest prices, the lowest prices, and trading volumes from March 1, 2013 to October 31, 2017 (1137 trading days) are from CSMAR database. We consider range-based volatility including more information, and previous studies have demonstrated that range-based volatility can estimate index fluctuates more effectively than other low-frequency methods in both Chinese and foreign stock markets [24, 25]. So, we define intraday volatility of index as follows [26]:

$$V_{i,t} = \frac{1}{2} H_P L_{p_{i,t}}{}^2 - (2\ln 2 - 1) O_P C_{p_{i,t}}{}^2, \tag{1}$$

where $H_P L_{p_{i,t}}$ is the difference in natural logarithms of the highest and lowest prices for index i on day t and $O_P C_{p_{i,t}}$ is the difference in natural logarithms of the opening and closing prices for index i on day t.

Table 1 reports the statistical property of index returns, volume, volatility, and Weibo attention in this paper, and we also give the results of Jarque-Bera statistic test and Ljung-Box statistic test in this table. And we use natural logarithm to deal with different volumes. From this table, we can obtain that most of the variables fit Gaussian distribution except the returns of SME and ChiNext. Also, the means of returns across different stock markets are almost positive except SME. Besides, the volume and attention of different markets have little difference. And we also find that the intraday volatility has the highest value in kurtosis, and skewness in four variables and the skewness of returns are all negative while others are all positive. We also observe that most of the variables fit Gaussian distribution except returns of SME and ChiNext. At the same time, all variables exist 20th-order serial correlation. Figure 1 illustrates the evolution of the all-trading-day Weibo Index of Shanghai Stock 50 Index (SH50), CSI 300 Index (CSI 300), Shenzhen Index (SZ), Small and Medium-Sized Enterprise Index (SME), and China Growth Enterprise Market Index (ChiNext) from March 1, 2013 to October 31, 2017. There are 1137 trading days, and we can find that Weibo attention of HS300, SME, and

Table 1: Statistical properties for the variables.

Variables	Mean	Max	Min	Median	Std.	Kurtosis	Skewness	JB	Q(20)
SH50_returns	0.04	7.84	−9.38	0.00	1.63	9.14	−0.46	110***	1825***
HS300_returns	0.05	6.71	−8.75	0.06	1.57	8.94	−0.87	113***	1814***
SZ_returns	0.03	6.45	−8.24	0.09	1.75	7.15	−0.86	64***	953***
SME_returns	−0.03	6.83	−100	0.16	3.46	614.50	−21.34	7	17801414***
ChiNext_returns	0.00	7.16	−100	0.11	3.67	487.08	−17.92	11	11162412***
SH50_volume	12.75	15.14	11.43	12.55	0.73	3.15	0.97	14755***	180***
HS300_volume	13.94	15.74	12.79	13.83	0.64	2.89	0.73	15774***	101***
SZ_volume	12.93	14.96	10.83	13.35	1.10	1.65	−0.30	20034***	103***
SME_volume	11.93	13.04	10.72	11.91	0.48	2.38	−0.03	14283***	18***
ChiNext_volume	11.42	12.57	9.81	11.44	0.55	2.32	−0.20	15749***	29***
SH50_volatility	2.01×10^{-4}	5.67×10^{-3}	2.68×10^{-6}	7.37×10^{-5}	4.62×10^{-4}	60.60	6.70	2418***	165676***
HS300_volatility	1.76×10^{-4}	4.34×10^{-3}	3.19×10^{-6}	6.64×10^{-5}	3.97×10^{-4}	50.58	6.15	3379***	114424***
SZ_volatility	1.99×10^{-4}	5.18×10^{-3}	1.93×10^{-6}	8.10×10^{-5}	4.25×10^{-4}	56.61	6.40	2337***	143913***
SME_volatility	2.02×10^{-4}	5.67×10^{-3}	0	7.99×10^{-5}	4.45×10^{-4}	66.36	6.89	2398***	199154***
ChiNext_volatility	2.95×10^{-4}	7.83×10^{-3}	0	1.30×10^{-4}	5.66×10^{-4}	56.94	6.17	2443***	145072***
SH50_attention	4.96	8.94	0.00	4.85	1.53	2.68	0.39	9462***	33***
HS300_attention	5.36	9.08	0.00	5.36	0.69	7.03	−0.09	4615***	770***
SZ_attention	2.52	6.83	0.00	2.48	1.11	3.44	0.43	2028***	44***
SME_attention	6.75	11.57	0.00	6.73	0.63	20.22	−0.01	2132***	14051***
ChiNext_attention	8.77	11.68	0.00	8.83	0.69	25.85	−1.93	5281***	25430***

