Sentiment, Convergence of Opinion, and Market Crash*

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Abstract

I construct a new measure of investor sentiment and differences of opinion among trend-chasing investors to forecast skewness in daily aggregate stock market returns. 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. 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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"When everyone thinks alike, everyone is likely to be wrong"

Neill (1997)

1 Introduction

Asymmetry is prevalent in stock returns. In particular, market returns display "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 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 cannot deviate

[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, which holds true especially for the institutional investors, who are usually believed to be able to move the market.

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. Despite of its plausibility, few empirical studies have examined this hypothesis formally.

The role of differences of opinion is much more controversial. Theoretical models of differences of opinion deliver opposite predictions. Hong and Stein (2003) predict that disagreement intensity decreases skewness, while Xu (2007) predicts that it increases skewness. Empirical studies fail to find that detrended turnover, a proxy for differences of opinion, forecasts market skewness. Unlike those studies, I focus on the differences of opinion among trend-chasing investors and examine its implication for 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 underly this argument: the margin restriction of investors and the synchronization problem of rational arbitragers. Investors usually have margin restrictions and cannot buy/sell without limitations. They hold one of the following beliefs: bearish, bullish, 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 argue that when the average belief is positive, a high dispersion of belief implies that many trend-following investors have neutral or bearish beliefs, but can become bullish to buy when the price continues to increase. Therefore, the bubble can sustain, and rational arbitragers are likely to choose to ride the bubble. On the other hand, when the average belief is positive but the dispersion of belief is very small, almost everyone is optimistic. Since the investors who became optimistic at an early stage have used up their capacity during a bubble, fewer investors can continue to buy. A bubble is therefore unlikely to sustain. Understanding the absence of further momentum, and understanding that other rational arbitragers are likely to perceive in a similar way, rational arbitragers can coordinate their attack on the bubble. If they do, a market crash is expected. Similarly, the convergence of opinion in the low sentiment period indicates that the market downturn is unlikely to sustain, so the rational arbitragers coordinate to buy. Then a strong rebound is expected.

Constructing a sentiment indicator from forecasts of trend-following strategies deserves more explanations. 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 data snooping is controlled for (e.g., Sullivan, Timmermann, and White (1999)). It is therefore appealing that the forecasts of trend-following trading strategies represent the sentiment rather than changes in fundamentals. I empirically validate this conjecture by showing high 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 rest of this paper is structured as follows. Section 2 contains a brief overview of literature. Section 3 presents the data and the universe of the 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

[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.

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 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 arrival of bad news than of good news. The stochastic bubble theory by Blanchard and Watson (1982) postulate 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 belief, 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, in contrast to Hong and Stein (2003), disagreement intensity increases 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 volatil-

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

ity feedback effect theories, which predict more negatively skewed returns following a stock price decline; It is also inconsistent with the stochastic bubble theory, which predicts more negatively skewed returns following a period of stock price increase.

This paper relates to the literature of 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 such studies comes from the difficulty in 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 [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 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 for forecasting 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 profitability of various trading rules and the implications for market efficiency. In contrast, I focus on how technical trading can be related to the market crash (skewness of aggregate stock return), which has not yet been studied empirically in the literature[4].

[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.

3 Data

This paper uses the Dow Jones Industry Average (DJIA) as a stock market index, which is obtained from Datastream. To calculate the excess return over the daily short term interest rate, I obtain the daily federal funds rate from the Federal Reserve Bank. Although longer series of the DJIA are available, the sample period runs from January 1952 to December 2008, since the daily federal fund rate has only been available since 1952.

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 the observation 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 the large negative value of SKEWNESS corresponds to a left skewed distribution, indicating that market return during this period is more "crash prone".

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 for 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 updays:

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

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.

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 the current finance internet such as Yahoo Finance. They also enjoy wide popularity among the finance media such as Wall Street Journal, 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 descriptions about the parameters of these trading rules are 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. 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 weight the trading signals according to the past performance of corresponding strategy. For example, for each time t, the weight for each trading strategy which has a positive mean excess return (over the daily federal fund rate) in the evaluation period 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. In the robustness check I consider the Sharpe ratio as an alternative per-

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

formance measure as well as other evaluation periods. For the ease of notation, however, I use "SENTIMENT_W" hereafter to denote the sentiment weighted by two-year mean excess returns unless otherwise stated. "DISAGREEMENT_W" is analogously defined.

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, the lagged first-day return on IPOs, the lagged NYSE turnover from NYSE Factbook, the closed-end fund discount, and the new issued debt and equity. Baker and Wurgler (2007) provide detailed descriptions and discussions of these variables[6]. In addition, I include the Consumer Confidence Index obtained from the Michigan Consumer Research Center, and a Bull-Bear spread from Lowerrisk.com. 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. I consider three versions of the new sentiment index: SENTIMENT, SENTIMENT_W, and "SENTIMENT_AVG", where the last one is the monthly average of daily SENTIMENT. As other sentiment variables except Bull-Bear spread are in monthly frequency, both SENTIMENT and SENTIMENT_W are taken at the end of month. In order to obtaining the correlation with the Bull-Bear spread, both SENTIMENT and SENTIMENT_W are taken at the same day as the survey day. Table I reports the correlation coefficient and the p-value from testing the null hypothesis that two sentiment indicators are independent. It shows that all three versions of new sentiment indicator highly correlate with other investor sentiment indicators, with the corresponding p-value almost always smaller than 1%. The signs of the coefficients are expected since higher values of lagged value-weighted dividend premium and closed-end fund discount proxy for lower investor sentiment, whereas higher values of other indicators proxy for higher investor sentiment. Remarkably, the correlation of the Bull-Bear spread with the new sentiment indicator is about 40%. Since the Bull-Bear spread is from an online survey, it provides a more convincing validation of the new sentiment through direct opinions of investors (similar arguments can be found in Qiu and Welch (2006)).

