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The momentum and reversal effects of investor sentiment on stock prices

Jinfang Li

School of Business, Key Laboratory of Large Data Processing and Analysis of Electronic Commerce in Henan, Luoyang Normal University, Luoyang 471934, China

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ABSTRACT

In this paper, we illustrate the real function relationship between the stock returns and change of investor sentiment based on the nonparametric regression model. The empirical results show that when the change of investor sentiment is moderate, the stock return is positively correlated with the change of investor sentiment, presenting an obvious momentum effect. However, the stock return is negatively correlated with the change of investor sentiment if the change of investor sentiment is dramatic, presenting significant reversal effects. Moreover, the degree of reversal effect caused by extremely optimistic sentiment is greater than that driven by extremely pessimistic sentiment, which shows a significant asymmetry. Our findings offer a partial explanation for financial anomalies such as the mean reversion of stock returns, the characteristic of slow rise and steep fall in China's stock market and so on.

1. Introduction

Non-normality is a typical feature of financial time-series data, potentially leading to regression problems with hypothesis testing based on normal probability distribution. Generally, the probability distribution of investor sentiment is characterized by fat tails (Li, 2015; Li & Yang, 2017). The fat tail and distortion to the left are caused by some extremely small value, and the fat tail on the right is caused by some extremely large value. Compared with the normal distribution, more values of investor sentiment are in the lower portion and upper portion of the distribution. So far, the existing empirical research has rarely involved the effects of extreme values of investor sentiment on stock prices. In this study, we therefore introduce the nonparametric regression model and illustrate the effects of extreme investor sentiment, namely, the momentum effect of moderate change of investor sentiment and reversal effect of dramatic change of investor sentiment on stock prices.

Both the effective market hypothesis of traditional financial theory and emerging behavioral finance regard the analyses of "noise" and "noise trader" as one of the foundations of theoretical formation. However, there are two opposite views on the relevance of noise traders in determining stock prices. On the one hand, Friedman (1953) argues that there are rational traders and irrational noise traders in the market, rational traders trade against irrational noise traders by taking long opposite positions and therefore that the latter ones are driven out of the market by rational traders eventually. Fama (1965) indicates that noise traders are irrelevant to each other and cannot survive in the long term. Moreover, West (1988) states that "there is little direct evidence that trading by naïve investors plays a substantial role in stock price determination." In short, the irrational noise traders cannot survive for a long time in the efficient market theory. The rational traders drive prices to the intrinsic value over time, and the noise would disappear gradually.

E-mail address: ychpgroup@hotmail.com.

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Therefore, the noise traders would disappear due to “market choices”, and the rational traders may denominate the market eventually.

On the contrary, Black (1986) argues that the noise traders sometimes trade on noise as if it were information, that the rational traders may not take large enough positions to eliminate the noise, and thus that the short term volatility of noise in price would be greater than the short term volatility of value. Trueman (1988) indicates that noise traders induce necessary liquidity in the market, and thus create the opportunity for informed investors to trade. Furthermore, the DSSW model of De Long, Shleifer, Summers, and Waldmann (1990) simulates the influence of noise trading on asset equilibrium prices. They indicate that irrational noise traders with erroneous stochastic beliefs affect prices and the unpredictability of their sentiment creates a risk in the price of the asset that deters rational arbitrageurs from aggressively betting against them. As a result, prices can diverge significantly from fundamental values, and thus noise traders create their own space because noise itself creates risk. Similarly, Shefrin and Statman (1994) present the behavioral capital asset pricing model and demonstrate the interaction between noise traders and informed traders. They claim that noise traders introduce a second driver into the market which takes prices away from efficiency.

Following these predictions, a considerable increase in empirical studies focuses on the issue of relationship between stock prices and investor sentiment. Many empirical results show that investor sentiment plays a systematic and significant role in stock prices (e.g., Lee, Jiang, & Indro, 2002; Brown & Cliff, 2004, 2005; Baker & Wurgler, 2006, 2007; Kumar & Lee, 2006; Yu & Yuan, 2011; Baker, Wurgler, & Yuan, 2012; Seybert & Yang, 2012; Stambaugh, Yu, & Yuan, 2012, 2014, 2015; Li, 2015; Li & Yang, 2017; Gao & Yang, 2018). Particularly, Baker and Wurgler (2006, 2007) employ principal component analysis to construct the composite market sentiment index. As Baker and Wurgler (2007) said, now the question is no longer whether investor sentiment affects stock prices, but rather how to measure investor sentiment. Li and Yang (2017) empirically study the cross-section and time-series effects of individual stock investor sentiment on stock prices. Their results show that individual stock sentiment has greater impact on small-firm stock prices than big-firm stock prices and that individual stock sentiment leads to much sharper fluctuations of stock prices in the stock market downturn than in the stock market expansion.

Overall, the emerging behavioral finance emphasizes that irrational investors’ actions are dependent on each other due to sentiment contagion and information generating process, and therefore that irrational investors can create risk and create their own space. Although the research results are slightly different, they form a more consistent conclusion that stock pricing is much higher with optimistic sentiment and is much lower with pessimistic sentiment. Moreover, the related research conclusions are supported by some financial experiments. The irrational investors with high sentiment would make optimistic decision-making, thus they would increase the perceived asset value and vice versa (Statman, Fisher, & Anginer, 2008; Kempf, Merkle, & Niessen, 2014).

Reviewing the rational arbitrager space represented by Friedman (1953) and the noise trader space represented by Black (1986), we believe that there are rational traders and noise traders in the market from both views. Their fundamental differences are the size of the proportion of noise traders. According to the view of Black (1986), noise traders account for the majority of traders, creating their own living space. Then, the noise traders with high sentiment lead to higher pricing of financial asset, namely, the momentum effect of investor sentiment on asset prices. Next, assuming that the sentiment of noise traders is extremely high, it would result in the overpricing of the financial assets, which leads to a serious sentimental bubble eventually; or when the investor sentiment rises over a certain threshold, the noise traders encounter the strong game strength of the rational arbitragers in the market, forcing the asset price to return to its intrinsic value. At this point, the rational arbitragers account for the majority of traders, in line with the market situation described by Friedman (1953). In the real market, we often see the latter. Thus, it raises a question of where the critical value of investor sentiment is, then the reversal effect of investor sentiment occurs on asset prices.

