Extreme Opinions on Social Media

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Abstract: In this study, we analyze the information value of extreme opinions on Twitter that are identified by the most positive and negative Twitter sentiments for each firm. We find that these extreme opinions predict stock returns without subsequent reversals. In addition, they contain incremental information regarding firm fundamentals that are identified by subsequent revisions in analysts' earnings forecasts and target prices. Finally, we find that the return predictability is attributed to the fundamental information contained in the extreme tweets. Our analysis sheds light on the role of extreme opinions on social media.

1.Introduction

An increasing number of studies analyzes the extent to which stock prices incorporate not only quantitative information but also qualitative information, as there are compelling theoretical and empirical reasons to do so. Theoretically, firm valuations should incorporate investors' information sets, which include quantitative and qualitative information. Empirically, substantial stock returns do not seem to correspond to quantitative information (Shiller, 1981; Roll, 1988), suggesting that qualitative information may help explain stock returns.

Accordingly, financial studies have been performing textual analyses on a wide variety of texts. First, studies have focused on texts written by professionals, including corporate disclosures (e.g., Henry, 2008; Li, 2010; Loughran and McDonald, 2011; Rogers et al., 2011; Price et al., 2012; Ferris et al., 2013; Jegadeesh and Wu, 2013; Arslan-Ayaydin et al., 2016) and media articles (e.g., Tetlock, 2007; Tetlock et al., 2008; Engelberg et al., 2012; Garcia, 2012).

Recently, studies have focused on social media. The importance of social media in financial markets has increased substantially over the past decade. However, despite their increasing importance, it is unclear whether textual opinions on social media have any investment value. Bollen et al. (2011) show that aggregated Twitter sentiments predict future stock returns. However, Antweiler and Frank (2004), Das and Chen (2007), and Sprenger et al. (2014) suggest that social media activities are not significantly related to future returns.

Although social media could be an essential communication tool between investors and firms, it is also true that most of the tweets merely reflect the opinions of non-professional and uninformed social media users. Their tweets may be driven by rumors and contain significant noise. The existence of low-quality and uninformed tweets could result in mixed findings regarding the informational value of aggregated (consensus) opinions on social media, even if there are some informative tweets. Conversely, the mixed results do not deny the possibility that there are informative opinions on social media.

Thus, in this study, we analyze the existence of informative opinions on social media by focusing on opinions that diverge from the consensus. The reason why we focus on such extreme opinions is that informed users' opinions could significantly differ from the opinions of many uninformed users. In other words, an informed user's opinions could be extreme relative to the consensus. Thus, extreme opinions could have more informational value than other (non-extreme) opinions. We identify these opinions by utilizing the textual sentiment of each tweet. Specifically, we identify the extreme opinions regarding each firm on a daily basis by the most positive and negative Twitter sentiment scores for the corresponding firm released over a 24-hour period.

The extremeness of a tweet's sentiment could be attributed to measurement errors. Therefore, we utilize a highly sophisticated Twitter sentiment indicator whose methodology is carefully examined—Bloomberg's social sentiment analytics. The sentiments are calculated using tweets from Twitter and StockTwits regarding a given firm. Bloomberg identifies tweets about a given firm and then determines the positiveness or negativeness of the tweet (story-level sentiment) and its confidence score by utilizing supervised machine learning. Sentiment scores are calculated based on the confidence-weighted average of the story-level sentiments at fixed intervals (e.g., two minutes).

In addition to the sophisticated methodology, there are advantages to using Bloomberg's social sentiment analytics. First, because the sentiment indicator information has been released regularly for more than five years, using Bloomberg's analytics makes our study replicable and transparent. Second, Bloomberg calculates firm-level news sentiments. The posts on social media could merely rehash what was reported in news media. We can address this possibility by controlling for news sentiments when testing the predictive ability of Twitter sentiments. In other words, we can examine whether Twitter sentiments provide incremental information relative to that contained in news media.

Our first main result is that the extreme opinions that are identified by the most positive and negative Twitter sentiments for each firm have predictive power for subsequent stock returns beyond the consensus opinions, which are identified by the average Twitter sentiments. This predictability is not subsumed by traditional return predictors and news sentiments.

Further, stock returns associated with extreme opinions are not reversed in the subsequent periods. This result indicates that extreme opinions have a permanent impact on stock prices, supporting the view that extreme tweets contain incremental information that is not incorporated in stock prices. On the other hand, returns associated with consensus opinions are significantly reversed. This casts doubt on the informational value of consensus opinions and suggests that such opinions contain no relevant information but only temporarily shift the demand for a stock.