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

[Insert Table I about here]

Table II presents the summary statistics. “Return" refers to the daily gross return of DJIA (in percentage). “SD” is the realized volatility of gross return from time $t - 59$ to t. “SKEWNESS” and “DUVOL" are the measures of return asymmetry calculated using the daily return from time t to $t + 60$ according to Equation 1 and 2.

[Insert Table II about here]

Consistent with the existing literature, the daily return of DJIA is negatively skewed, with a skewness of -1.41. The largest change in the daily return is -25.63%, which corresponds to the “Black Monday", October 19, 1987. Consistent with the skewness of the daily return, the SKEWNESS over 60 days return has a negative mean with a value of -0.06, while the DUVOL has a positive mean value of 0.01. The mean of SENTIMENT and the SENTIMENT_W are both positive[7], showing that the forecasts from trend-following strategies are on average optimistic.

Table III reports the correlation coefficient matrix for the major variables used in this study. “Return_120" is the gross return over the period of t-119 to t. Most notably, SKEWNESS and DUVOL are highly correlated, with a negative coefficient of -93%, similar to the findings in Chen et al. (2001). 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 that SENTIMENT and SENTIMENT_W to be positively correlated with the past 120 days return. I find a correlation coefficient of 21% and 18%, respectively.

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

[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 consider both a sorting-based approach and a regression-based approach. The empirical results are better explained when results from both approaches are taken together.

4.1 Sorting Approach: 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_W 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_W, and the corresponding mean of $Skew_t^{t+h}$ and t-statistics are calculated. Table IV reports the results for $Skew_t^{t+h}$ of 30 days and 60 days.[8] Panel A indicates that as the SENTIMENT_W becomes larger, the SKEWNESS declines uniformly, suggesting that the higher the sentiment, the more likely the crash will be. When the investor sentiment is at the highest quintile (quintile 5), the average 60 days skewness is -0.24, four times higher in absolute value than the unconditional skewness (-0.059 in Table II). However, an increase in DISAGREEMENT_W in Panel B does not correspond to a decline of SKEWNESS. Notably, when DISAGREEMENT_W is at the lowest category, the average SKEWNESS is much lower than the other four categories, showing a higher crash risk. Similar results are obtained for DUVOL with an expected reverse pattern.

[8] Similar results can be found for the SKEWNESS/DUVOL for other length of trading days.

[Insert Table IV about here]

Motivated by the consideration that the role of differences of opinion may differ in optimistic and pessimistic period, I report the mean skewness and the t-value when the SENTIMENT_W is above zero (optimistic state) or below zero (pessimistic state).

[Insert Table V about here]

Table V reveals an interesting pattern. When trend-following investors are on average optimistic (Panel A), an increase in DISAGREEMENT_W associates with an almost monotonic increase in SKEWNESS, indicating that the lower the disagreement, the more likely the crash will happen. The negative SKEWNESS is particularly pronounced at the lowest quintile, with a value of -0.32, more than five times higher in absolute value than the unconditional skewness of -0.059 in Table II, indicating that the crash risk is very high when the disagreement is extremely low. When trend-chasing investors are on average pessimistic (Panel B), DISAGREEMENT_W is in general negatively (positively) associated with the SKEWNESS (DUVOL), just the opposite to the results in Panel A. These results suggest that a convergence of opinion is likely to be associated with a crash in optimistic states and with a large rebound in pessimistic 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 past realized volatility.

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 proved 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.[9] 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 60 days[10] in table VI. 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.

[Insert Table VI about here]

Baseline Estimation Results

In the baseline estimation, I forecast thirty days' *Skew* with daily regressions. Regressions with other forecasting horizons, or at a monthly frequency, are considered in section 4.3.

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

[10] 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).

Table VII reports three model specifications for both SENTIMENT_W (m1, m2, and m3) and DISAGREEMENT_W (m4, m5, m6). In model 7 (m7), SENTIMENT_W and DISAGREEMENT_W are jointly considered to see the incremental information beyond each other for forecasting skewness. The results indicate that the investor sentiment has a strong forecasting ability for the skewness for all specifications, with a negative sign and significant at the 1% level. Furthermore, its coefficient and standard error are quite stable across different model specifications. The higher the trend-following investor sentiment, the lower skewness will be, showing a higher crash risk. Disagreement, however, does not have a significant predictive power for future skewness for all the model specifications considered. This contrasts to the theoretical predictions of Hong and Stein (2003) and Xu (2007), 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 and detrended turnover, a proxy for the extent of the differences of opinion.

[Insert Table VII about here]

For the control variables, past returns often have a significant forecasting power, similar to the findings in Chen et al. (2001) and Charoenrook and Daouk (2008). Negative skewness is more pronounced if the past returns are higher. This fits well with the theory of Blanchard and Watson (1982) and Xu (2007). As discussed in Charoenrook and Daouk (2008), this finding helps reject the theories of leverage effect and volatility feedback effect, since they both predict that lower stock returns forecast lower skewness. Lagged SKEWNESS is positive and significant, indicating persistency in the skewness. Past realized volatility 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 it helps to alleviate this concern. Nevertheless, the coefficient of past realized volatility is insignificant.

Table VIII reports the 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_W, DISAGREEMENT_W, and past returns in Table VII and Table VIII are opposite, which is expected since SKEWNESS and DUVOL are highly negatively correlated. Investor sentiment forecasts future DUVOL with a positive sign, indicating that the higher the investor sentiment, the higher the crash risk will be. DISAGREEMENT_W, on the other hand, does not forecast future skewness in this case.

[Insert Table VIII about here]

Estimation Results in Different Belief States

Differences of opinion, according to Hong and Stein (2003), reveal more information when more negative news come out, and hence higher disagreement should have a higher negative skewness when bad news comes. Past returns can be interpreted as news at its realization, and investor sentiment captures the change in this news. In this regard, higher disagreement is likely to forecast a crash when the investors are on average pessimistic. In the following, I test the role of disagreement in both pessimistic and optimistic states.