This table reports the statistical properties for returns, volume, volatility, and Weibo attention. JB denotes the Jarque-Bera statistic test with the null hypothesis of Gaussian distribution. Q(20) denotes the Ljung-Box statistic test for up to 20th-order serial correlation. *** indicates significant at 1% level.

ChiNext has smaller fluctuation than SH300 and SZ. We also observe that the peaks and troughs of different evolutions happen in the same period.

3. Empirical Methodology

We firstly analyze the correlation of the evolution of Weibo attention and market variables through Pearson correlation coefficient, Spearman correlation coefficient, and Kendall correlation coefficient. And then, Granger causality test captures the bidirectional relationships between investor attention and stock performance. Finally, we use quantile regression analysis to study the further relationships among different variables.

3.1. The Contemporaneous Correlation. In order to calculate the coefficients between different stock returns, trading volume, intraday volatility, and corresponding Weibo Index, with the consideration of the evolution of Weibo attention and market variables, we, respectively, use Pearson correlation coefficient, Spearman correlation coefficient, and Kendall correlation coefficient from linear to nonlinear aspects to analyze the relations among these variables [27]. We calculate different correlation coefficients as follows:

$$\rho_p = \frac{\mathrm{Cov}(WI, MV)}{\sigma_{WI}\sigma_{MV}}, \tag{2}$$

where ρ_p represents Pearson correlation coefficient. Cov(WI, MV) represents covariance between Weibo Index and market variables, and σ_{WI} and σ_{MV} are the standard deviations of Weibo Index and market variables.

$$\rho_s = 1 - \frac{6\sum d_i^2}{n(n^2-1)}, \tag{3}$$

where ρ_s represents Spearman correlation coefficient. And we calculate d_i through firstly rank Weibo Index and corresponding market variables separately and get the absolute value of the difference of the ranking.

$$\begin{aligned} \rho_k &= \frac{C-D}{\sqrt{(N_3-N_1)(N_3-N_2)}}, \\ N_3 &= \frac{1}{2}n(n-1), \\ N_1 &= \sum_1^s \frac{1}{2}U_i(U_i-1), \\ N_2 &= \sum_i^t \frac{1}{2}V_i(V_i-1), \end{aligned} \tag{4}$$