In order to realize the unity of opposites of the views of Friedman (1953) and Black (1986), it is assumed that the rational uninformed traders chase price increases caused by noise traders when the change of investor sentiment is moderate in the short term (Mendel & Shleifer, 2012). The rational uninformed traders act as if they were noise traders, thus overcoming the rational informed investors and creating the living space of noise traders (De Long, Shleifer, Summers, & Waldmann, 1990, 1991). However, when the change of investor sentiment is dramatic and the pricing of financial assets is too high or too low in the long term, the rational uninformed traders turn to bet against the noise traders who are influenced by sentiment (Mendel & Shleifer, 2012), appearing the arbitrage space of rational investors. The joining force of the two drives the asset price to move back toward its intrinsic value, presenting the reversal effect on the critical value of investor sentiment. The farther the asset price moves away from its intrinsic value, the faster it will tend to move back (Li, 2014).

The relevant interpretation of reversal effect of asset price can be found in behavioral finance. Daniel, Hirshleifer, and Subrahmanyam (1998) demonstrate that biased self-attribution adds positive short-lag autocorrelations of stock price changes (momentum) and long-lag negative correlation (reversal). Barberis, Shleifer, and Vishny (1998) present a parsimonious model of how people form expectations. The model illustrates that the behavior of a given firm’s earnings moves between two states. Earnings are mean-reverting in the first state and they trend in the second state. The work of Li (2014) models the process that the continuing overreactions lead to short-term momentum and long-term reversal if the initial overreaction is corrected in the long run. Li (2019) indicate that the market becomes infinitely resilient near the end of trading, so the initial overreactions are corrected by the rational investor in the long run. Yang and Yan (2011) develop the DSSW model of De Long, Shleifer, Summers, and Waldmann (1990) based on investor sentiment. They indicate that the risk asset has negative excess returns when investor sentiment is greater than a certain critical value, and it has positive excess returns when investor sentiment is less than this critical value. Li and Yu (2012) have empirically analyzed the overreaction of investor to information. So far, the existing empirical research has rarely analyzed the reversal effect of stock prices from the view of critical value of investor sentiment. In this paper, we attempt to empirical study the short-term momentum and long-term reversal of stock prices by combining the game of the rational investors and sentiment investors with the critical value of investor sentiment. Thus the two views of Black (1986) and Friedman (1953) are put in an unified empirical framework.

In fact, the functional relationship between dependent variable and explanatory variable is often unknown. Assume that they obey a particular linear function or a nonlinear function form, it may result in the model setting error. In view of the characteristics of the impact of investor sentiment on stock prices, we introduce a nonparametric regression model to explore the real relationship between stock prices and investor sentiment. Based on the nonparametric regression model, we demonstrate the momentum effect of the moderate change of investor sentiment and the reversal effect of the dramatic change of investor sentiment on stock prices. Furthermore, we construct a nonlinear parameter model[1] with three regimes to further verify the estimated results and test the significance of parameter values.

This paper contributes to the literature in several ways. Firstly, through the kernel estimation for the density function of the change of investor sentiment, it indicates that when the change of investor sentiment is dramatic, its probability distribution is higher than the normal distribution. Thus, the specific effect of the dramatic change of investor sentiment on stock returns is a topic worthy of further study. Secondly, we use the nonparametric regression model to find out the two critical values on the dramatic change of investor sentiment. Above the upper critical value, the greater the change of investor sentiment is, the lower the stock returns get, presenting an obvious reversal effect. Below the lower critical value, there is a similar relationship between the stock returns and the change of investor sentiment, presenting an obvious reversal effect too. When the changes of investor sentiment are between the lower critical value and the upper critical value, the greater the change of investor sentiment is, the higher the stock returns get, showing an obvious momentum effect. Thirdly, we further employ the nonlinear parameter model with three regimes to test the statistical significance and economic significance. The results show that the reversal degree caused by extremely optimistic sentiment is greater than that driven by extremely pessimistic sentiment, which presents a significant asymmetry. Finally, our empirical findings put the two opposite views of Black (1986) and Friedman (1953) in a unified framework. When the change of investor sentiment is moderate, the noise traders account for a considerable proportion of the total number of traders, eventually creating their own living space (Black, 1986). However, when the change of investor sentiment is dramatic, the arbitrage space of rational investors appears, driving the market prices to return to the fundamental values (Friedman, 1953).

The rest of the paper is organized as follows. In Section 2, we construct a composite investor sentiment index based on the principal component analysis. In Section 3, we design the empirical methodology. In Section 4, we describe the empirical results from nonparametric regression model to nonlinear parametric model. In Section 5, we provide some additional supporting evidences, such as empirical threshold, time-series effect and size effect. In Section 6, we conduct the robustness test on the extreme sentiment in Shenzhen stock market. Section 7 draws a conclusion.

2. Investor sentiment

In this part, we illustrate the construction process of market sentiment index. Although a single sentiment proxy characterizing investor sentiment provides a convenient measurement for investor sentiment, some researchers often question its validity and credibility (Brown & Cliff, 2004, 2005). There is no assurance that the single indicator of sentiment actually contains all related information about views. Now, various proxies for market sentiment are statistically complete and readily accessible, thus we are to extract a composite market sentiment index by using principal component analysis.

2.1. Investor sentiment proxies

Baker and Wurgler (2006) employ principal component analysis to construct a composite market sentiment index. The sentiment index is based on the common variation of six underlying sentiment proxies. They are closed-end fund discount, turnover rate, number of IPOs, average first-day returns on IPOs, equity share in new issues and dividend premium. Subsequently, Baker, Wang, and Wurgler (2008), Kurov (2010), Yu and Yuan (2011), Stambaugh, Yu, and Yuan (2012, 2014), Fong and Toh (2014) and Mclean and Zhao (2014) also adopt the above six proxies to build the comprehensive market sentiment index. Therefore, based on the approach of Baker and Wurgler (2006), we illustrate the construction of sentiment index in Shanghai Stock Exchange, which is similar to the forming process of sentiment index in Shenzhen Stock Exchange. Here, the sentiment proxies don't include the average first-day returns and number on IPOs, because IPOs have been forbidden several times in China's stock market. Moreover, we involve some specific sentiment proxies to exactly reflect the sentiment level in China's stock market, such as new stock accounts, new fund accounts and psychological line index. Yang and Gao (2014) and Yang and Zhou (2016) indicate that psychological line index can serve as a sentiment indicator and that it looks behind the market sentiment level. Eventually, we select new stock accounts (NSA), new fund accounts (NFA), closed-end fund discount rate (CFD), fund index (FI), stock trading volume (STV) and psychological line index (PLI) as sentiment proxies in Shanghai Stock Exchange.