Panel A of Table IX reports the results when investors are on average pessimistic, and the SKEWNESS over 30 trading days horizon as the dependent variable. It shows that DISAGREEMENT_W negatively forecasts the subsequent skewness, which, when taken at face value, seems to support the model of Hong and Stein (2003), which predicts higher differences of opinion are related to 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 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_W as evidence that convergence of opinion in a pessimistic state forecasts a crash. The investor sentiment, however, does not have a predictive ability when the average sentiment is below zero.

When trend-chasing investors are on average optimistic (Panel B), 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 forecasts large negative skewness. Taking the results in Panel A and Panel B together, neither Hong and Stein (2003) nor Xu (2007) can explain the findings in the pessimistic and optimistic periods at the same time.

[Insert Table IX about here]

What explains the differential role of differences of opinion then? One explanation is that differences of opinion reflects the sustainability of an ongoing bubble or market downturn, which can be used by rational arbitrager 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. The arbitragers have 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 up the price further. The change of belief is likely to happen because recent positive return leads to net buy by trend followers (in line with the average optimistic sentiment), which can in turn push the price higher, causing the still non-optimistic types to become optimistic. Therefore, a bubble is likely to sustain 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 sustain 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 differences 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 sustain, and the rational arbitragers coordinate to buy, then a strong recovery is expected.

[Insert Table X about here]

Table X reports the results when DUVOL is used as dependent variable. The evidence here corroborates strongly with that in Table IX. It shows that convergence of opinion strongly predicts a larger crash risk during an optimistic state, while predicts a large rebound in stock price during a pessimistic state.

4.3 Robustness Checks

Forecasting horizons

Admittedly, the choice of 30 days for calculating the measure of return asymmetry is arbitrary. Theoretical papers, however, do not provide guidelines in this regard. On the one hand, as discussed in Chen et al. (2001), estimates of skewness over a short horizon are subject to measurement errors. On the other hand, long-run skewness is presumably less interesting, and the overlapping observations in longer horizons result in more persistency in the variables. I consider predicting *Skew* over a range of forecasting horizons between 30 and 360 trading days. I report the results for a 60-day horizon below (Table XI and Table XII), while results for other horizons are available from the author upon request.

[Insert Table XI and Table XII about here]

Similar to Table VII and Table VIII, higher SENTIMENT_W predicts a lower SKEWNESS, and DISAGREEMENT_W has no predictive ability.

When conditional on the average investor sentiment, I also find differential roles of DISAGREEMENT_W. Table XIII and Table XIV report the results for SKEWNESS and DUVOL, respectively. The results reveal that convergence in differences of opinion forecasts a large rebound in a pessimistic state and a crash in an optimistic state, confirming the results for SKEWNESS/DUVOL of 30 trading days.

Alternative performance measures

The weights used above for weighting the forecasts are obtained from an evaluation period of two years. This is admittedly arbitrary. To check whether the results differ when different evaluation periods are used, I also consider an evaluation window of ten years. I find that the results are similar to those reported in the base case above. In addition, I consider a case in which investors naively believe the trading strategies and do not update their beliefs even though they can. In this case, I assign an equal weight of one to all forecasts. Table XVI shows that, similar to the case where investor learning is allowed, investor sentiment negatively predicts the SKEWNESS, and disagreement in a pessimistic state forecasts a large rebound while a lower disagreement forecasts a crash. Similar results are found for DUVOL.

[Insert Table XVI about here]

During the evaluation of the trading strategies' past performance, investors are likely to consider the risk associated with the average excess return. The Sharpe ratio is a commonly used performance measure to account for the risk. Therefore, I use the Sharpe ratio as an alternative way for investors to learn and select the desired trading rules. In untabulated regressions, I find qualitatively similar results as in the case of average excess return.

Monthly regressions

Above regressions are conducted at a daily frequency. This has the advantage of improving the statistical significance due to large number of observations. Furthermore, investors are unlikely to care about crash risk just 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 XV reports the results. The SENTIMENT_W or DISAGREEMENT_W is taken at the end of month, while the SKEWNESS to be forecasted is from daily returns of next 30 days. The monthly regression yields consistent results as in daily regression, indicating that the noise in daily returns or other variables cannot be the reasons driving the results. Similar findings are obtained for DUVOL of 30 trading days, but are omitted for brevity.

[Insert Table XV about here]

Sub-sample analysis

I have used the whole 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 “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.

5 Conclusion

This paper provides empirical evidence that both investor sentiment and differences of opinion have robust forecasting power for aggregate market skewness. High sentiment forecasts crashes. 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 forecast positively the market skewness. I argue that differences of opinion resemble the sustainability of bubbles/market downturn. For example, a bubble is unlikely to sustain when everyone is already optimistic. Moreover, rational arbitragers can take convergence of opinion as a coordination mechanism to attack the bubble, leading to a sudden market crash. Admittedly, the explanation about the differential role in different states of investor sentiment 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
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. SENTIMENT is the (equally weighted) average of forecast from the trading strategies. 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. "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). "bbspread" is the Bull-Bear spread calculated using the weekly investor sentiment data from Lowerrisk.com (05/1997-07/2006). Spearman correlation coefficient is reported with P-value in parenthesis.

