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Investor sentiment from internet message postings and the predictability of stock returns

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ABSTRACT

By using an extensive dataset of more than 32 million messages on 91 firms posted on the Yahoo! Finance message board over the period January 2005 to December 2010, we examine whether investor sentiment as expressed in posted messages has predictive power for stock returns, volatility, and trading volume. In intertemporal and cross-sectional regression analyses, we find no evidence that investor sentiment forecasts future stock returns either at the aggregate or at the individual firm level. Rather, we find evidence that investor sentiment is positively affected by prior stock price performance. We also find no significant evidence that investor sentiment from Internet postings has predictive power for volatility and trading volume. A distinctive feature of our study is the use of sentiment information explicitly revealed by retail investors as well as classified by a machine learning classification algorithm and a much longer sample period relative to prior studies.

1. Introduction

There has been considerable debate in the recent literature as to whether investor sentiment predicts stock returns.[2] Rational risk-based asset pricing models say that prices reflect the discounted value of expected future cash flows and even if some investors are not rational, their irrationalities are quickly offset by arbitrageurs. Thus, there is no significant impact of investor sentiment on asset prices. On the other hand, the behavioral approach in finance suggests that investor sentiment, as reflected by retail investor demand, may cause prices to deviate from the underlying fundamentals. Specifically, when sentiment rises, (noise) investors increase their investment allocations to risky assets, and this sentiment-driven (uninformed) demand for assets drives prices above the fundamental values of these assets. After periods of high sentiment, prices revert to the fundamental values. In other words, high levels of investor sentiment are followed by low subsequent returns and vice versa. Owing to limits to arbitrage, the deviation from the fundamental values can persist for a substantial period of time. This argument predicts an intertemporal relation between the level of investor sentiment and stock returns: a

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1 Supported by the National Research Foundation of Korea Grant funded by the Korean Government (NRF-2012-S1A5B1010341).
2 Investor sentiment is usually defined as investors' attitude or feeling toward a particular security or financial market, which tends to be revealed through an event (such as an earnings announcement) or price movement of the security traded in the market.

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positive contemporaneous relation and a subsequent negative relation. In particular, Baker and Wurgler (2006, 2007) argue that sentiment-based demand shocks affect stocks differently according to the degree of limits to arbitrage and thus cause a cross-sectional difference in average returns. The above arguments imply that investor sentiment is negatively related to subsequent stock returns both intertemporally and cross-sectionally.

Many researchers have conducted empirical investigations on the intertemporal relation between investor sentiment and stock returns. The empirical results are mixed, depending on the choice of proxy for investor sentiment. We classify studies into four groups according to the source of sentiment information from which the investor sentiment indexes are extracted. The four most frequently used in the literature are surveys of consumer and investor confidence, indirect sentiment measures using market variables, news and social media, and Internet message boards. The first group of studies extracts investor sentiment information from surveys of consumer and investor confidence. Examples of this group are Otoo (1999) and Charoenrook (2005) (using the University of Michigan consumer survey sentiment index);[3] Solt and Statman (1988), Lee et al. (2002), and Brown and Cliff (2004, 2005) (using a survey measure from *Investors' Intelligence*); Schmeling (2009) (using consumer confidence for 18 industrialized countries)[4]; and Lemmon and Portniaguina (2006) (using two surveys of consumer confidence conducted by the Conference Board and the University of Michigan Survey Research Center).[5] Studies in this group usually conduct time-series tests to examine the relation between the investor sentiment indexes and stock returns at the aggregate level and tend to report that investor sentiment is negatively related to future stock returns over a relatively long horizon from one month to multi-years. However, Otoo (1999) and Solt and Statman (1988) report no relation between their sentiment index and future returns, Lee et al. (2002) report a positive relation between shifts in sentiment and excess returns across the market indices, and Brown and Cliff (2004) report that investor sentiment does not have short-run predictive power for stock returns.

The second group of studies uses indirect sentiment measures obtained from several market variables. This group includes Neal and Wheatley (1998) (using the level of closed-end fund discount, the ratio of odd-lot sales to purchases, and net mutual fund redemptions)[6]; Baker and Wurgler (2006, 2007) (using a composite index of sentiment extracted from six market variables for the U.S.)[7,8]; Baker et al. (2012) (using a similar sentiment index to that of Baker and Wurgler (2006, 2007) for six developed countries); and Edelen et al. (2010) (using shifts in investment allocations to risky assets by retail investors relative to those of institutional investors). These studies also generally report a negative relation between investor sentiment and future stock returns.

The third group of studies uses investor sentiment proxies extracted from news and social media. This group includes Clarke and Statman (1998) (using the sentiment of newsletter writers); Fisher and Statman (2000) (using the sentiment of Wall Street strategists, newsletter writers, and individual investors); Tetlock (2007) (using media pessimism from the content of the *Wall Street Journal* column); Tetlock et al. (2008) (using negative words in financial media stories for individual firms' accounting earnings and stock returns)[9]; and Chen et al. (2012) (using articles published in a popular social media site for investors, *Seeking Alpha*).[10] Clarke and Statman (1998) and Fisher and Statman (2000) report no relation between their sentiment measures and future returns. However, Tetlock (2007), Tetlock et al. (2008), and Chen et al. (2012) report that views (particularly negative views) expressed in news and social media forecast firms' earnings and stock returns.

The fourth group of studies uses popular Internet message boards such as Yahoo! Finance and RagingBull.com to extract investor sentiment. To extract investor sentiment from the huge quantity of text messages, this group uses a distinct classifier machine learning algorithm. The first study in this line is Tumarkin and Whitelaw (2001), who downloaded 181,633 text messages on 73 stocks in the Internet service sector from RagingBull.com in the period April 7, 1999 to February 18, 2000 and found that message board activity does not predict industry-adjusted return or abnormal trading activity. Antweiler

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[3] Otoo (1999) find that growth in consumer sentiment and stock prices share a strong contemporaneous relationship, indicating that stock prices influence consumer sentiment (a wealth effect) but that the reverse is not true.

[4] Schmeling (2009) report that the impact of sentiment on returns differs across countries; it is higher for countries that have less market integrity and that are more culturally prone to herd-like behavior and overreaction.

[5] Lemmon and Portniaguina (2006) find that investor sentiment forecasts the returns of small stocks but does not appear to forecast time-series variation in the value and momentum premiums.

[6] Neal and Wheatley (1998) report that fund discount and net redemptions predict the size premium but that the odd-lot ratio does not predict returns.

[7] Baker and Wurgler (2006) extract a composite index of sentiment that captures a common component in six sentiment proxies by using principal component analysis. The six sentiment-related market variables are the close-end fund discount, NYSE share turnover, the number and average first-day returns on IPOs, the equity share in new issues, and the dividend premium. These authors find that when sentiment is estimated to be high, stocks that are relatively difficult to arbitrage and thus have relatively large arbitrage risk (such as younger, small, unprofitable, non-dividend paying, high volatility, extreme growth, and distressed stocks) tend to earn low subsequent returns. When sentiment is low, on the other hand, this cross-sectional relation is entirely reversed.

[8] Stambaugh et al. (2012) explore the role of investor sentiment in a broad set of 11 well-documented anomalies in the cross-section of stock returns by using the market-wide investor sentiment index constructed by Baker and Wurgler (2006). These authors find that long-short strategies exploiting the anomalies exhibit profits consistent with the setting where the presence of market-wide sentiment is combined with the Baker and Wurgler (2006, 2007) argument that overpricing should be more prevalent than underpricing because of short-sale impediments, which is one of the difficulties to arbitrage. Their results are consistent with those of Baker and Wurgler (2006, 2007).

[9] These authors find that the proportion of negative words in firm-specific news stories forecasts low firm earnings and that earnings and return predictability from negative words is greatest for stories that focus on fundamentals.

[10] These authors find that the social media effect is stronger for articles that receive more attention and for companies held mostly by retail investors, the primary generators and consumers of social media content.

Table 1
Basic Statistics.

	Gender		Age					Message length	
	Male	Female	20s	30s	40s	50s	60s	Long	Short
Panel A: Frequency of messages and authors									
#message	17,780,966	1,894,836	844,412	2,427,047	3,707,795	3,268,108	1,548,833	16,306,522	16,306,523
(%)	(90.4)	(9.6)	(7.2)	(20.6)	(31.4)	(27.7)	(13.1)	(50.0)	(50.0)
#author	211,544	31,776	17,930	37,964	39,114	25,607	12,339		
(%)	(86.9)	(13.1)	(13.5)	(28.5)	(29.4)	(19.3)	(9.3)		
#revealed message	4,626,521	493,982	197,428	644,860	995,270	858,496	359,402		
%Strong buy	60.88	64.29	60.63	59.95	62.62	62.10	52.29	59.49	61.34
%Buy	12.61	9.47	11.14	11.24	11.38	12.13	18.94	13.34	10.33
%Hold	7.74	7.93	6.34	7.23	7.35	7.13	11.09	7.79	6.10
%Sell	2.13	1.27	2.22	2.42	1.89	1.92	1.84	2.35	1.94
%Strong sell	16.63	17.04	19.67	19.17	16.77	16.72	15.85	17.03	20.29

Total #message: 32,613,045 (#messages of revealed sentiment: 8,454,954 (25.9%)).
Total authors: 547,912.
Total firms: 91.

Panel B: Daily message board activity (%)

By day of the week	Sun	Mon	Tue	Wed	Thurs	Fri	Sat					
	6.6	15.7	17.9	18.5	18.6	16.6	6.0					
By calendar month	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
	9.6	8.8	9.4	9.2	8.6	8.0	7.7	7.4	7.3	8.6	8.0	7.6
By hour	0	1	2	3	4	5	6	7	8	9	10	11
	2.0	1.3	0.8	0.5	0.4	0.4	0.8	1.9	4.0	6.4	7.9	7.7
	12	13	14	15	16	17	18	19	20	21	22	23
	7.5	7.4	7.7	8.4	7.1	5.2	4.5	4.2	3.9	3.7	3.5	2.9

Panel A presents the frequency of messages and authors from the Yahoo! Finance message board that reveal their demographic characteristics by gender and age. We also classify a message as "Long" if its length in number of words is longer than the median of total messages and "Short" otherwise. The sample period is from January 2005 to December 2010.

and Frank (2004) downloaded text messages (approximately 1.5 million) from Yahoo! Finance and RagingBull.com on 45 relatively large-sized firms in the calendar year 2000. These authors report that a positive shock to message board posting predicts negative returns on the next trading day and that investor sentiment from Internet posting messages has predictive power for volatility and trading volume. Das and Chen (2007) analyze text messages downloaded from Yahoo! Finance for 24 tech-sector stocks for two months from July 2001 to August 2001 (145,110 messages). These authors report that the aggregate sentiment index is positively related to the aggregate stock index return and level on the next trading day, but no strong relationship is found between sentiment and stock price changes on average across the individual stocks.[11]

This study also endeavors to examine the relation between investor sentiment and future stock returns by constructing sentiment indexes extracted from text messages posted on Yahoo! Finance message boards. Our study is therefore closely related to the fourth group of studies. However, our study differs from the studies in the fourth group in several respects. First, our sample covers a much longer period and a greater variety of stocks in terms of firm size and industry. We select 91 firms whose message boards on Yahoo! Finance are most active. The total number of downloaded text messages over the period January 2005 to December 2010 is more than 32 million. The market capitalization of the 91 sample firms ranges from $296 billion (Apple Inc.) to $6.7 million (Fonar Corp). Since the sample periods of previous studies are short (less than or equal to one year), those studies tend to be performed by using a daily horizon. However, since our sample covers a much longer sample period (six years), we perform analyses at several different horizons (monthly, weekly, and daily).

Second, we use more direct sentiment information that is explicitly revealed by retail investors. From 2004, Yahoo! Finance stock message boards have provided an option for retail investors to reveal their sentiment among five categories: "Strong Buy", "Buy", "Hold", "Sell", and "Strong Sell". This provides a much more promising environment in which the relation between investor sentiment and stock returns can be directly examined. Prior to 2004, when some previous studies (e.g., Tumarkin and Whitelaw, 2001; Antweiler and Frank, 2004) were conducted, Yahoo! Finance did not provide this option for retail investors to reveal their sentiment; they could only write their opinions on the message board. Thus, those previous studies rely on machine learning algorithms to classify each text message into sentiment categories; the accuracy of such classifications can be a critical issue. Das and Chen (2007) report that the Naïve Bayes algorithm, one of the most popular machine learning classification algorithms, has only approximately a 50% classification accuracy for text messages from Yahoo! Finance messages. Antweiler and Frank (2004, Table 1) also report significant misclassification when using the Naïve Bayes algorithm. Thus, our sample is free of this accuracy issue.

[11] These authors also develop a methodology for extracting small investor sentiment from stock message boards by using five distinct classifier algorithms and compare their classification accuracy of text messages.

Third, we analyze both intertemporal and cross-sectional relations between investor sentiment and stock returns at the individual firm level as well as at the aggregate level. Previous studies, including all four groups of studies, mainly focus on analyzing the relation at the aggregate level rather than at the individual firm level. When investor sentiment is aggregated market-wide, individual firm sentiment (e.g., overreaction or underreaction to firms' news) can be canceled out. In this case, aggregate sentiment measures may not correctly distinguish rational demand shifts (e.g., time-varying risk tolerance) from irrational demand shifts (e.g., overreactions). Another advantage of using investor sentiment at individual firm level is to examine cross-sectional relations between investor sentiment and average stock returns. To our knowledge, our study is the first to conduct cross-sectional tests for this relation by using individual firm sentiment data.

Contrary to the previous literature, we find no evidence in our intertemporal analyses that investor sentiment forecasts future stock returns either at the aggregate or at the individual firm levels. Rather, we find evidence that investor sentiment is positively affected by prior stock price performance. Our results differ somewhat from those of Antweiler and Frank (2004) and Das and Chen (2007), which use investor sentiment information extracted from a similar data source, namely Internet message boards. This difference may be caused by the different sample periods and sample firms. We find little evidence that investor sentiment from Internet postings has predictive power for volatility and trading volume for any horizon considered after controlling for serial correlation and lagged return. These results also differ from those of Antweiler and Frank (2004). Further, in cross-sectional regression (CSR) tests, we find no evidence that investor sentiment relates to future stock returns in the cross-section of average stock returns, irrespective of controlling for size and book-to-market ratio.

As a robustness check, we examine the event-specific cross-sectional predictability of investor sentiment, since retail investors would be more vigilant in a message around an event. We select a quarterly earnings announcement as an event. We also find no evidence that investor sentiment forecasts earnings surprise or returns around quarterly earnings announcements. Rather, our cross-sectional analyses show that investor sentiment is affected by concurrent stock price performance and earnings news. For the cases of extreme price changes, retail investor sentiment is also not informative in predicting stock returns, although message board activity is significantly increased ahead of extreme price changes.

We also examine whether there is a distinctive feature in prediction ability for the direction of the next period's stock price movement across characteristics such as the retail investor's gender, age, and message length. However, we find no distinct predictive ability for such a direction across these characteristics.

The remainder of this paper proceeds as follows. Section 2 describes the message board data and explains how we construct the proxy variables for investor sentiment by using these data. Sections 3 and 4 examine the intertemporal and cross-sectional predictability of investor sentiment for stock returns, respectively. Section 5 examines the predictability of investor sentiment for volatility and trading volume, and Section 6 examines whether there is a distinctive feature in the predictive ability for stock returns across author characteristics. Section 7 sets forth our conclusions.