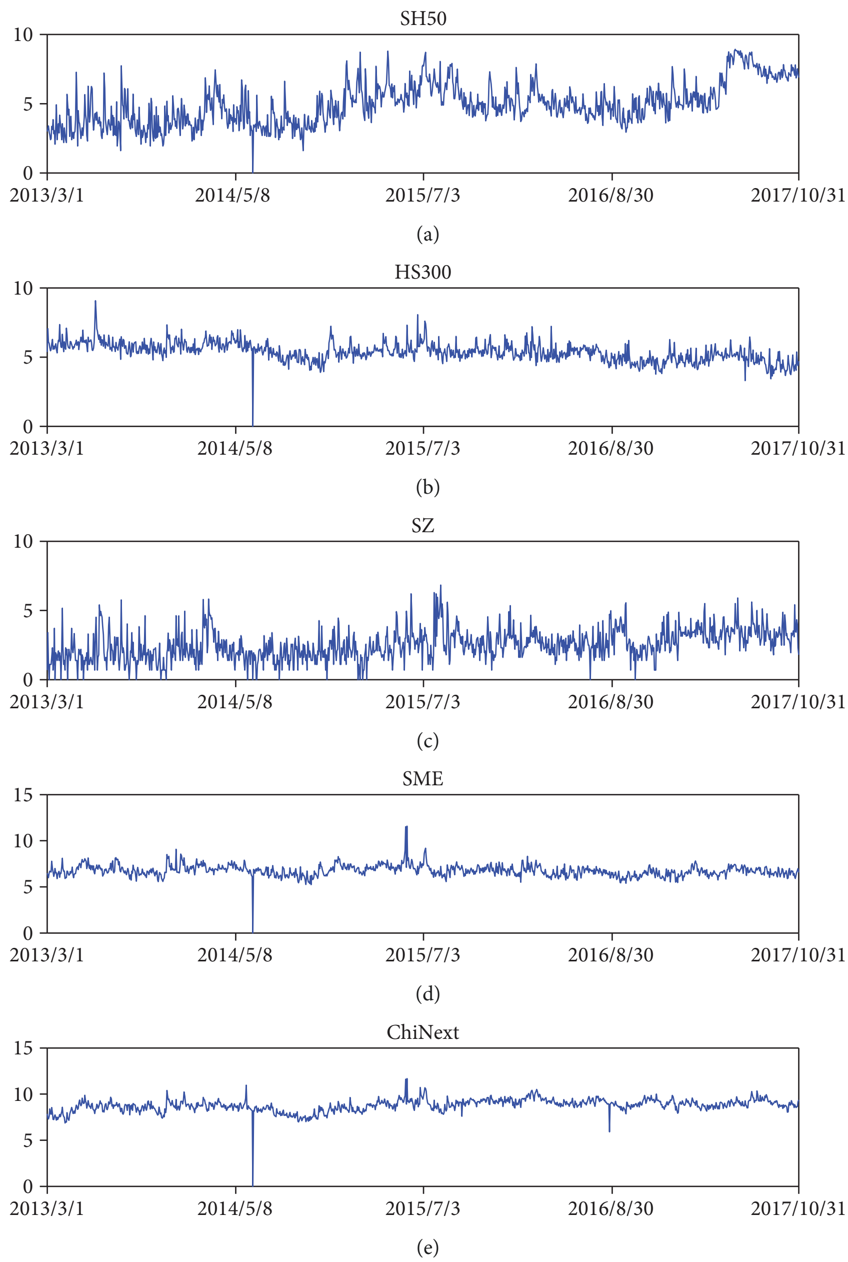

Figure 1: The evolution of Weibo attention. This figure shows the evolution of Weibo Index of different stock markets from March 1, 2013 to October 31, 2017. We notice that there are some zero values in the figure. After checking the data, we found that zeros fall into the nontrading days. In the following empirical analysis, these calendar days are removed from the sample.

where ρ_k denotes Kendall correlation. C is the number of consistent couples, and D is the number of inconsistent couples; U_i and V_i, respectively, mean the number of element in the ith set of Weibo Index and market variables. The correlation coefficients are all between +1 and −1, and the negative coefficient indicates the adverse relationship between market variables and Weibo Index.

3.2. Granger Causality. Shen et al. [28] have proved that there exist bidirectional relationships between open information and shock market performance. Zhang et al. [8] also find that there exist bidirectional relationships between investor attention measured by Baidu Index and stock market performance. So, we also use Granger causality test to analyze the bidirectional relationships of Weibo attention and different market variables. We construct the following regression models to test the Granger causality [26]:

$$\begin{aligned} WI_t &= u_{WI} + \sum_{i=1}^{p} \alpha_i WI_{t-i} + \sum_{j=1}^{p} \beta_j MV_{t-j} + \varepsilon_{t,WI}, \\ MV_t &= \mathrm{u}_{MV} + \sum_{i=1}^{p} \alpha_i MV_{t-i} + \sum_{j=1}^{p} \beta_j WI_{t-j} + \varepsilon_{t,MV}, \end{aligned} \quad (5)$$

Table 2: Correlation coefficients between Weibo Index and market variables.