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

Table II
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 $t+60$. "SKEWNESS" and "DUVOL" are the measures of return asymmetry calculated using the daily return from time t to $t+60$ 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	SD	Skewness	DUVOL	Sentiment	Disagreement	Sentiment_w	Disagreement_w
Mean	0.023	0.008	-0.059	0.011	0.197	0.355	0.216	1.441
SD	0.959	0.004	0.623	0.283	0.440	0.311	0.816	0.998
Min	-25.632	0.003	-5.960	-1.337	-0.845	0.000	-4.330	0.297
Max	10.508	0.044	4.441	2.004	0.886	0.976	3.125	12.870
Skewness	-1.410	3.770	-1.792	0.237	-0.449	0.513	-0.475	2.939
Kurtosis	47.175	26.535	12.189	4.175	2.021	1.849	3.611	19.810

Table III
Correlation Coefficient Matrix

This table presents the correlation coefficient matrix. "SD" is the realized volatility from time t to $t+60$. "SKEWNESS" and "DUVOL" are the measures of return asymmetry calculated using the daily return from time t to $t+60$ according to Equation 1 and 2. "Sentiment" and "Disagree" is the (equally weighted) average and the standard deviation of forecast from the trading strategies for time t. "SENTIMENT_W" and "Disagree_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."Return_120" is the gross return over the period of $t-119$ to t.

Variables	SD	Skewness	DUVOL	Disagree	Sentiment	Sentiment_w	Disagree_w	Return_120
SD	1.000							
Skewness	-0.162	1.000						
DUVOL	0.025	-0.928	1.000					
Disagree	0.069	0.126	-0.136	1.000				
Sentiment	-0.209	-0.278	0.323	-0.364	1.000			
Sentiment_w	-0.239	-0.259	0.292	-0.212	0.727	1.000		
Disagree_w	-0.043	0.067	-0.079	0.247	-0.069	-0.143	1.000	
Return_120	-0.028	-0.109	0.122	-0.094	0.211	0.179	-0.066	1.000

Table IV
Breakdown by sorts of sentiment and disagreement

This table reports the break-down results for dependent variables in each quintile of SENTIMENT_W or DISAGREEMENT_W. "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_W 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_W.

Panel A: Sort by SENTIMENT_W

	SKEWNESS_30		DUVOL_30		SKEWNESS_60		DUVOL_60	
Quintile	mean	t-stat	mean	t-stat	mean	t-stat	mean	t-stat
1	0.19	19.46	-0.13	-20.94	0.20	20.30	-0.13	-23.68
2	0.11	11.91	-0.08	-12.98	0.11	11.99	-0.07	-14.60
3	-0.01	-0.76	-0.01	-2.32	-0.08	-6.51	0.02	3.74
4	-0.09	-9.54	0.05	8.28	-0.16	-13.97	0.08	15.40
5	-0.15	-12.94	0.08	12.87	-0.24	-19.71	0.10	20.14

Panel B: Sort by DISAGREEMENT_W

	SKEWNESS_30		DUVOL_30		SKEWNESS_60		DUVOL_60	
Quintile	mean	t-stat	mean	t-stat	mean	t-stat	mean	t-stat
1	-0.16	-14.23	0.08	12.91	-0.25	-17.80	0.11	19.41
2	0.03	2.55	-0.03	-4.33	0.03	2.63	-0.02	-3.17
3	0.08	8.26	-0.07	-11.69	0.05	4.72	-0.05	-10.49
4	0.05	4.54	-0.04	-6.45	-0.00	-0.41	-0.02	-3.82
5	0.05	4.68	-0.04	-5.79	-0.01	-1.09	-0.01	-2.61

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_W 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_W 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_W 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	0.25	11.74	-0.17	-12.44	0.21	9.68	-0.13	-10.58
2	0.20	11.18	-0.14	-12.40	0.21	11.87	-0.13	-14.58
3	0.22	17.66	-0.15	-18.09	0.27	22.03	-0.17	-24.10
4	0.17	10.16	-0.12	-10.85	0.17	11.19	-0.10	-11.87
5	0.07	4.58	-0.05	-4.91	0.02	1.30	-0.02	-2.99

Panel A: Sort by DISAGREEMENT_W 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	-0.23	-18.96	0.12	18.96	-0.32	-21.03	0.14	25.49
2	-0.05	-4.14	0.02	3.44	-0.05	-4.30	0.04	6.30
3	-0.03	-2.29	-0.00	-0.60	-0.12	-8.30	0.04	5.65
4	-0.02	-1.43	0.00	0.21	-0.10	-7.67	0.03	5.09
5	0.03	2.20	-0.03	-3.33	-0.04	-2.77	-0.00	-0.67

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	Skew	DUVOL	Sentiment	Disagreement	Sentimentw	Disagreementw
ADF	-13.81***	-13.07***	-5.08***	-9.93***	-17.03***	-14.87***
Pperron	-12.50***	-11.99***	-10.82***	-17.73***	-15.64***	-11.40***
DF-GLS	-12.14***	-10.57***	-4.93***	-9.18***	-17.04***	-15.06***

Table VII
Forecasting the aggregate stock market crash: SKEWNESS (30 days)

The sample period runs from January 1952 to December 2008 and is based on return on DJIA in excess of the daily federal fund rate. 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%.

	m1	m2	m3	m4	m5	m6	m7
SENTIMENT_W	-0.111***	-0.106***	-0.110***				-0.108***
	(0.025)	(0.025)	(0.025)				(0.025)
DISAGREEMENT_W				0.028	0.025	0.025	0.015
				(0.021)	(0.022)	(0.022)	(0.022)
skew_past_30		0.104***	0.099***		0.113***	0.112***	0.099***
		(0.035)	(0.034)		(0.034)	(0.034)	(0.033)
return_120	-1.032**	-0.970**	-0.986**	-1.309***	-1.230***	-1.236***	-0.971**
	(0.423)	(0.401)	(0.395)	(0.426)	(0.404)	(0.401)	(0.395)
return_240	-0.779***	-0.680***	-0.682***	-0.920***	-0.807***	-0.809***	-0.671***
	(0.213)	(0.207)	(0.207)	(0.212)	(0.208)	(0.208)	(0.206)
return_360	-0.224	-0.141	-0.139	-0.262	-0.172	-0.172	-0.128
	(0.184)	(0.176)	(0.176)	(0.189)	(0.182)	(0.182)	(0.176)
return_480	-0.323	-0.295	-0.290	-0.339*	-0.309	-0.308	-0.289
	(0.200)	(0.200)	(0.200)	(0.200)	(0.200)	(0.199)	(0.199)
return_600	-0.045	-0.046	-0.020	-0.055	-0.054	-0.049	-0.038
	(0.216)	(0.211)	(0.210)	(0.216)	(0.211)	(0.211)	(0.209)
return_720	-0.138	-0.113	-0.100	-0.184	-0.153	-0.150	-0.123
	(0.196)	(0.195)	(0.196)	(0.199)	(0.198)	(0.198)	(0.196)
realized_sd_past_30			-4.757			-0.946	-4.571
			(4.999)			(5.083)	(5.009)
Constant	0.083***	0.074***	0.113**	0.027	0.022	0.030	0.089
	(0.022)	(0.022)	(0.049)	(0.037)	(0.037)	(0.058)	(0.058)
Adjusted R^2	0.07	0.08	0.08	0.05	0.06	0.06	0.08
N	13464	13464	13464	13464	13464	13464	13464