In a further analysis, we examine possible sources of cross-sectional return predictability with extreme opinions . To this end, we examine the informational role of extreme opinions by looking at two types of cross-sectional information flow indicators regarding firm fundamentals: changes in analysts' target prices and revisions in their quarterly earnings forecasts. We first examine whether extreme opinions predict subsequent changes in target prices and earnings forecasts. We then examine whether the cross-sectional return predictability with extreme opinions is explained by the fundamental information identified by the two indicators.

We find that the extreme opinions predict subsequent changes in target prices and earnings forecasts, whereas consensus opinions do not have any predictive power. The results support the view that extreme opinions, rather than consensus opinions, contain incremental information regarding firm fundamentals. Further, we find that the return predictability of tweets is mediated by the predictive power for the target prices and earnings forecasts. Together, these findings suggest that extreme opinions posted on social media (especially negative ones) contain new information about firm fundamentals, and this information drives the predictive power for cross-sectional returns.

Existing literature on social media focuses on consensus opinions. In contrast to these studies, we focus on extreme opinions on social media and provide robust evidence that they have significant informational value regarding stock valuation and firm fundamentals.

2.Hypotheses Development

2.1. Return Predictability

As discussed in Section 1, although most of the tweets are not informative, there could be a limited number of informative tweets, and those opinions could significantly differ from the consensus opinion. Thus, extreme tweets, which diverge from consensus opinions, could contain additional information regarding stock valuation. As such, the following hypothesis is proposed:

H1: Extreme tweets have incremental predictive power for subsequent returns.

However, even if H1 is supported, we cannot conclude that the extreme tweets contain incremental information regarding stock valuation. Stock prices could react to the tweets even when investors respond inappropriately to the incorrect or biased views of extreme tweets. However, in this case, returns would subsequently reverse. In contrast, if the extreme tweets contain incremental information, a price correction would not occur. This argument leads to the following hypothesis:

H2: Abnormal returns associated with extreme tweets are not reversed.

2.2. Fundamental Information

Because information flow regarding corporate fundamentals has a permanent price impact, extreme tweets, which also have a permanent price impact, likely contain relevant information about corporate fundamentals. Thus, the following hypothesis is given:

H3: Extreme tweets contain relevant information about firm fundamentals.

When the fundamental information contained in the extreme tweets is disclosed, the stock price reacts significantly to (incorporate) it. Thus, the return predictability with extreme tweets can be attributed to such information about corporate fundamentals. These intuitions lead to the following hypothesis:

H4: Return predictability with extreme tweets is attributed to fundamental information contained in the extreme tweets.

3 Extreme Opinion Measures

3.1. Twitter Opinion Measure

To identify the opinion of each tweet, we utilize the text-based sentiment of tweets for each firm. Specifically, we utilize Bloomberg's firm-level Twitter sentiment measures to identify the positive and negative opinions for each firm. Bloomberg uses supervised statistical machine-learning techniques to construct a firm-level Twitter sentiment index. Bloomberg's social sentiment classification engines are trained to mimic a human expert in processing textual information. Once the model is trained, when new tweets are tagged with company tickers, the model automatically assigns a probability of being positive, negative, or neutral to each tweet.

Bloomberg calculates the story-level sentiment (undisclosed data) and then provides the firm-level sentiment. The story-level sentiment is generated in real-time upon the arrival of tweets. It consists of two parts: score and confidence. The sentiment score is a categorical value, for example, 1, -1, and 0, which indicates a positive, negative, and neutral sentiment, respectively. Confidence is a numerical value ranging from 0% to 100%, which can be interpreted as the probability of being positive, negative, or neutral. Thus, the story-level sentiment, which is defined by multiplying the story-level sentiment score by the corresponding confidence score, varies from -1 to 1.

The firm-level average sentiment score (the average sentiment score for each firm), denoted as $Twitter_{i,t}^{Mean}$, is the average of the story-level Twitter sentiment over a 24-hour period from 9:20 a.m. on the previous day (*t*-1) to 9:20 a.m. on the current day (*t*). Bloomberg calculates the average of the story-level sentiment score every two minutes and provides the highest and lowest two-minute sentiment scores over the 24-hour period on a daily basis. Bloomberg provides these scores for all U.S. stocks each morning about 10 minutes before the U.S. stock market opens. Because the highest and lowest sentiment scores are likely to capture the most positive and negative opinions for each day, we utilize these scores as opinions of the extreme tweets.