2.2. Data

The research data for new stock accounts, new fund accounts and closed-end fund discount rate are from the RESSET[2] database. The

[1] Here, the nonlinear model does not include the nonparametric model, and the nonlinearity is only for the regression variables.

[2] RESSET Financial Research Database (RESSET) is mainly for colleges and universities, financial research institutions, research departments of financial enterprises in China, providing support for empirical research and model test. RESSET is designed by numerous experts from Tsinghua University, Peking University, and the London School of Economics, http://www.resset.cn/databases.

research data for the Shanghai composite index, fund index, stock trading volume and psychological line index are from the CSMAR[3] database. Moreover, we denote the return of Shanghai composite index in the form of first difference of logarithm. Given the fact that the high-frequency data contain potentially valuable information (see, Yang & Zhang, 2014) and are available in real time, the subsequent empirical analysis is performed at the weekly frequency. Weekly data range from January 4, 2006 through December 31, 2017, taking into account Chinese comprehensive reform of shareholder structure launched in 2005.

2.3. Investor sentiment index

To this end, we define investor sentiment index as the first principal component of six proxies according to the approach of Baker and Wurgler (2006). Therefore, the investor sentiment index can be written as

$$SI_t = 0.4436NSA_t + 0.2852NFA_t + 0.3773CFD_t + 0.4765FI_t + 0.3213STV_t + 0.4438PLI_t \tag{1}$$

Each of the six sentiment proxies has first been standardized, and only the first eigenvalue is significantly greater than 1. The first principal component explains 65.38% of the sample variance of orthogonalized variables, so one factor can capture much of the common variation. Since the fluctuation of stock prices is corresponding to the level of investor sentiment, the size of stock returns corresponds to the change of investor sentiment. Moreover, the change of investor sentiment is usually a stationary time series. The change of investor sentiment is given by $\Delta SI_t = SI_t - SI_{t-1}$, where $\Delta SI_t < 0$ means that investors get more pessimistic in week of t, whereas $\Delta SI_t > 0$ denotes that investors become more optimistic in week of t.

2.4. Summary statistics

Univariate summary statistics for the return of stock index and the change of investor sentiment in Shanghai stock market are presented in Table 1, and some important features are mentioned in the data description below.

From Table 1, we know that all sample statistics are very appealing. The mean of R_t at weekly frequency is 0.0026, and the standard deviation of R_t is 0.0413. The mean of ΔSI_t at weekly frequency is 0.0015, and the standard deviation of ΔSI_t is 0.4312. The coefficients of Skewness of R_t and ΔSI_t are 0.0424 and 0.3461, respectively. Each of the time series variables presents right-skewed, and a long tail on the right is caused by some extremely large values. The coefficients of Kurtosis of R_t and ΔSI_t are significantly greater than 0, which show that each of the time series variable presents the characteristics of high peak and fat tail. From the J-B statistics, we know that R_t and ΔSI_t do not follow normal distribution at 5% and 1% significance levels, respectively. The results from ADF unit root test indicate that each of the two variables can be treated as stationary variable, and pseudo regression problem does not exist. Non-normality is a typical feature for the two time series variables. As will be discussed in Section 3 and Section 4, more complicated nonlinear relationship between R_t and ΔSI_t is prevalent.

3. Model specification

Generally, the parametric regression model, whether is it a linear form or not, needs to be given the explicitly function relationship between the dependent variable and explanatory variables so as to estimate the corresponding parameters and then analyze the specific problem by using the estimated results of the model. However, the setting of functional relationship has a strong subjectivity. Modelers often need to try a variety of models before they can finally select the appropriate form based on a number of factors such as statistical tests and economic significance. In some cases, the error of model setting even occurs. Therefore, we first employ the nonparametric regression model, instead of the parametric regression, to determine the real relationship between the return of stock index and the change of investor sentiment. The unknown nonparametric model can be estimated by using kernel estimation.

3.1. Kernel estimation for univariate density function

The specific form of density function of random variable is often unknown, and the kernel estimation of density function can be considered when there is no related information about the density function of random variable. The idea of kernel density estimation comes from the histogram for displaying data. We use observations available in a neighborhood of x to construct an approximation to the density function of $f(x)$ at a given point x. For simplicity, $f(x)$ is a local average of the standard normal density function with mean X_t and standard deviation h. Thus, the estimation of density function of $f(x)$ at a given point x can be written as

$$\hat{f}(x) = \frac{1}{n}\sum_{t=1}^{n}\frac{1}{\sqrt{2\pi}h}e^{-\frac{(x-X_t)}{2h^2}} = \frac{1}{nh}\sum_{t=1}^{n}K(\frac{x-X_t}{h}) \tag{2}$$

$K(x) = \frac{1}{\sqrt{2\pi}}e^{-\frac{x^2}{2}}$ is called the kernel function, and h is the bandwidth parameter satisfying $\lim_{n\to\infty} h = 0$ and $\lim_{n\to\infty} nh = \infty$.

[3] The China Stock Market & Accounting (CSMAR) database offers access to China's largest collection of historical data covering the most recent working day, including intraday closing exchange prices, such as data of all A shares and B shares companies listed on the Shanghai Stock Exchange and the Shenzhen Stock Exchange from 1990 to present, http://www.gtarsc.com/.

Table 1
Summary statistics and statistical test.

Variable	Mean	Std. Dev.	Max.	Min.	Skewness	Kurtosis	J-B statistic	ADF
R_t	0.0026	0.0413	0.1498	−0.1382	0.0424	4.2914	7.8614**	−21.53***
ΔSI_t	0.0015	0.4312	1.5243	−1.3200	0.3461	4.1812	66.1254***	−22.16***

Note: ***, ** and * denote statistical significance at 1%, 5% and 10% levels, respectively.

