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SHORT SALE CONSTRAINTS, INVESTOR SENTIMENT, AND ANALYST FORECAST DISPERSION: IMPLICATIONS FOR STOCK RETURNS

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Article Info

Keywords: : analyst forecast dispersion, investor sentiment, stock returns, risk effect, mispricing effect, difference of opinion, short-sale constraints.

Abstract

This study examines the relationship between analyst forecast dispersion and subsequent stock returns in high and low sentiment periods, with a focus on reconciling previous research on the risk effect and mispricing effect. Using non-financial common stocks on the NYSE, AMEX, and Nasdaq from January 1983 to December 2010, the study shows that overvaluation only occurs for the most dispersed stocks following high sentiment periods. The results also demonstrate that investor sentiment has a substantial impact on stock prices, adding to the growing literature on the topic. By combining difference of opinion, short-sale constraints, and investor sentiment, the study offers a comprehensive framework for understanding the dispersion effect and its implications for stock returns. Overall, the study contributes to the literature by investigating the dispersion effect across different sentiment periods, reconciling the mixed results on risk effect and mispricing effect, and exploring the impact of investor sentiment on overpricing.

INTRODUCTION

What drives the variations in stock returns is a central issue in asset pricing. As a major stock return determinant, risk has been extensively explored in prior literature. Traditional asset pricing theory leaves no room for behavioral factors, e.g., investor sentiment, under the assumption of rational investors. Furthermore, even though some investors are irrational, the force of arbitrage will eliminate their effect on stock prices. However, behavioral finance literature highlights the importance of limits of arbitrage, such as short sale constraints. Thus, investor sentiment may have a dramatic implication for the crosssection of stock returns in the sense that during the high sentiment periods, investors suffer from psychological bias and that there are more optimistic investors than pessimistic ones.

Previous literature documents mixed results regarding the relationship between analyst forecast dispersion and future stock returns, and different explanations are proposed. The mispricing story combines difference of opinion

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and short sale constraints to explain the empirically documented negative relationship between analyst forecast dispersion and future stock returns. There are optimistic and pessimistic investors in the market. When short sale constraints bind, Miller (1977)'s hypothesis indicates that the stock prices are determined by the optimistic investors while the pessimistic investors are kept out of the market since they cannot be short. Thus, a higher degree of a difference of opinion implies that the stocks are more likely to be overvalued, leading to lower subsequent stock returns (dispersion effect). On the contrary, the risk approach considers analyst forecast dispersion to be a risk factor, and the positive relationship between analyst forecast dispersion and future stock returns are documented (Qu et al., 2003, Anderson et al., 2009; Ma, 2011).

In this paper, I revisit the relationship between analyst forecast dispersion and subsequent stock re-turns following the high and low sentiment periods separately. I find that overvaluation occurs only for the most dispersed stocks following the high sentiment periods and is insignificant otherwise. I combine three ingredients to explain the empirical finding: difference of opinion, short-sale constraints, and investor sentiment. During high sentiment periods, investors suffer from psychological bias, and there are more optimistic investors who are also more aggressive in stock valuation. Because of short sale constraints, they push up stocks' prices too high relative to the fundamental value. However, in low sentiment periods, there are not so many optimistic investors, and the dispersion effect is insignificant.

This paper contributes to the literature in several aspects. To my knowledge, my paper is among the first to investigate the dispersion effect across different sentiment periods. I provide robust evidence that the dispersion effect is significant only following high sentiment periods while it is insignificant otherwise. Secondly, this paper reconciles the puzzling findings of risk effect and mispricing effect in the prior literature. Lastly, my paper adds more evidence that investor sentiment exhibits a substantial impact on stock prices, an underexplored topic in traditional asset pricing models.

RELATED LITERATURE The Role of Difference of Opinion

Mixed results are found regarding the relationship between the difference of opinion (proxied by analyst forecast dispersion) and subsequent stock returns. On the one hand, Diether et al. (2002), among others, document a significantly negative relation between analyst forecast dispersion and subsequent stock returns. On the other hand, some studies show a positive correlation between analysts forecast dispersion and stock returns when analyst forecast dispersion is considered as a risk factor (Qu et al. 2003; Anderson et al., 2009; Ma, 2011).

One stream of literature, which considers short sale constraints as a limit of arbitrage that leads to overvaluation, establishes the negative relation between the difference of opinion and stock re- turns. Miller (1977) hypothesizes that stock prices are determined by the optimistic investors in the presence of short-sale constraints, therefore, a higher degree in the difference of opinion implies higher stock price and lower subsequent return. The hypothesis is empirically supported by Diether et al. (2002), which finds that stocks with higher dispersion in analysts' earnings forecasts, a proxy for the difference of opinion, earn lower subsequent returns. Theoretically, Chen et al. (2002) develop an analytical model in which short sale constraints bind when breadth is low, leading to an overvaluation of stocks. Using data on mutual fund holdings, they then test the relationship between ownership breadth (a proxy for the difference of opinions) and stock returns and find that lower ownership breadth leads to lower stock returns. Nagel (2005) proposes that short-sale constraints are more likely to be binding when institutional ownership is low. He finds that using institutional ownership as a proxy, short-sale constraints can explain stock return anomalies. Boehme et al. (2006) test the Miller (1977) hypothesis by examining the valuation effects of the interaction between differences of opinion and short-sale constraints. They find that only when both conditions are met simultaneously can the overvaluations arise. Why are short sale constraints so important in reality? Almazan et al. (2004) find that only 26.7% of mutual funds are allowed to a short sale, and only 3% of mutual funds do short sale stocks. Prior works also test the implication of Miller (1977)'s hypothesis in the corporate bond market and find mixed results. G Güntay and Hackbarth (2010) use analyst forecast dispersion as a proxy for future cash flow uncertainty in corporate bond markets and find that credit spreads are positively correlated with analyst forecast dispersion. Cremers and Yan (2016) develop a theoretical model and hypothesize that uncertainty about a firm's profitability increases its stock valuation and decreases its bond valuation. They empirically test the predictions and find support for the positive association between uncertainty and stock valuation but no support for the negative association between uncertainty and bond valuation.

Another stream of literature considers analyst forecast dispersion as an alternative risk factor in a frictionless market with rational investors, and thus predicts a positive relationship between analyst forecast dispersion and subsequent stock returns. Qu et al. (2003) find that analyst forecast dispersion embodies a measure of information risk and acts as a systematic risk factor. Zhang (2006) uses analyst forecast dispersion as a proxy for information uncertainty and finds that greater information uncertainty leads to higher (lower) future returns following good (bad) news, implying that information uncertainty delays the flow of information into stock prices. Anderson et al. (2009) use analyst forecast dispersions to proxy for uncertainty and return volatility for risk. Their theoretical results suggest a positive relationship between uncertainty and stock returns and find stronger empirical evidence for an uncertainty-return trade-off than for the traditional risk-return trade-off. Avramov et al. (2009) also find a positive relationship between analyst forecast dispersion and stock returns after controlling for credit rating. In addition to the evidence on individual stock levels, prior literature also provides evidence by examining the aggregate data. Ma (2011) finds a positive relationship between aggregate analyst forecast dispersion and future aggregate stock returns. Given the contradictory findings, it is important but challenging to reconcile these conflicting results.