3.2. Opinions of Extreme Tweets

For an opinion of the extreme tweets for firm *i* on day *t*, denoted as $Twitter_{i,t}^{Extreme}$, we calculate mid-range scores, that is, the arithmetic mean of the highest and lowest sentiment scores as:

$$Twitter_{i,t}^{Extreme} = \frac{Twitter_{i,t}^{Highest} + Twitter_{i,t}^{Lowest}}{2}$$

where $Twitter_{i,t}^{Highest}$ and $Twitter_{i,t}^{Lowest}$ are the highest and lowest two-minute sentiment scores for firm *i* over a 24-hour period from 9:20 a.m. on the previous day (*t*-1) to 9:20 a.m on the current day (*t*)[1]. Then, we examine whether $Twitter_{i,t}^{Extreme}$ has incremental predictive power for subsequent cross-sectional returns beyond $Twitter_{i,t}^{Mean}$.

The mid-range scores $Twitter_{i,t}^{Extreme}$ based on the highest and lowest sentiment scores mainly reflect the opinions of the extreme tweets, whereas the average sentiment $Twitter_{i,t}^{Mean}$ reflects not only the opinions of these extreme tweets but also those of a considerable number of non-extreme tweets. Thus, the mid-range scores reflect more precisely the opinions of extreme tweets than the average scores.

First, let us suppose that the informational value is no higher for extreme tweets than for others (tweets are equally informed). Specifically, suppose that each tweet's sentiment follows $\theta + \epsilon$, where θ is the information set regarding the firm valuation and ϵ is an error term. In this case, because the mid-range measures $Twitter_{i,t}^{Extreme}$ are more naïve (less efficient) estimators for θ than the average measures $Twitter_{i,t}^{Mean}$, the mid-range measures should have no predictive power for subsequent returns after controlling for $Twitter_{i,t}^{Mean}$.

Next, suppose that the extreme tweets contain an additional information set $\acute{\theta}$ (either the extreme positive or negative tweets reflect an incremental information set $\acute{\theta}$ regarding firm valuation). The mid-range measure, which is highly dependent on the opinions of these extreme tweets, is more likely to capture information set $\acute{\theta}$ (more efficient estimator for $\acute{\theta}$) than the average measure. Thus, the mid-quote measure $Twitter_{i,t}^{Extreme}$ could have additional predictive power for stock returns even after controlling for $Twitter_{i,t}^{Mean}$.

4. Return Predictability with Extreme Tweets

4.1. Methodology

To test H1, we investigate the predictive power of extreme tweets on stock returns. Specifically, we use daily cross-sectional regressions similar to those in Fama and MacBeth (1973). We first run cross-sectional regressions for each day, and then report the time-series averages of the daily coefficient estimates and the corresponding t-statistics based on the Newey-West standard errors.

[1] 720 two-minute sentiment scores are calculated at two-minutes interval over a 24-hour period from 9:20 a.m. on the previous day *t*-1 to 9:20 a.m on the current day *t*. We utilize the highest and lowest two-minute sentiments as $Twitter_{i,t}^{Highest}$ and $Twitter_{i,t}^{Lowest}$, respectively.

As previously mentioned, the Twitter sentiment is released in the morning right before the stock market opens. Thus, to analyze the return predictability with the Twitter sentiment, we analyze the predictive power of $Twitter_{i,t-1}^{Extreme}$ for the open-to-open return $Ret_{i,t}$ from stock *i*'s opening price on day *t*-1 to the opening price on day *t*. We also analyze the predictive power for the risk-adjusted open-to-open returns, defined as the residuals of the Fama-French-Carhart four-factor model. This approach also theoretically allows one to trade at the 9:30 a.m. market opening after observing the Twitter scores for the previous day released at 9:20 a.m. The regression specification is as follows:

$$Ret_{i,t} = \alpha + \beta_1 Twitter_{i,t-1}^{Extreme} + (Controls) + \varepsilon_{i,t} \qquad (1)$$

$$Ret_{i,t} = \alpha + \beta_1 Twitter_{i,t-1}^{Extreme} + \beta_2 Twitter_{i,t-1}^{Mean} + (Controls) + \varepsilon_{i,t} \qquad (2)$$

The coefficient of $Twitter_{i,t-1}^{Extreme}$ is our main parameter of interest. Following the study of Gu and Kurov (2018), in addition to $Twitter_{i,t-1}^{Mean}$, we control for return momentum, volatility, abnormal trading volume, and news sentiment.

Five lags of daily (open-to-open) returns ($Ret_{i,t-k}$: *k*=1,2,…,5) are included because return autocorrelation associated with a contemporaneous correlation of returns and sentiment can generate spurious evidence of lead-lag relations (e.g., Chordia and Swaminathan, 2000; Rapach et al., 2013). Hence, the regression controls include firm *i*'s five lags of daily (open-to-open) returns.