Table VIII
Forecasting the aggregate stock market crash: DUVOL (30 days)

The sample period runs from January 1952 to December 2008 and is based on the returns on DJIA in excess of the daily federal fund rate. The dependent variable is the DUVOL (Equation 2) 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. "duvol_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%.

	m1	m2	m3	m4	m5	m6	m7
SENTIEMENT_W	0.070***	0.067***	0.068***				0.067***
	(0.015)	(0.015)	(0.015)				(0.015)
DISAGREEMENT_W				-0.015	-0.014	-0.014	-0.008
				(0.012)	(0.013)	(0.013)	(0.013)
duvol_past_30		0.126***	0.125***		0.136***	0.136***	0.125***
		(0.034)	(0.034)		(0.034)	(0.034)	(0.033)
return_120	0.560**	0.507**	0.513**	0.738***	0.673***	0.671***	0.505**
	(0.244)	(0.231)	(0.228)	(0.245)	(0.231)	(0.230)	(0.229)
return_240	0.438***	0.368***	0.368***	0.529***	0.450***	0.450***	0.362***
	(0.119)	(0.116)	(0.116)	(0.121)	(0.118)	(0.118)	(0.116)
return_360	0.107	0.053	0.051	0.133	0.074	0.075	0.046
	(0.113)	(0.110)	(0.110)	(0.117)	(0.114)	(0.114)	(0.110)
return_480	0.136	0.117	0.115	0.147	0.126	0.127	0.115
	(0.114)	(0.114)	(0.114)	(0.114)	(0.114)	(0.114)	(0.113)
return_600	0.022	0.026	0.017	0.026	0.029	0.032	0.026
	(0.121)	(0.117)	(0.118)	(0.121)	(0.117)	(0.118)	(0.117)
return_720	0.034	0.022	0.016	0.060	0.044	0.046	0.028
	(0.115)	(0.114)	(0.115)	(0.116)	(0.116)	(0.115)	(0.114)
realized_sd_past_30			1.774			-0.480	1.673
			(2.792)			(2.848)	(2.789)
Constant	-0.058***	-0.051***	-0.065**	-0.026	-0.021	-0.017	-0.053
	(0.014)	(0.014)	(0.027)	(0.023)	(0.023)	(0.033)	(0.032)
Adjusted R^2	0.07	0.08	0.08	0.04	0.06	0.06	0.09
N	13464	13464	13464	13464	13464	13464	13464

Table IX
Forecasting the aggregate stock market crash in different sentiment states: SKEWNESS (30 days)

The sample period runs from January 1952 to December 2008 and is based on the returns on DJIA in excess of the daily federal fund rate. 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%.

	Pessimistic State			Optimistic State		
	m1	m2	m3	m4	m5	m6
SENTIMENT_W			-0.028			-0.152***
			(0.049)			(0.042)
DISAGREEMENT_W	-0.039*	-0.046**	-0.050**	0.057***	0.057***	0.076***
	(0.020)	(0.020)	(0.020)	(0.022)	(0.022)	(0.022)
skew_past_30	0.119**	0.091**	0.090**	0.097***	0.100***	0.091***
	(0.050)	(0.040)	(0.040)	(0.033)	(0.033)	(0.033)
return_120	-0.296	-0.281	-0.273	-1.128**	-1.096**	-1.047**
	(0.443)	(0.423)	(0.426)	(0.457)	(0.457)	(0.455)
return_240	-0.379	-0.352	-0.325	-0.694***	-0.688***	-0.676***
	(0.260)	(0.252)	(0.253)	(0.207)	(0.207)	(0.207)
return_360	-0.207	-0.249	-0.244	-0.084	-0.091	-0.061
	(0.251)	(0.252)	(0.250)	(0.168)	(0.167)	(0.166)
return_480	-0.123	-0.146	-0.140	-0.447**	-0.456**	-0.427**
	(0.244)	(0.243)	(0.244)	(0.198)	(0.197)	(0.198)
return_600	-0.252	-0.141	-0.147	-0.008	-0.030	-0.012
	(0.254)	(0.252)	(0.252)	(0.206)	(0.206)	(0.204)
return_720	-0.188	-0.193	-0.208	-0.096	-0.121	-0.074
	(0.257)	(0.262)	(0.265)	(0.192)	(0.192)	(0.190)
realized_sd_past_30		-14.194***	-14.105***		5.455	1.494
		(4.069)	(4.073)		(6.003)	(5.968)
Constant	0.244***	0.388***	0.374***	-0.083**	-0.124**	-0.016
	(0.043)	(0.060)	(0.063)	(0.036)	(0.060)	(0.065)
Adjusted R^2	0.04	0.06	0.06	0.06	0.06	0.07
N	4624	4624	4624	8840	8840	8840

Table X
Forecasting the aggregate stock market crash in different sentiment states: DUVOL (30 days)

The sample period runs from January 1952 to December 2008 and is based on the returns on DJIA in excess of the daily federal fund rate. The observations with "SENTIMENT_W" above zero (optimistic state) and below zero (pessimistic state) are considered separately. The dependent variable is the DUVOL (Equation 2) 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 past two years excess returns. "duvol_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%.