Index	Pearson	Spearman	Kendall
	Panel A: returns		
SH50	0.0365 (0.2188)	0.0705 (0.0174)**	0.0466 (0.0188)**
HS300	−0.1152 (0.0001)***	−0.0584 (0.0491)**	−0.0377 (0.0571)*
SZ	−0.0902 (0.0023)***	−0.0379 (0.2017)	−0.0244 (0.2253)
SME	0.0038 (0.8970)	0.0748 (0.0117)**	0.0518 (0.0089)***
ChiNext	−0.0865 (0.0035)***	−0.0636 (0.0319)**	−0.0433 (0.0287)**
	Panel B: trading volume		
SH50	0.2980 (0.0000)***	0.3661 (0.0000)***	0.2441 (0.0000)***
HS300	0.0755 (0.0109)**	−0.1971 (0.0000)***	−0.1212 (0.0000)***
SZ	0.3304 (0.0000)***	0.3955 (0.0000)***	0.2657 (0.0000)***
SME	0.2394 (0.0000)***	0.1787 (0.0000)***	0.1223 (0.0000)***
ChiNext	0.4732 (0.0000)***	0.5373 (0.0000)***	0.3686 (0.0000)***
	Panel C: volatility		
SH50	0.2056 (0.0000)***	0.1416 (0.0000)***	0.0969 (0.0000)***
HS300	0.2871 (0.0000)***	0.3993 (0.0000)***	0.2716 (0.0000)***
SZ	0.0972 (0.0010)***	−0.0258 (0.3844)	−0.0160 (0.4271)
SME	0.1698 (0.0000)***	0.3093 (0.0000)***	0.2082 (0.0000)***
ChiNext	0.2071 (0.0000)***	0.2270 (0.0000)***	0.1531 (0.0000)***

This table reports different correlation coefficients between returns, trading volume, and volatility of SH50, HS300, SZ, SME, and ChiNext and Weibo attention from March 1, 2013 to October 31, 2017. *** indicates significant at 1% level; ** indicates significant at 5% level; * indicates significant at 10% level.

where p means value range, WI_t and MV_t denote the value of Weibo Index and market variables at corresponding time, α and β denote the coefficient, u_{WI} and u_{MV} denote the intercept term, and $\varepsilon_{t,WI}$ and $\varepsilon_{t,MV}$ denote regression error.

3.3. Quantile Regression Analysis. Aouadi et al. [29] show that higher attention measured by Google search volume in France decreases stock liquidity and increases volatility. And quantile regression analysis can reflect how different distributions of independent variables influence dependent variables. So, we use quantile to analyze whether different levels of Weibo attention influence the market variables.

As for a continuous random variable y, the probability of y which is equal or lesser than $y(\tau)$ is τ and we call the τ quantile is $y(\tau)$ according to Koenker and Bassett [30]. We can express it as follows:

$$\tau = P(y \le y(\tau)) = F(y(\tau)), \tag{6}$$

where $F(y(\tau))$ is the cumulative distribution function of y. And we also have the following:

$$y(\tau) = F^{-1}(y(\tau)), \tag{7}$$

and it means the portion of y which is less than τ is $y(\tau)$. And we define check function as follows:

$$\rho_\tau(u) = \tau u l(u \ge 0) + (\tau - 1) u l(u < 0). \tag{8}$$

According to the equation, if we define u as $y - \xi$, we can get the following equation:

$$\rho_\tau(y-\xi) = \tau(y-\xi) l(y-\xi \ge 0) + (\tau-1)(y-\xi) l(y-\xi < 0). \tag{9}$$

The quantile regression of y is to find ξ to minimum $E[\rho_\tau(y-\xi)]$.

4. Empirical Results

This section presents our results of relations between Weibo attention and stock index performances. We calculate contemporaneous correlation in Section 4.1, perform the Granger causality test in Section 4.2, and provide quantile regression analysis in Section 4.3.

4.1. The Contemporaneous Correlation. We use Pearson correlation coefficient, Spearman correlation coefficient, and Kendall correlation coefficient to study the relationship between Weibo attention and stock performance.

Table 2 reports the correlation coefficients between Weibo Index and market variables. As for the correlation coefficients between stock returns and Weibo Index, we can see that SH50 and SME have positive coefficients though they are insignificant by Pearson correlation coefficient, while other three indices are negative. The correlation coefficients of all markets are significant by Spearman correlation coefficient and Kendall correlation coefficient except SZ index. The trading volume and Weibo Index are significant by three

Table 3: Granger causality between Weibo Index and market variables.