Banerjee (2011) develops a dynamic model that nests rational expectation and differences of opinion to reconcile the mixed results. According to the model, when investors are conditioned on prices (rational expectation approach), analyst forecast dispersion is positively correlated with future stock returns. On the contrary, when investors do not use prices (difference of opinion approach), the relation is reversed. Notably, the author explains the negative relationship between analyst forecast dispersion and stock returns without assuming short-sale constraints.

Investor Sentiment Although traditional asset pricing models don't pay much attention to the role investor sentiment plays in determining stock returns, prior literature in behavioral finance theorizes that investor sentiment can make the price systematically deviate from its fundamental value. The force of limits to arbitrage makes it costly to arbitrage based on sentiment (Shleifer & Vishny, 1997). Baker and Wurgler (2006, 2007) provide evidence that investor sentiment exhibits a dramatic effect in the cross-section of stock returns. They find that following the low sentiment periods, future returns are high for small and distressed stocks, while these stocks earn subsequent low returns in the high sentiment periods. They also propose a sentiment index based on the common variation in six underlying proxies for sentiment, which has been widely used afterward (Hribar & Mclnnis, 2012). Based on Baker and Wurgler (2006)'s sentiment index, Stambaugh et al. (2012) explore the role of sentiment in 13 anomalies and find that the anomalies are more manifested during the high sentiment periods. However, they do not investigate the relationship between analyst forecast dispersion and future stock return across different sentiment periods, which is the focus of my paper. Hribar and Mclnnis (2012) find that when sentiment is high, analyst forecasts are more optimistic for uncertain or difficult to value firms. Accounting for these forecast errors in a regression of stock returns on sentiments absorbs a large fraction of the explanatory power of sentiment on future stock returns. Mugenda et al. (2022) find that adding sentiment variables to the main effects model can enhance the significance of the profitability risk factor at the Nairobi Securities Exchange in Kenya.

A related and interesting paper is Cen et al. (2013), which finds that the relation between ownership breadth and return is positive when firm-level variation in sentiment is low where greater ownership breadth proxies for less-binding short-sale constraint. However, this relation is negative when firm-level variation in disagreement is low. My paper completes Cen et al. (2013) by exploring the relationship between analyst forecast dispersion and future stock returns and how this relation depends on aggregate market sentiment level.

Historically, high investor sentiment periods are usually followed by market crashes. For example, the period of the tech bubble coincides with high investor sentiment and is followed by a market crash. Another example is the 2008 financial crisis, which follows the high sentiment periods in the US real estate markets. These events suggest that investors are more optimistic during the high sentiment periods than in low sentiment periods, so overpricing is much more likely to happen in these periods. In addition, Miller (1977)'s hypothesis suggests that difference of opinion is essential for overpricing. The stocks with the highest analyst forecast dispersion have the highest degree in the difference of opinion, implying that overpricing is most likely to happen for the most dispersed stocks following the high sentiment periods. Thus, I propose the following hypotheses:

Hypothesis 1: Investor sentiment substantially impacts the most dispersed stocks, which are more likely to be overpriced during the high sentiment periods than low sentiment periods.

Hypothesis 2: Investor sentiment exhibits little effect on the least dispersed stocks, which do not tend to be overpriced, regardless of sentiment periods.

Hypothesis 3: Buying the least dispersed stocks and selling the most dispersed stocks can earn significantly positive returns during the high sentiment periods but not following the low sentiment periods.

DATA

The sample includes the non-financial common stocks on the NYSE, AMEX, and Nasdaq. The stock returns are drawn from the Center for Research in the Security Prices (CRSP) Monthly Stocks Combined File. The financial data is from the COMPUSTAT database. Institutional ownership data is taken from the Thomson Reuters Institutional (13f) Holdings-Type 3. Analyst forecast data is obtained from the earning forecast for horizon 1 (FPI=1) in the Institutional Brokers' Estimate System (I/B/E/S) unadjusted summary historical file, and I exclude the firm-month sample with only one analyst forecast. I collect the investor sentiment index from Jeffrey Wurgler's website (http://pages.stern.nyu.edu/_jwurgler), which is based on the first principal component of six proxies: closed-end fund discount, the equity share in new issues, New York Stock Exchange (NYSE) share turnover, number of IPOs, first-day IPO returns, and the dividend premium. The Baker Wurgler sentiment index is plotted in Fig. 1. The peaks of investor sentiment are usually followed by the subsequent market crashes, indicating that stocks are more likely to be overpriced during the high sentiment periods.

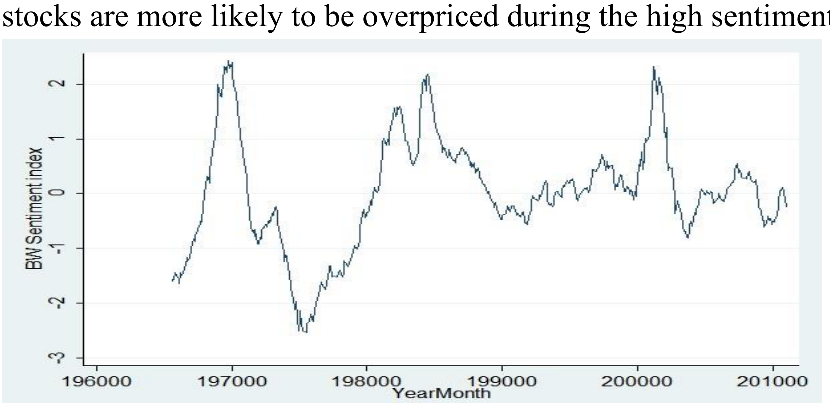

Figure 1. The sentiment index is from July 1965 to December 2010

To ensure that the small, illiquid stocks do not drive the results, I exclude the stocks with prices less than five dollars at the end of the previous month, following Cen et al. (2017), the sample period is from January 1983 to December 2010. I do not include samples after 2010 for the following reasons: (1) the sample periods after the financial crisis and the recent pandemic are excluded; (2) the recent data on the investor sentiment index is not available. Only firms that meet the following criteria are included in the sample: (1) The firm has financial data for the fiscal year ending in the previous calendar year in the COMPUSTAT database; (2) The firm has previous twelve months stock returns to compute cumulative returns from the end of month t-12 to the end of month t-2.

EMPIRICAL METHOD AND RESULTS Hypotheses and Empirical Method

The first hypothesis argues that investor sentiment substantially impacts most analyst forecast dispersed stocks, which is more likely to be overpriced during the high sentiment periods than during the low sentiment periods. The second hypothesis suggests that investor sentiment exhibits little effect on the least dispersed stocks, which do not tend to be overpriced, regardless of sentiment periods. The third hypothesis tells us that buying the least dispersed stocks and selling the most dispersed stocks can earn significantly positive returns during the high sentiment periods but not the low sentiment periods.

