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SENTIMENT, CONVERGENCE OF OPINION, AND MARKET CRASH

By

Qingwei Wang

Division of Financial Studies

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Bangor Business School
Bangor University
Hen Goleg
College Road
Bangor
Gwynedd LL57 2DG
United Kingdom
Tel: +44 (0) 1248 382277
E-mail: business@bangor.ac.uk

Sentiment, Convergence of Opinion, and Market Crash*

Qingwei Wang*

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Abstract

I introduce a novel proxy of investor sentiment and differences of opinion among trend-chasing investors to forecast skewness in daily aggregate stock market returns. The new proxy is an easy-to-construct, real time measure available at different frequencies for more than a century. Empirically I find that negative skewness is most pronounced when investors have experienced high sentiment. The role of differences of opinion depends on the states of average investor sentiment: it positively forecasts market skewness in an optimistic state, but negatively forecasts it in a pessimistic state. Conceptually, I provide an explanation for the role of differences of opinion based on the theory of Abreu and Brunnermeier (2003). I argue that convergence of opinion in an optimistic state indicates that the price run-up is unlikely to be sustained since fewer investors can remain net buyers in the future. Therefore rational arbitrageurs coordinate their attack on the bubble, leading to a market crash. Vice versa, the convergence of opinion in a pessimistic state promotes coordinated purchases among rational arbitrageurs, leading to a strong recovery.

Keywords: investor sentiment, differences of opinion, technical trading, skewness, stock market crash.

JEL Classification: G01, G12, G14

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*Bangor Business School and Centre for European Economic Research (ZEW), Hen Goleg, College Road, Bangor LL57 2DG, United Kingdom. Tel: +44 (0) 1248 382277. E-mail: q.wang@bangor.ac.uk

"When everyone thinks alike, everyone is likely to be wrong"

Neill (1997)

1 Introduction

Asymmetry is prevalent in stock returns. In particular, market returns "go up by the stairs and down by the elevator". This phenomena mirrors the empirical evidence of negative skewness, which is often taken as a measure of crash risk for the aggregate stock market [e.g., Chen, Hong, and Stein (2001), Hong and Stein (2003)]. Several theories have been proposed to explain the economic mechanism underlying the observed skewness. Most of the empirical literature, however, is unable to establish these economic links for the aggregate market return.

In this paper I study the role of investor sentiment and differences of opinion in forecasting skewness in the aggregate daily stock market returns. Motivated by experimental, empirical, and survey evidence that investors chase the trend,[1] I derive both measures of investor sentiment and differences of opinion from forecasts of a spectrum of commonly used trend following trading strategies. I find that negative (positive) skewness is most pronounced when investors have experienced high (low) sentiment. The role of differences of opinion depends on the states of average investor sentiment: when trend-chasing investors are on average pessimistic, differences of opinion negatively forecast market skewness; when they are on average optimistic, differences of opinion positively forecast market skewness. These results hold regardless of whether or not investors are allowed to learn and select desired trading strategies based on various measures of past performance.

Why investor sentiment? Our history has witnessed investor manias during famous bubbles, such as the Tulip mania and the South Sea Company bubble, which were followed by a crash. The notion of "Irrational Exuberance" in Shiller (2005) suggests that investors are inspired by past performances of stock market and become more optimistic, bidding up prices further. As the price

[1] See Andreassen and Kraus (1988), Hommes, Sonnemans, Tuinstra, and Van de Velden (2005), and Haruvy, Lahav, and Noussair (2007) for examples of experimental evidence, and Frankel and Froot (1988), Taylor and Allen (1992) and Gehrig and Menkhoff (2004) for survey evidence. Griffin, Harris, and Topaloglu (2006) show that the actual trades of day traders follow the trend.

cannot deviate too much from the fundamental, this eventually leads to a crash. Therefore, one would expect that high investor sentiment predicts a subsequent crash, which is confirmed by my findings.

The role of differences of opinion for skewness of market return is much more controversial. Theoretical model of Hong and Stein (2003) predict that disagreement intensity decreases subsequent skewness, while Xu (2007) predicts that it increases contemporaneous skewness. Empirical studies fail to find that detrended turnover, a proxy for differences of opinion, forecasts market skewness. Unlike those studies, I focus on differences of opinion among trend-chasing investors and examine its implication for market skewness. To this end, I construct a new measure of differences of opinion from the forecasts of trend-following trading strategies. Furthermore, I conjecture that the role of differences of opinion can change in different regimes of average investor sentiment. Intuitively, a situation in which almost everyone believes the market will go down has conceivably different implications for the market movement than a situation in which almost everyone believes the market will go up, although the differences of opinion are very low in both cases. My empirical evidence supports this conjecture.

What explains the distinct role of disagreement across sentiment regimes? I argue that differences of opinion resemble the sustainability of bubbles/market downturn, facilitating the coordination among rational arbitragers. Two key ingredients underlie this argument: limited wealth or margin restriction of investors and the synchronization problem of rational arbitragers. Investors usually have limited wealth or margin restrictions and cannot buy/sell without limitations. They hold one of the following beliefs: bearish, bullish, or neutral, which can be changed when observing new price information. Arbitragers can attack a bubble, but they have difficulty in temporally coordinating their strategies since they do not know when others will attack. Bubbles persist due to this synchronization problem [Abreu and Brunnermeier (2003)]. I augment this theory with heterogeneous beliefs among trend-chasing investors. I argue that convergence of opinions among trend-chasing investors can help rational arbitrageurs to coordinate their actions. The intuition is the following: when almost everyone is optimistic, the average belief is positive and the dispersion of beliefs is very small. Since the investors who became optimistic at an early stage have fully invested during a bubble, fewer investors can continue to buy. A bubble is therefore unlikely to be sustained. Understanding the absence of further momentum, and understanding that other rational arbitragers are likely to perceive it in a similar way, rational arbitragers can coordinate their attack on the bubble. If they do, a market crash is expected. On the other hand, when the average belief is positive, a high dispersion of beliefs implies that many trend-following investors have neutral or bearish beliefs, which can become bullish to fuel the rally when the price continues to increase. Therefore, the bubble can be sustained, and rational arbitragers are likely to choose to ride the bubble. Similarly, the convergence of opinion in the low sentiment period indicates that the market downturn is unlikely to be sustained, so the rational arbitragers coordinate to buy. As a result, a strong rebound is expected.

Constructing a sentiment indicator from forecasts of trend-following strategies deserves a more in-depth explanation. First, forecasts of trend-following trading strategies are widely held as deviations from fundamentals. Theoretical papers often take technical analysis as an example of investor sentiment [e.g., Shleifer and Summers (1990)]. Empirically, although earlier studies often report significant profitability by applying technical analysis, recent studies show that little profitability remains once the data snooping bias is controlled for [e.g., Sullivan, Timmermann, and White (1999)]. It is therefore appealing that forecasts of trend-following trading strategies represent investor sentiment rather than changes in fundamentals. I empirically validate this conjecture by showing significant correlations between trend-chasing sentiment and other common proxies of investor sentiment. Second, forecasts of trend-following trading strategies capture the sentiment of a wide range of people, such as technical analysts, investors who pick their stocks according to the recommendation of newsletters[2], or investors who entrust their money to other trend-followers.

The new proxy of investor sentiment and disagreement is an easy-to-construct, real-time measure, which is available at different frequencies for more than a century. It enables me to study interesting episodes, such as the Roaring Twenties and the Great Depression, whereas other commonly-used proxies, such as closed-end fund discounts are available only since the 1960s. It can be potentially useful for testing models of investor sentiment and differences of opinion for various asset markets as well as other countries, especially when other proxies are sparse.

[2] In his interview with Forbes, the editor of Investor's Intelligence stated that: "Most [newsletters] are trend followers...". See Forbes.com, March 19, 2002.

The rest of this paper is structured as follows. Section 2 contains a brief overview of the literature. Section 3 presents the data and the universe of trading strategies. Section 4 discusses empirical results on the forecasting ability of sentiment and differences of opinion. Section 5 concludes.

2 Literature

A number of theories have been proposed within a representative agent framework to explain negative skewness in aggregate stock market returns. Early models include the leverage effect, the volatility feedback effect and the stochastic bubble. The leverage effect [Black (1976) and Christie (1982)] suggests that the financial and operating leverage of the firm rises when its stock price drops, followed by an increase in subsequent stock return volatility. When the stock price increases, however, the return volatility is reduced due to a decline in the leverage. The asymmetric response of volatility to change in return renders negative skewness. Alternative theories by Pindyck (1984), French, Schwert, and Stambaugh (1987), and Campbell and Hentschel (1992) propose a volatility feedback effect by relating volatility and risk premium to the arrival of either good or bad news. Both good news and bad news increase volatility, and hence the risk premium. However, the risk premium offsets good news while amplifying bad news, resulting in a deeper drop at the arrival of bad news than of good news. The stochastic bubble theory by Blanchard and Watson (1982) postulates that negative skewness arises from the popping of bubbles, a rare event that leads to very large negative returns.

Hong and Stein (2003) deviate from the previous models by incorporating heterogeneity among agents. They explain skewness through the revelation of bad news hidden by short-sales constraints when investors hold different opinions. Since the higher the dispersion of beliefs, the higher trading volume will be, this model implies that trading volume negatively forecasts skewness. Xu (2007) adopts a similar framework, but investors disagree on the precision of a publicly observed signal. He shows that the equilibrium asset price is a convex function of the signal, due to the different information sensitivity of high and low precision investors. The model predicts that disagreement intensity increases contemporaneous skewness.