Following the study of Tetlock (2011), the regression also controls for volatility. In particular, we control for five lags of daily return volatility ($Volatility_{i,t-k}$: *k*=1,2,…,5). We use Rogers and Satchell's (1991) extreme value volatility estimator to measure daily volatility. The estimator is computed as follows:

$$Volatility_{i,t} = \left(P_{i,t}^{Highest} - P_{i,t}^{Close}\right)\left(P_{i,t}^{Highest} - P_{i,t}^{Open}\right) + \left(P_{i,t}^{Lowest} - P_{i,t}^{Close}\right)\left(P_{i,t}^{Lowest} - P_{i,t}^{Open}\right)$$

where $P_{i,t}^{Highest}$, $P_{i,t}^{Lowest}$, $P_{i,t}^{Open}$, and $P_{i,t}^{Close}$ are the log-transformed highest, lowest, opening, and closing prices of stock *i* on day *t*, respectively.

Five lags of the daily abnormal trading volume ($Volume_{i,t-k}$: *k*=1,2,…,5) are included to control for the high-volume return premium of Gervais et al. (2001). We use the abnormal trading volume to make the volume comparable across firms. Specifically, following the methodology of Gervais et al.'s (2001) study, we compute the abnormal trading volume ($Volume_{i,t}$) by dividing the trading volume for stock *i* on day *t* by the mean volume during the preceding 49-day period (from *t*-49 to *t*-1). Both abnormal volume and volatility are expressed as percentage points.

The news sentiment on day *t*-1, denoted as $News_{i,t-1}$, is added as an additional regressor because tweets could simply refer to firm-specific news. By adding the news sentiment, we can evaluate the incremental informational value of extreme tweets ($Twitter_{i,t-1}^{Extreme}$) beyond firm-specific news. If fundamental information diffuses from traditional media to social media, we should expect the predictive power of tweets for stock returns to disappear after controlling for the news sentiment. We obtain the firm-specific news sentiment from Bloomberg. It is measured by following the same procedure as that used to calculate the average Twitter sentiment ($Twitter_{i,t}^{Mean}$) and is based on all news published by Bloomberg. $News_{i,t}$ is the average of the story-level news sentiment over a 24-hour period from 9:20 a.m. on the previous day (*t*-1) to 9:20 a.m. on the current day (*t*). The value of the news sentiment ranges from +1 to –1 and is released before the market opens (at 9:20 am).

Finally, to control for the return predictability stemming from firm characteristics, we include the firm size, measured as the logarithm of the market value of equity ($Size_{i,t-1}$), book-to-market ratio ($Value_{i,t-1}$), and 12-month returns except for the most recent month ($Momentum_{i,t-1}$)[2].

To test H2, which posits that abnormal returns with extreme tweets are not reversed, five lags of the extreme tweets' sentiments ($Twitter_{i,t-k}^{Extreme}$: *k*=1, 2, …, 5) and the average sentiment ($Twitter_{i,t-k}^{Mean}$: *k*=1, 2, …, 5) are included in the regression model as:

$$Ret_{i,t} = \alpha + \sum_{k=1}^{5} \beta_{1,k} Twitter_{i,t-k}^{Extreme} + \sum_{k=1}^{5} \beta_{2,k} Twitter_{i,t-k}^{Mean} + (Controls) + \varepsilon_{i,t} \qquad (3)$$

In terms of control variables, we include lagged news sentiment measures ($News_{i,t-k}$: *k*=2, 3, 4, and 5). Other control variables are the same as in Equation (2). As discussed in Section 2.2.1, if the extreme tweet contains useful fundamental information about stocks, its effect on returns should be permanent. On the other hand, if the opinions of the extreme tweet simply reflect the incorrect or biased opinions of uninformed traders, the impact of the tweets on stock returns should be reversed over the next few trading days. To test whether returns associated with $Twitter_{i,t-1}^{Extreme}$ and $Twitter_{i,t-1}^{Mean}$ are temporary or permanent, we examine whether the coefficients of the lagged sentiment measures ($Twitter_{i,t-k}^{Extreme}$: *i*=2, 3, 4, and 5) are significantly negative.

[2] These variables are not included in the regression model when we analyze the predictive power for the risk-adjusted returns based on the Fama-French (1993) and Carhart (1997) four-factor models.

4.2. Result

We run regressions for both raw and risk-adjusted returns. Table 1 shows that not only the average sentiment ($Twitter_{i,t-1}^{Mean}$) but also the extreme tweets' sentiments ($Twitter_{i,t-1}^{Extreme}$) have significant predictive power for subsequent returns ($Ret_{i,t}$). Even after controlling for $Twitter_{i,t-1}^{Mean}$, the coefficient of $Twitter_{i,t-1}^{Extreme}$ is still significantly positive at the 1% level. Opinions of extreme tweets have incremental predictive power for subsequent returns beyond the consensus opinions. These results support H1.