To verify these hypotheses, I classify the months from January 1983 to December 2010 into two groups based on the median value of the monthly Baker and Wurgler (2006) sentiment index. Then following Diether et al. (2002) and Cen et al. (2013), in each month, I calculate analyst forecast dispersion as the coefficient of variation, i.e., the standard deviation of analyst forecast for firms' EPS of one-year horizon scaled by the absolute mean of the forecasts.

Most previous studies focus on the relationship between analyst forecast dispersion and the following one-month stock returns. But it may take longer for the analyst forecasts to be available for the public. Thus, as a robustness check, I also form portfolios based on analyst forecast dispersion in the previous two to six months and get similar results.

Empirical Results

Panel A in Table 1 reports the time-series averages of common statistics of the final sample. The final sample consists of observations from January 1983 to December 2010. I restrict the final sample by deleting observations with analyst forecast dispersion equal to zero or higher than two. The mean (median) of one month ahead stock return is 1.0% (0.6%), and the standard deviation is 11.5%. The mean (median) of market capitalization is 3.6 (0.65) billion with a standard deviation of approximately15.1 billion. Following Diether et al. (2002) and Cen et al. (2013), I use DIS_MEAN, defined as the standard deviation of annual EPS forecast scaled by the absolute mean of the forecasts, to measure the analyst forecast dispersion. The mean (median) of DIS_MEAN is 0.158 (0.056), and the standard deviation is 0.315.

Panel B in Table 1 presents the time-series average Pearson correlation coefficients between the variables. The correlation between analyst coverage and size is 0.47, indicating that analysts focus more on larger firms. The age is negatively correlated with the measure of analyst forecast dispersion, which means older firms are less dispersed.

Panel C in Table 1 illustrates the time-series average of statistics by groups sorted on analyst forecast dispersion. We can see that more dispersed stocks are usually found in smaller, younger firms and firms with lower institutional ownership and less analyst coverage. This is consistent with previous literature. For example, Zhang (2006) uses a smaller size, higher analyst forecast dispersion, fewer analyst coverage, and younger age to proxy for higher information uncertainty. In addition, Cremers and Yan (2016) also use younger firm age and higher analyst forecast dispersion as proxies for higher uncertainty.

Table 1. Summary Statistics and Correlation Matrix

	AGE	IO	B/M	SIZE	DIS_MEAN	1M	3M	6M	R(-7)	R(-12)	COV
AGE	1										
IO	0.192	1									
B/M	0.122	-0.052	1								
SIZE	0.353	0.057	-0.034	1							
DIS_MEAN	-0.031	-0.047	0.046	-0.036	1						
1M	0.013	0.019	0.011	0.000	-0.009	1					
3M	0.017	0.024	0.019	0.000	-0.013	0.567	1				
6M	0.027	0.024	0.031	0.001	-0.016	0.402	0.697	1			
R(-7)	-0.024	0.051	0.042	0.010	-0.037	0.025	0.040	0.051	1		
R(-12)	-0.040	0.074	0.011	0.011	-0.060	0.025	0.033	0.028	0.732	1	
COV	0.397	0.321	-0.021	0.470	-0.045	0.004	0.005	0.011	-0.034	-0.035	1

Panel C: Summary statistics by groups sorted by analyst forecast dispersion

Dispersion Decile	SIZE ($*10^6$)	B/M	IO	Age	R (-7, -2)	R (-12, -2)	DIS_MEAN	COV
1	8.335	0.515	0.548	23.808	0.101	0.2	0.012	11.668
2	5.2	0.574	0.534	22.568	0.104	0.203	0.02	11.254
3	3.9	0.605	0.521	21.613	0.105	0.2	0.027	10.725
4	3.544	0.626	0.509	20.795	0.107	0.204	0.036	10.261
5	3.369	0.643	0.492	19.882	0.105	0.199	0.048	9.739
6	3.314	0.828	0.478	19.045	0.104	0.189	0.065	9.616
7	2.938	0.693	0.455	17.846	0.091	0.174	0.091	9.233
8	2.496	0.736	0.442	16.524	0.086	0.156	0.136	8.913
9	1.708	0.751	0.419	15.582	0.075	0.132	0.238	8.224
10	1.216	1.448	0.41	14.671	0.041	0.063	0.905	7.531

To investigate whether investor sentiment substantially influences the dispersion effect, I sort the monthly Baker and Wurgler (2006) sentiment index into two groups. The periods in the higher group are defined as high sentiment periods. Similarly, the periods in the lower group are low sentiment periods. Table 2 shows the one-month-ahead portfolio excess returns during the low and high sentiment periods. The portfolio return is computed using an equal-weighted average.

For the most dispersed stock portfolio, the excess return following the high and low sentiment periods is -0.35% and 0.98%, respectively, statistically insignificant. Similarly, the excess returns following the high and low sentiment periods are 0.64% and 0.59% for the least dispersed stock portfolio. These results imply that investor sentiment substantially impacts the most dispersed stocks while its effect on the least dispersed stocks is not pronounced.

As for the hedging portfolio, following the high sentiment periods, the portfolio that longs stocks in the lowest analyst forecast dispersion decile and short stocks in the highest analyst forecast dispersion decile can earn a monthly abnormal return of 0.94%, which is statistically significant at the 5% significant level (t-statistic of 2.59). On the contrary, the portfolio return is insignificant during the low sentiment periods. The results strongly support the third hypothesis: buying the least dispersed stocks and selling the most dispersed can earn significantly positive returns only during the high sentiment periods.

Table 2. Portfolio raw returns in percent sorted by analyst forecast dispersion following the high and low sentiment periods

	Low Sentiment Periods	**High Sentiment Periods**
Dispersion Decile	Equal-weight	Equal-weight
D1 (L)	0.64*	0.59
t-statistic	(1.82)	(1.61)
D2	0.62*	0.51
t-statistic	(1.71)	(1.40)
D3	0.91**	0.47
t-statistic	(2.12)	(1.20)
D4	0.96**	0.46
t-statistic	(2.17)	(1.11)
D5	0.92**	0.43
t-statistic	(2.05)	(1.05)
D6	0.93*	0.42
t-statistic	(1.95)	(0.97)
D7	0.92*	0.30
t-statistic	(1.95)	(0.64)
D8	1.05**	0.02
t-statistic	(2.10)	(0.04)
D9	0.90*	0.01
t-statistic	(1.71)	(0.01)
D10 (H)	0.98	-0.35
t-statistic	(1.64)	(-0.63)
D1-D10 (L-H)	-0.34	0.94**
t-statistic	(-0.93)	(2.59)

To ensure that the common risk factors do not drive the results in Table 2, I adjust the returns by CAPM market factor, Fama-French factors (SMB, HML), momentum factor (UMD). Table 3 shows the abnormal returns of the portfolio with one month holding period.