The empirical literature, however, is unable to establish these links for the aggregate market return. For example, Chen et al. (2001), Hueng and McDonald (2005), and Charoenrook and Daouk (2008) do not find that detrended turnover forecasts market skewness.[3] Chen et al. (2001) and Xu (2007) find a negative relationship between skewness and past returns, which is consistent with the stochastic bubble theory of Blanchard and Watson (1982) and the price convexity theory of Xu (2007). However, Charoenrook and Daouk (2008) find returns are more negatively skewed following an increase in stock prices and are more positively skewed following a decrease in stock prices. They argue that these findings cannot be coherently explained by leverage effect and volatility feedback effect theories, which predict more negatively skewed returns following a stock price decline; this is only partly consistent with the stochastic bubble theory, which predicts more negatively skewed returns following a period of stock price increase.

This paper relates to the literature on the asset pricing implications of investor sentiment. Empirical studies have examined the role of investor sentiment for near-term and long-term returns, volatility and trading volume. One challenge of these studies arises from the difficulty of measuring sentiment. As a belief unjustified by fundamentals, sentiment is usually not directly observable. Existing literature has relied on proxies such as closed-end fund discounts [Lee, Shleifer, and Thaler (1991)], consumer confidence index [Lemmon and Portniaguina (2006) and Qiu and Welch (2006)]. Other papers call for the use of investor survey as a direct measure [see Brown and Cliff (2005), Qiu and Welch (2006)]. Unlike those papers, this paper constructs a novel sentiment indicator from forecasts of popular technical trading rules. The advantage of using trend-following forecasts lies in its clear interpretation as an example of demand shift without a fundamental rationalization. Furthermore, it can be simulated as long as the past asset price information is available, and thus has the potential to expand investor sentiment data to a longer history and more countries.

This paper can also be viewed as an empirical test for the economic impact of technical trading. Technical analysis attempts to use past prices and perhaps other related summary statistics to forecast price movements in order to make investment decisions. It has enjoyed wide popularity among traders for a long time. Existing literature on technical analysis focuses almost exclusively on the

[3] Chen et al. (2001) and Charoenrook and Daouk (2008) find that detrended turnover forecasts conditional skewness of individual stocks.

profitability of various trading rules and the implications for market efficiency. In contrast, I focus on how technical trading can be related to skewness of aggregate stock return, which has not yet been studied empirically in the literature.[4]

3 Data

I consider three samples in this paper. The baseline sample is the Dow Jones Industry Average (DJIA) between January 1952 and December 2008. The DJIA is available for a longer sample period. However, to construct a refined sentiment index (which is explained below), the daily federal fund rate is needed to obtain the excess return. As it has only been available since 1952, it puts constraint on the length of the baseline sample. To examine the robustness of the emprical findings, DJIA (1900-1951) is used as a "hold-out" sample, although the refined sentiment indicator is not considered. For an additional out-of-sample test, I conduct the same analysis on the S&P 500 index between 1964 and 2008. Both the DJIA (1952-2008) and the S&P 500 index are obtained from Datastream. The DJIA (1900-1951) is downloaded from http://www.analyzeindices.com/dow-jones-history.shtml. The daily federal funds rate is from the Federal Reserve Bank.

Dependent Variables

I use the "coefficient of skewness" as my baseline measure of skewness. It is calculated using the daily return from $t+1$ to $t+h$ as follows:

$$SKEWNESS = \frac{\frac{1}{h}\sum_{i=t+1}^{t+h}(r_i - \overline{r})^3}{\left(\frac{1}{h}\sum_{i=t+1}^{t+h}(r_i - \overline{r})^2\right)^{3/2}} \tag{1}$$

where h is the number of observations during this period, r_i is the daily return at time i, and $\overline{r}$ is the average daily return over this period. Note that a large negative value of SKEWNESS corresponds to a left skewed distribution, indicating that market return during this period is more "crash prone".

[4] A notable exception is Brunnermeier, Nagel, and Pedersen (2008), who argue that negative skewness in the currency market is due to a sudden unwinding of carry trades. Nagel (2004) also studies the impact of trading strategies, though his focus is on trading volume.

Following Chen et al. (2001), I use an alternative measure of asymmetry of stock returns, denoted as DUVOL for "down-to-up volatility". To calculate DUVOL from time $t+1$ to $t+h$, I first obtain the average return for this period. Then I separate the days during this period into a group whose daily return is above the average return (up days) and a group whose daily return is below the average returns (down days). DUVOL is then computed as the log of the ratio of the standard deviation on the down days to the one on the up days:

$$DUVOL = log\left\{\frac{(n_u - 1)\sum_{DOWN}(r_i - \overline{r})^2}{(n_d - 1)\sum_{UP}(r_i - \overline{r})^2}\right\} \tag{2}$$

where n_u and n_d are the number of days in up days group and down days group. The use of DUVOL is motivated by the concern that, for a relatively small sample, the calculation of SKEWNESS above is prone to estimation errors from calculating third moments. DUVOL, on the other hand, involves only the estimation of second moments, which therefore mitigates this concern.

Throughout this paper, I consider predicting skewness or DUVOL over 30 days horizon unless otherwise stated. Admittedly, the choice of this particular forecast horizon is somewhat arbitrary. It rather reflects an attempt to balance two considerations: on the one hand, shorter horizon is in principle deemed more interesting [Chen et al. (2001)]; on the other hand, estimation of skewness variables over such a horizon invites estimation errors. Table I shows that the average skewness (DUVOL) over 30 days of daily returns is slightly positive (negative). Their standard deviations are usually high relative the mean, indicating high variations over time. Also, SKEWNESS and DUVOL are notably highly correlated with a negative coefficient of -95%, as shown in Table II. This result is similar to the findings in Chen et al. (2001). Table II also shows that Skewness is negatively correlated with the return over the past 30 days. Taken at face value, it suggests that a smaller skewness follows a higher past return, which is consistent with the stochastic bubble theory of Blanchard and Watson (1982) and the price convexity theory of Xu (2007).

[Insert Table II about here]

Sentiment and Disagreement

I construct new measures of investor sentiment and differences of opinion from a spectrum of trading strategies. Admittedly, the choice of the universe of trading strategies is to some extent at the disposal of the researchers. To avoid the concern that the empirical results are driven by choosing a desired trading universe, I simply use the same universe of trading rules as in Qi and Wu (2006), which nests nearly all the trading rules studied in the top three finance journals. These trading rules have been in use for a long time, and are used in current financial web sites such as Yahoo Finance. They also enjoy wide popularity among the finance media such as the Wall Street Journal and the Financial Times.

More specifically, the trading rule universe includes Filter Rules, Moving Average, Trading Range Break (or Support and Resistance) Rules, and Channel Breakout Rules. As is common in the technical analysis literature, all these trading strategies generate one of the three trading recommendations, which assumes a value of 1 (buy signal), 0 (no position recommended), or -1 (sell signal). These strategies have been used for a long time, and have frequently been studied in the literature[5]. The total number of strategies I consider is 2127. The definitions of these trading strategies follow Sullivan et al. (1999) and Qi and Wu (2006). Detailed description of the trading strategies and their parameters is provided in the appendix.

I consider two ways of constructing the measures of investor sentiment and differences of opinion. The first one, denoted as “SENTIMENT” throughout the paper, is a simple average of forecasts from all the trading strategies at each time t. This amounts to assigning an equal weight to each trading strategy, without taking its past performance into account. Similarly, “DISAGREEMENT” is obtained as the standard deviation (a common measure of differences of opinion in the literature) of the forecasts from all the trading strategies. Alternatively, to capture the idea that better performing strategies are more likely to be used, I construct a refined indicator of sentiment and differences of opinion, which weights the trading signals according to the past performance of the corresponding strategy. More concretely, for each time t, the weight for each trading strategy with a positive mean excess return (over the daily federal fund rate) in the evaluation period

[5]More discussions of these trading strategies can be found in Sullivan et al. (1999)

equals the proportion of the mean excess return relative to the sum of mean excess returns from all these profitable strategies. The unprofitable strategies during the two-year evaluation period are weighted with zero. I use "SENTIMENT_W" hereafter to denote the sentiment weighted by two-year mean excess returns. "DISAGREEMENT_W" is analogously defined.

An inspection of Table I shows that the mean of SENTIMENT and the SENTIMENT_W are both positive[6], indicating that the forecasts from trend-following strategies are on average optimistic. The correlation between SENTIMENT and SENTIMENT_W is as high as 73%. Both SENTIMENT and SENTIMENT_W are highly correlated with the skewness variables, with an absolute value of correlation coefficient larger than 25%. DISAGREEMENT and DISAGREEMENT_W, on the other hand, have much lower correlations with the skewness variables. Note that trend chasing strategies are likely to have positive signals if past returns increase. Therefore one would expect SENTIMENT and SENTIMENT_W to be positively correlated with the past 30 days of return. I find a correlation coefficient of 71% and 52%, respectively. This strongly suggests a need to control for the past returns if one wants to isolate the effects of sentiment and disagreement beyond the past returns.