X	*Y*	*X* Granger cause *Y*	*Y* Granger cause *X*
		Panel A: returns	
Weibo Index	SH50	2.0340 (2.7100)	0.7788 (2.7100)
Weibo Index	HS300	0.9145 (2.7100)	6.6441 (2.7100)**
Weibo Index	SZ	2.7986 (2.7100)*	8.4985 (2.7100)***
Weibo Index	SME	1.1694 (2.7100)	0.1129 (2.7100)
Weibo Index	ChiNext	2.5922 (2.7100)	0.8979 (2.7100)
		Panel B: trading volume	
Weibo Index	SH50	0.0972 (2.7100)	2.6370 (2.7100)
Weibo Index	HS300	0.7149 (2.7100)	0.5240 (2.7100)
Weibo Index	SZ	0.0154 (2.7100)	14.3082 (2.7100)***
Weibo Index	SME	2.4014 (2.7100)	3.4286 (2.7100)**
Weibo Index	ChiNext	0.6812 (2.7100)	13.4979 (2.7100)***
		Panel C: volatility	
Weibo Index	SH50	0.6743 (2.7100)	1.2457 (2.7100)
Weibo Index	HS300	8.4079 (2.7100)***	1.8290 (2.7100)
Weibo Index	SZ	0.4745 (2.7100)	0.9255 (2.7100)
Weibo Index	SME	1.1209 (2.7100)	6.4183 (2.7100)**
Weibo Index	ChiNext	2.8049 (2.7100)*	1.6762 (2.7100)

This table reports the results for the Granger causality analysis between returns, trading volume, and volatility of SH50, HS300, SZ, SME, and ChiNext and Weibo attention. The *X* Granger cause *Y* means Weibo attention can Granger-cause the changes of market variables and *Y* Granger cause *X* means markets can Granger-cause the changes of Weibo attention. *** indicates significant at 1% level; ** indicates significant at 5% level; * indicates significant at 10% level.

kinds of correlation coefficient, and the coefficients are all positive except CSI300 with Spearman correlation coefficient and Kendall correlation coefficient. As far as intraday volatility of each index, the results suggest that all coefficients are positive and significant at 1% except for the SZ index calculated by Spearman regression and Kendall regression.

Above results show the relationship between Weibo attention and stock market performance. We can find 60% coefficients of Weibo attention and returns are adverse. But Weibo Index and trading volume or intraday volatility of index are nearly positive except for the coefficient between Weibo Index and trading volume of CSI300 through two nonlinear regressions. The results show that the correlations of Weibo attention and stock market trading volume or intraday volatility are more obvious than return, and Weibo attention has positive influence on them. It indicates that high volume of stock market will attract more investor attention and investors will also discuss more subsequent market performance in Sina Weibo. Although investors aim to make profit, the stock market returns have no obvious effect on investor attention.

4.2. Granger Causality. In order to analyze the bilateral relation between Weibo attention and stock variables, we set Granger causality test and Table 3 shows the results through above models.

The return of SZ can Granger-cause Weibo Index, and Weibo Index can also Granger-cause the return of SZ. However, except the return of HS300 can Granger-cause Weibo attention at 5% level, no Granger causality exists in Weibo Index and returns of other markets. The trading volume can Granger-cause Weibo Index in SZ, SME, and ChiNext, and no Weibo Index can Granger-cause the changes of trading volume. In terms of intraday volatility of index, the Weibo Index can Granger-cause intraday volatility of HS300 or ChiNext and SME can Granger-cause Weibo Index while no Granger causality in others. The empirical results suggest that trading volume has more influence on investor attention. When the trading volume increases, investors will discuss more about stock in Sina Weibo to exchange ideas. And the change of returns in HS300 and SZ can also lead to more discussions.

4.3. Quantile Regression Analysis. We use quantile regression analysis at 0.05, 0.2, 0.6, 0.8, and 0.95 to consider the influence on Weibo attention and distribution of different market variables in order to analyze the relationships between different levels of attention and stock market performance.