2. Message board data

2.1. Basic characteristics of the data

Yahoo! Finance provides the largest and most popular stock-related message boards. By using a specialized program written by the authors in the Python programming language, we download messages from the 91 most active firm message boards. We measure message board activity as the number of posted text messages from January 2005 to December 2010. The total number of text messages downloaded is 32,613,045 written by 547,912 authors. Appendix A shows a list of the 91 sample firms, with market capitalization, total number of downloaded messages, average number of words per message, and average values of the investor sentiment indexes (to be explained in the next section). The composition of the 91 firms by industry is as follows: 42 firms in technology, 14 firms in services, 11 firms in health care, 10 firms in basic materials, 9 firms in financials, 2 firms in industrial goods, 2 firms in consumer goods, and 1 firm in utilities. The sample firms are in general large firms. Among the 91 sample firms, 63 are in top 20% in terms of market capitalization of all the firms contained in the CRSP database. Downloaded messages contain information regarding not only the five categories of sentiment ("Strong Buy", "Buy", "Hold", "Sell", and "Strong Sell") but also author identification, posting time, content, the author's location, gender, age, and ticker symbol of the firm.[12] As shown in the examples of the posted messages listed in Appendix B, the authors do not reveal all the necessary information in each message. For example, the second and fourth examples explicitly reveal investor sentiment as "Strong Buy" and "Strong Sell", respectively, but the first and third examples reveal no explicit investor sentiment.

Table 1 presents the basic statistics of the posted messages with respect to the author's revealed characteristics (gender, age, and message length) (Panel A) and daily message board activities over time (Panel B) for the sample period of January 2005 to December 2010. The proportion of total messages explicitly revealing sentiment is 25.9% (or 8,454,954 out of the total of 32,613,045 messages).[13] Among the total messages revealing sentiment, "Strong Buy" and "Buy" are 60.42% and 11.84%, respectively, and "Strong Sell" and "Sell" are 18.66% and 2.15%, respectively. "Hold" is 6.95%. It is interesting to note

[12] In particular, investor sentiment is revealed under the item titled "Sentiment".

[13] Since investors do not reveal the full information of their characteristics such as gender, age, location, and investment sentiment, the sum by an investor characteristic does not equal the total number of posted messages. For example, only 17,780,966 (male) and 1,894,836 (female) messages among the total

that retail investors tend to reveal extreme sentiment such as “Strong Buy” and “Strong Sell” rather than moderate sentiment such as “Buy” and “Sell” (79.08% versus 13.99%). In this study, we classify a message as having a “buy sentiment” if it reveals “Strong Buy” or “Buy” and as “sell sentiment” if it reveals “Strong Sell” or “Sell”. Messages revealing “Hold” are excluded in computing investment sentiment measures as in Antweiler and Frank (2004). We also classify a message as “Long” if its length in number of words is longer than the median of all messages and “Short” otherwise. Panel B shows the percentage of the messages posted across days of the week, calendar months, and hours. Most messages are posted on weekdays. Only 12.6% are posted at the weekend. The messages are almost evenly posted across calendar months. Altogether, 60% of total messages are posted during the exchange operation hours of 9:30 to 16:00.[14]

2.2. Naïve Bayes classification algorithm

Several machine learning algorithms are available to classify a given text message as “buy” or “sell”. Among them, the Naïve Bayes algorithm is known as a simple and as the most successful natural language algorithm. We employ the Naïve Bayes classifier library in the Natural Language Toolkit (http://www.nltk.org) for the Python programming language. Of course, if all messages contain explicitly revealed sentiment, a machine learning classification is not needed. However, not all messages explicitly reveal investor sentiment. As noted earlier, only 25.9% of all sample messages explicitly reveal investor sentiment. We therefore rely on machine learning algorithms to classify the unrevealed text messages.

In the Naïve Bayes classification, a given text message is split into a group of words. This yields the “bag of words” representation for the given text message. Then, each word in the given text message is regarded as a “feature” and each text message has one “label”, namely “buy” or “sell”. One of these labels is then assigned to the text message. By using the Bayes rule, the probability of a label conditional on “features”, $P(\text{label}|\text{features})$, is computed as follows:

$$P(\text{label}|\text{features}) = \frac{P(\text{label}) \times P(\text{features}|\text{label})}{P(\text{features})}.$$

The Naïve Bayes classification method assumes that the occurrences of features are independent of each other, given “label”. If there are n (independent) features (i.e., a series of words), $f_1, f_2, \ldots, f_n$, then $P(\text{features}|\text{label}) = P(f_1|\text{label}) \times P(f_2|\text{label}) \times \cdots \times P(f_n|\text{label})$. Therefore, the probability of a label conditional on “features” can be rewritten as

$$P(\text{label}|\text{features}) = \frac{P(\text{label}) \times P(f_1|\text{label}) \times P(f_2|\text{label}) \times \cdots \times P(f_n|\text{label})}{P(\text{features})}.$$

$P(\text{label})$ is the probability that an input will receive each label, given no information about the input's features, and $P(f_j|\text{label})$ is the probability that a given feature j will occur, given the label. The probabilities, $P(\text{label})$ and $P(f_j|\text{label})$, can be estimated by using the training dataset.

Classifying text messages by using the machine learning classification algorithm can lead to the accuracy of the classification becoming an issue. To examine the accuracy of the Naïve Bayes classification algorithm, we first train the machine learning algorithm, the Naïve Bayes classifier, by using 2000 randomly selected revealed “buy” (“Strong Buy” or “Buy”) messages and another 2000 revealed “sell” (“Strong Sell” or “Sell”) messages. After setting up the classification algorithm by using the training dataset, we apply this algorithm to the 4000 in-sample (i.e., the training set) revealed messages in order to classify each into either the “buy” or the “sell” category. Since we know the true sentiment of each message, we can compute how accurately this algorithm classifies all in-sample messages. We repeat this in-sample training test 200 times. Fig. 1 illustrates the distribution of the hitting percentages (or classification accuracy) of the 200 in-sample tests (in light gray). The horizontal axis indicates the hitting percentage and the vertical axis indicates its frequency as a percentage. The mean of the 200 in-sample hitting percentages is 86.3%. To examine the out-of-the sample accuracy of the Naïve Bayes classification algorithm, we apply the previously trained algorithm to the randomly selected out-of-sample 2000 revealed “buy” messages and another 2000 revealed “sell” messages in order to classify each into either the “buy” or the “sell” category. We repeat this out-of-sample training test 200 times. Fig. 1 illustrates the distribution of the hitting percentages of the 200 out-of-sample tests (in dark gray). The mean of these 200 out-of-sample hitting percentages is 62.7%. As expected, the in-sample hitting percentage is higher than that in the out-of-sample case.

Antweiler and Frank (2004) also examine the accuracy of the Naïve Bayes classification algorithm in a similar way. Since their sample does not directly reveal investor sentiment, they identify the true sentiment of 1000 selected messages by manual classification. They train the algorithm by using these manually classified 1000 messages and apply the algorithm to the in-sample 1000 messages to classify each into the “buy”, “hold”, or “sell” categories. Among the 252 (25.2% of 1000 messages) manually classified “buy” messages, 181 are classified as “buy” by the Naïve Bayes algorithm. Among the 55 manually classified “sell” messages, 41 are classified as “sell” (“hold”) by the Naïve Bayes algorithm. Thus, the in-sample hitting percentage of “buy” or “sell” is approximately 72.3%. These results are from a one-time in-sample training test. In their case, the classification accuracy in the out-of-sample tests is not plausible to compute since out-of-sample messages

of 32,613,045 reveal the author's gender. Therefore, the difference between the total number of posted messages (32,613,045) and the sum of the messages by investors' gender (19,675,802) is the number of messages that do not reveal their gender. This is the same for age and investment sentiment.

[14] All hours are presented as Eastern Standard Time (EST).

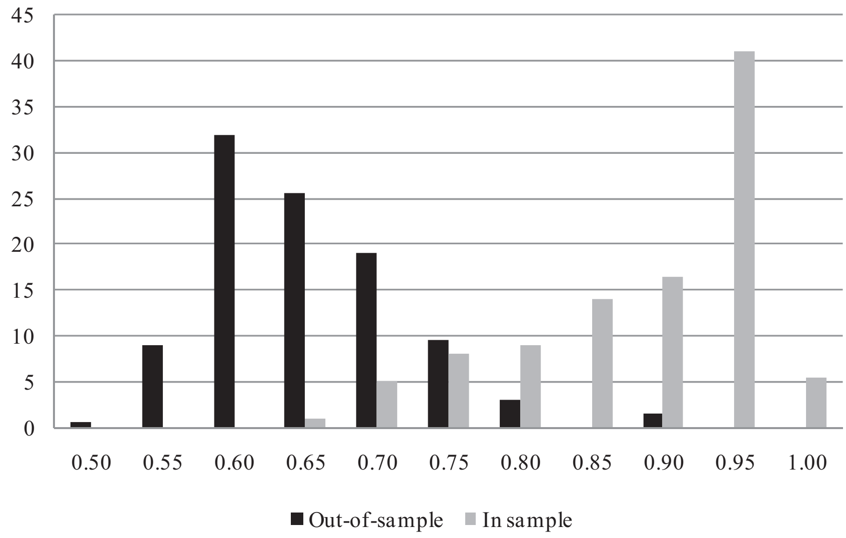

Fig. 1. Distribution of the accuracy of the Naïve Bayes classification algorithm. This figure shows the distributions of the hitting percentages of the Naïve Bayes classification algorithm in the in-sample (in light gray) and out-of-sample (in dark gray) tests for randomly selected 2000 revealed "buy" sentiment messages and another 2000 revealed "sell" sentiment messages in each test. The number of training tests is 200. The vertical axis indicates the frequency (in percent) of the hitting percentage. The averages of the 200 in-sample and out-of-sample hitting percentages are 86.3% and 62.7%, respectively.

do not have revealed sentiment unless they are manually reclassified. Das and Chen (2007) report that the Naïve Bayes algorithm has a 50% in-sample classification accuracy for the text messages from Yahoo! Finance messages. No previous studies report the out-of-sample accuracy of the Naïve Bayes classification algorithm for text messages, since they do not have revealed sentiment information and cannot measure such accuracy.

2.3. Measures of investor sentiment from message board data

Following Antweiler and Frank (2004), as a proxy for investor sentiment, we construct measures of investor sentiment based on explicitly revealed sentiment. The first revealed sentiment measure is defined as

$$\mathrm{RVD1}_t = \frac{M_t^{\text{Revealed Buy}} - M_t^{\text{Revealed Sell}}}{M_t^{\text{Revealed Buy}} + M_t^{\text{Revealed Sell}}}, \tag{1}$$

where $M_t^{\text{Revealed Buy}}$ ($M_t^{\text{Revealed Sell}}$) is the total number of messages explicitly revealed as "buy" ("sell") by the authors during period t.[15] We consider three periods: monthly, weekly, and daily. $\mathrm{RVD1}_t$ is bounded between −1 and +1; this is a measure of bullishness sentiment. The greater the value of $\mathrm{RVD1}_t$, the more bullishness there is for the stock. The second revealed sentiment measure is defined as

$$\mathrm{RVD2}_t = \ln\left[\frac{1 + M_t^{\text{Revealed Buy}}}{1 + M_t^{\text{Revealed Sell}}}\right]. \tag{2}$$

As shown in Antweiler and Frank (2004), $\mathrm{RVD2}_t \approx \mathrm{RVD1}_t \times \ln(1 + M_t)$, where $M_t = M_t^{\text{Revealed Buy}} + M_t^{\text{Revealed Sell}}$.[16]

To compare our results with those of previous studies that use classified sentiment measures because of the unavailability of revealed sentiment in the messages, we also construct sentiment measures based on the sentiment classified by the Naïve Bayes algorithm. The third and fourth sentiment measures, CLD1 and CLD2, are constructed in the same way as RVD1 and RVD2, respectively, by using classified sentiment rather than revealed sentiment. That is,

$$\mathrm{CLD1}_t = \frac{M_t^{\text{Classified Buy}} - M_t^{\text{Classified Sell}}}{M_t^{\text{Classified Buy}} + M_t^{\text{Classified Sell}}}, \tag{3}$$

[15] When counting the number of revealed messages, we also assign more weight to extreme sentiment ("Strong Buy" and "Strong Sell") than to moderate sentiment ("Buy" and "Sell"). For example, we assign 2 to "Strong Buy" and "Strong Sell" and 1 to "Buy" and "Sell". However, the overall results are qualitatively similar.

[16] We also compute the revealed sentiment measures, RVD1 and RVD2, by using only extreme sentiment such as "Strong Buy" and "Strong Sell" or by using only moderate sentiment such as "Buy" and "Sell", without clustering "Strong Buy" and "Buy" into "buy" and "Strong Sell" and "Sell" into "sell". The overall results are qualitatively similar to those of the case that extreme sentiment and moderate sentiment are clustered together.

Table 2
Investment sentiment and firm characteristics of portfolios sorted by the four sentiment measures.

Sentiment portfolio	RVD1			RVD2			CLD1			CLD2		
	Sentiment	Size	BM	Sentiment	Size	BM	Sentiment	Size	BM	Sentiment	Size	BM
Low	−0.248	45,446	0.536	−0.462	45,350	0.535	−0.639	63,783	0.382	−1.674	64,760	0.383
2	0.142	55,887	0.615	0.266	50,005	0.627	−0.187	79,782	0.652	−0.377	78,750	0.653
3	0.330	56,488	0.530	0.647	58,823	0.520	0.136	56,081	0.665	0.270	55,992	0.666
4	0.456	56,174	0.535	0.937	52,864	0.550	0.446	27,015	0.583	0.945	26,702	0.589
5	0.552	50,200	0.570	1.178	49,843	0.570	0.626	21,385	0.606	1.437	21,266	0.606
6	0.639	35,707	0.632	1.432	37,325	0.585	0.770	43,396	0.590	1.984	39,100	0.604
7	0.714	24,480	0.648	1.692	26,720	0.672	0.855	30,930	0.530	2.466	33,989	0.530
8	0.787	15,878	0.605	1.983	16,511	0.593	0.898	16,318	0.561	2.823	16,969	0.546
9	0.858	12,392	0.607	2.331	12,550	0.619	0.929	11,975	0.630	3.148	12,597	0.604
High	0.958	8430	0.583	3.051	9410	0.571	0.970	6202	0.641	3.818	7495	0.659

Sentiment portfolios are constructed by sorting all 91 sample firms into one of 10 decile equally-weighted portfolios according to the magnitude of the investment sentiment measure at the end of every month over the period from January 2005 to December 2010. Four investment sentiment measures are used. The first measure is RVD1, which is defined as $(M_t^{\text{Revealed Buy}} - M_t^{\text{Revealed Sell}})/(M_t^{\text{Revealed Buy}} + M_t^{\text{Revealed Sell}})$, where $M_t^{\text{Revealed Buy}}(M_t^{\text{Revealed Sell}})$ is the number of messages explicitly revealed "buy" ("sell") by the authors during period t. The second measure is RVD2, which is defined as $\ln[(1+M_t^{\text{Revealed Buy}})/(1+M_t^{\text{Revealed Sell}})]$. The third measure is CLD1, which is defined as $(M_t^{\text{Classified Buy}} + M_t^{\text{Classified Sell}})/(M_t^{\text{Classified Buy}} + M_t^{\text{Classified Sell}})$, where $M_t^{\text{Classified Buy}}(M_t^{\text{Classified Sell}})$ is the number of messages classified as "buy" ("sell") according to the Naïve Bayes algorithm. The fourth measure is CLD2, which is defined as $\ln[(1+M_t^{\text{Classified Buy}})/(1+M_t^{\text{Classified Sell}})]$. Portfolio 1 (Portfolio 10) contains firms that exhibit the lowest (highest) value of the investment sentiment measure. "Size" is market capitalization in millions of dollars and "BM" is the book-to-market ratio.

and

$$\text{CLD2}_t = \ln\left[\frac{1+M_t^{\text{Classified Buy}}}{1+M_t^{\text{Classified Sell}}}\right]. \tag{4}$$

To classify the messages for each firm, we first use all of its messages revealing investor sentiment as the training dataset for the Naïve Bayes algorithm, and then we apply this algorithm to the in-sample (i.e., the training set) and out-of-sample messages. By using these classified "buy" or "sell" sentiments, we compute CLD1 and CLD2 for all firms. Thus, RVD1 and RVD2 are obtained by using only the sentiment-revealed messages, while CLD1 and CLD2 are obtained by using all in-sample and out-of-sample sentiment-classified messages.