	Pessimistic State			Optimistic State		
	m1	m2	m3	m4	m5	m6
SENTIMENT_W			0.018			0.094***
			(0.029)			(0.023)
DISAGREEMENT_W	0.026**	0.030**	0.032***	-0.035***	-0.035***	-0.046***
	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.013)
duvol_past_30	0.143***	0.134***	0.133***	0.116***	0.118***	0.111***
	(0.045)	(0.042)	(0.043)	(0.033)	(0.033)	(0.032)
return_120	0.052	0.035	0.030	0.627**	0.601**	0.571**
	(0.283)	(0.273)	(0.275)	(0.258)	(0.258)	(0.257)
return_240	0.269	0.245	0.228	0.346***	0.342***	0.333***
	(0.167)	(0.163)	(0.162)	(0.114)	(0.114)	(0.113)
return_360	0.039	0.050	0.046	0.041	0.048	0.028
	(0.167)	(0.166)	(0.165)	(0.103)	(0.103)	(0.102)
return_480	0.007	0.011	0.007	0.214**	0.221**	0.203*
	(0.158)	(0.157)	(0.158)	(0.107)	(0.106)	(0.106)
return_600	0.170	0.105	0.109	-0.004	0.013	0.003
	(0.163)	(0.165)	(0.164)	(0.109)	(0.110)	(0.108)
return_720	0.053	0.049	0.059	0.012	0.033	0.003
	(0.159)	(0.161)	(0.163)	(0.106)	(0.106)	(0.104)
realized_sd_past_30		7.252***	7.187***		-4.413	-2.045
		(2.292)	(2.293)		(3.394)	(3.386)
Constant	-0.159***	-0.231***	-0.222***	0.047**	0.080**	0.014
	(0.028)	(0.035)	(0.038)	(0.022)	(0.033)	(0.036)
Adjusted R^2	0.04	0.06	0.06	0.06	0.06	0.07
N	4624	4624	4624	8840	8840	8840

Table XI
Forecasting the aggregate stock market crash: SKEWNESS (60 days)

The sample period runs from January 1952 to December 2008 and is based on the returns on DJIA in excess of the daily federal fund rate. The dependent variable is the SKEWNESS (Equation 1) of daily returns calculated from t to $t + 60$. "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_60" 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_60" is the lagged realized standard deviation, calculated from the daily returns between $t - 59$ and t. * significant at 10%; ** significant at 5%; *** significant at 1%.

	m1	m2	m3	m4	m5	m6	m7
SENTIMENT_W	-0.151***	-0.149***	-0.150***				-0.148***
	(0.036)	(0.035)	(0.035)				(0.035)
DISAGREEMENT_W				0.025	0.023	0.024	0.010
				(0.026)	(0.025)	(0.025)	(0.025)
skew_past_60		0.119***	0.118**		0.124***	0.134***	0.118**
		(0.046)	(0.047)		(0.045)	(0.048)	(0.047)
return_120	-0.945**	-0.806**	-0.806**	-1.334***	-1.185***	-1.157***	-0.796**
	(0.408)	(0.380)	(0.380)	(0.426)	(0.400)	(0.403)	(0.377)
return_240	-1.226***	-1.038***	-1.039***	-1.429***	-1.233***	-1.215***	-1.031***
	(0.350)	(0.352)	(0.352)	(0.342)	(0.349)	(0.350)	(0.345)
return_360	-0.363*	-0.256	-0.256	-0.424*	-0.314	-0.311	-0.249
	(0.215)	(0.211)	(0.210)	(0.224)	(0.222)	(0.222)	(0.212)
return_480	-0.592	-0.512	-0.511	-0.618*	-0.535	-0.544	-0.511
	(0.374)	(0.377)	(0.375)	(0.375)	(0.379)	(0.379)	(0.375)
return_600	-0.248	-0.227	-0.223	-0.249	-0.226	-0.264	-0.234
	(0.300)	(0.278)	(0.276)	(0.304)	(0.280)	(0.281)	(0.280)
return_720	-0.439	-0.390	-0.388	-0.483	-0.428	-0.449	-0.402
	(0.286)	(0.285)	(0.285)	(0.296)	(0.294)	(0.292)	(0.287)
realized_sd_past_60			-0.853			7.215	-0.675
			(6.408)			(6.824)	(6.458)
Constant	0.086***	0.077**	0.084	0.029	0.022	-0.039	0.068
	(0.031)	(0.030)	(0.068)	(0.049)	(0.047)	(0.083)	(0.079)
Adjusted R^2	0.13	0.14	0.14	0.09	0.10	0.10	0.14
N	13434	13434	13434	13434	13434	13434	13434

Table XII
Forecasting the aggregate stock market crash: DUVOL (60 days)

The sample period runs from January 1952 to December 2008 and is based on the returns on DJIA in excess of the daily federal fund rate. The dependent variable is the DUVOL (Equation 2) of daily returns calculated from t to $t + 60$. "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. "duvol_past_60" 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_60" is the lagged realized standard deviation, calculated from the daily returns between $t - 59$ and t. * significant at 10%; ** significant at 5%; *** significant at 1%.

