Divergent Opinions on Social Media

Abstract

In this study, we analyze the informational value of tweets in which opinions diverge from the consensus one. We identify them using the most positive and negative intraday Twitter sentiments for each firm. We find that these divergent opinions—specifically, negative ones—predict stock returns without subsequent reversals. In addition, they contain incremental information on firm fundamentals identified by subsequent revisions to analysts' earnings forecasts and target prices. Finally, we find that return predictability is attributed to the fundamental information contained in the divergent opinions on Twitter. Our analysis sheds light on the role of divergent opinions on social media.

Keywords: Social Media; Divergent opinions; Linguistic tone; Firm Fundamentals

JEL classification: G12, G14

1. Introduction

An increasing number of studies analyze 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 variety of texts.

Recently, studies have focused on textual sentiment (tone) on social media, because the importance of social media in financial markets has increased substantially over the past decade.

Nevertheless, it is still inconclusive that opinions reflected in textual sentiment on social media have informational value. Bollen et al. (2011) show that aggregated Twitter tone (sentiment) predicts 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. Previous studies have mainly analyzed the average tone (sentiment) of comments posted on social media as the consensus opinion. However, the average sentiment only represents some of the wide-ranging opinions on social media. Specifically, the average sentiment can capture the opinions of a majority group (consensus opinions) but not the opinions of a minority group. Further, since tweets considerably include low-quality and uninformed tweets posted by non-professionals, the informational value could be higher for opinions of a minority group than those of a majority group. Consistent with our view, Almatarneh and Gamallo (2018) suggest that opinions that diverge from the majority group's ones are useful for identifying the most relevant strengths and weaknesses of a product or organization. Hence, we should analyze not only consensus opinions but also divergent opinions, i.e., opinions that significantly diverge from the consensus opinion.

Therefore, in this study, to further clarify the informational value of social media, we analyze the informational value of divergent opinions. Specifically, we examine whether these divergent opinions contain additional information on stock valuation and company performance beyond consensus opinions.

We identify the divergent views of each firm for each day, using the most positive and negative intraday Twitter sentiment measures for each firm. The divergence of a tweet's opinions can be attributed to measurement errors. Therefore, we use 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 on a given firm. Bloomberg determines the positiveness or negativeness of the tweet (story-level sentiment) and its confidence score using supervised machine learning. Sentiment scores are then calculated based on the confidence-weighted average of the story-level sentiments at fixed intervals (e.g., two minutes). There are two additional advantages to using Bloomberg's social sentiment analytics. First, the measure has long-run visibility; the sentiment indicator has been released regularly for more than five years and is often referred to as Twitter's opinion by a considerable number of professional investors. This setting reduces the probability of data snooping and enables us to provide convincing evidence. Second, Bloomberg calculates firm-level news sentiments. Posts on social media could merely rehash what was reported in news media. We address this possibility by controlling for news sentiments.

Our first main result is that the divergent opinions identified by the most positive and negative intraday Twitter sentiments have predictive power for subsequent stock returns beyond the consensus opinions (identified by average Twitter sentiments). In particular, the negative opinions have more predictive power than the positive ones. This predictability is not subsumed by traditional return predictors and news sentiments. Further, the stock returns associated with divergent opinions do not reverse in subsequent periods. This result indicates that divergent opinions have a long-lasting impact on stock prices, supporting the view that divergent opinions contain incremental information that is not incorporated into stock prices. On the contrary, the returns associated with consensus opinions do significantly reverse. 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 the possible sources of cross-sectional return predictability with divergent opinions[1]. To this end, we examine the informational role of divergent opinions by investigating two types of cross-sectional information flow indicators of firm fundamentals: changes in analysts' target prices and revisions to their quarterly earnings forecasts. We first examine whether divergent opinions predict subsequent changes in target prices and earnings

[1] Most studies in this area focus on specific events. For example, Bartov et al. (2018) examine Twitter sentiments (consensus opinions on Twitter) around quarterly earnings announcements.

forecasts. We then examine whether cross-sectional return predictability with divergent opinions is explained by the fundamental information identified by the two indicators.