Table 1 Return Predictability with Extreme Tweets

a) Raw Returns

	(1)	(2)
$Twitter_{i,t-1}^{Excess}$	0.00200 ***	0.00112 ***
	(6.00)	(2.89)
$Twitter_{i,t-1}^{Mean}$		0.00081 ***
		(4.27)
Controls	Yes	Yes
R2	9.1%	9.1%

b) Risk-adjusted Returns

	(1)	(2)
$Twitter_{i,t-1}^{Excess}$	0.00204 ***	0.00117 ***
	(5.46)	(2.83)
$Twitter_{i,t-1}^{Mean}$		0.00082 ***
		(3.95)
Controls	Yes	Yes
R2	7.6%	7.6%

Table 2 shows the results of the predictive power of the five lags of the extreme tweets' measures. The coefficient of $Twitter_{i,t-1}^{Extreme}$ remains significantly positive. Further, the coefficient estimates on the four lags of the measures (lags of the extreme tweets' measures except for the most recent one; $Twitter_{i,t-k}^{Extreme}$: i=2,3,4, and 5) are not significantly negative. Thus, it suggests that the abnormal returns associated with $Twitter_{i,t-1}^{Extreme}$ are not reversed in a subsequent period, supporting H2. These findings are consistent with the notion that opinions of extreme tweets have a permanent price impact on stock prices and thus contain some information regarding stock valuation.

On the other hand, the results reveal that the coefficient of $Twitter_{i,t-2}^{Mean}$ is significantly negative, indicating that the abnormal return associated with the average sentiment $Twitter_{i,t-1}^{Mean}$ is significantly reversed on a subsequent day. This result casts doubt on the notion that the average sentiment, that is, the consensus opinion of tweets, contains incremental information regarding stock valuation, which is consistent with the mixed prior studies' findings regarding the informational value of consensus opinions on Twitter.

Table 2 Return Predictability with Lagged Tweets

	Raw	Risk-adjusted
$Twitter_{i,t-1}^{Excess}$	0.00164 ***	0.00171 ***
	(3.88)	(4.21)
$Twitter_{i,t-2}^{Excess}$	-0.00040	-0.00039
	(0.96)	(0.83)
$Twitter_{i,t-3}^{Excess}$	-0.00014	-0.00008
	(0.36)	(0.18)
$Twitter_{i,t-4}^{Excess}$	0.00003	-0.00037
	(0.09)	(0.90)
$Twitter_{i,t-5}^{Excess}$	0.00009	-0.00014
	(0.28)	(0.36)
$Twitter_{i,t-1}^{Mean}$	0.00082 ***	0.00086 ***
	(4.24)	(3.89)
$Twitter_{i,t-2}^{Mean}$	-0.00070 ***	-0.00074 ***
	(2.80)	(2.94)
$Twitter_{i,t-3}^{Mean}$	-0.00018	-0.00019
	(0.95)	(0.77)
$Twitter_{i,t-4}^{Mean}$	-0.00033	-0.00032
	(1.25)	(1.25)
$Twitter_{i,t-5}^{Mean}$	0.00028	0.00022
	(1.24)	(0.85)
Controls	Yes	Yes
R2	9.1%	7.8%

5. Predictive Power for Fundamentals

5.1. Methodology

The previous section shows that $Twitter_{i,t-1}^{Extreme}$ has predictive power for cross-sectional returns. This section examines the $Twitter_{i,t-1}^{Extreme}$ prediction of the cross-sectional information flow regarding corporate fundamentals. Then, we investigate whether the cross-sectional return predictability associated with $Twitter_{i,t-1}^{Extreme}$ is attributed to the cross-sectional information flow predicted by $Twitter_{i,t-1}^{Extreme}$.

To capture the cross-sectional information flow regarding corporate fundamentals, we utilize revisions in the analysts' earnings forecasts and target prices. Financial analysts continuously research time-varying corporate fundamentals, along with macroeconomic and microeconomic conditions, to update predictions about a company's performance (e.g., earnings). Then, they estimate each stock's fair value (target price) based on its outlook[3]. Thus, their earnings forecasts and target prices are expected to reflect information regarding corporate fundamentals in a timely manner[4]. Therefore, revisions in

[3] Finally, they recommend buying or selling a company's stock based upon the difference between the actual price and the estimated fair value.

[4] We do not include stock recommendations as an indicator for

earnings forecasts and target prices are expected to capture the information flow regarding corporate fundamentals. These revisions are suitable for identifying the cross-sectional distribution of new information sets regarding firm fundamentals.