After adjusting for common risk factors, the CAPM adjusted, three factors adjusted, and four factors adjusted, monthly returns are 1.07%, 0.92%, and 0.72%, respectively, showing that the zero-cost hedging portfolio earns positive returns during the high sentiment periods. However, the hedging portfolio's returns during the low sentiment periods are insignificant, both economically and statistically. This is consistent with the third hypothesis that buying the least dispersed stocks and selling the most dispersed can earn significantly positive returns during the high sentiment periods but not following the low sentiment periods.

The most dispersed stocks' adjusted excess returns are all significantly negative, with values ranging from -0.62% to -0.79%, implying that stocks with the highest difference of opinion during the high sentiment periods are overpriced. The findings can be explained by the Miller (1977) hypothesis, which argues that in short-sale constraints, stock prices are determined by the optimistic, and the pessimistic are kept out of the market. Stocks with the highest difference of opinion are mostly overpriced, leading to subsequent negative returns. The most dispersed stocks are not overpriced during the low sentiment periods. Therefore, the first hypothesis is supported, as investor sentiment substantially impacts the most dispersed stocks, and these stocks are overpriced only during the high sentiment periods.

The adjusted returns are not significantly different from zero for the least dispersed stocks, regardless of sentiment periods. This is consistent with the second hypothesis, in which investor sentiment has little effect on the least dispersed stocks, which do not tend to be overpriced following the high and low sentiment periods.

Table 3. Portfolio raw returns in percent sorted by analyst forecast dispersion during the high and low sentiment periods

	Low Sentiment Periods			High Sentiment Periods		
	CAPM	3F	4F	CAPM	3F	4F
Dispersion Decile	alpha	alpha	alpha	alpha	alpha	alpha
D1 (L)	-0.02	-0.06	-0.07	0.28	0.06	0.10
t-statistic	(-0.10)	(-0.38)	(-0.50)	(1.43)	(0.37)	(0.58)
D2	-0.08	-0.13	-0.13	0.18	0.00	0.12
t-statistic	(-0.56)	(-1.01)	(-1.10)	(0.98)	(0.01)	(0.73)
D3	0.12	0.05	0.09	0.13	-0.00	0.09
t-statistic	(0.78)	(0.39)	(0.73)	(0.73)	(-0.01)	(0.64)
D4	0.12	0.04	0.08	0.10	0.04	0.16
t-statistic	(0.77)	(0.39)	(0.72)	(0.56)	(0.27)	(1.16)
D5	0.07	-0.01	0.05	0.06	0.01	0.13
t-statistic	(0.42)	(-0.07)	(0.40)	(0.32)	(0.05)	(0.97)
D6	0.02	-0.06	-0.02	0.04	-0.02	0.06
t-statistic	(0.12)	(-0.48)	(-0.14)	(0.18)	(-0.10)	(0.41)
D7	-0.00	-0.08	0.01	-0.10	-0.09	0.04
t-statistic	(-0.00)	(-0.57)	(0.04)	(-0.43)	(-0.46)	(0.25)
D8	0.11	0.01	0.09	-0.40	-0.43**	-0.28
t-statistic	(0.57)	(0.05)	(0.70)	(-1.63)	(-2.52)	(-1.64)
D9	-0.08	-0.19	-0.11	-0.42	-0.44**	-0.31
t-statistic	(-0.38)	(-1.14)	(-0.69)	(-1.55)	(-2.35)	(-1.56)
D10 (H)	-0.08	-0.20	-0.06	-0.79**	-0.85***	-0.62***
t-statistic	(-0.28)	(-0.96)	(-0.29)	(-2.41)	(-3.98)	(-3.12)
D1-D10 (L-H)	0.06	0.14	-0.02	1.07***	0.92***	0.72**
t-statistic	(0.22)	(0.59)	(-0.07)	(3.14)	(3.15)	(2.51)

To further investigate the role investor sentiment plays in the relationship between analyst forecast dispersion and stock returns, I regress the abnormal portfolio returns on the monthly sentiment index of Baker and Wurgler (2006). Table 4 reports the results of regressing portfolio excess returns on the lagged sentiment index when the Fama-French Carhart four factors are controlled for or not. The regression functions are as follows:

$Yt=c + d\ SIt\text{-}1 + \varepsilon t$

$Y_t=c + d\ SI_{t-1} + e\ RMRF_t + f\ SMB_t + g\ HML_t + h\ UMD_t + \varepsilon_t$

For the long-short portfolio D1-D10 (L-H), the dependent variable is RH,t – RL,t. For the least and most dispersed portfolios, the dependent variables are the excess returns of one-month-ahead, which equal the raw portfolio minus the monthly risk-free rate. SIt-1 is the sentiment_orthogonal or sentiment index in month t-1 from Baker and Wurgler (2006). Sentiment_orthogonal is based on the first principal component of six sentiment proxies, and each proxy has first been orthogonalized to some macroeconomics variables. The macroeconomic variables are the growth in industrial production, the growth in durable, nondurable, and services consumption, the growth in employment, and a flag for NBER recessions. The sentiment index is similar, but it is not orthogonalized first.

The variable RMRF is the excess market return. Following Fama and French (1993), SMB is the return of the portfolio that longs small stocks and shorts big stocks. Similarly, HML is the return of the portfolio that longs high book-to-market ratio stocks and shorts low book-to-market ratio stocks. The variable UMD is the return on high-momentum stocks minus the return on low-momentum stocks, where the momentum is measured as the cumulative return from month t-12 to month t-2.

As shown from Table 4, for the least dispersed stock portfolio, the coefficient on the sentiment index is generally insignificant, implying that investor sentiment has little effect on the least dispersed stocks. The only exception is the coefficient of model 4, but it is just marginally significant. However, the coefficient on the sentiment index is usually significantly negative for the most dispersed stocks. This suggests that investor sentiment substantially impacts the most dispersed stocks, which are more likely to be overpriced during the high sentiment periods than in the low sentiment periods. For the long-short portfolio returns, the coefficient is positively significant, which means that buying the least dispersed stocks and selling the most dispersed can earn significantly positive returns during the high sentiment periods but not following the low sentiment periods.

Table 4. Regress portfolio excess returns on sentiment index and other factors

Decile	**Model 1** **SENTIMENT(t-1), not controlling for RMRF, SMB,HML,UMD**	**Model 2** **SENTIMENT(t-1),** controlling for RMRF, SMB,HML,UMD	**Model 3** **SENTIMENT_** orthogonal(t-1), not controlling for RMRF,SMB, HML,UMD	**Model 4** **SENTIMENT_** orthogonal(t-1), controlling for RMRF,SMB, HML,UMD
D1 (Low)	-0.24	0.27	-0.32	0.29*
t-statistic	(-0.60)	(1.62)	(-0.82)	(1.74)
D10 (High)	-1.48**	-0.47**	-1.56**	-0.47**
t-statistic	(-2.44)	(-2.13)	(-2.52)	(-2.00)
D1-D10 (L-H)	1.25***	0.74**	1.24***	0.76**
t-statistic	(2.91)	(2.34)	(2.85)	(2.32)

Next, I apply double sorting. Table 5 illustrates the results after controlling for book-to-market ratio, size, institutional ownership, cumulative returns in the past year (MOM12_2), and cumulative returns in the past half-year (RET7_2). First, at the beginning of each month, all stocks are sorted into ten deciles based on the variables that I want to control (SIZE, B/M, IO, MOM12_2, RET7_2). Next, I sort stocks into ten deciles within each decile based on analyst forecast dispersion. Stocks are held for one month, and the equal-weighted portfolio returns are computed. Then the ten portfolios sorted on analyst forecast dispersion are averaged over each of the ten book-to-market ratio deciles. We can see that the most dispersed stocks are overpriced during the high sentiment periods but not the low sentiment periods. The least dispersed stocks are not overpriced in both the high and low sentiment periods. Therefore, the long-short portfolio can earn positive returns only during the high sentiment periods. These findings are robust and consistent with Table 3.