We find that divergent opinions, specifically the negative ones, predict subsequent changes in target prices and earnings forecasts, whereas consensus opinions have much weaker predictive power. These results support the view that divergent opinions rather than consensus opinions contain incremental information on firm fundamentals. Further, we find that the return predictability of divergent opinions is mediated by their predictive power for target prices and earnings forecasts. Together, these findings suggest that divergent opinions posted on social media (especially negative ones) contain new information about firm fundamentals and that this information drives the predictive power for cross-sectional returns.

Our study is especially related to the study of Gu and Kurov (2020), who show that consensus opinions have predictive power for cross-sectional stock returns. We show that divergent opinions are informative about firm valuations as well as firm fundamentals. Further, we find that the association of divergent opinions with subsequent returns does not reverse in a subsequent period, while the association of consensus opinions does. These results indicate that divergent opinions rather than consensus opinions on social media have informational value.

The remainder of this paper is organized as follows. Section 2 presents the related literature and develops our hypotheses. Section 3 describes the sample and methodologies used. Section 4 explains the findings. Section 5 compares the informational value of the positive and negative opinions. Finally, in Section 6, we summarize the findings.

2. Related Literature and Hypotheses Development

2.1. Related Literature on Twitter Content

Reflecting the increasing importance of qualitative information in stock markets, financial studies have been performing textual analyses on a variety of texts. First, studies have focused on texts written by professionals, including corporate disclosures (e.g., Li, 2010; Loughran and McDonald, 2011; Rogers et al., 2011; Price et al., 2012; Jegadeesh and Wu, 2013; Arslan-Ayaydin et al., 2016; Li et al., 2019), media articles (e.g., Tetlock, 2007; Tetlock et al., 2008; Engelberg et al., 2012; Garcia, 2012), and analysts' reports (e.g., Huang et al., 2014; Miwa, 2021).

Recently, studies have focused on textual sentiment on social media, which reflects the many opinions of non-professionals. To analyze their informational value, a considerable number of studies have focused on Twitter because firms have been increasingly using it as a communication tool with investors (SEC, 2013; Blankespoor et al., 2014). Studies show mixed results on the informational value of opinions on Twitter. Bollen et al. (2011) show that the market-wide Twitter tone (sentiment) predicts Dow Jones Industrial Average returns. Further, Bartov et al. (2018) show that firm-level tweets contain information about forthcoming quarterly earnings. Gu and Kurov (2020) examine return predictability with firm-level Twitter sentiments and show that they predict short-term cross-sectional returns. On the contrary, Mao et al. (2015) find that although aggregated Twitter sentiment predicts several major U.S. stock indices, some of the index returns associated with Twitter sentiment do significantly reverse in a subsequent period. Sprenger et al. (2014) find that Twitter sentiments have no predictive power for subsequent firm-level abnormal returns.

However, prior studies mainly analyze the informational value of consensus opinions, which only captures some of the wide-ranging opinions on social media. Specifically, few studies empirically analyze opinions that diverge from the consensus opinion, that is, divergent opinions on social media. Almatarneh and Gamallo (2018) argue that such divergent opinions are useful for identifying the most relevant strengths and weaknesses of an organization. Thus, to further clarify the informational value of opinions on social media, we should analyze the informational value of these divergent opinions. We identify them using the highest and lowest Bloomberg Twitter sentiment measures for each firm. In terms of Bloomberg Twitter sentiment, Gu and Kurov (2020) show that the average sentiment can predict cross-sectional returns and some event returns. Our study extends their research by showing that divergent opinions, identified by the highest and lowest firm-level intraday sentiments, have more robust predictive power for cross-sectional returns and information on firm fundamentals.