2.4. Basic characteristics of the sentiment measures

To examine how the investor sentiment measures of individual firms are associated with their firm characteristics such as firm size and book-to-market ratio, we sort all 91 firms into one of 10 decile equally-weighted portfolios according to the magnitude of each of the four sentiment measures at the end of every month from January 2005 to December 2010. Table 2 presents the averages of the sorted sentiment measure, firm size, and book-to-market ratios of the portfolios. The smaller the firm size, the greater is the sentiment measure. That is, retail investors generally tend to exhibit strong bullish sentiment for small firms but weak bullish sentiment for large firms. However, there is no particular pattern in the bullishness sentiment across book-to-market ratios.

Table 3 presents the correlation coefficients among the above four aggregate sentiment indexes, the aggregate stock returns of the 91 firms with equal weight, a sentiment index obtained from analysts' recommendations, and the two Baker and Wurgler (2006) sentiment indexes. The first Baker and Wurgler sentiment index (SENT) is a composite sentiment index based on the first principal component of the six underlying proxies for sentiment (the closed-end fund discount, NYSE share turnover, the number and average first-day returns on IPOs, the equity share in new issues, and dividend premium). The second Baker and Wurgler (2006) index ($\text{SENT}^{\perp}$) is similarly constructed as the first sentiment index, SENT, except for the use of the six orthogonalized underlying proxies against macroeconomic business cycle variations.[17] Each aggregate sentiment index is obtained by aggregating the sentiment measure of all 91 firms for the same month with equal weight. The analyst sentiment index is similarly computed as RVD1. That is, it is defined as $(M_t^{\text{Buy Recom}} - M_t^{\text{Sell Recom}})/(M_t^{\text{Buy Recom}} + M_t^{\text{Sell Recom}})$, where $M_t^{\text{Buy Recom}}(M_t^{\text{Sell Recom}})$ is the aggregate number of all buy (sell) recommendations for the firm by analysts during month t. Analysts' recommendations are obtained from the I/B/E/S database. All these variables are of monthly frequency. The correlation between the revealed and classified sentiment indexes is relatively high. The correlation coefficients between RVD1 and CLD1 and between RVD2 and CLD2 are 0.551 and 0.499, respectively, which are statistically significant at the 1% level. The revealed sentiment indexes (RVD1 and RVD2) are not significantly correlated with the first Baker and Wurgler

[17] Baker and Wurgler (2006) suggest the second sentiment index ($SENT^{\perp}$), since their first sentiment index (SENT) cannot distinguish between a common sentiment component and a common business cycle component.

Table 3
Correlations among the sentiment indexes and stock returns.

	RVD1	RVD2	CLD1	CLD2	$SENT^{\perp}$	SENT	$\Delta SENT^{\perp}$	ΔSENT	Ret(0)	Ret(+1)	Ret(−1)
RVD2	0.975***										
CLD1	0.551***	0.525***									
CLD2	0.462***	0.499***	0.855***								
$SENT^{\perp}$	−0.199	−0.168	0.102	0.177							
SENT	−0.157	−0.046	0.314*	0.677***	0.570***						
$SENT^{\perp}$	−0.047	−0.034	−0.091	−0.042	0.366**	0.051					
ΔSENT	0.139	0.151	−0.065	−0.088	−0.236	−0.182	0.370**				
Ret(0)	0.288**	0.294**	0.327***	0.345***	−0.284*	−0.073	−0.063	0.422**			
Ret(+1)	−0.098	−0.047	−0.116	−0.073	−0.077	−0.122	−0.170	−0.089	0.323***		
Ret(−1)	0.330***	0.370***	0.419***	0.387***	0.004	−0.068	−0.067	0.047	0.323***	0.071	
Analyst	−0.033	−0.049	0.286***	0.331***	0.294*	0.610***	0.186	0.289*	−0.113	−0.231*	−0.153

RVD1 is the investor sentiment index by aggregating all 91 sample firms' RVD1 (defined in Table 2) in every month with equal weights. RVD2, CLD1, and CLD2 are similarly defined. $SENT^{\perp}$, SENT, $\Delta SENT^{\perp}$, and ΔSENT are the sentiment indexes used in Baker and Wurgler (2006). "SENT" is a composite sentiment index constructed based on principal component analysis by using six market variables proxying for investor sentiment and $SENT^{\perp}$ is similarly constructed except for the use of the six orthogonalized market variables against several macroeconomic business cycle variables. $\Delta SENT^{\perp}$ and ΔSENT are the first differences of $SENT^{\perp}$ and SENT, respectively. "Return" is the aggregate return of all 91 sample firms. "Return(+1)" and "Return(−1)" are the one-month-ahead and one-month-lagged aggregate returns, respectively. "Analyst" is the analysts' sentiment index that is defined as $(M_t^{\text{Buy Recom}} - M_t^{\text{Sell Recom}})/(M_t^{\text{Buy Recom}} + M_t^{\text{Sell Recom}})$, where $M_t^{\text{Buy Recom}}(M_t^{\text{Sell Recom}})$ is the aggregate number of buy (sell) recommendations for the firm according to the analysts during month t from the I/B/E/S database. ***, **, and * indicate statistically significant at the 1%, 5%, and 10% levels, respectively.

(2006) sentiment index (SENT) and analyst sentiment index ('Analyst'), while the classified sentiment indexes (CLD1 and CLD2) are significantly correlated with them, but not with the second Baker and Wurgler (2006) index ($SENT^{\perp}$).

Table 3 also shows interesting results for the correlations between the sentiment indexes and aggregate stock returns. The sentiment indexes used in this study have a statistically significant and positive correlation with concurrent stock returns [Ret(0)] and one-month-lagged past returns [Ret(−1)], but an insignificantly negative correlation with one-month-ahead future returns [Ret(+1)]. These results provide preliminary evidence that investor sentiment has little predictive power for future returns, but that it may be rather affected by the past and contemporaneous performance of stock prices. In other words, retail investors tend to respond rather retroactively to an event or price movements of the stock than proactively, which will be confirmed in Section 4.1. The analyst sentiment index is insignificantly correlated with past and contemporaneous stock returns. This finding indicates that analysts tend to respond insensitively to stock price movement. Interestingly, the analyst sentiment index has a negatively significant correlation with one-month-ahead future returns. Baker and Wurgler (2006) sentiment indexes have mostly insignificant correlations with past, contemporaneous, and future returns.

3. Intertemporal predictability of investor sentiment for stock returns

3.1. At the aggregate level

To examine whether the investor sentiment indexes constructed from the revealed and classified sentiments on the Internet message boards forecast next-period stock returns and to assess how these two variables interact intertemporally, we consider the following two econometric equations:

$$\text{Equation 1}: R_t = \alpha_1 + \sum_{j=1}^{L} \beta_{1,j} R_{t-j} + \sum_{j=1}^{L} \gamma_{1,j} S_{t-j} + \varepsilon_{1t}, \tag{5}$$

$$\text{Equation 2}: S_t = \alpha_2 + \sum_{j=1}^{L} \beta_{2,j} R_{t-j} + \sum_{j=1}^{L} \gamma_{2,j} S_{t-j} + \varepsilon_{2t}, \tag{6}$$

where S_t is the investor sentiment index level at time t and R_t is the equally-weighted return of the 91 sample stocks at time t. These two equations are estimated as a system. There are two null hypotheses to test. The first is $H_{01}: \gamma_{1,1} = \gamma_{1,2} = \cdots = \gamma_{1,L} = 0$ in Eq. (5) [Equation 1], indicating that investor sentiment does not Granger-cause stock returns. The second is $H_{02}: \beta_{2,1} = \beta_{2,2} = \cdots = \beta_{2,L} = 0$ in Eq. (6) [Equation 2], indicating that past stock returns do not Granger-cause investor sentiment. The χ^2-test statistics for the null hypotheses in Eqs. (5) and (6) are used.[18] We set the lag $L = 3$.[19]

[18] Let the sum of the squared residuals from the unrestricted and restricted equations be denoted as $RSS_{\text{unrestricted}}$ and $RSS_{\text{restricted}}$, respectively. Then, the test statistic is $T \times (RSS_{\text{restricted}} - RSS_{\text{unrestricted}})/RSS_{\text{unrestricted}} \sim \chi^3(3)$, where T is the time-series sample size. If this statistic is greater than the given critical value, then the null hypothesis is rejected.

[19] We also estimate Eqs. (5) and (6) with $L = 2$. However, the results are qualitatively similar, as presented in Table 4A of the Internet Appendix.

We first perform the Granger-causality tests at the aggregate level. That is, the aggregate levels of the sentiment index and the aggregate return of the 91 sample firms are used. Table 4 presents the estimation results of Eqs. (5) and (6) by using monthly (Panel A), weekly (Panel B), and daily horizons (Panel C). Note that for the daily horizon, we count only messages posted during the regular operational hours of the exchanges from 9:30 to 16:00, since messages posted after market close and stock returns on the next day are contemporaneously influenced by the news released after hours, and thus the forecastability of investor sentiment is spuriously exaggerated. In Eq. (5), the coefficient estimates on the sentiment variables ($\hat{\gamma}_{1,j}$) are mostly statistically insignificant, except for the cases where RVD1 and CLD1 are used with one-month-lagged as the sentiment variable. However, when RVD2 and CLD2 are used with one-month-lagged, they are statistically insignificant in predicting stock returns. The Granger-causality tests also do not reject the null hypothesis H_{01} in all three horizons. For example, when RVD1 is used as the investor sentiment variable, the p-values of the χ^2-test statistics for H_{01} are 0.127, 0.284, and 0.774 for the monthly, weekly, and daily horizons, respectively. This finding implies that investor sentiment does not Granger-cause stock returns. We also use changes in investor sentiment (ΔS_{t-j}) instead of the investor sentiment level (S_{t-j}). However, the results are qualitatively similar.[20]

On the other hand, the estimation results of Eq. (6) show that the second null hypothesis H_{02} is rejected for the monthly and weekly horizons, indicating that investor sentiment may be positively Granger-caused by prior stock returns. Specifically, when RVD1 is used as the investor sentiment variable, the p-values of the χ^2-test statistics for H_{02} are 0.066 and 0.013 for the monthly and weekly horizons, respectively. For the daily horizon, the null hypothesis is not rejected. Overall, the investor sentiment indexes have little predictive power for stock returns, but they are rather positively affected by prior stock price performance.

As a robustness check, we also consider the value-weighted returns of the 91 sample stocks and the return on the Standard & Poor's 500 Index as the aggregate return in Eqs. (5) and (6). The results are qualitatively similar to those of the case that the value-weighted returns of the 91 sample stocks are used.[21]

3.2. At the individual stock level

To examine the Granger-causal relation between investor sentiment and stock returns at the individual firm level, we also estimate Eqs. (5) and (6) for each of the 91 sample firms and test the two null hypotheses H_{01} and H_{02}. Table 5 presents the percentage of rejection of each null hypothesis for all 91 individual stocks at the 5% significance level. When RVD1 is used as the investor sentiment variable with $L = 2$, the rejection rates of the null hypothesis H_{01} are only 3.30%, 8.79%, and 4.40% for the monthly, weekly, and daily horizons, respectively. The results are also similar with $L = 3$.[22] We obtain similar rejection rates for the other investor sentiment variables. These rejection rates, which indicate the actual statistical significance level, are close to the nominal significance level of 5%. In other words, this experiment has the actual Type I error, which almost equals the nominal Type I error. Thus, the null hypothesis H_{01} cannot be rejected. At the individual firm level, therefore, there is no evidence that investor sentiment proxied by revealed and classified sentiment measures have predictive power for future stock returns.[23]

To examine whether retail investor sentiment during the recent financial crisis is different, we also test the Granger-causal relation for two sub-periods: 2005–2006 (for the non-financial crisis period) and 2007–2009 (for the financial crisis period). The rejection rate of H_{01} for the sub-period 2007–2009 is slightly greater than that for the sub-period 2005–2006.[24] However, the rejection rates for the two sub-periods are also close to the nominal Type I error of 5%. The results show no significant difference between these two sub-periods with respect to return predictability.

Table 5 also presents the rejection rates of the null hypothesis H_{02} for the 91 stocks. When RVD1 is used as the investor sentiment variable with $L = 2$, the rejection rates of the null hypothesis H_{01} in the monthly, weekly, and daily horizons are 12.09%, 16.48%, and 20.88%, respectively. These rejection rates are far higher than the nominal significance level of 5%. Thus, the null hypothesis H_{02} can be rejected and we may conclude that investor sentiment is affected by prior stock returns. We reach a similar conclusion by using the other sentiment measures.

4. Cross-sectional predictability of investor sentiment for stock returns

4.1. Cross-sectional relations between investor sentiment and stock returns

In addition to the intertemporal relations between investor sentiment and stock returns, the cross-sectional relation between these two factors is also an important aspect of the predictability of investor sentiment for stock returns. As a preliminary investigation of the cross-sectional relationship, we sort all 91 firms into one of five quintile portfolios according

[20] The results are available in Table 4B of the Internet Appendix.

[21] The results are available in Table 4C and D of the Internet Appendix.

[22] We also estimate Eqs. (5) and (6) with higher lags of $L = 4$ and 5. However, the results are qualitatively similar, as presented in Table 5A of the Internet Appendix.

[23] As with the aggregate level, we also use changes in investor sentiment instead of the investor sentiment level. However, the results are qualitatively similar, as presented in Table 5B of the Internet Appendix.

[24] The results are available in Table 5C of the Internet Appendix.

Table 4
Time-series regression estimation for the investor sentiment indexes and stock returns at the aggregate level.