Table 5. Double sorting- portfolio returns based on analyst forecast dispersion following the high and low sentiment periods, after controlling for other variables (size, B/M, institutional ownership, past one-year return, past half-year return)

Panel A: Control for book-to-market ratio		
	Low Sentiment Periods	High Sentiment Periods

Dispersion Decile	CAPM Alpha	3F Alpha	4F Alpha	Dispersion Decile	CAPM Alpha	3F Alpha	4F Alpha
1 Low	0.06	0.02	-0.02	1 Low	0.39**	0.15	0.19
	(0.39)	(0.11)	(-0.14)		(2.02)	(0.93)	(1.17)
2	-0.01	-0.06	-0.06	2	0.23	0.05	0.21
	(-0.09)	(-0.48)	(-0.44)		(1.34)	(0.26)	(1.36)
3	-0.07	-0.14	-0.10	3	0.10	-0.06	0.05
	(-0.44)	(-1.18)	(-0.97)		(0.66)	(-0.41)	(0.37)
4	0.11	0.04	0.08	4	0.07	-0.02	0.10
	(0.76)	(0.34)	(0.59)		(0.40)	(-0.14)	(0.71)
5	0.17	0.08	0.14	5	0.03	-0.03	0.07
	(0.93)	(0.59)	(1.01)		(0.16)	(-0.15)	(0.47)
6	0.03	-0.06	-0.02	6	0.10	0.06	0.18
	(0.16)	(-0.55)	(-0.21)		(0.45)	(0.40)	(1.30)
7	-0.01	-0.10	-0.02	7	-0.12	-0.09	0.05
	(-0.05)	(-0.74)	(-0.19)		(-0.51)	(-0.51)	(0.30)
8	0.04	-0.05	0.04	8	-0.44	-0.45	-0.40
	(0.19)	(-0.35)	(0.33)		(-1.72)	(-2.62)	(-2.12)
9	0.05	-0.06	0.03	9	-0.46	-0.49	-0.32
	(0.22)	(-0.37)	(0.18)		(-1.63)	(-2.46)	(-1.63)
10 High	-0.19	-0.30	-0.15	10 High	-0.85**	-0.85***	-0.65***
	(-0.72)	(-1.52)	(-0.79)		(-2.50)	(-4.03)	(-3.20)
L-H	0.25	0.32	0.13	L-H	1.23***	1.00***	0.84***
	(0.92)	(1.33)	(0.55)		(3.54)	(3.48)	(2.99)

Panel B: Control for the market capitalization (size)

	Low Sentiment Periods				High Sentiment Periods		
Dispersion Decile	CAPM Alpha	3F Alpha	4F Alpha	Dispersion Decile	CAPM Alpha	3F Alpha	4F Alpha
1 Low	-0.08	-0.16	-0.15	1 Low	0.31	0.19	0.09
	(-0.46)	(-1.03)	(-0.92)		(1.45)	(1.10)	(0.53)
2	0.08	0.02	0.01	2	0.10	0.05	-0.06
	(0.47)	(0.19)	(0.04)		(0.54)	(0.30)	(-0.35)
3	0.02	-0.00	-0.05	3	0.20	0.16	0.04
	(0.12)	(-0.01)	(-0.47)		(1.02)	(1.12)	(0.27)
4	0.07	0.05	0.00	4	-0.01	0.05	-0.09
	(0.52)	(0.52)	(0.02)		(-0.06)	(0.31)	(-0.52)
5	0.04	0.00	-0.04	5	-0.08	0.00	-0.11
	(0.26)	(0.03)	(-0.28)		(-0.44)	(0.02)	(-0.79)
6	0.03	-0.00	-0.05	6	-0.04	0.04	-0.09
	(0.19)	(-0.00)	(-0.43)		(-0.20)	(0.25)	(-0.51)

7	0.02	-0.01	-0.07	7	-0.04	0.04	-0.06
	(0.13)	(-0.08)	(-0.54)		(-0.18)	(0.24)	(-0.37)
8	0.06	0.05	-0.03	8	-0.37	-0.29	-0.39
	(0.31)	(0.30)	(-0.19)		(-1.60)	(-1.51)	(-2.08)
9	0.02	0.02	-0.07	9	-0.39	-0.29	-0.44
	(0.13)	(0.13)	(-0.44)		(-1.48)	(-1.43)	(-2.31)
10 High	-0.09	-0.07	-0.19	10 High	-0.62**	-0.47**	-0.63***
	(-0.36)	(-0.34)	(-0.93)		(-2.10)	(-2.15)	(-2.87)
L-H	0.01	-0.09	0.05	L-H	0.93***	0.66**	0.73**
	(0.03)	(-0.33)	(0.18)		(2.91)	(2.14)	(2.38)

Panel C: Control for institutional ownership

	Low Sentiment Periods				High Sentiment Periods		
Dispersion Decile	CAPM Alpha	3F Alpha	4F Alpha	Dispersion Decile	CAPM Alpha	3F Alpha	4F Alpha
1 Low	-0.06	-0.12	-0.10	1 Low	0.20	0.06	0.02
	(-0.39)	(-0.84)	(-0.68)		(1.08)	(0.36)	(0.10)
2	-0.01	-0.04	-0.05	2	0.14	0.15	0.03
	(-0.07)	(-0.41)	(-0.46)		(0.77)	(0.83)	(0.15)
3	0.12	0.08	0.05	3	0.09	0.06	-0.04
	(0.72)	(0.61)	(0.34)		(0.59)	(0.43)	(-0.30)
4	0.05	0.02	-0.03	4	0.01	0.06	-0.08
	(0.29)	(0.15)	(-0.22)		(0.02)	(0.41)	(-0.49)
5	0.04	0.00	-0.04	5	-0.01	0.04	-0.06
	(0.29)	(0.00)	(-0.34)		(-0.08)	(0.24)	(-0.38)
6	0.10	0.07	0.01	6	0.05	0.14	0.03
	(0.54)	(0.52)	(0.09)		(0.27)	(1.13)	(0.21)
7	-0.09	-0.10	-0.19	7	-0.09	-0.01	-0.14
	(-0.55)	(-0.79)	(-1.29)		(-0.35)	(-0.06)	(-0.76)
8	0.19	0.15	0.09	8	-0.26	-0.16	-0.26
	(0.91)	(1.07)	(0.62)		(-1.10)	(-1.00)	(-1.70)
9	-0.09	-0.10	-0.21	9	-0.45	-0.37	-0.53
	(-0.43)	(-0.67)	(-1.33)		(-1.61)	(-1.70)	(-2.66)
10 High	-0.08	-0.07	-0.20	10 High	-0.63*	-0.49**	-0.69***
	(-0.29)	(-0.37)	(-1.01)		(-1.93)	(-2.32)	(-3.25)
L-H	0.02	-0.05	0.10	L-H	0.83**	0.54*	0.71**
	(0.06)	(-0.20)	(0.43)		(2.49)	(1.86)	(2.36)