2.2 Hypotheses Development

2.2.1. Return Predictability

Tweets considerably include low-quality and uninformed tweets. Thus, as argued in Section 1, opinions of a minority group (divergent opinions) might have a higher informational value than those of a majority group. Consistent with this view, Almatarneh and Gamallo (2018) argue that divergent opinions can be useful for identifying the strengths and weaknesses of organizations. Hence, they could contain additional information beyond consensus opinions. Since this information could be incorporated into stock prices in a subsequent period, they could have additional predictive power for subsequent stock returns. Thus, the following hypothesis is proposed:

H1: Divergent opinions on Twitter have incremental predictive power for subsequent returns.

However, even if H1 is supported, we cannot conclude that divergent opinions contain incremental information on stock valuation. Stock prices could react to tweets even when investors respond inappropriately to incorrect or biased opinions on Twitter. However, as argued by Tetlock et al. (2008), in this case, returns would subsequently reverse. By contrast, if divergent opinions contain incremental information, no price correction would occur. This argument leads to the following hypothesis:

H2: The abnormal returns associated with divergent opinions do not reverse.

2.2.2. Fundamental Information

Because the information flow on firm fundamentals has a long-lasting price impact, divergent opinions, which also have a long-lasting price impact, are likely to contain relevant information about firm fundamentals. Almatarneh and Gamallo (2018) argue that divergent opinions are useful for identifying the strengths and weaknesses of products and services. In addition, they argue that these opinions affect sales. Thus, the following hypothesis is proposed:

H3: Divergent opinions contain relevant information about firm fundamentals.

When the fundamental information contained in divergent opinions is disclosed, stock prices could react significantly. Thus, return predictability with divergent opinions can be attributed to such information about firm fundamentals. This argument leads to the following hypothesis:

H4: Return predictability with divergent opinions is attributed to the fundamental information contained in them.

3 Methodology

3.1. Twitter Opinion Measure

To identify the opinion of each tweet, we use the text-based sentiment of tweets for each firm. Specifically, we use Bloomberg's firm-level Twitter sentiment measures to identify the positive and negative opinions of each firm for each day. Bloomberg uses supervised machine learning techniques to construct a firm-level Twitter sentiment index. Its 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 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 (e.g., 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.

Bloomberg calculates intraday sentiments (the average of the story-level Twitter sentiment over two minutes) at two-minute intervals. Bloomberg provides the daily firm-level average sentiment score (the average sentiment score for each firm), denoted as $Twitter_{i,t}^{Mean}$, which is calculated as the average of Twitter sentiments 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*). In addition, it provides the highest and lowest intraday sentiments over the 24-hour period on a daily basis. These daily basis sentiments for all U.S. stocks are provided each morning about 10 minutes before the U.S. stock market opens.

3.2. Measure of Divergent Opinions

We detect incremental information contained in divergent opinions for each day, using the highest and lowest intraday sentiments ($Twitter_{i,t}^{Highest}$ and $Twitter_{i,t}^{Lowest}$), for the following reasons. Suppose that most tweets (opinions of majority group) reflect information sets θ_i and opinions of a minority group (divergent opinions) additionally reflect information sets $\acute{\theta_i}$. Specifically, the sentiments (tone measures) of the majority group's opinions are supposed to follow $\theta_i + \epsilon_i$, while those of the minority group's opinions (divergent opinions) are supposed to follow $\theta_i + \acute{\theta_i} + \epsilon_i$, where ϵ_i is an error term ($E[\epsilon_i] = 0$)). As shown in figure 1(a), as $\acute{\theta_i}$ takes a more positive value (the minority group's opinions are more positively diverse from the majority group's opinions), the highest sentiments $Twitter_{i,t}^{Highest}$ is expected to increase proportionally; in other words, $Twitter_{i,t}^{Highest}$ could be highly sensitive to the positivity of divergent opinions. Meanwhile, since the average sentiment (tone) measures mainly reflect the majority group's opinions, the average measures are much less influenced by the positivity of divergent opinions (the minority group's opinions). Similarly, as shown in figure 1(b), as $\acute{\theta_i}$ takes a more negative value (the minority group's opinions are more negatively diverse from the majority group's opinions), the lowest sentiments $Twitter_{i,t}^{Lowest}$ is expected to decrease proportionally; $Twitter_{i,t}^{Lowest}$ is sensitive to the negativity of divergent opinions. In sum, the highest and lowest sentiments ($Twitter_{i,t}^{Highest}$ and $Twitter_{i,t}^{Lowest}$) could be an estimator of the positivity and negativity of divergent opinions, respectively. Therefore, to assess tones of the divergent opinion of firm i on day t, denoted as $Twitter_{i,t}^{Divergent}$, we calculate the mid-range scores, that is, the arithmetic mean of the highest and lowest sentiment scores as:

$$Twitter_{i,t}^{Divergent} = \frac{Twitter_{i,t}^{Highest} + Twitter_{i,t}^{Lowest}}{2} \qquad (1)$$

where $Twitter_{i,t}^{Highest}$ and $Twitter_{i,t}^{Lowest}$ are the highest and lowest intraday sentiments 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)[2]. $Twitter_{i,t}^{Divergent}$ are expected to identify both the positivity and negativity of divergent opinions. To confirm our theoretical prediction, we perform simulation tests[3]. Untabulated results reveal that the mid-range scores could be a more efficient estimator for information set contained in divergent opinions ($\acute{\theta}_{\iota}$) than the average measure.

3.3. Return Predictability with Divergent Opinions

To test H1, we investigate the predictive power of divergent opinions 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 corresponding t-statistics based on Newey–West standard errors.

As previously mentioned, Twitter sentiment measures are released in the morning right before the stock market opens. Thus, we analyze the predictive power of $Twitter_{i,t-1}^{Divergent}$ for a open-to-open return ($Ret_{i,t}$) that is defined as a return from stock i's opening price on day t-1 to the opening price on day t. We also analyze predictive power for risk-adjusted open-to-open

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[2] Altogether, 720 two-minute sentiments are calculated at two-minutes interval over the 24-hour period. We use the highest and lowest two-minute sentiments as $Twitter_{i,t}^{Highest}$ and $Twitter_{i,t}^{Lowest}$, respectively.

[3] Suppose that each stock (we set the number of stocks to be 500) is followed by posters (we set the number of posters for each stock to be 100). Those posters are randomly assigned to a majority group, and a minority group, under the condition that the number of posters assigned to the majority group is larger than that of the minority group. Then, the sentiments (tone measures) of the majority group's opinions are supposed to follow $\theta_i + \epsilon_i$; those of the minority group's opinions (divergent opinions) are supposed to follow $\theta_i + \acute{\theta}_{\iota} + \epsilon_i$. Then, we calculate average sentiment and mid-range scores of the simulated posters' sentiments for each stock. Finally, we regress $\acute{\theta}_{\iota}$ on the average and mid-range scores to test whether which scores are more efficient estimators for $\acute{\theta}_{\iota}$.

returns, defined as the residuals of the Fama–French–Carhart four-factor model.[4] This approach theoretically allows one to trade at 9:30 a.m. after observing the Twitter scores released at 9:20 a.m. The regression specification is as follows:

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

The coefficient of $Twitter_{i,t-1}^{Divergent}$ is our main parameter of interest. As a control variable, in addition to $Twitter_{i,t-1}^{Mean}$, five lags of daily (open-to-open) returns ($Ret_{i,t-k}$: k=1,2,…,5) are included because the 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).

Further, following 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. Next, 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. (2001), we compute the abnormal trading volume 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 the abnormal trading volume and volatility are expressed in percentage points.