Equation 1 : $R_t = \alpha_1 + \sum_{j=1}^{3} \gamma_{1,j} S_{t-j} + \sum_{j=1}^{3} \beta_{1,j} R_{t-j} + \varepsilon_t$

Explanatory variable	Measure of investor sentiment			
	RVD1	RVD2	CLD1	CLD2
Panel A: Monthly horizon				
Intcpt	0.133 (1.19)	0.092 (1.08)	0.588 (1.93)*	0.509 (1.87)*
S_{t-1}	−0.677 (−2.13)**	−0.188 (−1.50)	−1.346 (−2.00)**	−0.232 (−1.08)
S_{t-2}	0.060 (0.16)	0.113 (0.74)	1.051 (1.40)	0.200 (0.86)
S_{t-3}	0.380 (1.20)	0.009 (0.08)	−0.917 (−1.32)	−0.307 (−1.42)
R_{t-1}	0.458 (3.19)***	0.443 (3.02)***	0.460 (3.38)***	0.394 (2.82)***
R_{t-2}	0.042 (0.27)	−0.046 (−0.29)	−0.117 (−0.77)	−0.130 (−0.86)
R_{t-3}	0.078 (0.61)	0.093 (0.71)	0.172 (1.33)	0.184 (1.39)
χ^2-stat	5.701	2.696	7.583	5.264
[p-Value]	[0.127]	[0.441]	[0.055]	[0.153]
Panel B: Weekly horizon				
Intcpt	0.023 (1.00)	0.016 (1.03)	−0.024 (−0.39)	0.044 (0.79)
S_{t-1}	−0.043 (−0.70)	−0.023 (−0.84)	0.252 (1.76)*	0.013 (0.28)
S_{t-2}	−0.084 (−1.32)	−0.036 (−1.15)	−0.063 (−0.40)	−0.077 (−1.55)
S_{t-3}	0.090 (1.49)	0.049 (1.79)*	−0.132 (−0.93)	0.034 (0.74)
R_{t-1}	0.024 (0.36)	0.031 (0.45)	−0.039 (−0.64)	−0.006 (−0.09)
R_{t-2}	0.163 (2.49)**	0.173 (2.57)**	0.092 (1.52)	0.140 (2.25)**
R_{t-3}	−0.055 (−0.90)	−0.062 (−1.04)	−0.028 (−0.47)	−0.041 (−0.68)
χ^2-stat	3.803	4.469	3.397	2.603
[p-Value]	[0.284]	[0.215]	[0.334]	[0.457]
Panel C: Daily horizon (9:30–16:00)				
Intcpt	0.000 (0.23)	0.000 (0.15)	0.000 (0.20)	0.001 (0.47)
S_{t-1}	0.001 (0.40)	−0.000 (−0.25)	−0.003 (−0.71)	−0.001 (−0.52)
S_{t-2}	−0.001 (−0.90)	−0.000 (−0.39)	0.001 (0.30)	−0.000 (−0.13)
S_{t-3}	0.001 (0.68)	0.001 (0.95)	0.002 (0.36)	0.000 (0.41)
R_{t-1}	−0.054 (−2.08)**	−0.052 (−2.02)**	−0.052 (−2.03)**	−0.053 (−2.04)**
R_{t-2}	−0.076 (−2.94)***	−0.076 (−2.95)***	−0.078 (−3.01)***	−0.077 (−3.00)***
R_{t-3}	0.005 (0.20)	0.004 (0.14)	0.005 (0.21)	0.006 (0.23)
χ^2-stat	1.112	0.903	0.523	0.405
[p-Value]	[0.774]	[0.825]	[0.914]	[0.939]

Equation 2 : $S_t = \alpha_2 + \sum_{j=1}^{3} \gamma_{2,j} S_{t-j} + \sum_{j=1}^{3} \beta_{2,j} R_{t-j} + \varepsilon_t$

Explanatory variable	Measure of investor sentiment			
	RVD1	RVD2	CLD1	CLD2
Panel A: Monthly horizon				
Intcpt	0.102 (2.02)**	0.182 (1.81)*	0.168 (2.75)***	0.410 (2.34)**
S_{t-1}	0.393 (2.73)***	0.551 (3.77)***	0.303 (2.25)**	0.349 (2.53)**
S_{t-2}	0.226 (1.36)	0.188 (1.06)	0.283 (1.88)*	0.259 (1.73)*
S_{t-3}	0.190 (1.33)	0.117 (0.83)	0.064 (0.46)	0.115 (0.83)
R_{t-1}	0.171 (2.64)**	0.463 (2.71)***	0.089 (3.28)***	0.261 (2.91)***
R_{t-2}	−0.016 (−0.23)	−0.137 (−0.74)	−0.008 (−0.26)	−0.047 (−0.48)
R_{t-3}	−0.011 (−0.19)	−0.056 (−0.37)	−0.006 (−0.23)	−0.081 (−0.95)
χ^2-stat	7.204	7.371	11.102	9.028
[p-Value]	[0.066]	[0.061]	[0.011]	[0.029]
Panel B: Weekly horizon				
Intcpt	0.092 (3.74)***	0.093 (2.55)**	0.136 (5.32)***	0.362 (4.86)***
S_{t-1}	0.345 (5.27)***	0.501 (7.42)***	0.483 (8.08)***	0.388 (6.26)***
S_{t-2}	0.205 (3.03)***	0.124 (1.64)	0.118 (1.80)*	0.097 (1.46)
S_{t-3}	0.281 (4.38)***	0.297 (4.50)***	0.112 (1.88)*	0.256 (4.19)***
R_{t-1}	0.173 (2.42)**	0.326 (1.95)*	0.008 (0.33)	0.131 (1.55)
R_{t-2}	0.091 (1.31)	0.095 (0.58)	−0.004 (−0.14)	0.098 (1.19)
R_{t-3}	−0.147 (−2.29)**	−0.339 (−2.35)**	0.061 (2.45)**	−0.012 (−0.16)
χ^2-stat	10.836	7.925	6.436	3.699
[p-Value]	[0.013]	[0.048]	[0.092]	[0.296]
Panel C: Daily horizon (9:30–16:00)				
Intcpt	0.214 (10.59)***	0.300 (8.67)***	0.101 (7.57)***	0.358 (8.65)***
S_{t-1}	0.241 (9.53)***	0.304 (12.01)***	0.360 (14.36)***	0.327 (13.03)***
S_{t-2}	0.183 (7.12)***	0.209 (8.04)***	0.262 (10.14)***	0.244 (9.48)***
S_{t-3}	0.211 (8.35)***	0.219 (8.65)***	0.236 (9.41)***	0.232 (9.23)***
R_{t-1}	0.615 (1.23)	0.525 (0.55)	0.143 (1.02)	0.806 (1.35)
R_{t-2}	−0.485 (−0.97)	−1.392 (−1.46)	−0.062 (−0.44)	−0.234 (−0.39)
R_{t-3}	0.530 (1.06)	1.434 (1.50)	−0.057 (−0.41)	0.091 (0.15)
χ^2-stat	3.675	4.895	1.504	2.042
[p-Value]	[0.299]	[0.180]	[0.681]	[0.564]

This table presents the Granger-causality test results based on the aggregate sentiment index and aggregate stocks return. The following two econometric models are used for the Granger-causality test and these are estimated as a system:

$$\text{Equation 1}: \ R_t = \alpha_1 + \sum_{j=1}^{L} \beta_{1,j} R_{t-j} + \sum_{j=1}^{L} \gamma_{1,j} S_{t-j} + \varepsilon_{1t}$$

$$\text{Equation 2}: \ S_t = \alpha_2 + \sum_{j=1}^{L} \beta_{2,j} R_{t-j} + \sum_{j=1}^{L} \gamma_{2,j} S_{t-j} + \varepsilon_{2t}$$

where S_t is the equal-weighted aggregate investor sentiment index at time t and R_t is the equally-weighted return of the 91 sample stocks at time t. The first null hypothesis is $H_0 : \gamma_{1,1} = \gamma_{1,2} = \cdots = \gamma_{1,L} = 0$ in Equation 1, which indicates that investor sentiment does not Granger-cause stock returns. The second null hypothesis is $H_0 : \beta_{2,1} = \beta_{2,2} = \cdots = \beta_{2,L} = 0$ in Equation 2, which indicates that stock returns do not Granger-cause investor sentiment. The χ^2-test statistics for the null hypotheses in Equations 1 and 2 are reported and their p-values are in brackets. We set $L = 3$. Four measures of investment sentiment are used, namely RVD1, RVD2, CLD1, and CLD2. These measures are defined in Table 2. RVD1 and RVD2 are the measures of explicitly revealed investor sentiment, while CLD1 and CLD2 are the measures of investor sentiment classified by the Naïve Bayes classification. Numbers in parentheses are t-values. The sample period is from January 2005 to December 2010.

Table 5
Granger-causality tests for the relation between investor sentiment and stock returns at the individual firm level.

Lag (L)	Monthly				Weekly				Daily			
	RVD1	RVD2	CLD1	CLD2	RVD1	RVD2	CLD1	CLD2	RVD1	RVD2	CLD1	CLD2
Equation 1: $R_t = \alpha_1 + \sum_{i=1}^{L} \beta_{1,j} R_{t-j} + \sum_{i=1}^{L} \gamma_{1,j} S_{t-j} + \varepsilon_{1t}$, $H_0: \gamma_{1,1} = \gamma_{1,2} = \cdots = \gamma_{1,L} = 0$												
$L=2$	3.30	4.40	9.89	8.79	8.79	6.59	6.59	5.49	4.40	3.30	4.40	8.79
$L=3$	4.40	4.40	6.59	7.69	6.59	5.49	5.49	4.40	9.89	3.30	7.69	9.89
Equation 2: $S_t = \alpha_2 + \sum_{j=1}^{L} \beta_{2,j} R_{t-j} + \sum_{j=1}^{L} \gamma_{2,j} S_{t-j} + \varepsilon_{2t}$, $H_0: \gamma_{2,1} = \gamma_{2,2} = \cdots = \gamma_{2,L} = 0$												
$L=2$	12.09	12.09	6.59	4.40	16.48	16.48	4.40	4.40	20.88	38.46	12.09	18.68
$L=3$	18.68	20.88	8.79	6.59	13.19	17.58	3.30	6.59	20.88	38.46	10.99	16.48

This table presents the percentage of rejection of the null hypothesis for the Granger causality of 91 individual stocks at the 5% significance level. For each of the 91 stocks, the following two econometric models are used for the Granger-causality test and these are estimated as a VAR system:

$$\text{Equation 1}: R_t = \alpha_1 + \sum_{j=1}^{L} \beta_{1,j} R_{t-j} + \sum_{j=1}^{L} \gamma_{1,j} S_{t-j} + \varepsilon_{1t},$$

$$\text{Equation 2}: S_t = \alpha_2 + \sum_{j=1}^{L} \beta_{2,j} R_{t-j} + \sum_{j=1}^{L} \gamma_{2,j} S_{t-j} + \varepsilon_{2t},$$

where S_t is the investor sentiment index at time t and R_t is the stock return at time t of an individual stock. The first null hypothesis to test is $H_0: \gamma_{1,1} = \gamma_{1,2} = \cdots = \gamma_{1,L} = 0$ in Equation 1, which indicates that investor sentiment does not Granger-cause stock returns. The second null hypothesis is $H_0: \beta_{2,1} = \beta_{2,2} = \cdots = \beta_{2,L} = 0$ in Equation 2, which indicates that stock returns do not Granger-cause investor sentiment. The χ^2-test statistics for the null hypotheses in Equations 1 and 2 are used. Four measures of investment sentiment are used, namely RVD1, RVD2, CLD1, and CLD2. These measures are defined in Table 2. RVD1 and RVD2 are the measures of explicitly revealed investor sentiment, while CLD1 and CLD2 are the measures of investor sentiment classified by the Naïve Bayes classification. The sample period is from January 2005 to December 2010.

to the magnitude of the investor sentiment variable at the end of each period (month, week, or day) over the whole sample period January 2005 to December 2010. Table 6 presents the average returns of the five equally-weighted (in Panel A) and value-weighted (in Panel B) sentiment portfolios sorted by each sentiment variable at the monthly, weekly, daily (whole day), and daily (9:30–16:00) horizons. In any case, there is no monotonic pattern in average returns across investor sentiment. One noteworthy observation is that when the daily horizon is the whole day, there is a somewhat monotonic pattern in average returns across investor sentiment. As investor sentiment increases, average returns also tend to increase. However, since news released after hours affects investor sentiment contemporaneously (as reflected in the messages posted after hours) and stock returns on the next day, this positive relation is not surprising. With messages posted after hours excluded (i.e., using the daily horizon 9:30–16:00), this position relation in the daily horizon disappears.

To more thoroughly examine the cross-sectional relations between investor sentiment and stock returns, we estimate the following CSR model within the Fama and MacBeth (1973) framework. At each period t,

$$R_{i,t+j} = \alpha_t + \beta_t S_{it} + \gamma_t \ln(\text{Size}_{it}) + \delta_t \ln(\text{BM}_{it}) + \varepsilon_{it}, \quad i = 1, \ldots, N, \tag{7}$$

where $R_{i,t+j}$ is the j-period-ahead return of stock i at time t, S_{it} is the investor sentiment index level of firm i at time t, and Size_{it} and BM_{it} are the market capitalization and book-to-market ratio of firm i at time t, respectively. We consider the future-ahead cases of $j = 0, 1, 2, 3$, and 4. As a proxy variable for investor sentiment, we also use RVD1, RVD2, CLD1, and CLD2.

Table 7 presents the time-series averages of the CSR coefficient estimates of Eq. (7) for the monthly (Panel A), weekly (Panel B), daily (whole hours) (Panel C), and daily (9:30–16:00) (Panel D) horizons. The contemporaneous cross-sectional relation between investor sentiment and average stock returns ($j = 0$) is strongly positive for all sentiment variables used and in any horizon, irrespective of controlling for size and book-to-market ratio. However, there is no evidence that the predictive cross-sectional relation is statistically significant in any case. For example, for one-period-ahead predictive regressions ($j = 1$), time-series averages of the estimated coefficients on RVD1 ($\bar{\hat{\beta}}$) are −0.19% (t-statistic of −0.25), −0.02% (t-statistic of −0.16), and 0.02% (t-statistic of 0.76) for the monthly, weekly, and daily (9:30–16:00) horizons, respectively. This insignificance of the coefficient estimates is found to be similar in the other cases. When the daily horizon is whole hours (Panel C), we obtain a statistically significant and positive coefficient estimate on the sentiment variable for the one-day-ahead case ($j = 1$: 0.08% (t-statistic of 3.70). Again, the reason for this significant relation is the concurrence of investor sentiment made after hours and stock returns on the next trading day. When this concurrence does not take effect (i.e., when the length of the lead days is longer than one day, $j = 2, 3,$ or 4), this positive significance disappears. These results, together with those from Table 6, indicate that retail investors tend to respond retroactively to an event or price movements of the stock rather than proactively, which is a typical behavior of noise traders.

Table 6
Average returns of portfolios sorted by investor sentiment.