Similarly, the kernel function may be introduced using some other existing density function. The kernel form of uniform density function is $K(x) = \frac{1}{2}I[-1 \leqslant x \leqslant 1]$. Thus, the form of $K(x)$ can be specified in a general form. The bandwidth of h determines the smoothness of density estimate. The larger the bandwidth is, the smoother the estimation gets, but the greater the estimation bias is. It can be proved that in the case of large sample, the smaller the bandwidth is, the smaller the estimation bias gets, but the larger the variance is and vice versa. The choice of optimal bandwidth must be a tradeoff between the two statistics. Minimizing the mean square error of $\hat{f}(x)$ to find an optimal bandwidth value of $h_{optimal}$, i.e., $MSE(x; h_{optimal}) = \underset{over\ all\ h}{min} MSE(x; h)$.

3.2. Univariate nonparametric regression model

Let the random variable Y_t be the dependent variable, and X_t be the explanatory variable, which is the important factor influencing Y_t. A natural nonparametric model can be written as

$$Y_t = m(X_t) + e_t \tag{3}$$

where $\{e_t\}$ is a sequence of stationary time series errors with $E(e_t) = 0$ and $E(e_t^2) = 1$. For a given value x, we have that $m(x) = E(Y_t|X_t = x)$, i.e., $e_t = Y_t - E(Y_t|X_t = x)$. In the nonparametric setting, a typical assumption is that $m(x)$ is a smooth and unknown function of x. Here, we focus on the kernel smoothing method. Given bivariate data (Y_t, X_t), we use the local average of X_t around the neighborhood of a point x to estimate $m(x)$. Thus, a nonparametric optimization method is given by

$$\sum_{t=1}^{n}(Y_t - \alpha)^2 K\left(\frac{x - X_t}{h}\right) = min! \tag{4}$$

To this end, we only need to estimate the constant of α. This means that we may estimate $m(x)$ by

$$\hat{m}(x) = \alpha = \frac{\sum_{t=1}^{n} K\left(\frac{x-X_t}{h}\right) Y_{tt}}{\sum_{t=1}^{n} K\left(\frac{x-X_t}{h}\right)} \tag{5}$$

In the Section 4, we are to demonstrate how to use kernel smoothing in practice.

3.3. Nonlinear parametric model with three regimes

According to the influence characteristics of the change of investor sentiment on stock index returns, it is necessary to take into account the specific impact of dramatic change in investor sentiment. The nonparametric model assumes that the relationship between the two variables obeys a potential process. It can well capture the functional relationship between the stock index returns and change of investor sentiment, especially the special impact of dramatic change of investor sentiment on stock index returns. Such detailed illustrations may be found from Hardle (1990) and Hardle, Liang, and Gao (2000). Thus, we first use the nonparametric model to find out the influence characteristics of change of investor sentiment on stock index returns, and then employ the nonlinear parametric model with dummy variables to carry out the significance test and specific analysis. The nonlinear parametric model with dummy variables is constructed on the basis of the results of nonparametric model. It not only considers the potential function form between the stock index returns and the change of investor sentiment, but also performs the significant test, and gives the sizes of different sensitivity of the two variables, which is the extension of the nonparametric model. This flexible parametric-nonparametric mixed analysis method may greatly improve the accuracy of the sentiment influence.

We conjecture that there may be certain critical values for the impact of change of investor sentiment on stock index returns when the change of investor sentiment is dramatic. In Section 4, we happen to verify the existence of critical values. When the change of investor sentiment is extremely optimistic and greater than the critical value, it has a negative effect on stock index returns; when the change of investor sentiment is moderate and lower than the critical value, it has a positive effect on stock index returns. Correspondingly, there is another critical value when the change of investor sentiment is extremely pessimistic. Assuming that we have found these two critical values by using nonparametric model, one represents extremely optimistic sentiment threshold denoted by ΔSI_O, and the other represents extremely pessimistic sentiment threshold denoted by ΔSI_P. Therefore, according to the threshold of ΔSI_O, we can define the following dummy variable

$$D_{Ot} = \begin{cases} 1, & if\ \Delta SI_t \geqslant \Delta SI_O; \\ 0, & if\ \Delta SI_t < \Delta SI_O. \end{cases} \tag{6}$$

If the change of investor sentiment is more than the threshold of ΔSI_O then $D_{Ot} = 1$, and If the change of investor sentiment is less than the threshold of ΔSI_O then $D_{Ot} = 0$. Similarly, according to the threshold of ΔSI_P, we can define the other dummy variable as follow

$$D_{Pt} = \begin{cases} 1, & if\ \Delta SI_t \leqslant \Delta SI_P; \\ 0, & if\ \Delta SI_t > \Delta SI_P. \end{cases} \tag{7}$$

If the change of investor sentiment is less than the threshold of ΔSI_P then $D_{Pt} = 1$, and If the change of investor sentiment is more than the threshold of ΔSI_P then $D_{Pt} = 0$. Combining Eqs. (6) and (7) with general regression model, we can obtain the following nonlinear regression model with three regimes

$$R_t = \alpha + \beta_S \Delta SI_t + \beta_O(\Delta SI_t - \Delta SI_O)D_{Ot} + \beta_P(\Delta SI_t - \Delta SI_P)D_{Pt} + \varepsilon_t \tag{8}$$

The coefficient β_S measures the effect of moderate change of investor sentiment on stock returns, $(\beta_S + \beta_O)$ measures the effect of investor sentiment if it is more than the threshold of ΔSI_O, and $(\beta_S + \beta_P)$ measures the effect of investor sentiment if it is less than the threshold of ΔSI_P. If $\beta_S > 0$ and $(\beta_S + \beta_O) < 0$, it means that investor sentiment exerts reversal effect on stock returns when investor sentiment is extremely optimistic. If $\beta_S > 0$ and $(\beta_S + \beta_P) < 0$, it implies that investor sentiment also exerts reversal effect on stock returns when the investor sentiment is extremely pessimistic.

4. Empirical results

4.1. Kernel density estimation results for the change of investor sentiment

As discussed above, we use kernel density estimation to describe the plot of density function of the change of investor sentiment. For comparison, the plot of normal density function is also presented in the same panel. The estimation results for the density function of change of investor sentiment are given in Fig. 1.