Validation of Sentiment Indicator

To validate the new investor sentiment indicator, I provide its pairwise correlation with other commonly used proxies for investor sentiment. These sentiment proxies include lagged value-weighted dividend premium, IPO volume, lagged first-day return on IPOs, lagged NYSE turnover from NYSE Factbook, closed-end fund discount, and new issued debt and equity. Baker and Wurgler (2007) provide detailed descriptions and discussions of these variables.[7] These sentiment indicators are at monthly frequency and available since the 1950s or the 1960s till 12/2005. I also consider the top-down sentiment index of Baker and Wurgler (2007) based on first principal component of above six (standardized) sentiment proxies over 1962-2005 data. In addition, I include the monthly Consumer Confidence Index between Jan. 1978 and Dec. 2008, which

[6]Note that performance-weighted forecasts are rescaled by 1000 times to facilitate reporting coefficients in the regression studies.

[7]I thank Jeffrey Wurgler for providing these data at his web page.

is obtained from the Michigan Consumer Research Center, and a weekly Bull-Bear spread from Lowerrisk.com. Consumer confidence index has been considered as a sentiment indicator by Lemmon and Portniaguina (2006) and Qiu and Welch (2006), among others. The Bull-Bear spread is calculated as the difference between the proportion of investors holding bullish opinion and the proportion of investors holding bearish opinions. It is based on the weekly investor sentiment data from an online survey conducted by Lowerrisk.com from May, 1997 to July, 2006. To calculate the correlation with other monthly sentiment indicators, I consider the third version of the new sentiment index, "SENTIMENT_AVG", which is the monthly average of daily SENTIMENT. As other sentiment variables, except the Bull-Bear spread, are in monthly frequency, both SENTIMENT and SENTIMENT_W are taken at the end of the month.[8] In order to obtain the correlation with the Bull-Bear spread, both SENTIMENT and SENTIMENT_W are taken on the same day as the survey day.

[Insert Table III about here]

4 Empirical Results

In this section I examine the role of the investor sentiment and differences of opinion in forecasting skewness of market return. I start with a sorting-based approach, which examines the skewness in different quintiles of sentiment and disagreement. Then I proceed with a regression-based analysis to account for potential effects from control variables. The empirical results are better explained when results from both approaches are taken together.

[8]Similar correlations are obtained when SENTIMENT and SENTIMENT_W are taken at the beginning of the month.

4.1 Skewness in Different Quintiles of Sentiment and Disagreement

I use $Skew_t^{t+h}$ to denote SKEWNESS or DUVOL of DJIA calculated from daily returns from t to $t+h$ (see Equation 1 and 2). I sort $Skew_t^{t+h}$ by SENTIMENT at time t into quintiles of equal number of observations, with quintile 1 as the lowest quintile and quintile 5 as the highest quintile. For each quintile, the mean of $Skew_t^{t+h}$ within the quintile is reported. I also report a "t" statistic obtained from testing whether mean $Skew_t^{t+h}$ equals zero. A similar sorting procedure is applied to DISAGREEMENT, and the corresponding mean of $Skew_t^{t+h}$ and t-statistics are calculated.

[Insert Table IV about here]

Table IV reports the results for $Skew_t^{t+h}$ of 30 days and 60 days of the baseline sample (DJIA, 1952-2008).[9] Panel A indicates that as the SENTIMENT becomes larger, the SKEWNESS declines uniformly, suggesting that the higher the sentiment, the more likely the crash will be. When the investor sentiment is in the highest quintile (quintile 5), the average 30 days skewness is -0.17, about twenty times higher in absolute value than the unconditional skewness (0.009 in Table I). An increase in DISAGREEMENT in Panel B corresponds to a rise of SKEWNESS. Notably, when DISAGREEMENT is in the lowest quintile, the average SKEWNESS is much lower than the other four quintiles, showing higher crash risk. Similar results are obtained for DUVOL with an expected reverse pattern.

The monotonic relationship between skewness and disagreement obscures the possible role of the investor sentiment. Differences of opinion are very low both in the very high sentiment period and very low sentiment period. Intuitively, however, a situation with almost everyone believes the market will go up has considerable different implication than a situation that almost everyone believes the market will go down. Motivated by this intuition, I report the mean skewness and the t-value when the SENTIMENT is above zero (optimistic state) or below zero (pessimistic state).

[9] Similar results can be found for the SKEWNESS/DUVOL for other length of trading days, and for the other two samples: DJIA (1900-1951) and S&P 500 (1964-2008).

[Insert Table V about here]

Table V reveals an interesting pattern. When trend-following investors are on average pessimistic (Panel A), an increase in DISAGREEMENT is associated with a monotonic decline in SKEWNESS, indicating that the lower the disagreement, the more likely a large rebound will occur. The positive SKEWNESS is particularly pronounced in the lowest quintile, with a value of 0.38, i.e., more than forty times higher than the unconditional skewness of 0.009 in Table I. When trend-chasing investors are on average optimistic (Panel B), DISAGREEMENT is in general positively(negatively) associated with the SKEWNESS (DUVOL), which is just the opposite from the results in Panel A. Relative to the unconditional skewness, the large negative average skewness of -0.19 at the lowest quintile indicates that the crash risk is very high when the disagreement is extremely low. These results suggest that a convergence of opinion is likely to be associated with a crash in optimistic states. Nevertheless, these results are still descriptive and ignore other potential predictors of skewness. Therefore, I now turn to regression analysis for a more rigorous investigation.

4.2 Regression Analysis

Similar to Chen et al. (2001), and Charoenrook and Daouk (2008), I use standard predictive regressions to investigate the role of the sentiment and differences of opinion for forecasting skewness of subsequent market returns. It takes the following form:

$$Skew_t^{t+h} = \beta_0 + \beta_1' X_t + \beta_2' Z_t + \epsilon_t^{t+h}, \tag{3}$$

where z_t is either a measure of investor sentiment or differences of opinion or both. X_t contains a vector of control variables similar to Chen et al. (2001), such as past returns and volatility of past returns.

Due to overlapping observations of the dependent variable, this approach is plagued by econometric problems of serial correlation in the residuals. I adjust the p-value using Newey-West standard errors [Newey and West (1987)], which are robust against heteroscedasticity and serial correlation. I also consider a moving block bootstrap methodology, which is particularly suitable in a setting with highly dependent data. The consistency of the MBB standard error estimator has recently been proven by Goncalves and White (2005). MBB is a (non-parametric) bootstrap which draws blocks of re-sampled observations randomly with replacement from the time series of original observations, where the block length can be fixed or data-driven.[10] The results are similar when using different standard errors, so I only report Newey-West standard errors for the sake of brevity.

Another potential concern is whether the dependent variables, the sentiment, and disagreement variables contain a unit root. I provide the unit root test results for a forecasting horizon of 30 days[11] in table VI for the baseline sample. Three unit root tests have been conducted: the Augmented Dickey-Fuller test, the Phillips-Perron test, and the DF-GLS test, which performs a modified Dickey-Fuller t test for a unit root in which the series has been transformed by a generalized least-squares regression. All tests reject the existence of a unit root at the 1% level. The results for the other two samples are qualitatively similar.

[Insert Table VI about here]

Baseline Estimation Results

In the baseline estimation, I forecast *Skew* over thirty days' with daily regressions for the baseline sample (DJIA 1952-2008). In the regressions reported by Table VII, I consider three sentiment states. "Both" indicates that the whole sample is used for regression, while "Pessimistic"/"Optimistic" indicates that only the observations with "SENTIMENT" below/above zero are considered. The first and fourth columns of Panel A indicate that the investor sentiment has a strong forecasting ability for the skewness for both specifications, with a negative sign and significant at the 1% level.

[10]As recommended by Goncalves and White (2005), I use a data-driven block length, following the procedure by Andrews (1991).

[11]Unit root tests become less significant as the forecasting horizon grows. Still, no unit root can be detected for the horizons we considered (up to 360 days).

The higher the trend-following investor sentiment, the lower skewness will be, showing a higher crash risk. Disagreement, however, does not have a significant incremental predictive power for future skewness beyond sentiment when both sentiment states are considered together. This stands in contrast to the theoretical predictions of Hong and Stein (2003), but is consistent with the empirical findings of Chen et al. (2001), Hueng and McDonald (2005), and Charoenrook and Daouk (2008), who find no significant relationship between conditional skewness of aggregate market returns and detrended turnover, a proxy for the extent of the differences of opinion.

Splitting the sample into optimistic state and pessimistic state reveals a differential predictive role of DISAGREEMENT across different sentiment states. When investors are on average pessimistic (second column in Panel A), DISAGREEMENT negatively forecasts the subsequent skewness. This result, when taken at face value, seems to support the model of Hong and Stein (2003), which predicts that higher differences of opinion are related to a higher crash risk. Recall that, however, even in the highest quintile of differences of opinion during a pessimistic state, the average skewness is positive (Table IV). Therefore a higher disagreement does not seem to predict a crash, which is by definition a large negative skewness. Instead, it is more evident that convergence of opinion is associated with a higher conditional skewness (large rebound in returns). Hence, I interpret the negative coefficient of DISAGREEMENT as evidence that convergence of opinion in a pessimistic state forecasts a large rebound.