The news sentiment on day *t*-1, denoted as $News_{i,t-1}$, is added as an additional regressor

[4] Since we analyze open-to-open returns, betas of Fama–French–Carhart factors are also estimated using open-to-open returns.

because tweets could simply refer to firm-specific news. By adding news sentiment, we can evaluate the incremental informational value of divergent opinions ($Twitter_{i,t-1}^{Divergent}$) beyond firm-specific news. If firm 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. This is measured following the similar 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). [5]

Finally, to control for return predictability stemming from firm characteristics, we include 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 ($Momentum_{i,t-1}$). [6]

To test H2, which posits that abnormal returns with divergent opinions do not reverse, five lags of the divergent opinion measures ($Twitter_{i,t-k}^{Divergent}$: *k*=1, 2, …, 5) and the consensus opinion measures ($Twitter_{i,t-k}^{Mean}$: *k*=1, 2, …, 5) are included in the regression model as follows:

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

In terms of the control variables, we additionally include lagged news sentiment measures ($News_{i,t-k}$: *k*=2, 3, 4, and 5). The other control variables are the same as in Equation (2). As discussed in Section 2.2.1, if divergent opinions contain useful fundamental information about stocks, their effect on returns should be long-lasting. On the contrary, if their opinions simply reflect the incorrect or biased view, the impact of the opinions on stock returns should reverse

[5] Since the number of firm-specific news published by Bloomberg are limited, intraday news sentiments are not available.

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

over the next few trading days. To test whether the returns associated with $Twitter_{i,t-1}^{Divergent}$ are temporary or long-lasting, we examine whether the coefficients of the lagged divergent opinion measures ($Twitter_{i,t-k}^{Divergent}$ k=2, 3, 4, and 5) are significantly negative.

3.4. Predictive Power for Fundamentals

The previous section shows that $Twitter_{i,t-1}^{Divergent}$ has predictive power for cross-sectional returns. This section examines the predictive power of $Twitter_{i,t-1}^{Divergent}$ for the cross-sectional information flow on firm fundamentals. We then investigate whether the cross-sectional return predictability associated with $Twitter_{i,t-1}^{Divergent}$ is attributed to the cross-sectional information flow predicted by $Twitter_{i,t-1}^{Divergent}$.

To capture the cross-sectional information flow on firm fundamentals, we use revisions to analysts' earnings forecasts and target prices. Financial analysts continuously research time-varying firm fundamentals, along with the 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.[7] Thus, their earnings forecasts and target prices are expected to reflect and provide information on firm fundamentals in a timely manner.[8] Studies (e.g., Francis and Soffer, 1997; Brav and Lehavy, 2003) show that stock prices significantly react to these revisions. The results indicate that the revisions provide meaningful fundamental information to investors (cause information flow). Therefore, revisions to earnings forecasts and target prices are expected to indicate the information flow on firm fundamentals. Further, these revisions are suitable for identifying the cross-sectional distribution of new

[7] Finally, they recommend buying or selling a company's stock based on the difference between the actual price and estimated fair value.
[8] We do not include stock recommendations as an indicator of firm fundamentals because recommendations can be upgraded or downgraded because of stock price changes (even if firm fundamentals do not change).

information sets on firm fundamentals.[9] Hence, 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 the end of day *t*, $\mathrm{Earnings}_{i,t}$ is the average earnings forecast of firm *i* for the most recent quarter at the end of day *t*, and $\mathrm{Price}_{i,t}$ is the closing price of stock *i* on day *t*. Thus, $\Delta\mathrm{TP}_{i,t}$ and $\Delta\mathrm{Earnings}_{i,t}$ represents revisions in analysts' target prices and earnings forecasts on day *t*.

To test H3, which posits that the divergent opinions on Twitter contain relevant information about firm fundamentals, revisions in analysts' target prices and earnings forecasts on day *t* are regressed on Twitter sentiments of day *t*-1. We regress these two indicators as:

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

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. The other control variables are the same as in Equation (2).

Next, we analyze whether return predictability with $Twitter_{i,t-1}^{Divergent}$ is attributed to the predictive power of $Twitter_{i,t-1}^{Divergent}$ 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:

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

In this model, contemporaneous target price changes and earnings revisions ($\Delta\mathrm{TP}_{i,t}$ and $\Delta\mathrm{Earnings}_{i,t}$) are included as control variables to test the mediation effect. The other control variables are the same as in Equation (2). We first analyze whether the coefficients of $\Delta\mathrm{TP}_{i,t}$ and

[9] On the contrary, new information on firm fundamentals is not always captured by firms' event indicators such as earnings announcements, as these indicators are scheduled.