Panel D: Control for RET7_2

	Low Sentiment Periods			High Sentiment Periods			
Dispersion Decile	CAPM Alpha	3F Alpha	4F Alpha	Dispersion Decile	CAPM Alpha	3F Alpha	4F Alpha
1 Low	-0.06	-0.09	-0.12	1 Low	0.19	0.09	0.04
	(-0.36)	(-0.61)	(-0.79)		(0.98)	(0.56)	(0.23)
2	0.17	0.13	0.12	2	0.12	0.17	0.04
	(1.23)	(1.16)	(0.97)		(0.62)	(1.00)	(0.21)
3	0.02	0.00	-0.05	3	0.04	0.04	-0.07
	(0.12)	(0.00)	(-0.36)		(0.20)	(0.24)	(-0.44)
4	0.01	-0.00	-0.06	4	0.08	0.17	0.06
	(0.09)	(-0.02)	(-0.59)		(0.49)	(1.34)	(0.49)
5	0.08	0.05	0.00	5	-0.03	0.12	-0.01
	(0.50)	(0.39)	(0.01)		(-0.13)	(0.68)	(-0.07)
6	0.03	-0.01	-0.05	6	0.04	0.08	-0.03
	(0.19)	(-0.06)	(-0.42)		(0.21)	(0.57)	(-0.21)
7	0.03	0.01	-0.05	7	-0.05	-0.01	-0.15
	(0.18)	(0.09)	(-0.37)		(-0.24)	(-0.08)	(-0.84)
8	-0.04	-0.10	-0.14	8	-0.45	-0.35	-0.50
	(-0.23)	(-0.94)	(-1.25)		(-2.01)	(-2.13)	(-2.84)
9	0.04	0.02	-0.06	9	-0.25	-0.19	-0.32
	(0.20)	(0.11)	(-0.40)		(-0.89)	(-0.90)	(-1.60)
10 High	-0.05	-0.08	-0.17	10 High	-0.59*	-0.45**	-0.65***
	(-0.20)	(-0.40)	(-0.84)		(-1.94)	(-2.34)	(-3.20)
L-H	-0.01	-0.01	0.05	L-H	0.78***	0.54*	0.69**
	(-0.02)	(-0.04)	(0.21)		(2.61)	(1.97)	(2.45)

Panel E: Control for MOM12_2

	Low Sentiment Periods			High Sentiment Periods			
Dispersion Decile Alpha	CAPM Alpha	3F	4F Alpha	Dispersion Decile	CAPM Alpha	3F Alpha	4F Alpha
1 Low	-0.07	-0.11	-0.13	1 Low	0.24	0.21	0.12
	(-0.45)	(-0.79)	(-0.90)		(1.24)	(1.35)	(0.78)
2	0.01	-0.01	-0.05	2	0.14	0.14	0.02
	(0.04)	(-0.06)	(-0.37)		(0.78)	(0.95)	(0.14)
3	-0.04	-0.07	-0.11	3	-0.09	-0.07	-0.19
	(-0.30)	(-0.57)	(-0.89)		(-0.58)	(-0.49)	(-1.28)
4	0.11	0.08	0.03	4	0.19	0.21	0.11
	(0.68)	(0.62)	(0.26)		(0.96)	(1.42)	(0.72)

5	0.14	0.12	0.06	5	0.10	0.13	0.03
	(0.90)	(0.98)	(0.45)		(0.55)	(0.88)	(0.18)
6	-0.04	-0.06	-0.12	6	0.10	0.14	0.02
	(-0.24)	(-0.49)	(-0.95)		(0.47)	(0.84)	(0.08)
7	0.09	0.07	0.01	7	-0.15	-0.01	-0.17
	(0.58)	(0.58)	(0.08)		(-0.73)	(-0.04)	(-1.06)
8	-0.06	-0.10	-0.16	8	-0.20	-0.13	-0.28
	(-0.30)	(-0.69)	(-1.12)		(-0.83)	(-0.71)	(-1.55)
9	0.13	0.09	0.03	9	-0.27	-0.26	-0.39
	(0.71)	(0.69)	(0.20)		(-1.02)	(-1.41)	(-2.32)
10 High	0.05	0.02	-0.07	10 High	-0.44	-0.37*	-0.53**
	(0.18)	(0.10)	(-0.35)		(-1.45)	(-1.91)	(-2.52)
L-H	-0.12	-0.13	-0.06	L-H	0.68**	0.58**	0.65**
	(-0.46)	(-0.54)	(-0.25)		(2.26)	(2.15)	(2.41)

Further evidence on the firm level is required to ensure the credibility of the results. In Table 6, I use one-month-ahead stock return as dependent variable and control for risk factors, including logMEi,t (the logarithm of firm i's market value at the end of month t), logBMi,t (the logarithm of firm i's book to market ratio), MOMi,t-12,t-2 (the cumulative return for stock i from the end of month t-12 to the end of month t-2), as well as RETi,t-1 (returns in the past one month), ACi,t (the number of forecasts for stock i at the end of month t) and AGEi,t (firm age). One may be interested in the relationship between analyst forecast dispersion and next month's stock return. During the high sentiment periods, the coefficients on analyst forecast dispersion throughout model 1 to model 5 are all significantly negative, with t statistics ranging from -2.38 to -2.78.

One can see that throughout model 1 to model 5, the magnitude and significance of the coefficient on analyst forecast dispersion are nearly the same. As expected, the coefficients are always significantly negative during the high sentiment periods, while they are insignificant and positive when low investor sentiment. It is because those investors are less rational during high sentiment periods. As a result, they push the stock price up too high. Consistent with Miller (1977) 's hypothesis, when short sale constraint binds, and investors disagree about the stock valuation, the optimists determine the stock prices. The pessimistic investors' opinion is not incorporated into prices. Thus, stocks with a higher difference of opinion, proxied by analyst forecast dispersion in this paper) are overpriced more substantially, therefore leading to lower future stock returns. But this effect is only significant during the high sentiment periods. During the low sentiment periods, it is rare for the stocks to be over-valued.