When trend-chasing investors are on average optimistic (third column of Panel A), the coefficient of DISAGREEMENT_W becomes positive. Since in the optimistic state, the SKEWNESS is mostly negative in different quintiles (Table IV), the positive coefficient is best interpreted as lower disagreement forecasting larger negative skewness. That is, when trend-chasing investors' opinions converge in an optimistic state, it forecasts a subsequent higher crash risk. Taking the results in the optimistic state and pessimistic state together, neither Hong and Stein (2003) nor Xu (2007) explains the findings in the pessimistic and optimistic periods at the same time.

[Insert Table VII about here]

What explains the differential role of differences of opinion then? One explanation is that differences of opinion reflect the sustainability of an ongoing bubble or market downturn, which can be used by rational arbitragers to coordinate their attack at the bubble/market downturn. Consider a market with rational arbitragers similar to Abreu and Brunnermeier (2003), each of whom is small and unable to move the market alone. Arbitragers have a synchronization problem in temporarily coordinating with other rational arbitragers. For example, during a bubble period in which the average belief is usually positive, the arbitrager has the option to either ride the bubble or attack the bubble. Attacking a bubble can result in a loss if other arbitragers continue to buy. Therefore, an arbitrager's decision hinges upon her belief about what other arbitragers will do. Note also that trend-chasing investors require a different extent of price change to change their beliefs. For example, a 2% increase from a recent low in the stock price may invite a long position from one trend follower, but may not be sufficient for another investor to become bullish if she relies on at least a 3% increase to ensure her confidence in an up-trend. The later investor can become a buyer if the price continues to increase. A high dispersion of belief during an optimistic state among trend chasers implies that many trend-following investors are of more pessimistic/neutral type, but can subsequently become optimistic and then drive the price up further. The change of belief is likely to happen because a recent positive return leads to a net buy by trend followers (in line with the average optimistic sentiment), which can in turn push the price higher, causing the yet non-optimistic types to become optimistic. Therefore, a bubble is likely to be sustained when disagreement is high and trend chasers are on average optimistic. In this case, the rational arbitragers are likely to choose to ride the bubble. By contrast, there is less of a chance for the price run-up to be sustained when the dispersion of belief converges in an optimistic state. This is due to the fact that fewer trend-following investors who still hold non-optimistic beliefs can join the party, while previous optimistic investors have margin restrictions and used up their buying capacity during the bubble. Understanding this, and understanding that other rational arbitragers are likely to perceive the same way, the convergence of opinion helps arbitragers to attack the bubble jointly. As a result, the market crashes. Vice versa, the convergence of opinion in the low sentiment period indicates that the market downturn is unlikely to be sustained and that the rational arbitragers coordinate to buy, hence, a strong recovery is expected.

For the control variables, past returns in most cases do not have a significant forecasting power, which seems inconsistent with the findings in Chen et al. (2001) that negative skewness is more pronounced following positive returns. However, in untabulated regressions, once SENTIMENT and DISAGREEMENT are omitted from the regression, past returns become significant and negative predictors of future skewness. Results in Table VII suggests that much of the effect from past returns has been captured by the SENTIMENT and/or DISAGREEMENT when they are included jointly in the regressions. Lagged SKEWNESS is positive and significant, indicating persistency in the skewness. Volatility of past returns is included as in Chen et al. (2001) to address the concern that SENTIMENT or DISAGREEMENT forecasts volatility, which in turn is reflected in skewness such that we are probably forecasting volatility instead of skewness. As argued by Chen et al. (2001), past realized volatility is probably the best univariate predictor for future volatility, hence controlling for it helps to alleviate this concern. Nevertheless, the coefficient of the volatility of past returns is seldom significant.

Panel B of Table VII reports results with DUVOL as a dependent variable following Chen et al. (2001), which is calculated using daily returns over thirty trading days. They corroborate well the findings with SKEWNESS as the dependent variable. The signs of the coefficients on SENTIMENT and DISAGREEMENT are opposite to those in Panel A, which is expected since SKEWNESS and DUVOL are highly negatively correlated. The opposite sign of the coefficients on DISAGREEMENT in the second and third columns of Panel B confirms the differential role of differences of opinion across pessimistic and optimistic states.

So far I have used the whole baseline sample to investigate the role of investor sentiment and disagreement. To address the robustness of the results in different sub-samples, I have conducted a sub-sample analysis by splitting the sample into two sub-periods: before 1980 and after 1980, which divides the sample into roughly equal-sized sub-samples. I find that the results in each sub-sample are qualitatively similar to the whole sample analysis. Detailed results are not included for the sake of space, but are available from the author upon request.

Another concern that may emerge is the extreme price movement on the "Black Monday", October 19, 1987, which might dominate the findings. In an untabulated regression which excludes October 1987, I find that the results virtually do not change.

Out-of-sample Test

As argued in the introduction, this paper has introduced a new way of constructing investor sentiment and differences of opinion through commonly used technical trading rules. Since the forecasts of trading rules need only past prices as the input, it enables me to examine the roles of sentiment and disagreement in forecasting market skewness as long as market index information is available. This greatly expands the potential data for such an analysis since commonly used sentiment indicators go back only to the 1960s.

In the following, I examine the robustness of the results by conducting the same analysis on the sample of DJIA between 1900 and 1951. This sample period includes interesting episodes such as the Roaring Twenties and the Great Depression.

[Insert Table VIII about here]

Table VIII shows that the results are remarkably similar to those in Table VII. Investor sentiment negatively (positively) predicts future SKEWNESS (DUVOL). The role of differences of opinion depends on the average investor sentiment. It predicts negatively (positively) SKEWNESS (DUVOL) in a pessimistic state, but predicts positively (negatively) in an optimistic state.

Past returns occasionally have positive significant coefficients when predicting future market skewness. When both investor sentiment and differences of opinion are omitted from the regression, past returns have again negative coefficients as in Chen et al. (2001). Past volatility has a significant predictive power in all model specifications compared to the weak predictive ability in the sample of DJIA during 1952-2008. It indicates a higher crash risk when past return volatility is high. Similar findings can be found in Chen et al. (2001). Finally, the model fit reflected in Adjusted R^2 is similar to the one in Table VII, and comparable to the findings in Chen et al. (2001).

Additional out-of-sample tests have been conducted for the S&P 500 index during 1964 to 2008. DJIA is computed from the stock prices of 30 of the largest and most widely held public companies in the United States, which are presumably the most liquid stocks. It is interesting to examine whether the above results hold for S&P 500, which includes smaller firms and is hence less liquid than the DJIA.

Table IX shows that the investor sentiment continues to be a strong predictor of future return asymmetry, whose coefficient is significant at the 1% level when forecasting either SKEWNESS or DUVOL. The predictive ability of DISAGREEMENT, on the other hand, becomes quite weak. Nevertheless, the direction of predictive ability of DISAGREEMENT remains the same as before, despite less statistical significance in its coefficients. That is, it negatively (positively) predicts SKEWNESS (DUVOL) in a pessimistic state, and positively (negatively) predicts SKEWNESS (DUVOL) in an optimistic state. Note that the forecasting horizon is 30 days. When the forecasting horizon is extended to 60 days, 90 days or 120 days, DISAGREEMENT regains its significance, . Given the fact theoretical models do not provide guidance for the exact choice of the forecasting horizon, and the observation that the signs of the coefficients are the same for 30 days and longer forecasting horizons, I conclude that the results based on S&P 500 are consistent with the findings based on DJIA. Nevertheless I report only results for a forecasting horizon of 30 days in the paper for the consistency of exposition. Results for other forecasting horizons are available from the author upon request.

[Insert Table IX about here]

Monthly regressions

The above regressions are conducted at a daily frequency. This has the advantage of improving the statistical significance due to the large number of observations. Furthermore, investors are unlikely to care about crash risk only once a month, rather, they get alert once they find it is likely to occur during their daily trading. Still, one may argue that daily changes have more noise, and major episodes develop over months or even years. I therefore run monthly regressions. Table X reports the results. The SENTIMENT or DISAGREEMENT is taken at the end of month, while the SKEWNESS to be forecasted is from daily returns of the next 30 days. Although the statistical significance becomes weaker, the monthly regression yields consistent results as in the daily regression, indicating that the noise in daily returns or other variables cannot be the reasons for driving the previous results.

[Insert Table X about here]

Regressions with Refined Measures of Sentiment and Disagreement

Investors are likely to engage in model selection. They can choose the models with more success in the past. Furthermore, investors who used unsuccessful trading rules can be driven out of the market or intentionally stay out of the market. This implies that better performing strategies are more likely to be used among trend-chasing investors. To capture this idea, I construct a refined indicator of sentiment and differences of opinion, which weights the trading signals according to the past performance of corresponding strategies. I examine whether the predictive role of investor sentiment and differences of opinion continue to hold for the refined measures.

Table XI and Table XII report the regression results for DJIA (1952-2008) and S&P 500 (1964-2008) respectively. The results for the DJIA (1900-1951) are not reported since the refined measure needs to calculate the excess return over daily federal fund rate, which has only been available since 1952. Still, when ignoring the federal fund rate in the calculation of excess returns, I find that the results for DJIA 1900-1951 are qualitatively similar to those for DJIA 1952-2008.