From Fig. 1, we know that the plot of kernel density estimate is not close to that of normal density function. As demonstrated in the above section of summary statistics, the change of investor sentiment at weekly frequency presents a characteristic of high peak and fat tail. From the above figure, it can be seen that when the change of investor sentiment is dramatic, its probability distribution is higher than the normal distribution. It shows that the probability of some extreme values is relatively large, so their specific effects on the stock index returns are a topic worthy of further study.

4.2. Nonparametric estimation results

We make use of the kernel estimation method of nonparametric regression to describe the real function relationship between the stock returns and change of investor sentiment. Moreover, the kernel function is employed by the form of Epanechnikov. Taking into account the scales of stock returns and change of investor sentiment, the bandwidths are set to 0.10, 0.25 and 0.40, respectively. Correspondingly, the estimation results are showed in Figs. 2, 3, and Fig. 2, respectively.

As discussed in Section 3, the bandwidth parameter h controls the smoothness of functional estimation. The larger the bandwidth parameter is, the smoother the estimate gets, but the larger the bias component is. The smaller the bandwidth parameter is, the smaller the bias of kernel estimation is. Combining Figs. 2, 3 with Fig. 4, we find that the functional relationship between the stock returns and

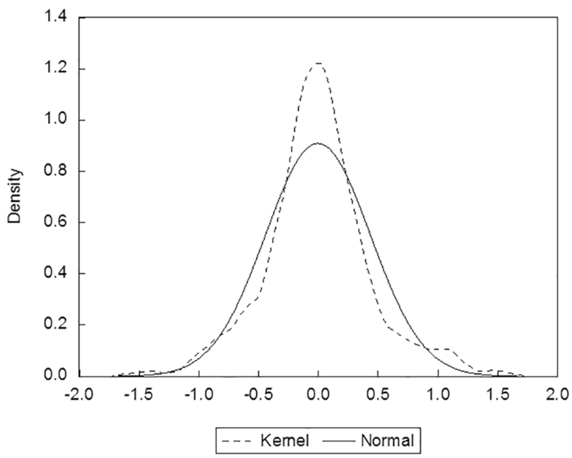

Fig. 1. The probability distribution for the change of investor sentiment.

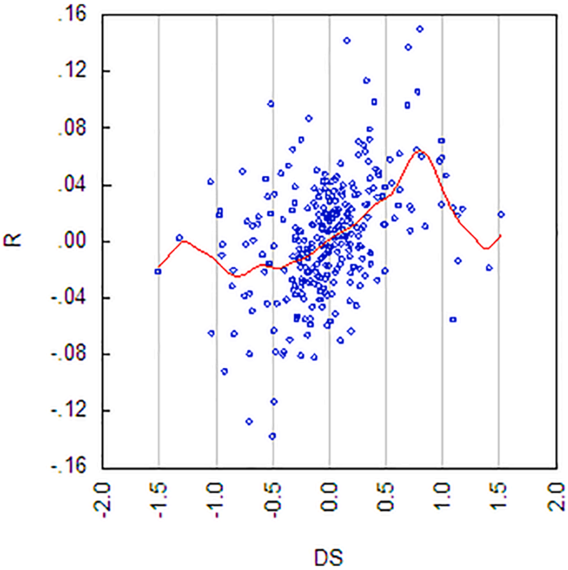

Fig. 2. The function relationship between stock returns and change of investor sentiment when h = 0.10.

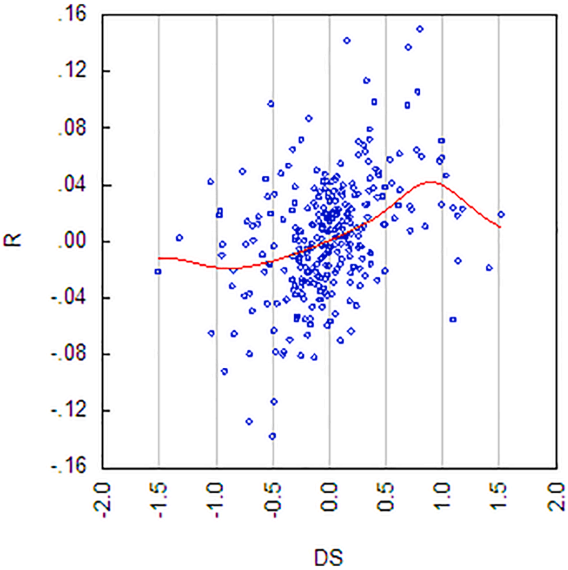

Fig. 3. The function relationship between stock returns and change of investor sentiment when h = 0.25.

change of investor sentiment becomes more and more smooth with the increase of bandwidth. When the bandwidth parameter h is equal to 0.40, the functional relationship between the two stationary variables is close to estimation result of common parameter regression. To the end, we focus on the analysis of estimation result in Fig. 2. When investor sentiment expand dramatically, there is a significant inflection point between 0.50 and 1.00. Above the inflection point, the greater the change of investor sentiment is, the lower the stock returns get, presenting an obvious reversal effect. Below the inflection point, the greater the change of investor sentiment is, the higher the stock returns get, showing an obvious momentum effect. Correspondingly, when investor sentiment contracts dramatically, there is another significant inflection point between -1.00 and -0.50. Below the inflection point, the greater the change of investor sentiment is, the lower the stock returns get, presenting an obvious reversal effect too. Eventually, in the case of $h = 0.10$, the threshold values are set to $\Delta SI_O = 0.7838$ and $\Delta SI_P = -0.7226$ respectively according to the fitting results of nonparametric regression.

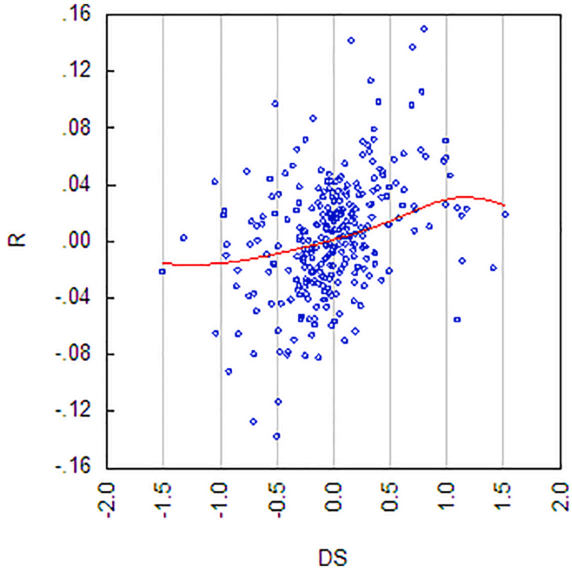

Fig. 4. The function relationship between stock returns and change of investor sentiment when h = 0.40.