In addition, the coefficient on B/M is positive, which means that value stocks earn a higher stock return in the next month, consistent with the value-growth premium. The coefficient on momentum factor is also significantly positive, indicating that past winners outperform past losers. Following Líubosí and Veronesi (2003), I use the reciprocal of one plus firm age to control firm age. They propose the functional form for age based on a theoretical model of the Bayesian learning process. During the high sentiment periods, the coefficients on Inverse_(1+AGE) are negative and significant, meaning that the correlation between age and stock return is positive. The explanation is that younger firms are more uncertain and easier to be overpriced, leading to lower subsequent stock returns. The mispricing effect is only significant during the high sentiment periods. This is consistent with Zhang (2006) and Cremers and Yan (2016), who use age to proxy uncertainty.

Table 6. Firm-level Fama-Macbeth regression

Panel A: Low sentiment period

Dependent Variable: One-Month-Ahead Stock Return

Return	MODEL1	MODEL2	MODEL3	MODEL4	MODEL5
constant	0.019	0.019*	0.019*	0.027**	0.026**
t-statistic	(1.63)	(1.66)	(1.69)	(2.19)	(2.30)
$LogME_{i,t}$	-0.001	-0.001	-0.001	-0.002*	-0.002**
t-statistic	(-1.02)	(-1.06)	(-1.27)	(-1.92)	(-1.99)
$LogBM_{i,t}$	0.000	-0.000	0.000	0.000	0.000
t-statistic	(0.00)	(-0.03)	(0.02)	(0.04)	(0.14)
ANALYST FORECAST $DISPERSION_{i,t}$	0.003	0.002	0.002	0.002	0.002
t-statistic	(1.01)	(0.89)	(0.84)	(0.71)	(0.73)
MOMi,t-12,t-2	0.006*	0.006*	0.006	0.006*	0.006*
t-statistic	(1.70)	(1.74)	(1.64)	(1.77)	(1.74)
RETi,t-1		0.001	0.001	0.002	0.002
t-statistic		(0.12)	(0.14)	(0.24)	(0.24)
$IO_{i,t}$			0.005	0.005	0.005
t-statistic			(1.62)	(1.43)	(1.46)
$AC_{i,t}$				0.000**	0.000**
t-statistic				(2.18)	(2.23)
Inverse ($1+AGE_{i,t}$)					0.003
t-statistic					(0.47)

Panel B: High sentiment period

Dependent Variable: One-Month-Ahead Stock Return

	MODEL1	MODEL2	MODEL3	MODEL4	MODEL5
constant	0.004	0.003	0.006	0.005	0.017*
t-statistic	(0.35)	(0.27)	(0.51)	(0.43)	(1.68)
$LogME_{i,t}$	0.001	0.001	0.000	0.000	-0.001
t-statistic	(0.89)	(0.94)	(0.01)	(0.09)	(-0.86)
$LogBM_{i,t}$	0.006***	0.006***	0.006***	0.006***	0.005***
t-statistic	(3.21)	(3.45)	(3.55)	(3.50)	(3.33)
ANALYST FORECAST $DISPERSION_{i,t}$	-0.008***	-0.008***	-0.007**	-0.007**	-0.007**
t-statistic	(-2.78)	(-2.76)	(-2.44)	(-2.50)	(-2.38)
MOMi,t-12,t-2	0.009***	0.008***	0.008***	0.008***	0.008***
t-statistic	(3.16)	(3.09)	(2.94)	(2.91)	(3.25)
RETi,t-1		0.002	0.002	0.002	0.003

t-statistic	(0.33)	(0.32)	(0.30)	(0.44)
$IO_{i,t}$		0.012***	0.012***	0.010***
t-statistic		(3.30)	(3.28)	(2.74)
$AC_{i,t}$			-0.000	-0.000
t-statistic			(-0.40)	(-0.20)
Inverse (1+$AGE_{i,t}$)				-0.032***
t-statistic				(-3.74)

Robustness Checks

Lag in Portfolio Formation

Diether et al. (2002) suggest that the information in analyst forecast dispersion may not be available to the public immediately, so I formed stock portfolios based on lagged analyst forecast dispersion several months ago. I vary the time lag from two months to six months and present panel A to panel E results. For example, panel A shows the single-sorted results for portfolios sorted by analyst forecast dispersion two months ago. The portfolios are held for one month, and the equal-weighted portfolio returns are computed. As shown in Table 7, the results are the same as those in Table 3. Due to the space constraint, I only report the robustness check results after sorting on analyst forecast dispersion in month t-2. The panels B, C, D, and E controls for analyst forecast dispersion in month t-3, t-4, t-5, and t-6. Results are similar and available upon request.

In almost all specifications, the most dispersed stocks are overpriced only during the high sentiment periods but not in the low sentiment periods. Going long the least dispersed stocks and short the most dispersed stocks can only make significant positive returns following the high sentiment periods. The exceptions are when the time lag is longer than four months. Under some circumstances, the most dispersed stocks' excess returns and the long-short hedging portfolio returns are insignificant after adjusting for three or four factors. This is consistent with Diether et al. (2002) robustness check that if the lag is longer than five months, the return difference is not statistically significant anymore.

Table 7. Robustness check: lag in portfolio formation

Panel A: Sort on analyst forecast dispersion in month t-2

	Low Sentiment Periods				High Sentiment Periods			
Dispersion Decile	Excess return	CAPM alpha	3F alpha	4F alpha	Excess return	CAPM alpha	3F alpha	4F alpha
D1 (L)	0.70**	-0.01	-0.04	-0.01	0.56	0.34*	0.11	0.20
t-statistic	(2.12)	(-0.04)	(-0.25)	(-0.06)	(1.43)	(1.67)	(0.65)	(1.21)
D2	0.76**	0.02	-0.03	-0.03	0.47	0.23	0.09	0.19
t-statistic	(2.18)	(0.11)	(-0.24)	(-0.20)	(1.18)	(1.23)	(0.58)	(1.24)
D3	0.96**	0.14	0.08	0.13	0.37	0.11	0.02	0.15
t-statistic	(2.50)	(0.85)	(0.61)	(0.98)	(0.82)	(0.60)	(0.16)	(1.01)
D4	0.80**	-0.09	-0.15	-0.13	0.29	0.02	-0.02	0.14
t-statistic	(2.01)	(-0.54)	(-1.37)	(-1.19)	(0.61)	(0.11)	(-0.18)	(1.03)
D5	1.01**	0.13	0.06	0.10	0.39	0.11	0.05	0.16

t-statistic	(2.58)	(0.80)	(0.57)	(0.93)	(0.83)	(0.61)	(0.32)	(1.04)
D6	0.97**	0.03	-0.03	0.04	0.33	0.05	0.04	0.11
t-statistic	(2.30)	(0.14)	(-0.26)	(0.42)	(0.69)	(0.25)	(0.29)	(0.77)
D7	1.17**	0.21	0.13	0.19	0.04	-0.26	-0.26	-0.08
t-statistic	(2.57)	(0.89)	(0.89)	(1.35)	(0.08)	(-1.22)	(-1.43)	(-0.51)
D8	1.08**	0.11	0.03	0.09	0.00	-0.31	-0.33*	-0.17
t-statistic	(2.46)	(0.57)	(0.28)	(0.83)	(0.00)	(-1.27)	(-1.85)	(-1.02)
D9	1.14**	0.15	0.06	0.13	-0.20	-0.53**	-0.54***	-0.39**
t-statistic	(2.38)	(0.60)	(0.34)	(0.75)	(-0.34)	(-2.02)	(-2.80)	(-2.07)
D10 (H)	1.22**	0.08	-0.01	0.11	-0.51	-0.84***	-0.81***	-0.56***
t-statistic	(2.30)	(0.33)	(-0.08)	(0.67)	(-0.84)	(-2.67)	(-3.58)	(-2.68)
D1-D10 (L-H)	-0.51	-0.08	-0.03	-0.12	1.07***	1.18***	0.92***	0.76***
t-statistic	(-1.55)	(-0.32)	(-0.11)	(-0.51)	(2.95)	(3.71)	(3.17)	(2.63)