[Insert Table XI about here]

An inspection of Table XI indicates that, for the sample of DJIA 1952-2008, the role of investor sentiment is unaffected by applying the refined investor sentiment indicator (SENTIMENT_W). Its coefficient is significant at 1% level for all the specifications for whenever it is included in the regression. Refined measure of differences of opinion (DISAGREEMENT_W) predicts in the same direction as in Table VII, although in the pessimistic state the coefficient is not significant. Note that in untabulated regressions at 90 days forecasting horizon, DISAGREEMENT_W regains its statistical significance at the 1% level in the pessimistic state. For the sample of the S&P 500 between 1964 and 2008, the refined sentiment indicator has again a strong predictive power. The refined measure of differences of opinion has significant predictive power for both pessimistic and optimistic states. Taking these results together, I conclude that the regression results with refined measures of sentiment and disagreement support the major findings of this paper.

[Insert Table XII about here]

5 Conclusion

This paper provides empirical evidence that both investor sentiment and differences of opinion have a robust forecasting power for aggregate market skewness. High sentiment forecasts market crash. The role of differences of opinion depends on the status of investor sentiment. When trend-chasing investors are on average optimistic, differences of opinion negatively forecast the market skewness; when they are on average pessimistic, differences of opinion positively forecast the market skewness.

I provide an explanation for the role of differences of opinion by augmenting the theory of Abreu and Brunnermeier (2003) with heterogeneous beliefs among trend-chasing investors. I argue that convergence of opinion in an optimistic state indicates that the price run-up is unlikely to be sustained since fewer investors can remain net buyers in the future. Therefore rational arbitrageurs coordinate their attack on the bubble, leading to a market crash. Vice versa, the convergence of opinion in a pessimistic state promotes coordinated purchases among rational arbitrageurs, leading to a strong recovery. Admittedly, the explanation is tentative and informal. Therefore, it calls for a rigorous model to incorporate the states of investor sentiment into the differences of opinion framework.

The novel way of constructing trend-chasing investor sentiment and differences of opinion can be applied to various asset markets, as long as trend-chasing behavior is prevalent. It has the potential to greatly expand the availability of sentiment indicators and measures of differences of opinion to a much longer history and to countries where data on other sentiment indicators are limited. Thus, an immediate extension of this paper would be to examine whether our results hold for other asset markets, such as stock markets of other countries or foreign exchange markets. Another interesting extension would be to study how the trend-chasing investor sentiment and disagreement help explain the cross-sectional variation in individual stocks. I leave these interesting extensions to future research.

6 Tables and Figures

Table I
Summary Statistics

This table presents the summary statistics. “Return" refers to the daily gross return of DJIA (in percentage). “SD” is the realized volatility from time t to $t + 30$. “SKEWNESS” and “DUVOL" are the measures of return asymmetry calculated using the daily return from time t to $t + 30$ according to Equation 1 and 2. “Sentiment" and “Disagreement” are the (equally weighted) average and the standard deviation of the forecasts from the trading strategies for time t. “Sentiment_w” and “Disagreement_w” are the average and the standard deviation of the forecasts weighted according to the past two years excess returns. Note that performance-weighted forecasts are re-scaled by 1000 times for the ease of reporting coefficients in the regression studies.

	Return_30	SD_30	Skewness	DUVOL	Sentiment	Disagreement	Sentiment_w	Disagreement_w
Mean	0.006	0.008	0.009	-0.019	0.191	0.850	0.216	1.441
Std. Dev.	0.052	0.005	0.557	0.331	0.445	0.123	0.816	0.998
Min	-0.387	0.002	-4.372	-1.661	-0.845	0.449	-4.330	0.297
Max	0.188	0.057	3.598	2.111	0.886	0.998	3.125	12.870
Skewness	-0.917	4.475	-0.786	0.117	-0.423	-0.782	-0.475	2.939
Kurtosis	6.721	37.387	6.713	3.510	1.975	2.701	3.611	19.810

Table II
Correlation Coefficient Matrix

This table presents the correlation coefficient matrix. “Return_30” is the gross return over the period of $t-30$ to t. “SD_30” is the volatility of daily return from time $t-30$ to t. “Skewness” and “DUVOL” are the measures of return asymmetry calculated using the daily return from time t to $t + 30$ according to Equation 1 and 2. “Sentiment” and “Disagreement” is the (equally weighted) average and the standard deviation of forecast from the trading strategies for time t. “Sentiment_W” and “Disagreement_w” is the average and the standard deviation of the forecasts weighted according to the past two years excess returns. Note that performance-weighted forecasts are re-scaled by 1000 times for the ease of reporting coefficients in the regression studies.

Variables	Return_30	SD_30	Skewness	DUVOL	Sentiment	Disagreement	Sentiment_w	Disagreement_w
Return_30	1.000							
SD_30	-0.354	1.000						
Skewness	-0.137	0.061	1.000					
DUVOL	0.153	-0.078	-0.951	1.000				
Sentiment	0.707	-0.359	-0.237	0.255	1.000			
Disagreement	-0.258	0.132	0.121	-0.127	-0.429	1.000		
Sentiment_w	0.516	-0.262	-0.206	0.215	0.727	-0.276	1.000	
Disagreement_w	-0.030	-0.038	0.075	-0.072	-0.069	0.277	-0.143	1.000

Table III
Correlation with other sentiment indicators

This table presents the pairwise correlation of the sentiment index from trend-following trading strategies with other commonly used sentiment index. “pdnd_lag” is the lagged value-weighted dividend premium, “nipo” is IPO volume, “ripo_lag” is the lagged first-day return on IPOs, “turn_lag” is the lagged NYSE turnover from NYSE Factbook, “cefd” is the closed-end fund discount, and “sd”(“se”) the new issued debt (equity). These sentiment indicators are at monthly frequency and available since 1950s or 1960s till 12/2005. “sent_bw” is the Sentiment index in Baker and Wurgler (2007) based on first principal component of six (standardized) sentiment proxies over 1962-2005 data. “bbspread” is the Bull-Bear spread calculated using the weekly investor sentiment data from Lowerrisk.com (05/1997-07/2006). SENTIMENT is the (equally weighted) average of forecast from the trading strategies. “cci” is the Consumer Confidence Index obtained from the Michigan Consumer Research Center, which is available at monthly frequency since 1978. SENTIMENT_W is the average of forecast weighted according to past two years excess return. Both SENTIMENT and SENTIMENT_W are taken at the end of month. SENTIMENT_AVG is the monthly average of the daily sentiment index SENTIMENT. Spearman correlation coefficient is reported with P-value in parenthesis.

	pdnd_lag	nipo	ripo_lag	turn_lag	cefd	se	sd	sent_bw	bb_spread	cci
SENTIMENT	-0.119	0.310	0.137	0.148	-0.082	0.175	0.133	0.113	0.433	0.119
	(0.006)	(0.000)	(0.002)	(0.000)	(0.070)	(0.000)	(0.001)	0.013	(0.000)	(0.011)
SENTIMENT_W	-0.130	0.367	0.120	0.185	-0.233	0.216	0.198	0.116	0.364	0.152
	(0.002)	(0.000)	(0.007)	(0.000)	(0.000)	(0.000)	(0.000)	0.011	(0.000)	(0.001)
SENTIMENT_AVG	-0.126	0.344	0.197	0.175	-0.087	0.204	0.133	0.123	–	0.152
	(0.003)	(0.000)	(0.000)	(0.000)	(0.054)	(0.000)	(0.001)	0.007	–	(0.001)

Table IV
Breakdown by sorts of sentiment and disagreement

This table reports the break-down results for dependent variables in each quintile of SENTIMENT or DISAGREEMENT. "SKEWNESS_30" ("SKEWNESS_60") is the skewness (Equation 1) of daily return obtained from time t to $t + 30$ ($t + 60$). "DUVOL_30" ("DUVOL_60") is the DUVOL (Equation 2) of daily return obtained from time t to $t + 30$ ($t + 60$). Panel A of this table reports the average SKEWNESS or DUVOL when SENTIMENT is sorted into quintiles of equal number of observations. "t-stat" is the t-value obtained from testing whether the mean of SKEWNESS/DUVOL equals zero. Panel B reports similar results when the sorting procedure is applied to the DISAGREEMENT.

Panel A: Sort by SENTIMENT

	SKEWNESS_30		DUVOL_30		SKEWNESS_60		DUVOL_60	
Quintile	mean	t-stat	mean	t-stat	mean	t-stat	mean	t-stat
1	0.20	21.82	-0.14	-23.29	0.20	21.36	-0.13	-24.79
2	0.08	7.99	-0.06	-10.10	0.04	4.45	-0.03	-7.18
3	-0.03	-2.93	0.00	0.26	-0.08	-6.62	0.02	3.63
4	-0.11	-10.25	0.06	9.77	-0.15	-13.86	0.07	14.71
5	-0.17	-15.53	0.09	14.75	-0.30	-21.00	0.13	23.85

Panel B: Sort by DISAGREEMENT

	SKEWNESS_30		DUVOL_30		SKEWNESS_60		DUVOL_60	
Quintile	mean	t-stat	mean	t-stat	mean	t-stat	mean	t-stat
1	-0.12	-10.99	0.06	9.44	-0.25	-17.28	0.10	17.41
2	-0.03	-2.74	0.00	0.44	-0.07	-6.12	0.02	3.30
3	0.01	0.91	-0.02	-3.32	-0.02	-2.00	-0.00	-0.79
4	0.04	4.22	-0.04	-6.29	0.02	1.61	-0.02	-5.03
5	0.06	5.90	-0.05	-8.30	0.03	2.83	-0.03	-6.62

Table V
Breakdown by sorts of disagreement in different states of sentiment

This table reports the break-down results for dependent variables conditional on SENTIMENT is below zero (pessimistic state) or above zero (optimistic state). "SKEWNESS_30" ("SKEWNESS_60") is the skewness (Equation 1) of daily return obtained from time t to $t+30$ ($t+60$). "DUVOL_30" ("DUVOL_60") are the DUVOL (Equation 2) of daily return obtained from time t to $t+30$ ($t+60$). Panel A of this table reports the average SKEWNESS or DUVOL when DISAGREEMENT is sorted into quintiles of equal number of observations and when the average sentiment is pessimistic. "t-stat" is the t-value obtained from testing whether the mean of SKEWNESS/DUVOL equals zero. Panel B reports similar results when DISAGREEMENT_W is sorted into quintiles of equal number of observations and when the average sentiment is optimistic.