Sentiment portfolio	Sorting variable (measure of investor sentiment)															
	RVD1	RVD2	CLD1	CLD2	RVD1	RVD2	CLD1	CLD2	RVD1	RVD2	CLD1	CLD2	RVD1	RVD2	CLD1	CLD2
	Monthly				Weekly				Daily (whole day)				Daily (9:30∼16:00)			
Panel A: Equally-weighted																
Low	1.123	1.038	0.683	0.660	0.294	0.314	0.231	0.230	−0.005	−0.017	0.029	0.025	0.044	0.040	0.027	0.030
2	1.162	0.954	1.190	1.259	0.277	0.229	0.315	0.274	0.032	0.061	0.053	0.049	−0.013	0.069	0.062	0.045
3	0.810	0.779	1.137	1.178	0.207	0.293	0.291	0.329	−0.003	0.043	0.091	0.079	−0.030	0.043	0.079	0.096
4	0.298	0.591	1.496	1.447	0.064	0.063	0.204	0.259	0.063	0.060	0.032	0.073	−0.167	0.080	−0.005	0.058
High	2.273	2.191	1.043	1.004	0.532	0.438	0.313	0.261	0.083	0.138	0.088	0.068	0.024	0.059	0.088	0.057
P5–P1	1.150	1.153	0.360	0.344	0.238	0.124	0.081	0.031	0.088	0.155	0.059	0.043	−0.020	0.019	0.061	0.027
t-Value	(1.29)	(1.25)	(0.53)	(0.50)	(1.59)	(0.67)	(0.49)	(0.17)	(2.55)**	(3.87)***	(1.78)*	(1.10)	(−0.49)	(0.45)	(2.01)**	(0.69)
Panel B: Value-weighted																
Low	0.370	0.539	0.143	0.112	0.104	0.157	0.094	0.099	−0.027	−0.035	0.011	0.007	0.054	0.014	0.015	0.014
2	0.199	0.114	0.339	0.384	0.044	0.002	−0.012	−0.027	0.034	0.010	0.015	0.021	0.026	0.013	0.012	0.016
3	0.914	0.885	0.523	0.582	0.116	0.059	0.107	0.119	0.016	0.024	0.030	0.017	0.037	0.020	0.042	0.013
4	−0.470	−0.300	0.384	0.416	0.004	0.170	0.068	0.059	0.125	0.073	0.056	0.038	−0.111	0.001	−0.036	0.036
High	1.298	0.708	0.959	0.796	0.143	0.102	0.258	0.299	0.033	0.093	0.025	0.052	0.028	0.046	0.038	0.067
P5–P1	0.928	0.168	0.816	0.684	0.039	−0.055	0.165	0.200	0.060	0.128	0.014	0.045	−0.025	0.032	0.023	0.054
t-Value	(1.53)	(0.24)	(1.10)	(1.02)	(0.24)	(−0.32)	(0.94)	(1.15)	(2.04)**	(3.77)***	(0.38)	(1.24)	(−0.71)	(0.91)	(0.76)	(1.52)

This table presents the average returns (in percent) of five quintile portfolios sorted by the measure of investor sentiment. All 91 sample firms are sorted into one of five quintile equally-weighted portfolios according to the magnitude of the investment sentiment measure at the end of each period (month, week, or day) over the period from January 2005 to December 2010. Four measures of investment sentiment are used, namely RVD1, RVD2, CLD1, and CLD2. These measures are defined in Table 2. RVD1 and RVD2 are the measures of explicitly revealed investor sentiment, while CLD1 and CLD2 are the measures of investor sentiment classified by the Naïve Bayes classification algorithm.

Table 7
Estimation results of cross-sectional predictive regressions of investor sentiment for stock returns.

Look-ahead Period (j)	Explanatory variables											
	RVD1 ($\bar{\hat{\beta}}$)	Size ($\bar{\hat{\gamma}}$)	BM ($\bar{\hat{\delta}}$)	RVD2 ($\bar{\hat{\beta}}$)	Size ($\bar{\hat{\gamma}}$)	BM ($\bar{\hat{\delta}}$)	CLD1 ($\bar{\hat{\beta}}$)	Size ($\bar{\hat{\gamma}}$)	BM ($\bar{\hat{\delta}}$)	CLD2 ($\bar{\hat{\beta}}$)	Size ($\bar{\hat{\gamma}}$)	BM ($\bar{\hat{\delta}}$)
Panel A: Monthly horizon												
Contemp	3.74 (5.87)***			1.67 (6.61)***			0.65 (1.79)			0.24 (1.99)		
	4.09 (6.50)***	0.29 (2.23)**	−0.48 (−1.32)	1.78 (7.64)***	0.33 (2.58)**	−0.47 (−1.30)	1.22 (3.23)***	0.21 (1.66)	−0.37 (−0.99)	0.41 (3.11)***	0.21 (1.65)	−0.38 (−1.03)
1-month	−0.19 (−0.25)			0.11 (0.38)			0.27 (0.73)			0.09 (0.67)		
	−0.95 (−1.37)	−0.26 (−1.85)*	−0.31 (−0.83)	−0.25 (−0.97)	−0.26 (−1.88)*	−0.33 (−0.90)	0.23 (0.56)	−0.2 (−1.37)	−0.36 (−0.96)	0.07 (0.48)	−0.21 (−1.39)	−0.36 (−0.95)
2-month	0.21 (0.33)			0.06 (0.25)			0.16 (0.44)			0.04 (0.31)		
	−0.64 (−1.11)	−0.25 (−1.66)	−0.32 (−0.86)	−0.23 (−1.02)	−0.25 (−1.76)*	−0.33 (−0.89)	0.11 (0.28)	−0.22 (−1.42)	−0.37 (−0.98)	0.03 (0.18)	−0.22 (−1.44)	−0.37 (−0.97)
3-month	−0.12 (−0.14)			0.02 (0.07)			0.25 (0.70)			0.04 (0.34)		
	−1.24 (−1.60)	−0.27 (−1.85)*	−0.33 (−0.88)	−0.40 (−1.49)	−0.28 (−1.93)*	−0.34 (−0.93)	0.14 (0.36)	−0.21 (−1.44)	−0.38 (−1.00)	0.01 (0.09)	−0.22 (−1.48)	−0.36 (−0.95)
4-month	0.09 (0.13)			−0.18 (−0.76)			0.23 (0.64)			0.06 (0.43)		
	−0.70 (−1.07)	−0.28 (−2.03)**	−0.46 (−1.11)	−0.50 (−2.23)**	−0.31 (−2.31)**	−0.46 (−1.11)	0.08 (0.21)	−0.24 (−1.72)*	−0.50 (−1.21)	−0.02 (−0.11)	−0.24 (−1.78)*	−0.49 (−1.18)
Panel B: Weekly horizon												
Contemp	1.59 (13.61)***			0.79 (14.05)***			0.24 (2.66)***			0.11 (3.25)***		
	1.64 (13.98)***	0.1 (3.26)***	−0.13 (−1.70)*	0.81 (15.03)***	0.12 (4.26)***	−0.12 (−1.60)	0.38 (3.92)***	0.05 (1.86)*	−0.07 (−0.90)	0.15 (4.52)***	0.06 (2.08)**	−0.08 (−1.01)
1-week	−0.02 (−0.16)			0.02 (0.30)			−0.01 (−0.14)			0.00 (−0.13)		
	−0.09 (−0.76)	−0.06 (−2.00)**	−0.07 (−0.89)	−0.03 (−0.58)	−0.06 (−2.12)**	−0.07 (−0.94)	−0.03 (−0.31)	−0.06 (−1.98)**	−0.07 (−0.88)	−0.02 (−0.53)	−0.06 (−2.11)**	−0.07 (−0.87)
2-week	−0.09 (−0.72)			−0.01 (−0.14)			0.02 (0.26)			0.01 (0.38)		
	−0.19 (−1.64)	−0.07 (−2.27)**	−0.06 (−0.8)	−0.07 (−1.41)	−0.07 (−2.32)**	−0.07 (−0.85)	0.01 (0.08)	−0.05 (−1.79)*	−0.07 (−0.82)	0.00 (0.04)	−0.05 (−1.87)*	−0.07 (−0.82)
3-week	−0.10 (−0.86)			0.01 (0.18)			−0.01 (−0.15)			0.00 (−0.08)		
	−0.21 (−1.71)*	−0.07 (−2.25)**	−0.07 (−0.83)	−0.05 (−0.89)	−0.06 (−2.2)**	−0.07 (−0.94)	−0.03 (−0.27)	−0.05 (−1.81)*	−0.07 (−0.91)	−0.01 (−0.34)	−0.06 (−1.91)*	−0.07 (−0.87)
4-week	−0.02 (−0.16)			0.00 (−0.09)			0.04 (0.38)			0.01 (0.21)		
	−0.11 (−0.90)	−0.06 (−1.98)**	−0.08 (−0.96)	−0.07 (−1.22)	−0.06 (−2.17)**	−0.08 (−1.04)	0.03 (0.34)	−0.05 (−1.67)*	−0.08 (−0.95)	0.00 (0.07)	−0.05 (−1.81)*	−0.07 (−0.94)
Panel C: Daily horizon (Whole day)												
Contemp	0.58 (28.24)***			0.38 (29.21)***			0.12 (6.47)***			0.06 (7.84)***		
	0.61 (31.67)***	0.03 (4.51)***	−0.12 (−6.71)***	0.39 (32.04)***	0.04 (7.38)***	−0.11 (−6.46)***	0.17 (9.15)***	0.02 (2.66)***	−0.09 (−5.07)***	0.08 (10.38)***	0.02 (3.28)***	−0.09 (−5.35)***
1-day	0.08 (3.70)***			0.04 (2.99)***			0.03 (1.52)			0.01 (1.32)		
	0.07 (3.33)***	−0.01 (−1.70)*	−0.08 (−4.72)***	0.03 (2.65)***	−0.01 (−2.18)**	−0.08 (−4.93)***	0.02 (1.24)	−0.02 (−2.28)**	−0.08 (−4.77)***	0.01 (1.02)	−0.02 (−2.38)**	−0.08 (−4.71)***
2-day	−0.03 (−1.29)			−0.02 (−1.55)			0.00 (0.18)			0.00 (−0.24)		
	−0.02 (−0.94)	−0.01 (−2.08)**	−0.08 (−4.44)***	−0.02 (−1.96)**	−0.02 (−2.84)***	−0.08 (−4.68)***	0.01 (0.47)	−0.02 (−2.36)**	−0.08 (−4.70)***	0.00 (−0.18)	−0.02 (−2.57)**	−0.08 (−4.60)***
3-day	−0.02 (−1.08)			−0.02 (−1.25)			0.01 (0.30)			0.00 (0.13)		
	−0.04 (−1.97)**	−0.02 (−2.7)***	−0.07 (−3.99)***	−0.03 (−2.1)**	−0.02 (−2.83)***	−0.07 (−4.47)***	0.01 (0.40)	−0.02 (−2.29)**	−0.08 (−4.48)***	0.00 (−0.08)	−0.02 (−2.49)**	−0.08 (−4.43)***
4-day	−0.03 (−1.17)			−0.01 (−0.87)			−0.01 (−0.40)			0.00 (−0.24)		
	−0.03 (−1.25)	−0.02 (−2.25)**	−0.08 (−4.17)***	−0.02 (−1.44)	−0.02 (−2.75)***	−0.08 (−4.55)***	0.00 (−0.07)	−0.02 (−2.40)**	−0.08 (−4.52)***	0.00 (−0.30)	−0.02 (−2.52)**	−0.08 (−4.42)***
Panel D: Daily horizon (9:30–16:00)												
Contemp	0.56 (27.80)***			0.41 (28.96)***			0.12 (6.65)***			0.07 (8.07)***		
	0.59 (31.27)***	0.03 (3.98)***	−0.13 (−6.84)***	0.43 (32.18)***	0.04 (7.39)***	−0.11 (−6.29)***	0.17 (9.92)***	0.02 (2.73)***	−0.09 (−5.16)***	0.09 (11.01)***	0.02 (3.43)***	−0.09 (−5.44)***
1-day	0.02 (0.76)			0.00 (−0.02)			0.02 (1.38)			0.01 (0.65)		
	0.00 (0.13)	−0.01 (−1.95)*	−0.07 (−4.14)***	−0.01 (−0.70)	−0.02 (−2.68)***	−0.08 (−4.77)***	0.02 (0.91)	−0.02 (−2.32)**	−0.08 (−4.75)***	0.00 (0.21)	−0.02 (−2.53)**	−0.08 (−4.63)***
2-day	−0.02 (−0.92)			−0.02 (−1.55)			0.01 (0.43)			0.00 (−0.08)		
	−0.02 (−1.00)	−0.02 (−2.03)**	−0.07 (−4.09)***	−0.03 (−2.01)**	−0.02 (−2.81)***	−0.07 (−4.46)***	0.02 (0.91)	−0.01 (−2.21)**	−0.08 (−4.53)***	0.00 (−0.07)	−0.02 (−2.50)**	−0.08 (−4.43)***
3-day	−0.01 (−0.60)			−0.01 (−0.95)			0.01 (0.44)			0.00 (0.49)		
	−0.02 (−1.08)	−0.02 (−2.54)**	−0.07 (−4.11)***	−0.02 (−1.44)	−0.02 (−2.79)***	−0.08 (−4.60)***	0.01 (0.64)	−0.02 (−2.28)**	−0.08 (−4.61)***	0.00 (0.33)	−0.02 (−2.41)**	−0.08 (−4.54)***
4-day	−0.01 (−0.45)			−0.01 (−0.74)			−0.01 (−0.39)			0.00 (−0.22)		
	−0.02 (−0.92)	−0.01 (−2.00)**	−0.07 (−3.92)***	−0.02 (−1.46)	−0.02 (−2.74)***	−0.08 (−4.55)***	0.00 (0.14)	−0.02 (−2.31)**	−0.08 (−4.46)***	0.00 (−0.26)	−0.02 (−2.51)**	−0.08 (−4.39)***

This table presents the estimation results of the Fama–MacBeth cross-sectional predictive regression of individual stock returns on the measure of investor sentiment after controlling for size and book-to-market ratio as follows: for each time t, $R_{i,t+j} = \alpha_t + \beta_t S_{it} + \gamma_t \ln(\text{Size}_{it}) + \delta_t \ln(\text{BM}_{it}) + \varepsilon_{it}$, $i = 1, \ldots, N$, where $R_{i,t+j}$ is the j-period-ahead return of stock i and S_{it} is the measure of investor sentiment of stock i at time t. The reported coefficients (in percent) are the time-series averages of the estimated regression coefficients. Four measures of investor sentiment are used, namely RVD1, RVD2, CLD1, and CLD2. They are defined in Table 2. RVD1 and RVD2 are the measures of explicitly revealed sentiment, while CLD1 and CLD2 are the measures of investor sentiment classified by the Naïve Bayes classification. "contemp" indicates contemporaneous regression (with $j = 0$). Numbers in parentheses are t-statistics. The sample period is from January 2005 to December 2010.

Table 8
Predictability of investor sentiment for earnings and stock return around earnings announcement days.