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

3.5. Interaction Effects

Bartov et al. (2018) show that the average sentiments (as a proxy for consensus opinions on Twitter) can predict the content of quarterly earnings announcements. Thus, our interest is in examining whether the predictive power of divergent opinions is specifically strong around an earnings announcement. The analysis tells us whether our findings are subsumed by those of Bartov et al. (2018). To this end, we analyze the predictive power around earnings announcements by running the following regression:

$$Ret_{i,t} = \alpha + \beta_1 Twitter_{i,t-1}^{Divergent} * Announcement[t-1,t]_i + \beta_2 Twitter_{i,t-1}^{Divergent} + (Controls) + \varepsilon_{i,t} \quad (6)$$

where $Announcement[t-1,t]_i$ is a dummy variable that takes 1 if there is an earnings announcement for days *t*-1 through *t*; otherwise, 0.

If the informativeness of divergent opinions is attributed to predictive power for earnings announcement events or earnings announcement returns, the coefficient of the interaction (β_1) should be significantly positive.

Next, we analyze whether predictive power for subsequent returns differs across past company performance. To this end, we analyze whether predictive power is stronger or weaker for firms with low ROA and SUE. To this end, we run the following regression and examine whether the coefficients of the interactions ($Twitter_{i,t-1}^{Extreme} * ROA_{i,t-1}$, $Twitter_{i,t-1}^{Extreme} * SUE\_P_{i,t-1}$) are positive or negative:

$$Ret_{i,t} = \alpha + \beta_1 Twitter_{i,t-1}^{Divergent} * ROA_{i,t-1} + \beta_2 Twitter_{i,t-1}^{Divergent} + (Controls) + \varepsilon_{i,t} \quad (7)$$

$$Ret_{i,t} = \alpha + \beta_1 Twitter_{i,t-1}^{Divergent} * SUE\_P_{i,t-1} + \beta_2 Twitter_{i,t-1}^{Divergent} + (Controls) + \varepsilon_{i,t} \quad (8)$$

where ROA is return on assets (defined as operating income before depreciation over total assets) and SUE_P is the SUE of the latest quarterly earnings announcement. A significant positive (negative) coefficient indicates that predictive power is stronger for firms that perform well (poorly).

4. Empirical Results

4.1. Sample Selection and Summary Statistics

Following Gu and Kurov (2020) and Bartov et al. (2018), we analyze Twitter opinions (tweets) for Russell 3000 component stocks, which account for about 99% of the market capitalization of the U.S. equity market. Because Bloomberg started releasing Twitter sentiment data in January 2015, our sample ranges from 2015 to 2019 and contains 1,252 trading days.

Panel (a) of Table 1 presents the summary statistics for our full sample. The panel shows that the averages of $Twitter_{i,t}^{Divergent}$ and $Twitter_{i,t}^{Mean}$ are both slightly positive (0.021 and 0.034, respectively), indicating that, on average, the content of tweets is slightly positive. The mean open-to-open return $Ret_{i,t}$ is about 6 basis points, consistent with the general upward trend of the stock market during our sample period.

Panel (b) presents the correlations between the variables. The panel indicates that $Twitter_{i,t}^{Divergent}$ is associated with $Twitter_{i,t}^{Mean}$.[10] The measures of divergent opinions $Twitter_{i,t}^{Divergent}$ are also weakly associated with contemporaneous stock returns and news sentiments.

[Table 1]

4.2. Return Predictability

[10] This is self-evident, as the most positive and negative sentiments are utilized for calculating both $Twitter_{i,t}^{Mean}$ and $Twitter_{i,t}^{Divergent}$. Thus, we calculate the average sentiment measures based on intraday sentiments except the highest and lowest sentiments. Then we replace the average tone measure used in the regression models by the calculated ones. We found that the result continues to hold.