Alternative Analyst Forecast Dispersion Measure

Some previous studies also use the standard deviation of the annual EPS forecast scaled by the absolute median of the forecasts (Banerjee 2011), which might also be a good candidate for analyst forecast dispersion in this study. We can see that the results in Table 8 are very similar to those in Table 3 and 4 using the alternative measure. Once again, the most dispersed stocks are only overpriced following the high sentiment periods.

Table 8. Robustness check: sort by other analyst forecast dispersion measure

		Low Sentiment Periods (EW)				**High Sentiment Periods (EW)**		
Dispersion Deciles	Excess return	CAPM Alpha	3F Alpha	4F Alpha	Excess return	CAPM Alpha	3F Alpha	4F Alpha
D1 (L)	0.64*	-0.02	-0.06	-0.08	0.60	0.29	0.07	0.11
t-statistic	(1.81)	(-0.13)	(-0.41)	(-0.54)	(1.63)	(1.47)	(0.42)	(0.64)
D2	0.63*	-0.08	-0.13	-0.13	0.50	0.17	-0.01	0.11
t-statistic	(1.71)	(-0.53)	(-0.98)	(-1.04)	(1.37)	(0.94)	(-0.06)	(0.67)
D3	0.90**	0.11	0.05	0.08	0.46	0.12	-0.00	0.09
t-statistic	(2.11)	(0.75)	(0.36)	(0.68)	(1.19)	(0.71)	(-0.01)	(0.62)
D4	0.96**	0.12	0.04	0.08	0.45	0.09	0.02	0.15
t-statistic	(2.18)	(0.78)	(0.41)	(0.71)	(1.09)	(0.50)	(0.16)	(1.02)
D5	0.94**	0.09	0.01	0.07	0.43	0.06	0.00	0.12
t-statistic	(2.08)	(0.53)	(0.05)	(0.55)	(1.05)	(0.33)	(0.02)	(0.90)
D6	0.95**	0.04	-0.04	0.01	0.45	0.07	0.02	0.11
t-statistic	(2.00)	(0.24)	(-0.34)	(0.04)	(1.03)	(0.31)	(0.10)	(0.70)
D7	0.87*	-0.06	-0.14	-0.05	0.28	-0.13	-0.11	0.01
t-statistic	(1.84)	(-0.33)	(-0.93)	(-0.37)	(0.60)	(-0.57)	(-0.63)	(0.08)
D8	1.06**	0.14	0.03	0.11	0.04	-0.38	-0.39**	-0.26
t-statistic	(2.14)	(0.69)	(0.20)	(0.86)	(0.08)	(-1.51)	(-2.25)	(-1.45)
D9	0.89*	-0.09	-0.20	-0.13	0.01	-0.42	-0.44**	-0.30
t-statistic	(1.68)	(-0.42)	(-1.18)	(-0.80)	(0.02)	(-1.54)	(-2.33)	(-1.55)
D10 (H)	0.95	-0.12	-0.24	-0.09	-0.40	-0.84**	-0.90***	-0.67***

t-statistic	(1.59)	(-0.44)	(-1.14)	(-0.45)	(-0.73)	(-2.55)	(-4.26)	(-3.35)
D1-D10 (L-H)	-0.32	0.10	0.18	0.01	1.00***	1.13***	0.97***	0.78***
t-statistic	(-0.86)	(0.35)	(0.71)	(0.03)	(2.73)	(3.29)	(3.30)	(2.70)

CONCLUSION

In this paper, I investigate the role investor sentiment plays in the relationship between analyst forecast dispersion and future stock returns. Empirically, stocks with the highest analyst forecast dispersion are overpriced following high sentiment periods, leading to significantly negative future returns. In contrast, those with the least analyst forecast dispersion are not overpriced because the degree of belief dispersion is low. However, following the low sentiment periods, neither stocks with the least nor the most analyst forecast dispersion are overpriced.

My findings can potentially reconcile the two effects proposed in the previous literature, namely, the risk effect and the mispricing effect. The risk effect suggests a positive relation between analyst forecast dispersion and the future stock return, while the mispricing effect predicts the opposite. Presumably, the magnitude of the mispricing effect depends on the proportion of irrational investors and their bias, which is positively related to investor sentiment. During the high sentiment period, the mispricing effect takes over, and there is an overall negative relation between analyst forecast dispersion and stock return. During the low sentiment period, the percentage of irrational investors is mediated. The mispricing effect and the risk effect counter each other, leading to an insignificant relationship between analyst forecast dispersion and future stock return.

Prior literature has documented mixed results regarding how analyst forecast dispersion affects stock returns, which can be explained by the risk effect or the mispricing effect. In this paper, I try to reconcile the contradictory findings by exploring the moderating role of investor sentiment. Using the market-wide investor sentiment index constructed by Baker and Wurgler (2006) to measure sentiment, stocks with the most analyst forecast dispersion earn significantly negative returns following high-sentiment periods. Those with the least analyst forecast dispersion are not overpriced. In contrast, neither stocks with most nor those with least analyst forecast dispersion earn abnormal returns following low-sentiment periods. Furthermore, they are hedging portfolios that long the stocks with the least analyst forecast dispersion and short those with most analyst forecast dispersion yield positive returns following high sentiment. Overall, these results highlight that it's necessary to consider investor sentiment when exploring the relationship between analysts forecast dispersion and stock returns.

My findings can potentially reconcile the risk effect and the mispricing effect of analyst forecast dispersion. The risk effect suggests a negative relationship between analyst forecast dispersion and future stock returns since forecast dispersion is considered an alternative risk factor under the assumption of rational investors and frictionless markets. On the contrary, the mispricing effect predicts a positive relationship. With short-sale impediments, stock prices are determined by optimistic investors. Greater analyst dispersion implies greater overvaluation and, therefore, lower future stock returns.

Presumably, the magnitude of the mispricing effect depends on the proportion of irrational investors and their bias, which is positively related to investor sentiment. When investor sentiment is high, optimistic investors dominate the market, and the mispricing effect takes over. We observe an overall negative relation between analyst forecast dispersion and stock return. By contrast, the percentage of irrational investors is moderate during the low sentiment period. The risk effect is counterbalanced by the mispricing effect, leading to the overall insignificant relation between analyst forecast dispersion and future stock return.

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