4.3. Estimation results for nonlinear parametric model

In this section, we employ the nonlinear parametric model with dummy variables to further carry out the significance test and specific analysis. In order to make a comparative analysis, we also give the estimation results for general linear regression model. The estimation results for the two models are shown in Table 2.

From Table 2, we know that the sentimental sensitivity coefficient of general linear regression is 0.0378, which is statistically significant at 1% level. The adjusted coefficient of determination is 0.1523, which means that 15.23% of the variation in stock returns is explained by the variation of sentiment factor. In the nonlinear regression model with three regimes, all beta loadings are statistically significant at 1% significance level. The beta coefficient of the moderate change of investor sentiment (β_S) is 0.0593, which is 56.88% more than that of general linear regression. When the optimistic change of investor sentiment is higher than the threshold of ΔSI_O, the sentimental beta coefficient is equal to -0.0824 ($\beta_S + \beta_O$). It means that if the change of extremely optimistic sentiment increases by one unit, then the stock return decreases by 8.24 percentage points, presenting an obvious reversal effect. When the pessimistic change of investor sentiment is lower than the threshold of ΔSI_P, the sentimental beta coefficient is equal to -0.0571 ($\beta_S + \beta_P$). It implies that if the change of extremely pessimistic sentiment increases by one unit, then the stock return decreases by 5.71 percentage points, presenting an obvious reversal effect too. Moreover, the degree of reversal effect of the extremely optimistic sentiment is more than that of extremely pessimistic sentiment. Furthermore, the adjusted coefficient of determination in nonlinear regression is equal to 0.2347, which is more than that in linear regression.

In short, the moderate change of investor sentiment is positively correlated with stock index returns, showing an obvious momentum effect. It can be thought of as a particular consistency with the argument of Black (1986) that the uninformed noise traders overcome the informed rational investors and create their own living space when the change of investor sentiment is moderate in the short term. However, when the change of investor sentiment is dramatic, the stock return presents a significant reversal effect in the long term. It is consistent with the claim of Friedman (1953) that the living space of noise traders disappears and the arbitrage space of rational investors appears driving market price to return to the fundamental value when the financial asset pricing is too high (low) in the long term. Moreover, the reversal degree under extremely optimistic sentiment is greater than that under extremely pessimistic sentiment, presenting an obvious asymmetry. To a certain extent, the empirical results offer a partial explanation to financial

Table 2
The estimation results of general linear regression and nonlinear regression with three regimes.

Model	α	β_S	β_O	β_P	Adj-R^2	F statistic
Linear regression	0.0026 (1.23)	0.0378^{***} (7.46)			0.1523	54.18
Nonlinear regression	0.0034 (1.56)	0.0593^{***} (8.92)	-0.1417^{***} (-4.26)	-0.1164^{***} (-3.43)	0.2347	28.94

Note: ***, ** and * denote significance at 1%, 5% and 10% levels, respectively. The value in parentheses denotes the corresponding t-statistic for each parameter. The general linear regression model is set to $R_t = \alpha + \beta_S \Delta SI_t + \varepsilon_t$. R_t denotes the aggregate stock index returns at weekly frequency in Shanghai stock market. ΔSI_t denotes the change of aggregate market sentiment index at weekly frequency in Shanghai stock market. β_S measures the aggregate effect of the change of investor sentiment on stock returns.

anomalies such as the mean reversion of stock returns, the characteristic of slow rise and steep fall in China's stock market and so on.

5. Additional supporting evidence

Our results so far indicate that extreme observations of sentiment change exhibit a reverse return pattern. The nonlinear parametric model with dummy variables further supports the use of a nonparametric model to determine the thresholds. In this section, we provides some supports to our main expressing that the nonparametric design is necessary and therefore that the extremely sentiment may exert significant reversal effects on stock prices. First, we directly use the standard deviation to set threshold, such as 2 times standard deviation above the mean of sentiment change set to extremely positive sentiment threshold, and 2 times standard deviation below the mean set to extremely negative sentiment threshold. Second, considering the time effect, we demonstrate the question of whether the relationship between stock prices and investor sentiment is different at different intervals, such as during different market states. Third, given the size effect, we use the small and medium enterprise (SME) stock index to represent the small stocks, and study the relationship between stock prices and investor sentiment in small-cap stocks.

5.1. *Estimation results of empirical threshold*

The empirical rules help us measure how the values distribute above and below the mean and can help us identify outliers. The empirical rules indicate that approximately 95% of the values are within a range of ± 2 standard deviations from the mean for bell-shaped distribution, and the Chebyshev rule states that, regardless of shape, at least 75% of the values must be found within ± 2 standard deviations of the mean. Both rules imply that values not found in the interval of ± 3 standard deviations from the mean are almost always considered outliers. Therefore, we set 2 times standard deviation above the mean to represent the extremely positive sentiment threshold, and set 2 times standard deviation below the mean to denote the extremely negative sentiment threshold. The estimation results for empirical thresholds are shown in Table 3.

Table 3 shows that all the sentimental sensitivity coefficients are statistically significant at 1% level. In the empirical threshold model, the adjusted coefficient of determination is 0.2945, which is greater than that of nonlinear parametric model in the section 4.3. When the sentiment changes are within a range of ± 2 standard deviation from the mean, the sentimental beta coefficient is equal to 0.0524. When the sentiment changes are less than the threshold of $\mu - 2\sigma$, the beta coefficient of extremely negative sentiment is -0.0839, presenting a significant reversal effect. When the sentiment changes are greater than the threshold of $\mu + 2\sigma$, the beta coefficient of extremely positive sentiment is -0.1062, showing a significant reversal effect too. Thus, it further verifies the claim of the momentum of the moderate change of investor sentiment on stock returns and the reversal effect of the dramatic change of investor sentiment.