Table 4 shows the results for the quantile regression analysis. We can find that at 0.95 quantile, the coefficients between stock returns and Weibo Index are the highest and significant at 1% level. We also find that higher quantile will lead higher coefficient. But as for the trading volume, the highest coefficient happens at different quantiles. The highest coefficient of SH50 and SME happens at 0.8 quantile, and HS300, SZ, and ChiNext happen, respectively, at 0.95 quantile, 0.4 quantile, and 0.6 quantile. With regard to intraday volatility of index, we can find that most of the indices have the highest relationship at 0.95 quantile except SME.

From the above results, we observe that the highest Weibo attention always means the highest coefficients between market returns and intraday volatility. That means in this case where stock market is discussed frequently, the relations between the market return and intraday volatility and investors are larger. But the highest Weibo attention does not always mean the highest trading volume, and we consider different markets have different quantiles because of the different stock market structures so that Weibo investors have different opinions on the change of different stock markets.

5. Conclusions

This paper employs the Weibo Index as the proxy for investor attention and uses the return, trading volume, and intraday volatility of SH50, HS300, SZ, SME, as well as ChiNext to represent different stock market performances. We investigate the relations between Weibo attention and stock market performance. We firstly find that the statistical property of Weibo Index and the coefficient of Weibo Index and trading volume or intraday volatility are positive regardless of linear regression or nonlinear regression except HS300 while the relations between returns and Weibo Index are 60% adverse. Secondly, we use Granger causality test to analyze the bilateral relation between Weibo attention and market stock performance. The results show that trading volume

Table 4: Results for the quantile regression analysis.

Indices	Quantile regression 0.05	0.2	0.4	0.6	0.8	0.95
Panel A: returns						
SH50	−0.3718***	0.0252	0.0328	0.0752***	0.1059***	0.3492***
HS300	−1.2600***	−0.4090***	−0.1226**	−0.0668	0.2057***	0.9803***
SZ	−0.9174***	−0.1622***	−0.0354	−0.0121	−0.0825	0.3389***
SME	−0.8412	−0.2953**	0.0198	0.2887***	0.5507***	0.9357***
ChiNext	−1.5149***	−0.5379***	−0.2338**	−0.0720	0.2259	0.7316**
Panel B: trading volume						
SH50	0.0685***	0.0727***	0.0902***	0.1532***	0.3290***	0.3052***
HS300	−0.2416***	−0.2277***	−0.1841***	−0.0657***	0.2200***	0.3326***
SZ	0.1505***	0.4418***	0.5550***	0.3858***	0.1683***	0.0799***
SME	0.0107***	0.0383***	0.1076***	0.1982***	0.2855***	0.1804***
ChiNext	0.3937***	0.4471***	0.4436***	0.4705***	0.4288***	0.2215***
Panel C: volatility						
SH50	0.0000	0.0002	0.0001	0.0013***	0.0052***	0.0230***
HS300	0.0008***	0.0016***	0.0031***	0.0061***	0.0122***	0.0393***
SZ	−0.0002	0.0005**	0.0005	0.0010**	0.0045***	0.0163***
SME	0.0008***	0.0018***	0.0040***	0.0067***	0.0136***	0.0143
ChiNext	0.0005	0.0009	0.0035***	0.0079***	0.0189***	0.0392**

*** indicates significant at 1% level; ** indicates significant at 5% level.

can Granger-cause Weibo attention for 3 out of 5 but no Granger causality exists on return and intraday volatility. Thirdly, the results of quantile regression show that higher Weibo attention always means higher coefficient of Weibo attention and market performance, especially for market returns and intraday volatility.

These findings demonstrate that there exists a relation between Weibo attention and stock market performance. Therefore, investors can pay attention to Weibo attention to analyze the change of stock market and adjust the proportion of stocks from different stock market. However, in this paper, we do not find the underlying mechanisms behind those phenomena. We attempt to explain the reason for the phenomena from the perspectives of different investor structures and the users from different websites in further work.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this article.

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