	m1	m2	m3	m4	m5	m6	m7
SENTIMENT_W	0.081***	0.078***	0.078***				0.077***
	(0.017)	(0.016)	(0.017)				(0.017)
DISAGREEMENT_W				-0.014	-0.012	-0.013	-0.005
				(0.013)	(0.012)	(0.012)	(0.012)
duvol_past_60		0.197***	0.197***		0.206***	0.209***	0.197***
		(0.053)	(0.053)		(0.053)	(0.054)	(0.053)
return_120	0.464**	0.352*	0.353*	0.672***	0.550***	0.537***	0.347*
	(0.200)	(0.180)	(0.181)	(0.210)	(0.189)	(0.192)	(0.181)
return_240	0.548***	0.399***	0.400***	0.657***	0.499***	0.496***	0.396***
	(0.139)	(0.132)	(0.132)	(0.140)	(0.134)	(0.134)	(0.131)
return_360	0.146	0.066	0.067	0.179	0.095	0.098	0.063
	(0.114)	(0.110)	(0.110)	(0.120)	(0.117)	(0.116)	(0.111)
return_480	0.187	0.138	0.140	0.201	0.149	0.159	0.140
	(0.145)	(0.141)	(0.141)	(0.148)	(0.143)	(0.143)	(0.140)
return_600	0.090	0.077	0.081	0.091	0.076	0.103	0.088
	(0.141)	(0.127)	(0.128)	(0.140)	(0.125)	(0.127)	(0.127)
return_720	0.108	0.084	0.087	0.131	0.105	0.120	0.094
	(0.126)	(0.122)	(0.122)	(0.130)	(0.125)	(0.124)	(0.121)
realized_sd_past_60			-0.704			-4.668	-0.805
			(3.116)			(3.289)	(3.119)
Constant	-0.051***	-0.041***	-0.035	-0.020	-0.012	0.027	-0.027
	(0.016)	(0.015)	(0.032)	(0.025)	(0.024)	(0.038)	(0.036)
Adjusted R^2	0.13	0.17	0.17	0.08	0.12	0.12	0.17
N	13434	13434	13434	13434	13434	13434	13434

Table XIII
Forecasting the aggregate stock market crash in different sentiment states: SKEWNESS (60 days)

The sample period runs from January 1952 to December 2008 and is based on the returns on DJIA in excess of the daily federal fund rate. 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 $t + 60$. "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_60" 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_60" is the lagged realized standard deviation, calculated from the daily returns between $t - 59$ and t. * significant at 10%; ** significant at 5%; *** significant at 1%.

	Pessimistic State			Optimistic State		
	m1	m2	m3	m4	m5	m6
SENTIMENT_W			-0.063			-0.204***
			(0.063)			(0.060)
DISAGREEMENT_W	-0.046**	-0.058**	-0.067***	0.050*	0.051*	0.076***
	(0.023)	(0.024)	(0.021)	(0.028)	(0.028)	(0.029)
skew_past_60	0.143**	0.088	0.092	0.110**	0.117***	0.103**
	(0.061)	(0.057)	(0.059)	(0.043)	(0.044)	(0.043)
return_120	-0.061	0.012	0.038	-1.055**	-0.989**	-0.924**
	(0.476)	(0.458)	(0.458)	(0.458)	(0.472)	(0.469)
return_240	-0.627**	-0.609**	-0.540*	-1.129***	-1.117***	-1.106***
	(0.310)	(0.299)	(0.292)	(0.339)	(0.337)	(0.339)
return_360	-0.241	-0.305	-0.288	-0.247	-0.273	-0.229
	(0.328)	(0.328)	(0.325)	(0.209)	(0.205)	(0.202)
return_480	0.051	0.024	0.046	-0.852**	-0.879**	-0.841**
	(0.320)	(0.317)	(0.316)	(0.396)	(0.394)	(0.394)
return_600	-0.277	-0.170	-0.177	-0.229	-0.283	-0.256
	(0.335)	(0.336)	(0.333)	(0.285)	(0.284)	(0.281)
return_720	-0.289	-0.300	-0.328	-0.448	-0.526*	-0.455
	(0.317)	(0.323)	(0.317)	(0.305)	(0.306)	(0.299)
realized_sd_past_60		-16.736***	-16.581***		16.693**	9.236
		(6.095)	(6.089)		(8.231)	(7.903)
Constant	0.262***	0.447***	0.415***	-0.087*	-0.213**	-0.052
	(0.050)	(0.087)	(0.100)	(0.046)	(0.089)	(0.091)
Adjusted R^2	0.08	0.10	0.11	0.09	0.10	0.12
N	4594	4594	4594	8840	8840	8840

Table XIV
Forecasting the aggregate stock market crash in different sentiment states: DUVOL (60 days)

The sample period runs from January 1952 to December 2008 and is based on the returns on DJIA in excess of the daily federal fund rate. The observations with "SENTIMENT_W" above zero (optimistic state) and below zero (pessimistic state) are considered separately. The dependent variable is the DUVOL (Equation 2) of daily returns calculated from t to $t + 60$. "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. "duvol_past_60" 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_60" is the lagged realized standard deviation, calculated from the daily returns between $t - 59$ and t. * significant at 10%; ** significant at 5%; *** significant at 1%.

	Pessimistic State			Optimistic State		
	m1	m2	m3	m4	m5	m6
SENTIMENT_W			0.042			0.091***
			(0.031)			(0.024)
DISAGREEMENT_W	0.026**	0.032**	0.038***	-0.029**	-0.030**	-0.041***
	(0.013)	(0.013)	(0.012)	(0.012)	(0.012)	(0.013)
duvol_past_60	0.196***	0.173***	0.178***	0.184***	0.181***	0.174***
	(0.065)	(0.062)	(0.064)	(0.050)	(0.049)	(0.048)
return_120	0.019	-0.052	-0.069	0.453**	0.409*	0.378*
	(0.257)	(0.244)	(0.244)	(0.202)	(0.209)	(0.208)
return_240	0.336*	0.295*	0.249	0.390***	0.389***	0.381***
	(0.174)	(0.165)	(0.163)	(0.123)	(0.119)	(0.119)
return_360	0.004	0.016	0.005	0.083	0.106	0.084
	(0.192)	(0.191)	(0.188)	(0.101)	(0.099)	(0.098)
return_480	-0.044	-0.053	-0.067	0.270**	0.292**	0.274**
	(0.185)	(0.181)	(0.180)	(0.125)	(0.124)	(0.123)
return_600	0.118	0.043	0.048	0.081	0.119	0.108
	(0.186)	(0.192)	(0.191)	(0.114)	(0.115)	(0.112)
return_720	0.055	0.046	0.065	0.103	0.160	0.127
	(0.172)	(0.175)	(0.174)	(0.114)	(0.114)	(0.111)
realized_sd_past_60		8.242***	8.218***		-11.936***	-8.700**
		(2.697)	(2.671)		(3.659)	(3.599)
Constant	-0.146***	-0.235***	-0.214***	0.052**	0.142***	0.071*
	(0.029)	(0.041)	(0.047)	(0.023)	(0.038)	(0.040)
Adjusted R^2	0.08	0.11	0.11	0.11	0.13	0.15
N	4594	4594	4594	8840	8840	8840