5.2. *The time-series effect under different market states*

In the previous research, we indicate that the different impact of investor sentiment on the stock prices under different market states belongs to the time-series analysis (Li & Yang, 2017). Thus, we need to analyze whether extremely investor sentiment has different effect on stock prices in different market states. Following the approach of Pagan and Sossounov (2003), we employ a nonparametric diagnostic approach to sort the Shanghai stock market into intervals that can be designated as bull and bear markets. Table 4 presents the regression results on the periods of bear market state and bull market state. The second sets of column show the results of the benchmark case, the third sets of column show the results of bear market state, and the fourth sets of column show the results of bull market state.

From Table 4, the beta coefficient of β_S is equal to 0.0633 in the bear market state, which is greater than that in the bull market state. It means that the moderate change of investor sentiment exerts greater momentum on stock index returns in the stock market downturn. In the bear market state, when the optimistic change of investor sentiment is higher than the threshold of ΔSI_O, the sentimental beta coefficient is equal to -0.0524 ($\beta_S + \beta_O$). In the bull market state, when the optimistic change of investor sentiment is higher than the corresponding threshold, the sentimental beta coefficient is -0.0862, whose absolute value is much greater than that in the bear market state. It implies that the degree of reversal effect of the extremely optimistic sentiment in the bull market state is greater than that of bear market state. In the bear market state, when the pessimistic change of investor sentiment is lower than the

Table 3
The estimation results of empirical thresholds.

Statistic	Within $\mu \pm 2\sigma$	Below $\mu - 2\sigma$	Above $\mu - 2\sigma$
β_S	0.0524***	−0.0839***	−0.1062***
t-Statistic	8.67	−2.72	−3.86
Adj-R^2	0.2945		

Note: ***, ** and * denote significance at 1%, 5% and 10% levels, respectively. The parameter of μ denotes the mean of sentiment change, and σ denotes the standard deviation of sentiment change.

Table 4
The estimation results in different market states.

Statistic	Benchmark	Bear market	Bull market
α	0.0034 (1.56)	-0.0065^{**} (−2.29)	0.0163^{***} (5.19)
β_S	0.0593^{***} (8.92)	0.0633^{***} (6.71)	0.0421^{***} (4.78)
β_O	-0.1417^{***} (−4.26)	−0.1157 (−1.59)	-0.1283^{***} (−3.78)
β_P	-0.1164^{***} (−3.43)	−0.1076 (−1.39)	−0.0636* (−1.66)
Adj-R^2	0.2347	0.2515	0.1539

Note: ***, ** and * denote significance at 1%, 5% and 10% levels, respectively. The value in parentheses denotes the corresponding t-statistic for each parameter.

threshold of ΔSI_P, the sentimental beta coefficient is equal to -0.0443 ($\beta_S + \beta_P$). In the bull market state, the corresponding beta coefficient is -0.0215. The absolute value of the former is greater than that of the latter. It means that the degree of reversal effect of the extremely pessimistic sentiment in the bull market in less than that of bear market state. In short, the momentum and reversal effects of investor sentiment on stock index returns are different at different periods.

5.3. The small-cap stocks effect

Generally, the investor sentiment have larger impact on small-cap stocks, as their valuations are highly subjective and difficult to arbitrage (Baker & Wurgler, 2006; Yang & Zhou, 2015). Considering the size effect, we would examine the effect of investor sentiment on small stocks, especially the effect of extremely investor sentiment. We employ SME stock index of Shenzhen stock exchange as the proxy of small stocks portfolio. Then, we use nonparametric regression model to depict the function relationship between SME stock index returns and change of investor sentiment. The corresponding fitting results are showed in Fig. 5.

From Fig. 5, there are two obvious inflection points on the fitting curve. It means that there are significant reversal effects of extremely investor sentiment in small stocks. Based on the fitting results of nonparametric regression, the two thresholds are set to $\Delta SI_O = 0.6718$ and $\Delta SI_P = -0.6489$ respectively. In addition, we use nonlinear parametric model with three regimes to conduct the specific test. As a comparison, we give the estimation results for general linear regression model too. The related estimation results are reported in Table 5.

In the linear regression, the sentimental beat coefficient of small stocks is equal to 0.0429. In the nonlinear regression, the beta coefficient of moderate change of investor sentiment is 0.0697. When the change of investor sentiment is lower than the extremely negative sentiment threshold, the beta coefficient is -0.0264. When the change of investor sentiment is more than the extremely positive sentiment threshold, the beta coefficient is -0.0708. Compared with estimation results of large-cap stocks in Table 2, the investor sentiment exerts greater momentum on small-cap stocks. However, the extreme investor sentiment exerts smaller reversal effect on small stocks in the sample period of our study.

6. Robustness

Taking into account the important position of Shanghai stock exchange in the Chinese stock market, the sample in the above study is the trading data in Shanghai stock exchange with the exception of small stocks effect. In order to further confirm the conclusions of this paper, the same empirical analyses are conducted on the stock index returns and the change of investor sentiment in Shenzhen stock exchange based on the nonparametric regression model. The estimation results are showed in Fig. 6.

There are two obvious inflection points about the functional relationship between the stock index returns and the change of investor sentiment in Shenzhen stock market. If the change of investor sentiment is more than the threshold of extreme optimism, then the stock index returns are negative correlated with the change of investor sentiment, showing a obvious reversal effect. If the change of investor sentiment is less than the threshold of extreme pessimism, then the stock index returns are also negative correlated with the change of investor sentiment, presenting a reversal effect too.

To the end, we make use of the nonlinear parametric model with dummy variables to evaluate the inferences about the sentiment slope. Similarly, we set the two extremely sentiment thresholds according to the fitting results of nonparametric regression. The estimation results for the nonlinear regression with three regimes are reported in Table 6. As a comparison, we also gives the benchmark case by the general linear regression.