Panel B: Sort by DISAGREEMENT in Pessimistic State

	SKEWNESS_30		DUVOL_30		SKEWNESS_60		DUVOL_60	
Quintile	mean	t-stat	mean	t-stat	mean	t-stat	mean	t-stat
1	0.38	19.01	-0.28	-20.33	0.37	19.99	-0.24	-19.60
2	0.25	16.07	-0.18	-17.25	0.26	16.44	-0.17	-19.21
3	0.15	9.78	-0.10	-10.61	0.15	9.90	-0.10	-11.59
4	0.10	6.78	-0.06	-6.71	0.08	5.21	-0.05	-6.33
5	0.09	5.82	-0.06	-7.11	0.06	3.82	-0.05	-6.30

Panel A: Sort by DISAGREEMENT in Optimistic State

	SKEWNESS_30		DUVOL_30		SKEWNESS_60		DUVOL_60	
Quintile	mean	t-stat	mean	t-stat	mean	t-stat	mean	t-stat
1	-0.19	-16.61	0.11	16.58	-0.33	-21.58	0.15	25.75
2	-0.14	-11.30	0.07	10.64	-0.20	-14.55	0.09	15.72
3	-0.07	-4.89	0.03	3.21	-0.12	-8.47	0.05	7.91
4	0.01	0.37	-0.02	-2.59	-0.02	-1.78	-0.01	-1.10
5	0.04	2.80	-0.04	-4.81	0.01	0.36	-0.02	-3.19

Table VI
Unit Root Test

This table presents the results from unit root tests. ADF is the augmented Dickey-Fuller unit-root test, PPerron is the Phillips-Perron unit-root test that a variable has a unit root, and DF-GLS performs a modified Dickey-Fuller t test for a unit root in which the series has been transformed by a generalized least-squares regression. $***, **, *$ indicate significance at the 1%, 5%, and 10% levels.

Tests	SKEWNESS	DUVOL	SENTIMENT	DISAGREEMENT	SENTIMENT_W	DISAGREEMENT_W
ADF	-13.81***	-13.07***	-5.08***	-10.17***	-17.03***	-14.87***
Pperron	-12.50***	-11.99***	-10.82***	-16.19***	-15.64***	-11.40***
DF-GLS	-12.14***	-10.57***	-4.93***	-2.58***	-17.04***	-15.06***

Table VII
Forecasting the Aggregate Stock Market Crash (DJIA 1952-2008)

The sample period runs from January 1952 to December 2008 and is based on return on DJIA. "Both" indicates that the whole sample is used for regression, while "Pessimistic"/"Optimistic" indicates that only the observations with "SENTIMENT" below/above zero (pessimistic/optimistic state) are considered. The dependent variable is the SKEWNESS (Equation 1) or DUVOL (Equation 2) of daily returns calculated from t to $t+30$. "SENTIMENT" and "DISAGREEMENT" are the sentiment and disagreement defined as the average and the standard deviation of equally weighted forecasts without taking past performance into account. "skew_past_30" is the lagged dependent variable. "Return_120" is the gross return over the period of $t-119$ to t, and "Return_240" is the gross return over the period of $t-239$ to $t-120$. Other lagged returns are similarly defined. "realized_sd_past_30" is the lagged realized standard deviation, calculated from the daily returns between $t-29$ and t. * significant at 10%; ** significant at 5%; *** significant at 1%.

	Panel A: SKEWNESS				Panel B: DUVOL			
Sentiment State	Both	Pessimistic	Optimistic	Both	Both	Pessimistic	Optimistic	Both
SENTIMENT	-0.364***			-0.369***	0.229***			0.232***
	(0.071)			(0.072)	(0.041)			(0.043)
DISAGREEMENT		-0.956***	0.531***	-0.027		0.715***	-0.307***	0.022
		(0.272)	(0.183)	(0.137)		(0.172)	(0.106)	(0.081)
SKEW_past_30	0.124***	0.106**	0.125***	0.124***				
	(0.033)	(0.041)	(0.033)	(0.034)				
DUVOL_past_30					0.149***	0.125***	0.152***	0.149***
					(0.032)	(0.039)	(0.032)	(0.032)
Return_30	0.562	0.095	0.223	0.575	-0.340	-0.189	0.130	-0.351
	(0.510)	(0.667)	(0.649)	(0.513)	(0.313)	(0.403)	(0.381)	(0.316)
Return_60	0.707	0.908	-0.069	0.709	-0.443*	-0.454	0.025	-0.445*
	(0.477)	(0.650)	(0.466)	(0.475)	(0.259)	(0.350)	(0.265)	(0.259)
Return_90	-0.105	-0.357	-0.222	-0.103	-0.012	0.318	-0.015	-0.013
	(0.343)	(0.417)	(0.375)	(0.342)	(0.199)	(0.245)	(0.218)	(0.199)
Realized_sd_past_30	-0.594	-5.533	12.000*	-0.607	0.179	3.874	-10.612***	0.185
	(3.654)	(3.977)	(6.896)	(3.661)	(2.264)	(2.419)	(3.879)	(2.262)
Constant	0.075**	1.081***	-0.596***	0.099	-0.056**	-0.795***	0.358***	-0.076
	(0.035)	(0.250)	(0.166)	(0.126)	(0.022)	(0.157)	(0.096)	(0.074)
Adjusted R^2	0.07	0.07	0.03	0.07	0.09	0.08	0.05	0.09
N	13685	4598	9084	13685	13685	4598	9084	13685

Table VIII
Forecasting the Aggregate Stock Market Crash (DJIA 1900-1951)

The sample period runs from January 1900 to December 1951 and is based on return on DJIA. “Both” indicates that the whole sample is used for regression, while “Pessimistic”/“Optimistic” indicates that only the observations with “SENTIMENT” below/above zero (pessimistic/optimistic state) are considered. The dependent variable is the SKEWNESS (Equation 1) or DUVOL (Equation 2) of daily returns calculated from t to $t+30$. “SENTIMENT” and “DISAGREEMENT” are the sentiment and disagreement defined as the average and the standard deviation of equally weighted forecasts without taking past performance into account. “skew_past_30” is the lagged dependent variable. “Return_120” is the gross return over the period of $t-119$ to t, and “Return_240” is the gross return over the period of $t-239$ to $t-120$. Other lagged returns are similarly defined. “realized_sd_past_30” is the lagged realized standard deviation, calculated from the daily returns between $t-29$ and t. * significant at 10%; ** significant at 5%; *** significant at 1%.

	SKEWNESS				DUVOL			
Sentiment State	Both	Pessimistic	Optimistic	Both	Both	Pessimistic	Optimistic	Both
SENTIMENT	-0.343***			-0.350***	0.227***			0.231***
	(0.074)			(0.075)	(0.045)			(0.046)
DISAGREEMENT		-1.495***	0.867***	-0.116		0.908***	-0.510***	0.061
		(0.287)	(0.259)	(0.202)		(0.172)	(0.156)	(0.120)
SKEW_past_30	0.101***	0.115***	0.080***	0.100***				
	(0.026)	(0.030)	(0.030)	(0.026)				
DUVOL_past_30					0.110***	0.136***	0.075**	0.109***
					(0.026)	(0.031)	(0.030)	(0.026)
Return_30	0.138	0.742*	-0.243	0.179	-0.054	-0.418	0.282	-0.076
	(0.338)	(0.411)	(0.487)	(0.353)	(0.207)	(0.254)	(0.281)	(0.215)
Return_60	0.443*	0.972***	-0.326	0.456*	-0.312*	-0.622***	0.188	-0.318**
	(0.261)	(0.299)	(0.349)	(0.265)	(0.160)	(0.177)	(0.213)	(0.162)
Return_90	-0.110	-0.068	-0.240	-0.095	0.018	0.008	0.108	0.010
	(0.223)	(0.240)	(0.316)	(0.228)	(0.131)	(0.143)	(0.188)	(0.134)
Realized_sd_past_30	10.220***	12.138***	14.186***	10.181***	-6.036***	-6.974***	-8.959***	-6.016***
	(2.471)	(3.009)	(3.749)	(2.456)	(1.525)	(1.797)	(2.356)	(1.518)
Constant	-0.249***	1.115***	-1.085***	-0.152	0.150***	-0.690***	0.654***	0.099
	(0.036)	(0.245)	(0.219)	(0.167)	(0.022)	(0.150)	(0.131)	(0.100)
Adjusted R^2	0.07	0.06	0.04	0.07	0.08	0.07	0.04	0.08
N	15413	6753	8652	15413	15413	6753	8652	15413

Table IX
Forecasting the Aggregate Stock Market Crash (S&P 500 Index 1964-2008)

The sample period runs from January 1964 to December 2008 and is based on return on S&P 500 Index. "Both" indicates that the whole sample is used for regression, while "Pessimistic"/"Optimistic" indicates that only the observations with "SENTIMENT" below/above zero (pessimistic/optimistic state) are considered. The dependent variable is the SKEWNESS (Equation 1) or DUVOL (Equation 2) of daily returns calculated from t to $t+30$. "SENTIMENT" and "DISAGREEMENT" are the sentiment and disagreement defined as the average and the standard deviation of equally weighted forecasts without taking past performance into account. "skew_past_30" is the lagged dependent variable. "Return_120" is the gross return over the period of $t-119$ to t, and "Return_240" is the gross return over the period of $t-239$ to $t-120$. Other lagged returns are similarly defined. "realized_sd_past_30" is the lagged realized standard deviation, calculated from the daily returns between $t-29$ and t. * significant at 10%; ** significant at 5%; *** significant at 1%.