Sample used	Sentiment variable	Event day included $SUE_i = a_0 + a_1 \Delta S_{i,[-10,0]} + \varepsilon_i$		Event day not included $SUE_i = a_0 + a_1 \Delta S_{i,[-10,-1]} + \varepsilon_i$	
		$\hat{a}_0$	$\hat{a}_1$	$\hat{a}_0$	$\hat{a}_1$
Panel A: Dependent variable = SUE					
Whole sample	RVD1	1.241 (7.93)***	0.577 (1.67)*	1.217 (7.78)***	0.197 (0.57)
	RVD2	1.183 (7.56)***	0.473 (2.79)***	1.221 (7.75)***	−0.013 (−0.07)
	CLD1	1.174 (7.38)***	1.191 (1.52)	1.197 (7.57)***	0.671 (0.90)
	CLD2	1.136 (7.05)***	0.520 (2.09)**	1.179 (7.44)***	0.352 (1.48)
Only positive ΔS_i	RVD1	1.180 (3.97)***	0.711 (1.37)	1.008 (4.12)***	0.632 (1.37)
	RVD2	1.029 (3.23)***	0.647 (2.04)**	1.064 (3.55)***	0.035 (0.11)
	CLD1	0.874 (3.05)***	2.717 (2.84)***	1.293 (4.77)***	0.773 (0.85)
	CLD2	0.998 (2.72)***	0.762 (1.57)	1.597 (4.12)***	−0.087 (−0.16)
Only negative ΔS_i	RVD1	1.204 (3.36)***	0.376 (0.48)	1.738 (4.07)***	0.788 (0.90)
	RVD2	0.932 (2.03)**	0.181 (0.35)	1.598 (3.32)***	0.398 (0.71)
	CLD1	0.771 (3.31)***	−0.606 (−0.54)	0.843 (3.24)***	0.433 (0.42)
	CLD2	1.066 (3.80)***	0.438 (0.91)	1.019 (3.44)***	0.411 (0.92)
Sample used	**Sentiment variable**	**Event day included $Ret_{1,[0,0]} = b_0 + b_1 \Delta S_{i[-10,0]} + \varepsilon_i$**		**Event day not included $Ret_{[0,0]} = b_0 + b_1 \Delta S_{i[-10,-1]} + \varepsilon_i$**	
		$\hat{b}_0$	$\hat{b}_1$	$\hat{b}_0$	$\hat{b}_1$
Panel B: Dependent variable = Raw return					
Whole sample	RVD1	0.001 (0.81)	0.013 (4.25)***	0.001 (0.50)	−0.002 (−0.73)
	RVD2	0.000 (−0.09)	0.010 (6.57)***	0.001 (0.57)	−0.001 (−0.84)
	CLD1	0.000 (0.06)	0.014 (2.00)**	0.001 (0.47)	0.000 (−0.04)
	CLD2	0.000 (−0.21)	0.006 (2.67)***	0.001 (0.49)	0.000 (−0.18)

This table presents the results from the regression of the SUE scores from the I/B/E/S database (Panel A) or raw returns (Panel B) on changes in investor sentiment. The SUE score is computed as (actual EPS – average EPS of analysts' forecasts)/standard deviation of analysts' forecasts. Raw returns are returns on the quarterly earnings announcement day ($t = 0$). The explanatory variable $\Delta S_{i,[-10,0]}$ is the change in investor sentiment over the period $[-10, 0]$ (the period from 10 days before the announcement to the announcement day) and $\Delta S_{i,[-10,-1]}$ is the change in investor sentiment over the period $[-10, -1]$ (the period from 10 days before to 1 day before the announcement). "Only positive (negative) ΔS_i" means the sample that has a positive (negative) change in investor sentiment. RVD1 and RVD2 are the measures of explicitly revealed sentiment, while CLD1 and CLD2 are the measures of investor sentiment classified by the Naïve Bayes classification algorithm. The total number of quarterly earnings announcements is 1798. Numbers in parentheses are t-statistics.

4.2. Return and earnings predictability around an event

In the preceding section, we examined the event-free cross-sectional predictability of investor sentiment for stock returns. It would also be interesting to examine the event-specific cross-sectional predictability of investor sentiment, since investors would be more vigilant in a message around an event.[25] To do so, we select a quarterly earnings announcement as an event. To examine the predictability of investor sentiment for earnings and stock returns, we estimate the following event-specific CSR models:

$$\left.\begin{aligned} SUE_i &= a_0 + a_1 \Delta S_{i,[-10,0]} + \varepsilon_i \\ Ret_{i,[-0,0]} &= b_0 + b_1 \Delta S_{i,[-10,0]} + \varepsilon_i \end{aligned}\right\} \quad \text{(Event day included in } \Delta S) \tag{8}$$

$$\left.\begin{aligned} SUE_i &= a_0 + a_1 \Delta S_{i,[-10,-1]} + \varepsilon_i \\ Ret_{i,[-0,0]} &= b_0 + b_1 \Delta S_{i,[-10,-1]} + \varepsilon_i \end{aligned}\right\} \quad \text{(Event day not included in } \Delta S) \tag{9}$$

where SUE_i is the standardized unanticipated earnings (SUE) score of the ith quarterly earnings announcement obtained from the I/B/E/S database, which is computed as the ratio of actual earnings per share (EPS) minus the average EPS of analysts' forecasts divided by the standard deviation of analysts' forecasts, and $Ret_{i,[-0,0]}$ is the return on the quarterly earnings announcement day ($t = 0$). The explanatory variable $\Delta S_{i,[-10,0]}$ is the change in investor sentiment over the window $[-10,0]$, and $\Delta S_{i,[-10,-1]}$ is the change in investor sentiment over the window $[-10, -1]$. The total number of quarterly earnings announcements is 1798.[26]

[25] The average numbers of posted messages around the quarterly earnings announcements of all 91 sample firms are 170.5, 160.1, 166.4, 188.0, 263.7 606.3, 398.2, 219.4, 178.4, 184.7, and 186.6, respectively, over the 11-day period of $[-5, +5]$. Note that day '0' is the day that quarterly earnings are announced. The average numbers of the authors over the same 11-day period are 68.4, 67.9, 70.8, 72.5, 86.1, 175.6, 124.6, 90.8, 76.3, 73.7, and 69.6, respectively.

[26] The values of all 1798 SUEs obtained from the I/B/E/S database range from 136.923 to −69.38. The mean, median, and standard deviation of the SUEs are 1.238, 0.988, and 6.479, respectively.

Table 8 presents the estimation results of Eqs. (8) and (9). The change in investor sentiment over the window [−10, 0] has a significant positive relation with the SUE. That is, the coefficient estimates on the change in investor sentiment measured with RVD1 and RVD2 are 0.577 (t-statistic of 1.67) and 0.473 (t-statistic of 2.79), respectively. However, when investor sentiment on the event day is not included (i.e., over the window [−10, −1]), these coefficient estimates are no longer statistically significant: 0.197 (t-statistic of 0.57) and −0.013 (t-statistic of −0.07), respectively. This pattern is also found in the regression coefficient estimates of stock returns on the change in investor sentiment (Panel B). When investor sentiment on the event day is included, the coefficient estimates on the change in investor sentiment measured with RVD1 and RVD2 are 0.013 (t-statistic of 4.25) and 0.010 (t-statistic of 6.57), respectively. However, when investor sentiment on the event day is not included, these coefficient estimates are also no longer significant: −0.002 (t-statistic of −0.73) and −0.001 (t-statistic of −0.84), respectively. Similar results are obtained with the classified sentiment measures used. These results show that retail investor sentiment does not predict earnings surprises and stock returns; rather, these are affected by contemporaneous stock price movements and earnings news.

Tetlock (2007), Tetlock et al. (2008), and Chen et al. (2012) report that negative words or views expressed in news and social media predict firms earnings and stock returns. To examine whether negative sentiment in our sample can predict earnings surprises, we divide the sample into two groups: negative and positive changes in investor sentiment. Negative changes in investor sentiment over the window could be regarded as negative views by retail investors. Panel A of Table 8 also reports the estimation results when only the cases with negative changes in investor sentiment are used in the regression. We still find no significant predictive power of investor sentiment for earnings surprises, even when investor sentiment on the event day is included. The reason for the difference between the results of previous studies and our own is that the sources of investor sentiment differ. Previous studies extract sentiment information from relatively informed sources such as the *Wall Street Journal* column (Tetlock, 2007), financial media stories (Tetlock et al., 2008), and a popular social media site for investors, *Seeking Alpha* (Chen et al., 2012), while we use sentiment information from Internet messages posted by relatively uninformed retail investors.

4.3. Extreme return predictability of investor sentiment

Since retail investors tend to be more vigilant and active on a message board when stock price drastically changes, it would be interesting to reexamine whether retail investor sentiment extracted from the message board is informative in predicting stock returns when stock prices change by extreme levels. We define an extreme price change as the case that daily returns are above or below two standard deviations from the average return. We compute the average return and standard deviations by using the past 240 daily returns.

Fig. 2 shows the average daily number of posted messages over six days prior to extreme price changes. Clearly, the message board activity of retail investors is higher for the case of extreme price changes than for the case of moderate price

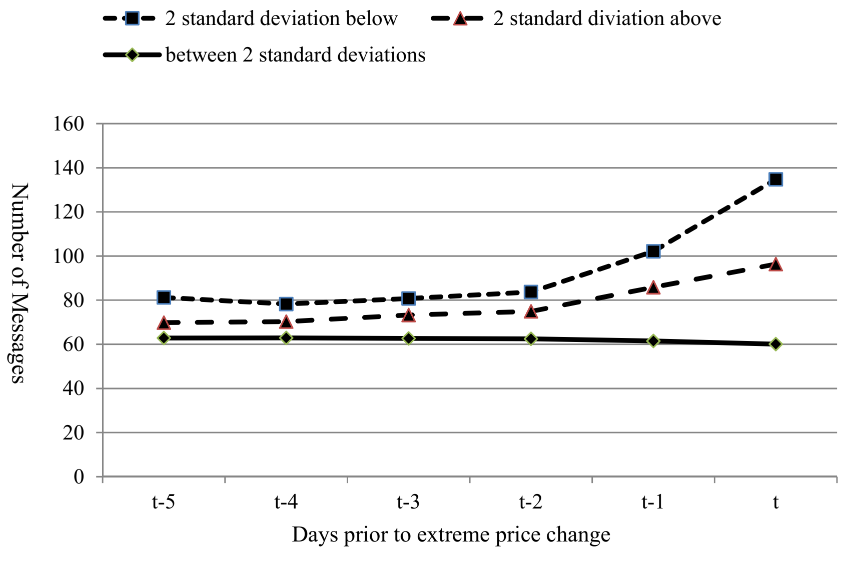

Fig. 2. Retail Investors' Message Board activity prior to extreme stock price changes. This figure shows the average daily number of messages posted on Yahoo! Finance message boards over the six days prior to the extreme price changes. The extreme price change is defined as the case that daily returns are above or below two standard deviations from the average return. The average return and standard deviations are computed by using the past 240 daily returns. '$t-j$' indicates j days before the extreme stock price change.

Table 9
Pooled regression estimation results of stock returns on investor sentiment prior to extreme price changes.

Investor sentiment measure	Equation: $R_t = \gamma_0 + \gamma_1 \Delta S_{t-1} + \gamma_2 \Delta S_{t-2} + \beta_1 R_{t-1} + \beta_2 R_{t-2} + \varepsilon_t$				
	$\hat{\gamma}_0$	$\hat{\gamma}_1$	$\hat{\gamma}_2$	$\hat{\beta}_1$	$\hat{\beta}_2$
Panel A: Above two standard deviations (4656 obs)					
RVD1	9.15	0.009	0.294	12.729	3.395
	(49.85)***	(0.02)	(0.68)	(4.98)***	(1.32)
RVD2	9.14	0.294	0.238	12.161	3.517
	(49.75)***	(1.05)	(0.89)	(4.68)***	(1.36)
CLD1	9.15	−0.868	−0.088	12.848	3.514
	(49.81)***	(−0.99)	(−0.10)	(5.06)***	(1.37)
CLD2	9.16	−0.317	−0.312	12.926	3.605
	(49.85)***	(−1.03)	(−1.03)	(5.08)***	(1.40)
Panel B: Below two standard deviations (2890 obs)					
RVD1	−9.64	0.487	0.108	2.39	−0.058
	(−66.05)***	(1.46)	(0.34)	(1.21)	(−0.02)
RVD2	−9.64	0.379	−0.042	2.13	0.392
	(−66.10)***	(1.79)*	(−0.20)	(1.07)	(0.17)
CLD1	−9.64	0.14	−0.09	2.74	−0.104
	(−66.02)***	(0.21)	(−0.13)	(1.40)	(−0.04)
CLD2	−9.64	0.04	0.055	2.735	−0.125
	(−66.04)***	(0.16)	(0.22)	(1.39)	(−0.05)
Panel C: Within two standard deviations (107,698 obs)					
RVD1	−0.053	0.029	0.019	−2.191	−1.245
	(−4.76)***	(1.08)	(0.71)	(−8.14)***	(−4.74)***
RVD2	−0.053	0.02	−0.003	−2.221	−1.199
	(−4.76)***	(1.21)	(−0.16)	(−8.14)***	(−4.51)***
CLD1	−0.053	0.063	0.032	−2.176	−1.241
	(−4.76)***	(1.19)	(0.60)	(−8.13)***	(−4.74)***
CLD2	−0.053	0.014	−0.004	−2.173	−1.228
	(−4.77)***	(0.75)	(−0.22)	(−8.10)***	(−4.68)***

This table presents the coefficient estimates (×100) of the pooled regression of daily returns of 91 individual stocks on the lagged investor sentiment changes (ΔS_{t-j}, $j = 1, 2$) for the cases of extreme stock price changes (daily returns are above or below two standard deviations from the average return) and the cases of moderate price change (daily returns are within two standard deviations). The average return and standard deviations are computed by using the past 240 days. Numbers in parentheses indicate t-value.

changes (daily returns within two standard deviations). Furthermore, message board activity increases as the day of the extreme price change approaches, while it shows no change over time for the case of moderate price changes.

To examine whether this increased message board activity of retail investors contains any informativeness in predicting stock returns, we estimate the pooled regression model of the (extreme) daily returns of all 91 individual stocks on lagged investor sentiment changes ($\Delta S_{t-j}, j = 1, 2$ days) after controlling for the serial correlations of returns:

$$R_t = \gamma_0 + \gamma_1 \Delta S_{t-1} + \gamma_2 \Delta S_{t-2} + \beta_1 R_{t-1} + \beta_2 R_{t-2} + \varepsilon_t. \tag{10}$$

Table 9 presents the coefficient estimates (×100) of the pooled regression Equation (10) for three cases that returns are above (Panel A), below (Panel B), and within (Panel C) two standard deviations from the average return. The pooled numbers of observations are 4656, 2890, and 107,698 for these three cases, respectively. In all cases, the coefficient estimates on the investor sentiment variables ($\hat{\gamma}_1$ and $\hat{\gamma}_2$) are statistically insignificant.[27] For the case of positive extreme price changes (Panel A), daily returns show a strong positive serial correlation. This finding indicates that the increased message board activity shown in Fig. 2 may be a result of the concurrent increase in stock price rather than predictive behavior ahead of an extreme price increase.

5. Volatility, trading volume, and investor sentiment

Besides the issue of the return predictability of investor sentiment, another interesting issue in the literature is whether investor sentiment predicts volatility and trading volume. According to the noise trader model, retail investors (or noise traders) affect the price level by trading on some noisy signal and thereby causing volatility. If the (bullish or bearish) noisy

[27] Even when only the lagged investment sentiment variables are included as regressors in Eq. (10) (i.e., not controlling for the serial correlations of returns), the coefficient estimates on the lagged sentiment variables (ΔS_{t-j}) are also statistically insignificant.

Table 10
Volatility, trading volume, and investor sentiment.