We compute the target price change $\Delta \mathrm{TP}_{i,t}$ and earnings revisions $\Delta \mathrm{Earnings}_{i,t}$ as

$$\Delta \mathrm{TP}_{i,t} = \frac{\mathrm{TP}_{i,t}}{\mathrm{TP}_{i,t-1}} - 1$$

$$\Delta \mathrm{Earnings}_{i,t} = \frac{\mathrm{Earnings}_{i,t} - \mathrm{Earnings}_{i,t-1}}{\mathrm{Price}_{i,t-1}}$$

where $\mathrm{TP}_{i,t}$ is the average target price for firm *i* at *t*, $\mathrm{Earnings}_{i,t}$ is the average earnings forecast of firm *i* for the most recent quarter at *t*, and $\mathrm{Price}_{i,t}$ is the stock price of firm *i* at *t*.

To test H3, which posits that extreme tweets contain some relevant information about corporate fundamentals, we regress these two indicators as:

$$y_{i,t} = \alpha + \beta_1 Twitter_{i,t-1}^{Extreme} + \beta_2 Twitter_{i,t-1}^{Mean} + \beta_3 \Delta \mathrm{TP}_{i,t-1} + \beta_4 \Delta \mathrm{Earnings}_{i,t-1} + (Controls) + \varepsilon_{i,t} \quad (4)$$

where $y_{i,t}$ is either $\Delta \mathrm{TP}_{i,t}$ or $\Delta \mathrm{Earnings}_{i,t}$. We additionally include $\Delta \mathrm{TP}_{i,t-1}$ and $\Delta \mathrm{Earnings}_{i,t-1}$ as control variables to account for the gradual update of analysts' target prices and earnings forecasts. Other control variables are the same as in Equation (2).

Next, we analyze whether the return predictability with $Twitter_{i,t-1}^{Extreme}$ is attributed to the predictive power for $\Delta \mathrm{TP}_{i,t}$ and $\Delta \mathrm{Earnings}_{i,t}$. To this end, we perform a mediation analysis by running the following regression model:

$$Ret_{i,t} = \alpha + \beta_1 Twitter_{i,t-1}^{Extreme} + \beta_2 Twitter_{i,t-1}^{Mean} + \beta_3 \Delta \mathrm{TP}_{i,t} + \beta_4 \Delta \mathrm{Earnings}_{i,t} + (Controls) + \varepsilon_{i,t} \quad (5)$$

In regression model (5), $\Delta \mathrm{TP}_{i,t}$ and $\Delta \mathrm{Earnings}_{i,t}$ are included as control variables for testing the mediation effect. Other control variables are the same as in Equation (2).

We first analyze whether the coefficients of $\Delta \mathrm{TP}_{i,t}$ and $\Delta \mathrm{Earnings}_{i,t}$ (β_3 and β_4 in Equation (5)) are significantly positive. Then, we examine whether the coefficients of $Twitter_{i,t-1}^{Extreme}$ are significantly reduced by adding $\Delta \mathrm{TP}_{i,t}$ and $\Delta \mathrm{Earnings}_{i,t}$; in other words, the estimated β_1 in Equation (5) is significantly lower than the estimated β_1 in Equation (2).

5.2. Results

Table 3 shows the regression results of regression model (4) estimated using the Fama-MacBeth approach. The results reveal that $\Delta \mathrm{TP}_{i,t}$ and $\Delta \mathrm{Earnings}_{i,t}$ are significantly associated with $Twitter_{i,t-1}^{Extreme}$, whereas the association is much weaker with $Twitter_{i,t-1}^{Mean}$. An upgrade (downgrade) in a firm's target price and earnings forecasts is more likely to occur after Twitter users express extremely positive (negative) views about the firm. This result indicates that the extreme tweets contain incremental information regarding firm fundamentals beyond analysts' earnings forecasts, target prices, and consensus opinions on Twitter, supporting H3.

Table 3 Fundamentals of Extreme Tweets

	Earnings Forecast (x1000)	Target Price (x1000)
$Twitter_{i,t-1}^{Excess}$	0.0271 ***	1.1514 ***
	(2.63)	(7.61)
$Twitter_{i,t-1}^{Mean}$	0.0063	0.2343 **
	(0.99)	(2.27)
Controls	Yes	Yes
R2	3.7%	4.7%

Table 4 shows the results of the mediation analysis, that is, regression results of regression model (5) estimated using the Fama-MacBeth approach. The significant positive coefficients of $\Delta \mathrm{TP}_{i,t}$ and $\Delta \mathrm{Earnings}_{i,t}$ on $Ret_{i,t}$ indicate that revisions in analysts' target prices and earnings forecasts have a significant impact on stock prices. As $Twitter_{i,t-1}^{Extreme}$ predicted $\Delta \mathrm{TP}_{i,t}$ and $\Delta \mathrm{Earnings}_{i,t}$, the results suggest that the association between $Twitter_{i,t-1}^{Extreme}$ and $Ret_{i,t}$ could be mediated by the predictive power of $Twitter_{i,t-1}^{Extreme}$ for $\Delta \mathrm{TP}_{i,t}$ and $\Delta \mathrm{Earnings}_{i,t}$. In other words, the extreme tweets contain fundamental information that is subsequently reflected in (disclosed by) analysts' earnings forecasts and target prices, and the return predictability with the extreme tweets could be attributed to the price impact caused by the disclosure of the information.