	SKEWNESS				DUVOL			
Sentiment State	Both	Pessimistic	Optimistic	Both	Both	Pessimistic	Optimistic	Both
SENTIMENT	-0.408***			-0.446***	0.225***			0.247***
	(0.084)			(0.087)	(0.051)			(0.052)
DISAGREEMENT		-0.528	0.253	-0.245		0.378*	-0.092	0.147
		(0.370)	(0.268)	(0.182)		(0.217)	(0.158)	(0.112)
SKEW_past_30	0.117***	0.188***	0.087**	0.110***				
	(0.037)	(0.045)	(0.040)	(0.038)				
DUVOL_past_30					0.140***	0.211***	0.109***	0.133***
					(0.037)	(0.046)	(0.040)	(0.038)
Return_30	0.172	-0.577	-0.312	0.236	0.080	0.446	0.508	0.044
	(0.523)	(0.684)	(0.784)	(0.524)	(0.323)	(0.405)	(0.440)	(0.322)
Return_60	0.533	0.465	0.101	0.532	-0.305	-0.205	-0.039	-0.303
	(0.535)	(0.825)	(0.513)	(0.532)	(0.286)	(0.411)	(0.295)	(0.284)
Return_90	-0.393	-0.486	-0.575	-0.392	0.217	0.304	0.330	0.216
	(0.369)	(0.577)	(0.363)	(0.368)	(0.221)	(0.329)	(0.219)	(0.220)
Realized_sd_past_30	-5.253	-7.953*	1.382	-5.539	2.976	5.667**	-3.190	3.107
	(3.720)	(4.468)	(7.577)	(3.747)	(2.391)	(2.708)	(3.929)	(2.394)
Constant	0.126***	0.703**	-0.280	0.332**	-0.085***	-0.488***	0.115	-0.208**
	(0.041)	(0.316)	(0.215)	(0.156)	(0.026)	(0.184)	(0.130)	(0.096)
Adjusted R^2	0.08	0.08	0.01	0.08	0.08	0.08	0.02	0.08
N	11212	3424	7782	11212	11212	3424	7782	11212

Table X
Forecasting the Aggregate Stock Market Crash at Monthly Frequency (DJIA 1952-2008)

The sample period runs from January 1952 to December 2008 and is based on return on DJIA. "Both" indicates that the whole sample is used for regression, while "Pessimistic"/"Optimistic" indicates that only the observations with "SENTIMENT" below/above zero (pessimistic/optimistic state) are considered. The dependent variable is the SKEWNESS (Equation 1) or DUVOL (Equation 2) of daily returns calculated from t to $t+30$. "SENTIMENT" and "DISAGREEMENT" are the sentiment and disagreement defined as the average and the standard deviation of equally weighted forecasts without taking past performance into account. "skew_past_30" is the lagged dependent variable. "Return_120" is the gross return over the period of $t-119$ to t, and "Return_240" is the gross return over the period of $t-239$ to $t-120$. Other lagged returns are similarly defined. "realized_sd_past_30" is the lagged realized standard deviation, calculated from the daily returns between $t-29$ and t. * significant at 10%; ** significant at 5%; *** significant at 1%.

	SKEWNESS				DUVOL			
Sentiment State	Both	Pessimistic	Optimistic	Both	Both	Pessimistic	Optimistic	Both
SENTIMENT	-0.349***			-0.340***	0.192***			0.192***
	(0.089)			(0.095)	(0.053)			(0.056)
DISAGREEMENT		-0.771	0.716**	0.060		0.593*	-0.371**	0.005
		(0.472)	(0.319)	(0.200)		(0.303)	(0.183)	(0.119)
SKEW_past_30	0.107**	0.073	0.116**	0.108***				
	(0.041)	(0.066)	(0.054)	(0.042)				
DUVOL_past_30					0.135***	0.106	0.141***	0.135***
					(0.041)	(0.070)	(0.052)	(0.042)
Return_30	0.414	-0.772	0.432	0.388	-0.093	0.614	0.017	-0.095
	(0.746)	(1.126)	(1.217)	(0.751)	(0.440)	(0.719)	(0.694)	(0.444)
Return_60	0.783	0.125	0.553	0.781	-0.364	0.251	-0.295	-0.364
	(0.542)	(0.809)	(0.783)	(0.542)	(0.321)	(0.517)	(0.450)	(0.322)
Return_90	-0.152	-0.500	-0.239	-0.153	0.137	0.419	0.203	0.137
	(0.490)	(0.673)	(0.701)	(0.491)	(0.291)	(0.431)	(0.403)	(0.291)
Realized_sd_past_30	1.491	-7.251	13.321	1.542	-2.014	4.955	-12.361*	-2.011
	(5.443)	(6.935)	(11.475)	(5.450)	(3.224)	(4.429)	(6.569)	(3.228)
Constant	0.041	0.870**	-0.786***	-0.013	-0.025	-0.644**	0.435***	-0.029
	(0.054)	(0.438)	(0.276)	(0.186)	(0.032)	(0.281)	(0.158)	(0.110)
Adjusted R^2	0.06	0.03	0.03	0.06	0.07	0.05	0.04	0.07
N	630	211	419	630	630	211	419	630

Table XI
Forecasting the Aggregate Stock Market Crash with Learning (DJIA 1952-2008)

The sample period runs from January 1952 to December 2008 and is based on the returns on DJIA. "Both" indicates that the whole sample is used for regression, while "Pessimistic"/"Optimistic" indicates that only the observations with "SENTIMENT" below/above zero (pessimistic/optimistic state) are considered. The observations with "SENTIMENT_W" above zero (optimistic state) and below zero (pessimistic state) are considered separately. The dependent variable is the SKEWNESS (Equation 1) of daily returns calculated from t to $t + 30$. "SENTIMENT_W" and "DISAGREEMENT_W" are the performance-based sentiment and disagreement, defined as the average and the standard deviation of the forecasts, weighted according to the past two years excess returns. "skew_past_30" is the lagged dependent variable. "Return_120" is the gross return over the period of $t - 119$ to t, and "Return_240" is the gross return over the period of $t - 239$ to $t - 120$. Other lagged returns are similarly defined. "realized_sd_past_30" is the lagged realized standard deviation, calculated from the daily returns between $t - 29$ and t. * significant at 10%; ** significant at 5%; *** significant at 1%.

	SKEWNESS				DUVOL			
Sentiment State	Both	Pessimistic	Optimistic	Both	Both	Pessimistic	Optimistic	Both
SENTIMENT_W	-0.103***			-0.098***	0.062***			0.059***
	(0.027)			(0.027)	(0.015)			(0.015)
DISAGREEMENT_W		-0.030	0.064***	0.023		0.017	-0.038***	-0.012
		(0.020)	(0.020)	(0.019)		(0.012)	(0.011)	(0.011)
SKEW_past_30	0.135***	0.122***	0.111***	0.134***				
	(0.034)	(0.043)	(0.032)	(0.033)				
DUVOL_past_30					0.160***	0.147***	0.136***	0.159***
					(0.032)	(0.041)	(0.031)	(0.032)
Return_30	-0.846**	-1.315***	-0.303	-0.855**	0.567**	0.922***	0.381	0.572**
	(0.352)	(0.401)	(0.466)	(0.352)	(0.223)	(0.257)	(0.264)	(0.224)
Return_60	-0.178	0.268	-0.232	-0.160	0.125	0.080	0.075	0.115
	(0.416)	(0.519)	(0.404)	(0.415)	(0.230)	(0.298)	(0.232)	(0.230)
Return_90	-0.630**	-0.406	-0.416	-0.612*	0.325*	0.402*	0.099	0.315*
	(0.316)	(0.365)	(0.345)	(0.317)	(0.186)	(0.230)	(0.199)	(0.187)
Realized_sd_past_30	-0.919	-8.482**	11.080*	-0.554	0.439	7.098***	-9.728***	0.237
	(3.953)	(3.482)	(6.014)	(3.921)	(2.525)	(2.163)	(3.249)	(2.518)
Constant	0.049	0.253***	-0.221***	0.012	-0.040	-0.173***	0.142***	-0.019
	(0.038)	(0.052)	(0.053)	(0.045)	(0.024)	(0.033)	(0.032)	(0.028)
Adjusted R^2	0.06	0.04	0.03	0.07	0.08	0.05	0.04	0.08
N	13685	4707	8978	13685	13685	4707	8978	13685

Table XII
Forecasting the Aggregate Stock Market Crash with Learning (S&P 500 Index 1964-2008)

The sample period runs from January 1964 to December 2008 and is based on the returns on S&P 500 Index. "Both" indicates that the whole sample is used for regression, while "Pessimistic"/"Optimistic" indicates that only the observations with "SENTIMENT" below/above zero (pessimistic/optimistic state) are considered. The observations with "SENTIMENT_W" above zero (optimistic state) and below zero (pessimistic state) are considered separately. The dependent variable is the SKEWNESS (Equation 1) of daily returns calculated from t to $t + 30$. "SENTIMENT_W" and "DISAGREEMENT_W" are the performance-based sentiment and disagreement, defined as the average and the standard deviation of the forecasts, weighted according to the past two years excess returns. "skew_past_30" is the lagged dependent variable. "Return_120" is the gross return over the period of $t - 119$ to t, and "Return_240" is the gross return over the period of $t - 239$ to $t - 120$. Other lagged returns are similarly defined. "realized_sd_past_30" is the lagged realized standard deviation, calculated from the daily returns between $t - 29$ and t. * significant at 10%; ** significant at 5%; *** significant at 1%.