Type of sentiment	Horizon	Explanatory variables				
		Intercept	Y_{t-1}	Y_{t-2}	Return	DisAgree
Panel A: $\text{Volatility}_t = a_0 + a_1\text{Volatility}_{t-1} + a_2\text{Volatility}_{t-2} + a_3R_{t-1} + \text{DisAgree}_{t-1} + \varepsilon_t$						
Revealed	Monthly	−0.046 (−4.45)***				0.170 (7.65)***
	Weekly	−0.024 (−5.72)***				0.119 (13.02)***
	Monthly	−0.005 (−0.54)	0.731 (5.39)***	0.047 (0.36)	−0.021 (−1.86)*	0.026 (1.17)
	Weekly	0.000 (−0.05)	0.442 (8.77)***	0.457 (9.30)***	−0.041 (−4.78)***	0.007 (1.05)
Classified	Monthly	−0.138 (−3.77)***				0.329 (4.66)***
	Weekly	−0.024 (−5.72)***				0.119 (13.02)***
	Monthly	−0.008 (−0.31)	0.769 (5.83)***	0.062 (0.48)	−0.022 (−1.95)*	0.026 (0.52)
	Weekly	−0.014 (−1.67)*	0.447 (9.19)***	0.454 (9.33)***	−0.039 (−4.67)***	0.032 (1.98)**
Panel B: $\text{Turnover}_t = b_0 + b_1\text{Turnover}_{t-1} + b_2\text{Turnover}_{t-2} + b_3\lvert R_{t-1}\rvert + b_4\text{DisAgree}_{t-1} + \varepsilon_t$						
Revealed	Monthly	0.038 (4.51)***				0.019 (1.02)
	Weekly	0.945 (9.41)***				0.326 (1.48)
	Daily	0.091 (51.85)***				0.009 (2.29)***
	Monthly	0.028 (2.81)***	0.354 (2.74)***	0.009 (0.08)	0.013 (0.69)	0.003 (0.15)
	Weekly	0.613 (5.71)***	0.330 (5.92)***	0.131 (2.38)***	1.681 (3.54)***	−0.171 (−0.81)
	Daily	0.043 (15.55)***	0.514 (16.70)***	0.045 (1.70)*	−0.143 (−1.71)*	0.000 (0.06)
Classified	Monthly	0.036 (1.41)				0.022 (0.44)
	Weekly	0.975 (2.91)***				0.220 (0.35)
	Daily	0.097 (41.59)***				−0.012 (−1.75)*
	Monthly	0.021 (0.85)	0.355 (2.75)***	0.013 (0.11)	0.013 (0.75)	0.014 (0.31)
	Weekly	0.594 (1.89)*	0.329 (5.87)***	0.127 (2.32)***	1.560 (3.41)***	−0.093 (−0.16)
	Daily	0.044 (13.45)***	0.514 (16.77)***	0.045 (1.69)*	−0.145 (−1.74)*	−0.002 (−0.39)

This table presents the results from the regression of the volatility of aggregate returns on the measure of disagreement or agreement among retail investors after controlling for the aggregate return. The measure of disagreement, "DisAgree", using revealed sentiment data is defined as $|1-|\text{RVD1}||$ where $\text{RVD1} = (M_t^{\text{Revealed Buy}} - M_t^{\text{Revealed Sell}})/(M_t^{\text{Revealed Buy}} + M_t^{\text{Revealed Sell}})$ and $M_t^{\text{Revealed Buy}}(M_t^{\text{Revealed sell}})$ is the total number of messages explicitly revealed "buy" ("sell") by the authors during period t The measure of disagreement using investor sentiment classified by the Naïve Bayes classification algorithm is defined as $|1-|\text{CLD1}||$ where CLD1 similarly defined as RVD1 by using classified investor sentiment instead of revealed investor sentiment. "Turnover" is a measure of trading volume, which is defined as the ratio of trading volume for the period to the number of shares outstanding. Turnover is rescaled by dividing by 10 for the monthly horizon and multiplying by 10 for the weekly and daily horizons. Volatility is measured by the standard deviation of the aggregate daily returns of all 91 individual stocks for each period. Y_{t-1} and Y_{t-2} are the one-lagged and two-lagged dependent variables as explanatory variables (i.e., "Volatility" in Panel A and "Turnover" in Panel B), and "Return" is the aggregate return of the 91 stocks. Numbers in parentheses indicate t-statistics. The sample period is from January 2005 to December 2010.

signal is generated from their sentiment, trading volume and volatility should be correlated with investor sentiment. To examine such a relation, we estimate the following time-series regression model:

$$\text{Volatility}_t = a_0 + a_1\text{Volatility}_{t-1} + a_2\text{Volatility}_{t-2} + a_3R_{t-1} + a_4\text{DisAgree}_{t-1} + \varepsilon_t, \tag{11}$$

$$\text{Turnover}_t = b_0 + b_1\text{Turnover}_{t-1} + b_2\text{Turnover}_{t-2} + b_3\left|R_{t-1}\right| + b_4\text{DisAgree}_{t-1} + \varepsilon_t, \tag{12}$$

where volatility is simply measured by the standard deviation of the aggregate daily returns of all 91 individual stocks for period t; turnover is a measure of trading volume, which is defined as the ratio of trading volume for the period to the number of shares outstanding; and R_{t-1} is the aggregate return of all 91 stocks for period $t-1$. DisAgree_{t-1} is the measure of disagreement for period $t-1$ obtained from Das and Chen (2007) and this is defined as

$$\text{DisAgree}_{t-1} = \begin{cases} \left|1-\left|\text{RVD1}_{t-1}\right|\right| & \text{if revealed sentiment is used} \\ \left|1-\left|\text{CLD1}_{t-1}\right|\right| & \text{if classified sentiment is used.} \end{cases} \tag{13}$$

This measure of disagreement has its smallest value, zero, when there is a buy sentiment only or a sell sentiment only on Internet postings and has the largest value, one, when the buy sentiment and sell sentiments are exactly balanced. Since disagreement is considered to be a possible motivation for trading and volatility, we expect a positive relation of disagreement with trading volume and volatility (for the hypothesis that disagreement makes investors trade, see Hirshleifer, 1977; Harris and Raviv, 1993). For volatility, one-lagged volatility and return are used as control variables since volatility tends to be highly persistent and related to previous returns (see, e.g., Black, 1976; French et al., 1987; Campbell and Hentschel, 1992; Bekaert and Wu, 2000). For trading volume, the one-lagged turnover ratio and absolute return are used as control variables since the turnover ratio also tends to be highly persistent and positively related to previous absolute returns (see, e.g., Karpoff, 1987; Wang, 1994).

Table 10 presents the estimation results of the regression Eqs. (11) and (12) for volatility (Panel A) and trading volume (Panel B). Note that turnover is rescaled by dividing by 10 for the monthly horizon and multiplying by 10 for the weekly and daily horizons. When the disagreement variable is alone in the volatility Eq. (11), the coefficient estimates on the

Table 11
Prediction accuracy of investor sentiment for stock returns according to retail investor characteristics.

Gender				Age					Message length		
Horizon	Male	Female	Difference	20s	30s	40s	50s	60s	Long	Short	Difference
Panel A: Not using firms characteristics											
Monthly	0.478	0.476	0.002 [0.355]	0.478	0.477	0.480	0.480	0.480	0.476	0.475	0.001 [0.555]
Weekly	0.486	0.485	0.001 [0.556]	0.483	0.485	0.485	0.487	0.485	0.486	0.484	0.003 [0.002]
Daily	0.494	0.493	0.001 [0.508]	0.494	0.495	0.495	0.493	0.491	0.493	0.493	0.000 [0.668]

Firm characteristic		Whole sample	Male	Female	20s	30s	40s	50s	60s	Long	Short
Panel B: Using firm characteristics – Monthly horizon											
Firm size	Small	0.441	0.443	0.444	0.442	0.443	0.447	0.447	0.448	0.442	0.440
	Big	0.498	0.499	0.496	0.498	0.496	0.502	0.503	0.503	0.498	0.498
	Difference	−0.057	−0.057	−0.053	−0.056	−0.053	−0.055	−0.056	−0.055	−0.056	−0.057
BM	Low	0.480	0.482	0.479	0.478	0.478	0.482	0.488	0.487	0.472	0.478
	High	0.469	0.471	0.470	0.478	0.475	0.478	0.471	0.472	0.467	0.471
	Difference	0.011	0.011	0.009	−0.001	0.003	0.003	0.016	0.015	0.015	0.007
Exchange	NYSE/AMEX	0.504	0.505	0.499	0.508	0.506	0.513	0.505	0.508	0.501	0.507
	NASDAQ	0.463	0.465	0.465	0.463	0.464	0.466	0.468	0.464	0.464	0.462
	Difference	0.041	0.040	0.035	0.045	0.042	0.047	0.038	0.044	0.037	0.045
Panel C: Using firm characteristics – Weekly horizon											
Firm size	Small	0.467	0.466	0.468	0.464	0.466	0.465	0.471	0.466	0.466	0.467
	Big	0.499	0.500	0.497	0.494	0.497	0.500	0.499	0.502	0.501	0.496
	Difference	−0.032	−0.035	−0.028	−0.031	−0.032	−0.035	−0.029	−0.037	−0.035	−0.029
BM	Low	0.490	0.491	0.493	0.492	0.492	0.491	0.492	0.491	0.491	0.489
	High	0.478	0.478	0.472	0.468	0.475	0.478	0.480	0.478	0.480	0.476
	Difference	0.013	0.013	0.021	0.024	0.018	0.012	0.013	0.013	0.012	0.014
Exchange	NYSE/AMEX	0.504	0.506	0.494	0.498	0.501	0.503	0.505	0.506	0.507	0.503
	NASDAQ	0.477	0.477	0.480	0.475	0.478	0.478	0.478	0.475	0.477	0.476
	Difference	0.028	0.029	0.014	0.024	0.024	0.025	0.027	0.032	0.029	0.026
Panel D: Using firm characteristics – Daily horizon											
Firm size	Small	0.475	0.476	0.474	0.473	0.474	0.477	0.475	0.475	0.477	0.474
	Big	0.508	0.509	0.508	0.507	0.509	0.510	0.508	0.507	0.507	0.508
	Difference	−0.033	−0.033	−0.034	−0.034	−0.034	−0.033	−0.033	−0.032	−0.030	−0.035
BM	Low	0.497	0.498	0.497	0.495	0.498	0.498	0.497	0.498	0.497	0.496
	High	0.488	0.489	0.488	0.493	0.490	0.491	0.488	0.482	0.487	0.489
	Difference	0.009	0.009	0.009	0.002	0.009	0.007	0.009	0.016	0.010	0.007
Exchange	NYSE/AMEX	0.506	0.507	0.505	0.508	0.509	0.508	0.504	0.501	0.505	0.507
	NASDAQ	0.488	0.489	0.488	0.487	0.489	0.490	0.488	0.486	0.488	0.488
	Difference	0.018	0.018	0.016	0.021	0.020	0.018	0.016	0.015	0.017	0.019

This table presents the prediction accuracy of retail investor sentiment for stock returns on the next period across retail investor demographic characteristics. The table presents a percentage of correctly predicting messages, which is defined as the ratio of the number of messages that correctly predict the direction of the next period's stock price movement to total messages in that period. When an author posts multiple messages for the same stock in a period, only the last message is considered. We classify a message as "Long" if its length in number of words is longer than the median of total messages and "Short" otherwise. Numbers in brackets are *p*-values. The sample period is from January 2005 to December 2010.

disagreement variable are strongly significantly positive, regardless of whether revealed sentiment or classified sentiment is used for the measure of disagreement. For example, when disagreement is computed by using revealed sentiment, the coefficient estimates on the disagreement variable, $\hat{a}_4$, are 0.170 (t-statistic of 7.65) and 0.119 (t-statistic of 13.02) for the monthly and weekly horizons, respectively.[28] When the disagreement variable is alone in the trading volume Eq. (12) and revealed sentiment is used for disagreement, the coefficient estimates on the disagreement variable are significantly positive at the 5% level for the daily horizon but only barely significant for the monthly and weekly horizons. Specifically, the coefficient estimates on the disagreement variable, $\hat{b}_4$, are 0.019 (t-statistic of 1.02), 0.326 (t-statistic of 1.48), and 0.009 (t-statistic of 2.29) for the monthly, weekly, and daily horizons, respectively. The above results are consistent with those

[28] Because of the difficulty in computing daily volatility by using one daily return observation, the regression model of volatility for the daily horizon is not estimated.

of Antweiler and Frank (2004). By using no control variables, these authors report that volatility and trading volume are significantly negatively related to the measure of agreement, which is exactly opposite to our measure of disagreement.[29]

However, when the control variables are included in the model, the statistical significance of the coefficient estimates on the disagreement variable almost disappears. For volatility, the coefficient estimates on the disagreement variable are no longer statistically significant. Specifically, when revealed sentiment is used for disagreement, the coefficient estimates, $\hat{a}_4$, are 0.026 (t-statistic of 1.17) and 0.007 (t-statistic of 1.05) for the monthly and weekly horizons, respectively. When classified sentiment is used for disagreement, the estimation results are similar. For trading volume, the coefficient estimates on the disagreement variable, $\hat{b}_4$, are not significant at any horizon considered. Note that most of the coefficient estimates on the control variables are strongly significant. In particular, the coefficient estimates on volatility and trading volume are positive and strongly significant, indicating that they are highly positively serially correlated.

In summary, investor sentiment from Internet postings has no predictive power for volatility and trading volume for any horizon considered after controlling for serial correlation and lagged absolute return. These results differ from those of Antweiler and Frank (2004), although the source of investor sentiment is similar in Internet posting messages.

6. Predictability of stock returns across the retail investor's characteristics

Our sample also contains information on the message author's characteristics such as gender, age, and message length. To examine whether there is a distinctive feature in prediction ability for stock returns across these characteristics, we count the number of messages that correctly predict the direction of the next period's stock price movement. When an author posts multiple messages for the same stock in a period, only the most recently posted message is used. Table 11 presents the percentages of correctly predicted messages across retail investor characteristics. These percentages are computed as the ratio of the number of messages that correctly predict the direction of the next period's stock price movement to the total messages used during that period. A percentage of 0.5 implies an almost random prediction. The table shows that all the correctly predicted percentages are slightly below 0.5 in any horizon considered (monthly, weekly, and daily), ranging from 0.475 to 0.495, regardless of the retail investor's gender, age, and message length.

To examine further the predictive ability of retail investors, we divide the sample firms into two groups according to firm characteristics: small and large firm size and high and low book-to-market ratio. We still find the prediction accuracy percentages to be slightly below 0.5 in any subgroup. When the sample firms are divided into NYSE/AMEX-listed and NASDAQ-listed firms, the prediction accuracy percentages for NYSE/AMEX-listed firms are slightly higher than 0.5 for the monthly horizon, ranging from 0.499 to 0.513 across retail investor characteristics, while those for NASDAQ-listed firms are slightly below 0.5, ranging from 0.462 to 0.468. The difference in the prediction accuracy percentages between these two exchange-listed groups is relatively small, ranging from 0.035 to 0.047. For the weekly and daily horizons, we obtain similar prediction accuracy percentages. Overall, we find no significant prediction ability of investor sentiment for the direction of the next period's stock price movement across retail investor characteristics.