The magnitude and statistical significance of the coefficient of $Twitter_{i,t-1}^{Extreme}$ are reduced by adding $\Delta \mathrm{TP}_{i,t}$ and $\Delta \mathrm{Earnings}_{i,t}$ as control variables. As shown in Tables 1 and 4, the coefficient declines significantly (from 0.00112 to 0.00071 when we utilize raw returns and from 0.00117 to 0.00056 when we utilize risk-adjusted returns). Precisely, fundamental information that is subsequently reflected in (disclosed by) analysts' target prices and earnings forecasts explains about 51.6% ((0.00117-0.00056)/0.00117) of the predictive power of the extreme tweets for the risk-adjusted return. Further, the coefficient of $Twitter_{i,t-1}^{Extreme}$ is no longer significant after controlling for the mediation effects. Thus, these results suggest that the return predictability with extreme tweets is grounded in the fundamental information

corporate fundamentals because recommendations could be upgraded or downgraded due to stock price changes (even if corporate fundamentals do not change).

contained in the tweets, supporting H4.

However, a significant decline is not observed for the coefficient of $Twitter_{i,t-1}^{Mean}$, which drops only by approximately 20%, and the coefficients remain statistically significant. The return predictability with a consensus opinion on Twitter is not significantly grounded in information regarding firm fundamentals. This might result in a strong reversal of the abnormal returns associated with consensus opinions on Twitter ($Twitter_{i,t-1}^{Mean}$).

Table 4 Fundamentals of Extreme Tweets

	Raw	Risk-adjusted
$Twitter_{i,t-1}^{Excess}$	0.00071	0.00056
	(1.89)	(1.41)
$Twitter_{i,t-1}^{Mean}$	0.00067 ***	0.00063 **
	(3.61)	(3.13)
$\Delta \mathrm{TP}_{i,t}$	0.33292 ***	0.31617 ***
	(27.15)	(28.50)
$\Delta Earnings_{i,t}$	1.79070 ***	1.47980 ***
	(4.44)	(4.00)
Controls	Yes	Yes
R2	14.3%	12.3%

6. Conclusion

In this study, we empirically analyze whether extreme opinions on social media contain incremental information regarding intrinsic firm value beyond the consensus opinions. To this end, we analyze whether the opinions of extreme tweets that are identified by the highest and lowest firm-specific Twitter sentiments have incremental predictive power for subsequent cross-sectional stock returns.

Our empirical analysis reveals that not only the consensus opinions but also the extreme tweets' opinions have predictive power for cross-sectional returns. Furthermore, the abnormal returns associated with the extreme tweets are not significantly reversed, whereas those with consensus opinions are significantly reversed.

These findings support the view that extreme opinions on Twitter contain incremental information regarding firm valuation, but they cast doubt on whether consensus opinions have enough informational value.

In addition, we find that the opinions of extreme tweets predict subsequent revisions in analysts' target prices and earnings forecasts, suggesting that they contain information regarding firm fundamentals. Moreover, the return predictability with the extreme tweets can be explained by their predictive power for firm fundamentals.

In sum, our findings suggest that extreme opinions on Twitter contain incremental information regarding firm fundamentals and valuation. The contributions of our findings to existing studies can be summarized as follows.

Our study is the first to provide evidence for the informational value of extreme tweets. Because studies only analyze consensus (averaged) opinions on Twitter, it is inconclusive regarding the informational (investment) value of the extreme opinions. We provide evidence by showing their significant predictive power for cross-sectional returns and firm fundamentals.

These results also raise the possibility that there are informative opinions regarding firm valuation on social media. Studies have focused on consensus opinions on social media and show mixed results regarding their informational value. In this study, we provide robust evidence regarding the existence of informed opinions on social media by focusing on extreme tweets.

References

Antweiler, W., and Frank, M., 2004. Is all that talk just noise? The information content of internet stock message boards. *Journal of Finance*, 59, 1259–1294.

Arslan-Ayaydin, O., Boudt, K., and Thewissen, J., 2016. Managers set the tone: Equity incentives and the tone of earnings press releases. *Journal of Banking and Finance*, 72, 132–147.

Bartov, E., Faurel, L., and Mohanram, P., 2018. Can Twitter help predict firm-level earnings and stock returns? *Accounting Review*, 93(3), 25–57.