	SKEWNESS				DUVOL			
Sentiment State	Both	Pessimistic	Optimistic	Both	Both	Pessimistic	Optimistic	Both
SENTIMENT_W	-0.072***			-0.072***	0.034**			0.035**
	(0.027)			(0.027)	(0.016)			(0.016)
DISAGREEMENT_W		-0.048*	0.106***	0.057***		0.032*	-0.060***	-0.031**
		(0.027)	(0.021)	(0.021)		(0.017)	(0.013)	(0.013)
SKEW_past_30	0.133***	0.137***	0.081**	0.127***				
	(0.037)	(0.047)	(0.036)	(0.036)				
DUVOL_past_30					0.152***	0.162***	0.102***	0.147***
					(0.037)	(0.047)	(0.036)	(0.036)
Return_30	-1.393***	-1.442***	-0.378	-1.227***	0.981***	1.016***	0.413	0.891***
	(0.378)	(0.455)	(0.494)	(0.382)	(0.242)	(0.302)	(0.285)	(0.242)
Return_60	-0.307	-0.085	0.213	-0.164	0.184	0.129	-0.147	0.106
	(0.498)	(0.653)	(0.469)	(0.497)	(0.267)	(0.363)	(0.262)	(0.267)
Return_90	-0.916***	-0.734	-0.481	-0.830**	0.523**	0.464	0.242	0.476**
	(0.353)	(0.474)	(0.351)	(0.355)	(0.210)	(0.292)	(0.212)	(0.211)
Realized_sd_past_30	-5.234	-12.710***	4.590	-2.950	3.018	8.747***	-4.830	1.743
	(4.254)	(3.755)	(6.406)	(4.312)	(2.765)	(2.403)	(3.431)	(2.827)
Constant	0.085*	0.336***	-0.244***	-0.020	-0.061**	-0.223***	0.139***	-0.005
	(0.044)	(0.067)	(0.062)	(0.057)	(0.028)	(0.042)	(0.037)	(0.036)
Adjusted R^2	0.06	0.06	0.04	0.07	0.07	0.07	0.05	0.07
N	11212	3415	7797	11212	11212	3415	7797	11212

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Appendix A: Description of Trading Rules

Our descriptions of simple trading rules draw heavily on Sullivan et al. (1999), Qi and Wu (2006) and Hsu and Kuan (2005), though we have made some modifications to avoid ambiguities.

Filter Rules

The filter rule strategy for generating trading signal follows Sullivan et al. (1999) and Qi and Wu (2006). The basic filter rule could be stated as follows: if the daily closing price of a particular security moves up by $x\%$ or more from its most recent low, the speculator buys and holds the security until its price moves down at least $x\%$ from a subsequent high, at which time the speculator sells and goes short. Two definitions of the subsequent high (low) are considered. One is the highest (lowest) closing price over the period of holding a particular long (short) position. The alternative high (low) refers to the most recent closing price that is greater (less) than e previous closing price. We also consider that a given long or short position is held for prespecified c days during which period all other signals are ignored.

Moving Average Rules

Moving averages are among the oldest trading rules used by chartist. The (equally weighted) moving average of a security price for a given day t over the n days is $\frac{1}{n}\sum_{i=0}^{n-1} s_{t-i}$. Under a simple single moving average rule, when the current price is above the moving average by an amount larger than the band with $b\%$, the speculator buys and holds the security. Similarly, when the current price is below the moving average by $b\%$, the speculator sells and goes short. Under dual moving average rule, when the short moving average of a security price is above the long moving average by an amount larger than the band with $b\%$, the speculator buys and holds the security. If the short moving average of a security price penetrates the long moving average from above, the speculator sells and goes short.

Following Sullivan et al. (1999) and Qi and Wu (2006), we implement the moving average rules with a time delay filter in addition to the fixed percentage band filter as described above. The time delay filter requires that the long or short signals remain valid for d days before action is taken. Similarly to the filter rule case, we also consider holding a given long or short position for *c* days during which period all other signals are ignored.

Support and Resistance (or Trading Range Break) Rules

The support and resistance level refers to certain price levels acting as barriers to prevent traders from pushing the price of an underlying asset in a certain direction. Under a trading range break rule, when the price of a security moves above the maximum price (resistance level) over the previous *n* days by *b%*, the speculator buys and holds the security. When the price falls below the minimum price over the previous *n* days by *b%*, the speculator sells and goes short. Alternatively, we use the local maximum (minimum), which represents the most recent closing price higher (lower) than the e previous closing prices, as the definition for the resistance level. Here we also allow a time delay filter, d, as well as the holding period of *c* days to be included, as in the case of moving average rules.

Channel Breakout Rules

A channel occurs when the high price of a security over the previous *n* days is within *x%* of the low over the previous *n* days. Under a channel breakout rule, when the closing price of the security exceeds the channel by *b%*, a signal is generated for the speculator to buy and hold the security. Likewise, when the closing price of the security drops below the channel by *b%*, a signal is generated for the speculator to sell and go short. Again, we consider a holding period of *c* days.

Appendix B: Documentation of Trading Rules Parameters

Filter Rules (FR)

x: increase in the log return required to generate a "buy" signal

y: decrease in the log return required to generate a "sell" signal

e: the number of the most recent days needed to define a low (high) based on which the filters are applied to generate a "long" ("short") signal

c: number of days a position is held during which all other signals are ignored

$x = 0.0005, 0.001, 0.005, 0.01, 0.05, 0.10$ (6 values)

$y = 0.0005, 0.001, 0.005, 0.01, 0.05$ (5 values)

$e = 1, 2, 5, 10, 20$ (5 values)

$c = 1, 5, 10, 25$ (4 values)

Note that y must be less than x, there are 15 (x,y) combinations

Number of rules in FR class = $x \times c + x \times e + x \times y+$ ((x,y) combinations)) = 24 + 30 + 15 = 69

Moving Average Rules (MA)

n: number of days in a moving average

m: number of fast-slow combinations of n

b: fixed band multiplicative value

d: number of days for the time delay filter

c: number of days a position is held, ignoring all other signals during that time

$n = 2, 5, 10, 15, 20, 25, 50, 100, 150, 200, 250$ (11 values)

$m = \sum_{i=1}^{n-1} i = 55$

$b = 0, 0.0005, 0.001, 0.005, 0.01, 0.05$ (6 values)

$d = 2, 3, 4, 5$ (4 values)

$c = 5, 10, 25$ (3 values)

Number of rules in MA class: $= b \times (n + m) + d \times (n + m) + c \times (n + m) = 396 + 264 + 198 = 858$

Support and Resistance (SR, or Trading Range Break) Rules

n: number of days in the support and resistance range;

e: used for an alternative definition of extrema where a low (high) can be defined as the most recent closing price that is less (greater) than the n previous closing prices;

b: fixed band multiplicative value;

d: number of days for the time delay filter;

c: number of days a position is held, ignoring all other signals during that time

$n = 5, 10, 15, 20, 25, 50, 100$ (7 values);

$e = 2, 3, 4, 5, 10, 25, 50$ (7 values);

$b = 0.0005, 0.001, 0.005, 0.01, 0.05$ (5 values);

$d = 2, 3, 4, 5$ (4 values);

$c = 1, 5, 10, 25$ (4 values);

Number of rules in SR class = $c \times (n + e) + b \times (n + e) \times c + d \times c \times (n + e) = 100 + 800 + 320 = 1220$

Channel Breakout Rules (CBO)

n: number of days for a channel

x: difference between the high price and the low price ($x\times$low price) required to form a channel

b: fixed band multiplicative value ($b < x$)

c: number of days a position is held, ignoring all other signals during that time

$n = 5, 10, 15, 20, 25, 50, 100, 200$ (8 values)

$x = 0.001, 0.005, 0.01, 0.05, 0.10$ (5 values)

$b = 0.0005, 0.001, 0.005, 0.01, 0.05$ (5 values)

$c = 1, 5, 10, 25$ (4 values)

Note that b must be less than x. There are 15 (x,b) combinations.

Number of rules in CBO class = $n \times x \times c + n \times c\times$((x,b) combinations)= 160 + 480 = 640

Total number of trading rules = 2127