7. Conclusion

We examine the predictability of investor sentiment for stock returns by extracting investor sentiment from text messages posted on the Yahoo! Finance message board. To do this, we download more than 32 million messages on 91 firms over the period January 2005 to December 2010. The most notable features of our analysis are the use of sentiment information explicitly revealed by retail investors for individual firms and a longer sample period relative to previous studies using similar data sources. As a proxy for investor sentiment, we use the investor sentiment indexes constructed from sentiment explicitly revealed by retail investors as well as classified by the Naïve Bayes classification algorithm. We consider three horizons (monthly, weekly, and daily) for predictability tests for both the intertemporal and the CSR analyses.

In the intertemporal regression analyses, we find little evidence that investor sentiment forecasts future stock returns either at the aggregate or at the individual firm level. Rather, we find evidence that investor sentiment is positively affected by prior stock price performance. We also find that investor sentiment from Internet postings has no predictive power for volatility and trading volume for any horizon considered after controlling for serial correlation and lagged return. In the CSR analyses, we also find no evidence that investor sentiment is related to future stock returns in the cross-section of average stock return, irrespective of controlling for size and book-to-market ratio. Our cross-sectional analyses show that investor sentiment is rather affected by contemporaneous stock price performance. To our knowledge, this study is the first to conduct cross-sectional tests for the relation by using individual firm sentiment data.

We also examine whether there is a distinctive feature in predictive ability for the direction of the next period's stock price movement across characteristics such as the retail investor's gender, age, and message length. However, we find no significant predictive ability of retail investors for the direction of the next period's stock price movement across these

[29] The Antweiler and Frank (2004) measure of agreement is defined as $\text{Agree}_t = 1 - \sqrt{1 - RVD1_t^2}$ If revealed sentiment is used and $\text{Agree}_t = 1 - \sqrt{1 - \text{CLD}1_t^2}$ If classified sentiment is used. This measure of agreement also lies between zero and one. When this measure of agreement is used instead of the measure of disagreement of Eq. (13), the results are very similar.

characteristics. Overall, it is difficult to say that Internet posting messages are informative in predicting stock market activity such as stock return, volatility, and trading volume.

Appendix A. List of the sample stocks

No.	Company name	Ticker	Exchange	Market cap ($000)	# total messages	Average words	RVD1	RVD2	CLD1	CLD2
1	APPLE INC	AAPL	NSADAQ	295,886,543	1,812,817	29	0.58	1.33	0.84	2.44
2	MICROSOFT CORP	MSFT	NSADAQ	238,784,645	483,963	43	0.09	0.19	−0.74	−1.92
3	GENERAL ELECT	GE	NYSE	194,874,801	804,313	33	0.25	0.52	−0.03	−0.07
4	WAL MART	WMT	NYSE	192,098,337	398,252	44	0.10	0.21	0.64	1.52
5	IBM	IBM	NYSE	182,328,893	85,743	44	0.35	0.73	−0.07	−0.14
6	JP MORGAN CHSE	JPM	NYSE	165,827,450	148,246	32	−0.42	−0.89	−0.54	−1.20
7	ORACLE CORP	ORCL	NSADAQ	158,096,296	236,137	54	0.39	0.83	−0.49	−1.06
8	GOOGLE INC	GOOG	NSADAQ	147,546,298	993,153	27	0.16	0.32	0.33	0.69
9	PFIZER INC	PFE	NYSE	140,254,243	303,845	41	0.76	2.01	0.90	2.89
10	CITIGROUP INC	C	NYSE	137,404,608	1,223,823	25	0.55	1.24	0.00	−0.01
11	BANK OF AMER	BAC	NYSE	134,535,862	1,089,219	26	0.47	1.02	−0.05	−0.09
12	INTEL CORP	INTC	NSADAQ	117,305,343	313,753	29	0.38	0.81	0.70	1.74
13	CISCO SYSTEMS	CSCO	NSADAQ	112,130,072	1,158,219	31	0.31	0.65	0.54	1.21
14	HEWLETT PACKD	HPQ	NYSE	92,216,931	232,745	52	0.35	0.72	−0.48	−1.04
15	GOLDMAN SACHS	GS	NYSE	85,970,624	502,355	29	−0.27	−0.55	−0.66	−1.58
16	BERKSHIRE HAT	BRK.B	NYSE	83,138,078	220,610	48	0.67	1.60	−0.01	−0.02
17	AMAZON COM	AMZN	NSADAQ	80,790,660	407,932	35	−0.56	−1.27	−0.96	−3.86
18	QUALCOMM	QCOM	NSADAQ	80,060,619	128,024	30	0.70	1.72	0.86	2.58
19	FORD MOTOR	F	NYSE	57,116,275	859,607	33	0.52	1.14	−0.36	−0.75
20	E M C CORP MA	EMC	NYSE	47,183,067	139,909	33	0.79	2.15	0.83	2.38
21	B P PLC	BP	NYSE	39,152,728	336,553	27	−0.35	−0.73	0.43	0.92
22	AIG	AIG	NYSE	38,728,590	413,200	28	0.43	0.92	0.37	0.78
23	HALLIBURTON	HAL	NYSE	37,136,315	2,413,227	29	0.19	0.39	0.50	1.11
24	GOLDCORP	GG	NYSE	36,688,085	180,023	41	0.72	1.8	0.95	3.76
25	EBAY	EBAY	NSADAQ	36,283,056	211,645	36	0.06	0.12	−0.68	−1.65
26	TIME WARNER	TWX	NYSE	35,686,082	39,659	32	0.39	0.83	0.82	2.31
27	LAS VEGAS SNDS	LVS	NYSE	31,463,344	409,053	28	0.76	2.00	0.63	1.50
28	RESEARCH IN MO	RIMM	NSADAQ	30,385,946	595,389	30	−0.19	−0.37	−0.83	−2.36
29	CORNING INC	GLW	NYSE	30,194,821	217,096	35	0.85	2.48	0.92	3.18
30	NEWMONT MING	NEM	NYSE	29,867,143	327,053	60	0.76	1.97	0.95	3.62
31	DELL INC	DELL	NSADAQ	26,151,500	105,463	38	0.07	0.14	−0.41	−0.88
32	BAIDU INC	BIDU	NSADAQ	25,781,328	300,681	24	0.15	0.31	0.08	0.16
33	YAHOO INC	YHOO	NSADAQ	21,677,203	441,961	27	0.53	1.19	0.59	1.36
34	TYCO INT'L	TYC	NYSE	20,282,517	160,634	51	0.63	1.48	0.96	3.99
35	BROADCOM	BRCM	NSADAQ	19,880,574	70,970	33	0.26	0.54	−0.19	−0.38
36	PRICELINE COM	PCLN	NSADAQ	19,616,306	73,640	19	0.59	1.35	0.60	1.39
37	JUNIPER NETWK	JNPR	NYSE	19,316,616	32,347	33	0.51	1.14	0.10	0.19
38	APPLD MATRIAL	AMAT	NSADAQ	18,771,755	43,029	33	0.56	1.27	−0.26	−0.54
39	CHESAPEAKE EN	CHK	NYSE	16,942,937	302,970	36	0.80	2.18	0.90	2.95
40	SANDISK CORP	SNDK	NSADAQ	11,692,319	373,832	33	0.58	1.34	0.85	2.51
41	FIRST SOLAR INC	FSLR	NSADAQ	11,155,600	194,829	29	−0.19	−0.37	−0.65	−1.55
42	NETFLIX INC	NFLX	NSADAQ	9,181,554	129,449	33	0.13	0.27	0.62	1.45
43	NVIDIA CORP	NVDA	NSADAQ	8,947,399	203,984	32	0.37	0.77	0.62	1.44
44	MICRON TECH	MU	NSADAQ	7,989,893	66,343	35	0.37	0.78	0.19	0.38
45	NYSE EURONEXT	NYX	NYSE	7,824,779	241,956	30	0.76	2.00	0.81	2.26
46	NOKIA	NOK	NYSE	7,488,532	40,108	35	0.58	1.32	0.56	1.26
47	SIRIUS X M RDIO	SIRI	NSADAQ	6,399,609	2,626,948	24	0.71	1.78	0.79	2.13
48	CALPINE CORP	CPN	NYSE	5,930,030	206,376	36	0.60	1.39	0.91	3.11
49	ATMEL CORP	ATML	NSADAQ	5,646,157	63,225	49	0.55	1.25	0.41	0.88
50	ADV MICRO DEV	AMD	NYSE	5,576,821	569,772	42	0.50	1.11	0.02	0.03
51	DENDREON CORP	DNDN	NSADAQ	5,039,968	689,993	33	0.72	1.83	0.88	2.75
52	E TRADE FIN	ETFC	NSADAQ	3,531,696	889,753	30	0.84	2.45	0.77	2.03
53	J D S UNIPHASE	JDSU	NSADAQ	3,162,171	176,941	33	0.58	1.32	0.88	2.78
54	HILL ROM HLD	HRC	NYSE	2,482,475	63,529	50	0.94	3.41	−0.44	−0.95
55	BROCADE COMM	BRCD	NSADAQ	2,468,218	85,616	29	0.83	2.38	0.91	3.05
56	RAMBUS INC	RMBS	NSADAQ	2,288,209	350,408	38	0.60	1.37	0.90	2.92
57	GRAN TIERRA E	GTE	AMEX	2,073,052	213,296	29	0.58	1.33	0.87	2.70
58	DRYSHIPS	DRYS	NSADAQ	2,029,378	378,830	30	0.59	1.34	0.89	2.81
59	R F MICRO	RFMD	NSADAQ	2,011,173	103,130	38	0.57	1.29	0.39	0.82
60	CIENA CORP	CIEN	NSADAQ	1,937,399	42,027	30	0.56	1.27	0.46	1.01
61	QLOGIC CORP	QLGC	NSADAQ	1,797,720	35,069	48	0.53	1.18	0.89	2.81
62	LEVEL 3 COMM	LVLT	NSADAQ	1,635,826	153,231	39	0.67	1.64	0.74	1.92
63	OMNIVISION TEC	OVTI	NSADAQ	1,620,022	259,993	37	0.77	2.05	0.89	2.80

Appendix A (*Continued*)

No.	Company name	Ticker	Exchange	Market cap ($000)	# total messages	Average words	RVD1	RVD2	CLD1	CLD2
64	TIVO	TIVO	NSADAQ	1,010,236	201,779	37	0.45	0.96	0.81	2.28
65	IVANHOE ENRGY	IVAN	NSADAQ	909,113	111,110	36	0.55	1.24	0.81	2.25
66	L D K SOLAR	LDK	NYSE	847,489	478,585	33	0.86	2.60	0.97	4.27
67	RITE AID CORP	RAD	NYSE	787,211	96,815	41	0.66	1.59	0.60	1.37
68	SONUS NETWRK	SONS	NSADAQ	738,174	424,738	42	0.86	2.57	0.92	3.24
69	DYNEGY INC DEL	DYN	NYSE	679,491	86,134	47	0.89	2.80	0.76	1.99
70	GERON CORP	GERN	NSADAQ	635,946	451,896	39	0.83	2.37	0.97	4.09
71	INTERNET CAPTL	ICGE	NSADAQ	522,519	28,446	50	0.51	1.13	0.21	0.42
72	AVANIR PHARM	AVNR	NSADAQ	493,606	140,269	35	0.77	2.04	0.33	0.68
73	INTERNAP NTWK	INAP	NSADAQ	315,600	176,234	37	0.82	2.29	0.83	2.36
74	INFOSPACE	INSP	NSADAQ	299,928	90,508	31	0.80	2.21	0.51	1.12
75	CELL THERAPE	CTIC	NSADAQ	297,395	446,725	26	0.81	2.27	0.88	2.74
76	TASER INT'L	TASR	NSADAQ	294,281	369,845	36	0.62	1.45	0.83	2.35
77	MODUSLINK GLB	MLNK	NSADAQ	293,354	134,791	29	0.59	1.35	0.56	1.27
78	ZIX CORP	ZIXI	NSADAQ	276,234	89,784	40	0.80	2.21	0.46	1.00
79	N V E CORP	NVEC	NSADAQ	271,858	126,740	35	0.70	1.72	0.24	0.49
80	NOVAVAX	NVAX	NSADAQ	269,975	401,184	35	0.78	2.09	0.89	2.87
81	QIAO XING U TEL	XING	NSADAQ	263,116	168,246	35	0.79	2.13	0.93	3.27
82	ENERGY CONV	ENER	NSADAQ	229,245	208,370	62	0.79	2.17	0.96	3.84
83	OPENWAVE SYS	OPWV	NSADAQ	178,781	69,725	37	0.69	1.69	0.88	2.73
84	Y R C WORLD	YRCW	NSADAQ	176,874	272,124	28	0.60	1.39	0.22	0.44
85	STEMCELLS	STEM	NSADAQ	137,192	129,261	32	0.81	2.23	0.89	2.86
86	DRDGOLD LTD	DROOY	NSADAQ	108,006	111,002	49	0.71	1.78	0.56	1.27
87	AASTROM BIO	ASTM	NSADAQ	98,856	217,854	35	0.88	2.74	0.90	2.94
88	INSMED INC	INSM	NSADAQ	82,222	332,869	35	0.90	2.91	0.90	2.95
89	APPLIED ENERER	AERG	NSADAQ	77,419	180,105	77	0.85	2.51	0.82	2.34
90	BEACON POWER	BCON	NSADAQ	43,996	603,484	27	0.75	1.97	0.85	2.51
91	FONAR CORP	FONR	NSADAQ	6678	88,526	40	0.59	1.36	−0.49	−1.06

Appendix B. Examples of the posted message

AUTHOR:::chkprof
Title:::Re: Lost $10K in After Hours
Cdate:::22-Oct-08 12:09 am
Firm:::Apple Inc. (AAPL)
Contents:::Thats funny! You have good humor man. Hope you get back some of your money. I am down $160K in two months after being up $84K on Dec 29, 2007 – which means I am down close to $240,000 – haeart burns.
Sentiment:::None
Charic:::44/Male/Austin, TX

Author:::killerwave2
Title:::Apple store is packed with shoppers buying
Cdate:::22-Oct-08 12:09 am
Firm:::Apple Inc. (AAPL)
Contents:::Great time to buy Apple.
Recession? There is no stinking recession. Only for lame companies with zero growth and zero demand.
Not apple. iphone, ipods, macbooks. load up, 135 here we come.
Sentiment:::Strong Buy
Charic:::32/Kona, HI

Author:::captiva_sun..
Title:::Re: if you think guidance is a problem, munster calls it comical and impossible guidance
Cdate:::22-Oct-08 12:08 am
Firm:::Apple Inc. (AAPL)
Contents:::Its people like you and posts like this that confirm the market is headed much lower. Still livin in the past and thinking AAPL will rule the world forever. You wouldn't be supporting Obama would you?
Sentiment:::None
Charic:::Male

Author:::bottleofbad
Title:::Re: Lost $10K in After Hours
Cdate:::22-Oct-08 12:08 am
Firm:::Apple Inc. (AAPL)
Contents:::Shorting at its best helps to price companies properly. Just as bubbles happen on the long side sometimes shorting can go too far and make companies fail but that is very very rare.
Sentiment:::Strong Sell
Charic:::26/HI

Appendix C. Supplementary data

Supplementary tables associated with this article can be found, in the online version, at http://dx.doi.org/10.1016/j.jebo.2014.04.015.

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