Blankespoor, E., Miller, G. S., and White, H. D., 2014. The role of dissemination in market liquidity: Evidence from firms' use of Twitter TM. *Accounting Review*, 89, 79–112.

Bollen, J., Mao, H., and Zheng, X., 2011. Twitter mood predicts the stock market. *Journal of Computational Science*, 2, 1–8.

Carhart, M. M., 1997. On the persistence of mutual fund performance. *Journal of Finance,* 52, 57-82.

Chordia, T., Swaminathan, B., 2000. Trading volume and cross-autocorrelations in stock returns. *Journal of Finance*, 55, 913-935.

as, R., and Chen, M., 2007. Yahoo! for Amazon: Sentiment extraction from small talk on the Web. *Management Science*, 53, 1375–1388.

Engelberg, J., Reed, A., and Ringgenber, M., 2012. How are shorts informed? Short sellers, news, and information processing. *Journal of Financial Economics*, 105(2), 260–278.

Fama, E. F., and French, R. K., 1993. Common risk factors in the returns of stocks and bonds. *Journal of Financial Economics,* 33, 3-56.

Fama, E. F., and Macbeth, J. D., 1973. Risk, return, and equilibrium: Empirical tests. *Journal of Political Economy,*

81, 607-636.
Ferris, P., Hao, G., and Liao, M., 2013. The effect of issuer conservatism on IPO pricing and performance. *Review of Finance*, 17(3), 993–1027.
Garcia, D., 2012. Sentiment during recessions. *Journal of Finance*, 68(3), 1267–1300.
Gervais, S., Kaniel, R., Mingelgrin, H. D., 2001. The high-volume return premium. *Journal of Finance*, 56, 877-919.
Gu, C., and Kurov, A., 2018. Informational role of social media: Evidence from Twitter sentiment, Working paper.
Henry, E., 2008. Are investors influenced by how earnings press releases are written? *Journal of Business Communication*, 45(4), 363–407.
Jegadeesh, N., and Wu, A., 2013. Word power: A new approach for content analysis. *Journal of Financial Economics*, 110(3), 712–729.
Kothari, P., Shu, S., and Wysocki, P., 2009. Do managers withhold bad news? *Journal of Accounting Research*, 47, 241–276.
Li, F., 2010. The information content of forward-looking statements in corporate filings: A naïve Bayesian machine learning algorithm approach. *Journal of Accounting Research*, 48, 1049–1102.
Loughran, T., and McDonald, B., 2011. When is a liability not a liability? Textual analysis, dictionaries, and 10-Ks. *Journal of Finance*, 66, 35–65.
Mao, H., Counts, S., and Bollen, J., 2015. Quantifying the effects of online bullishness on international financial markets. Statistics Paper Series 9, European Central Bank.
Miller, G., 2002. Earnings performance and discretionary disclosure. *Journal of Accounting Research*, 40, 173–204.
Price, M., Doran, J., Peterson, D., and Bliss, B., 2012. Earnings conference calls and stock returns: The incremental informativeness of textual tone. *Journal of Banking and Finance*, 36(4), 992–1011.
Rapach, D., Strauss, J., and Zhou, G., 2013. International stock return predictability: What is the role of the United States? *Journal of Finance*, 68, 1633-1662.
Rogers, L. C. G., and Satchell, S. E., 1991. Estimating variance from high, low and closing prices. *Annals of Applied Probability*, 1, 504-512.
Rogers, L. C. G., Van Buskirk, A., and Zechman, S., 2011. Disclosure tone and shareholder litigation. *Accounting Review*, 86(6), 2155–2183.
Roll, R., 1988. R-squared. *Journal of Finance*, 43, 541–566.
Securities and Exchange Commission (SEC). 2013. SEC says social media OK for company announcements if investors are alerted. Available at http://www.sec.gov/News/PressRelease/Detail/PressRelease/1365171513574
Shiller, R., 1981. Do stock prices move too much to be justified by subsequent changes in dividends? *American Economic Review*, 71, 421–436.
Sprenger, O., Tumasjan, A., Sandner, G., and Welpe, M., 2014. Tweets and trades: The information content of stock microblogs. *European Financial Management*, 20, 926-957.
Tetlock, C., 2007. Giving content to investor sentiment: The role of media in the stock market. *Journal of Finance*, 62, 1139–1168.
Tetlock, C., Saar-Tsechansky, M., and Macskassy, S., 2008. More than words: Quantifying language to measure firms' fundamentals. *Journal of Finance*, 63, 1437–1467.
Tetlock, C., 2011. All the news that's fit to reprint: do investors react to stale information? *Review of Financial Studies*, 24, 1481-1512.