Table XV
Forecasting the aggregate stock market crash at monthly frequency: SKEWNESS (30 days)

The sample period runs from January 1952 to December 2008 and is based on the returns on DJIA in excess of the daily federal fund rate. The dependent variable is the SKEWNESS (Equation 1) of daily returns calculated from t to $t + 30$. "SENTIMENT_W" and "DISAGREEMENT_W" are the end of month 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%.

	Pessimistic State		Optimistic State		Both States	
	m1	m2	m3	m4	m5	m6
SENTIMENT_W					-0.100***	-0.099***
					(0.028)	(0.029)
DISAGREEMENT_W	-0.062**	-0.069**	0.057*	0.060*		0.007
	(0.030)	(0.030)	(0.034)	(0.034)		(0.023)
skew_past_30	0.094*	0.048	0.124**	0.132**	0.121***	0.121***
	(0.054)	(0.056)	(0.054)	(0.055)	(0.040)	(0.040)
return_120	-0.046	0.007	-1.095*	-1.005*	-0.845**	-0.839*
	(0.600)	(0.593)	(0.587)	(0.589)	(0.427)	(0.428)
return_240	-0.709*	-0.690*	-0.579*	-0.573*	-0.701***	-0.697***
	(0.370)	(0.365)	(0.299)	(0.299)	(0.232)	(0.233)
return_360	-0.435	-0.446	0.211	0.204	-0.006	-0.001
	(0.369)	(0.364)	(0.277)	(0.277)	(0.222)	(0.222)
return_480	-0.123	-0.163	-0.317	-0.341	-0.184	-0.184
	(0.363)	(0.359)	(0.280)	(0.281)	(0.223)	(0.223)
return_600	-0.509	-0.393	0.473*	0.419	0.246	0.238
	(0.357)	(0.355)	(0.281)	(0.283)	(0.221)	(0.223)
return_720	-0.186	-0.210	0.154	0.088	0.066	0.055
	(0.323)	(0.319)	(0.302)	(0.305)	(0.222)	(0.225)
realized_sd_past_30		-15.599***		13.041	-3.686	-3.605
		(5.867)		(9.157)	(5.278)	(5.288)
Constant	0.289***	0.447***	-0.125**	-0.227**	0.077	0.066
	(0.064)	(0.087)	(0.059)	(0.093)	(0.052)	(0.063)
Adjusted R^2	0.05	0.07	0.05	0.05	0.07	0.07
N	228	228	391	391	619	619

Table XVI
Forecasting the aggregate stock market crash in different sentiment states without learning: SKEWNESS (30 days)

The sample period runs from January 1952 to December 2008 and is based on the returns on DJIA in excess of the daily federal fund rate. The dependent variable is the SKEWNESS (Equation 1) 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%.

	Pessimistic State		Optimistic State		Both States	
	m1	m2	m3	m4	m5	m6
SENTIMENT					-0.266***	-0.259***
					(0.034)	(0.035)
DISAGREEMENT	-0.220***	-0.211***	0.236***	0.227***		0.028
	(0.064)	(0.063)	(0.055)	(0.055)		(0.046)
skew_past_30	0.120**	0.091**	0.088***	0.090***	0.100***	0.100***
	(0.048)	(0.038)	(0.034)	(0.034)	(0.028)	(0.028)
return_120	-0.667	-0.718	-0.912**	-0.901**	-0.849**	-0.847**
	(0.469)	(0.452)	(0.437)	(0.438)	(0.337)	(0.337)
return_240	-0.349	-0.311	-0.799***	-0.792***	-0.657***	-0.662***
	(0.265)	(0.260)	(0.206)	(0.206)	(0.172)	(0.171)
return_360	-0.373	-0.420	-0.186	-0.188	-0.232	-0.233
	(0.267)	(0.267)	(0.168)	(0.167)	(0.148)	(0.148)
return_480	-0.252	-0.276	-0.544***	-0.545***	-0.423**	-0.430***
	(0.240)	(0.240)	(0.204)	(0.204)	(0.166)	(0.165)
return_600	-0.384	-0.261	0.181	0.166	0.026	0.030
	(0.244)	(0.246)	(0.215)	(0.215)	(0.170)	(0.171)
return_720	-0.447*	-0.424	0.051	0.036	-0.075	-0.069
	(0.259)	(0.263)	(0.194)	(0.194)	(0.160)	(0.161)
realized_sd_past_30		-14.418***		4.082	-6.568	-6.784*
		(3.528)		(5.871)	(4.101)	(4.094)
Constant	0.303***	0.433***	-0.087***	-0.115**	0.159***	0.149***
	(0.048)	(0.058)	(0.029)	(0.053)	(0.040)	(0.043)
Adjusted R^2	0.08	0.10	0.07	0.06	0.10	0.10
N	4461	4461	9003	9003	13464	13464

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Appendix

A Trading Rules Documentation

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