From Table 6, the empirical results are similar to the conclusions in Shanghai stock market. The adjusted coefficient of determination in nonlinear regression is equal to 0.1530, which is more than that in linear regression. It implies that the nonlinear regression can better explain the variation of stock returns. If the change of investor sentiment is between the upper threshold and lower threshold, the sentimental beta coefficient is 0.0614. The stock return is positively correlated with the moderate change of investor sentiment, showing a momentum. However, if the change of investor sentiment is greater than the upper threshold, the sentiment beta coefficient is equal to -0.0723. Thus, the stock return is negatively correlated with the investor sentiment of extreme optimism,

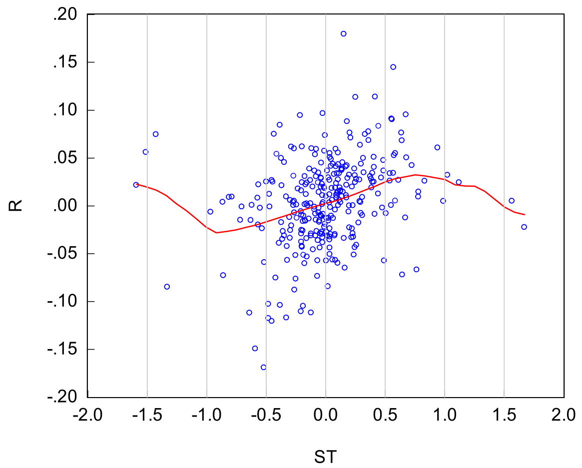

Fig. 5. The function relationship between SME stock returns and change of investor sentiment when h = 0.15.

Table 5
The related estimation results on small-cap stocks.

Model	α	β_S	β_O	β_P	Adj-R^2	F statistic
Linear regression	0.0048* (1.89)	0.0429*** (7.46)			0.1323	46.19
Nonlinear regression	0.0037 (1.48)	0.0697*** (8.51)	−0. 1405*** (−4.75)	−0.0961*** (−4.26)	0.2002	25.12

Note: ***, ** and * denote significance at 1%, 5% and 10% levels, respectively. The value in parentheses denotes the corresponding t-statistic for each parameter.

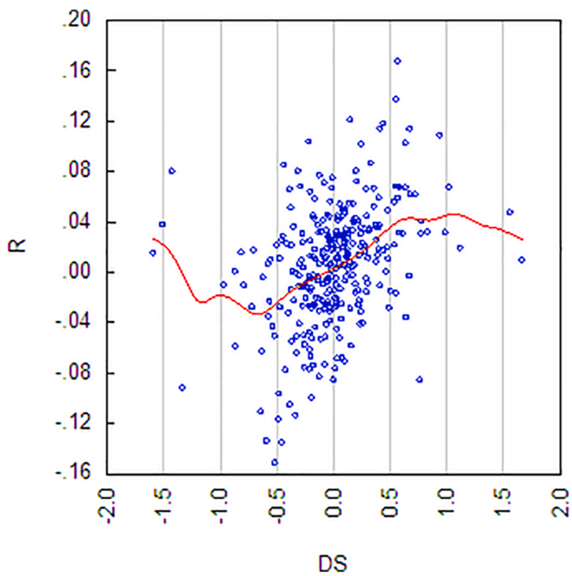

Fig. 6. The function relationship between stock returns and change of investor sentiment in Shenzhen stock market when h = 0.15.

presenting a reversal effect. If the change of investor sentiment is less than the lower threshold, then the sentimental beta coefficient is equal to −0.0602, showing a reversal effect too. Overall, when the change of investor sentiment is moderate in the short term, the greater the investor sentiment the higher the stock prices, presenting a momentum. When the change of investor sentiment is dramatic in the long term, the greater the investor sentiment is, the lower the stock prices get, exhibiting a mean reversion.

Table 6
The estimation results of general linear regression and nonlinear regression with three regimes on Shenzhen stock market.

model	α	β_S	β_O	β_P	Adj-R^2	F statistic
Linear regression	0.0034 (1.29)	0.0328*** (5.05)			0.0789	25.54
Nonlinear regression	0.0026 (1.03)	0.0614*** (7.29)	−0.1337*** (−4.41)	−0.1216*** (−3.62)	0.1530	17.82

Note: ***, ** and * denote significance at 1%, 5% and 10% levels, respectively. The value in parentheses denotes the corresponding t-statistic for each parameter.

7. Conclusion

The previous literature has suggested that the probability distribution of investor sentiment is characterized by fat tails (Li, 2015; Li & Yang, 2017). Hence, it is necessary to emphasize the effect of extreme values of investor sentiment on stock returns. This study extends the growing body of literature by testing whether the dramatic change of investor sentiment has a reversal effect on stock returns. Based on the trading data in Chinese stock market over the period January 4, 2006 through December 31, 2017, we first employ the nonparametric regression model to diagnose the real functional relationship between the stock returns and change of investor sentiment. Then we use the nonlinear parametric model with dummy variables to carry out the significant test and specific analysis. Summaries and conclusions for the characteristics of our empirical analyses are as follows:

Firstly, from the kernel density estimation of the change of investor sentiment, we may intuitively find that the probability distribution presents the characteristics of high peak and fat tail. When investor sentiment is extremely optimistic or pessimistic, its probability distribution is higher than the probability distribution of the normal distribution. It indicates that the probability of dramatic change in investor sentiment is relatively large, then its impact on the stock returns is a subject worthy of further study.

Secondly, we use the nonparametric regression model to find out the two critical values on the dramatic change of investor sentiment. One is the upper threshold of optimistic sentiment, and the other is the lower threshold of pessimistic sentiment. It indicates that the moderate change of investor sentiment is positively correlated with stock index returns, showing an obvious momentum effect. The stock returns present the obvious reversal phenomena if the change of optimistic sentiment (pessimistic sentiment) is much dramatic.

Thirdly, we further employ nonlinear regression model with three regimes to test the statistical significance and economic significance. The results show that all sentimental beta coefficients are statistical significance at 1% level. The reversal degree caused by extremely optimistic sentiment is greater than that driven by extremely pessimistic sentiment, which is consistent with the characteristics of the slow rise and steep fall in Chinese stock market.

Finally, the empirical findings of this paper are an important supplement to the conclusion of the DSSW model of De Long, Shleifer, Summers, and Waldmann (1990). When the change of investor sentiment is moderate, the noise traders account for a considerable proportion of the total number of traders, eventually defeating the rational investor and creating their own living space (Black, 1986). However, when investor sentiment is extremely optimistic (pessimistic) and financial asset pricing is too high (low), the survival space of noise traders disappears, and the arbitrage space of rational investors emerges, driving the market prices to return to the fundamental values (Friedman, 1953).

Overall, the empirical results indicate that the opposite views of Black (1986) and Friedman (1953) are just the different influence performance of investor sentiment under different market settings. There is a relationship of unity of opposites between the two views. Moreover, the research results offer a partial explanation for financial anomalies, such as the mean reversion of stock returns, the characteristic of slow rise and steep fall in China's stock market and so on.

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