We run regressions for both raw and risk-adjusted returns. In terms of the control variables, Table 2 shows that the coefficient of $News_{i,t-1}$ is significantly positive. This result indicates that the news sentiment has predictive power for subsequent returns, consistent with the findings of Gu and Kurov (2020) and Tetlock et al. (2008). The result also reveals that the coefficient of $Ret_{i,t-1}$ is significantly negative, indicating a strong short-term return reversal, consistent with the findings of Jegadeesh (1990) and Lehmann (1990).

In terms of the return predictability of Twitter opinions, the table shows that not only the consensus opinion measures ($Twitter^{Mean}_{i,t-1}$) but also the divergent opinion ones ($Twitter^{Divergent}_{i,t-1}$) have significant predictive power for subsequent returns ($Ret_{i,t}$). The coefficient of $Twitter^{Divergent}_{i,t-1}$ is significantly positive at the 1% level. These results suggest that divergent opinions have incremental predictive power for subsequent returns beyond consensus opinions, supporting H1.

[Table 2]

Table 3 shows the results of the predictive power of the five lags of the divergent opinion measures. The coefficient of $Twitter^{Divergent}_{i,t-1}$ remains significantly positive. Further, the coefficient estimates of the four lags of the measures (lags of the divergent opinion measures except for the most recent one; $Twitter^{Divergent}_{i,t-k}$: *i*=2,3,4, and 5) are not significantly negative. This suggests that the abnormal returns associated with $Twitter^{Divergent}_{i,t-1}$ do not reverse in a subsequent period, supporting H2. These findings are consistent with the notion that divergent opinions have a long-lasting price impact on stock prices and thus contain some information on stock valuation.

On the contrary, the results reveal that the coefficient of $Twitter^{Mean}_{i,t-2}$ is significantly negative, indicating that the abnormal return associated with the consensus opinion measures $Twitter^{Mean}_{i,t-1}$ does significantly reverse on a subsequent day. This result casts doubt on the notion that the average Twitter sentiment (i.e., the consensus opinion on Twitter) contains incremental information on stock valuation, which is consistent with the mixed findings of prior studies on the informational value of consensus opinions on Twitter.

[Table 3]

4.3. Predictive Power for Fundamentals

Table 4 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 $Twitter^{Divergent}_{i,t-1}$, whereas the association is much weaker with $Twitter^{Mean}_{i,t-1}$. An upgrade (downgrade) in a firm's target price and earnings forecasts is more likely to occur when the lagged divergent opinion measures are positive (negative). This result indicates that divergent opinions contain incremental information on firm fundamentals beyond analysts' earnings forecasts, target prices, and consensus opinions on Twitter, supporting H3.

[Table 4]

Table 5 shows the results of the mediation analysis, that is, the regression results of the 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 to analysts' target prices and earnings forecasts have a significant impact on stock prices. As $Twitter^{Divergent}_{i,t-1}$ predicts $\Delta\mathrm{TP}_{i,t}$ and $\Delta\mathrm{Earnings}_{i,t}$ the results suggest that the association between $Twitter^{Divergent}_{i,t-1}$ and $Ret_{i,t}$ is mediated by the predictive power of $Twitter^{Divergent}_{i,t-1}$ for $\Delta\mathrm{TP}_{i,t}$ and $\Delta\mathrm{Earnings}_{i,t}$. In other words, divergent opinions contain fundamental information that is subsequently reflected in (disclosed by) analysts' earnings forecasts and target prices, and return predictability with divergent opinions is (at least, partly) attributed to the price impact caused by the disclosure of the information.

In fact, the magnitude and statistical significance of the coefficient of $Twitter^{Divergent}_{i,t-1}$ are reduced by adding $\Delta\mathrm{TP}_{i,t}$ and $\Delta\mathrm{Earnings}_{i,t}$ as control variables. As shown in Tables 2 and 5, the coefficient declines significantly (from 0.0014 to 0.0011 when we use raw returns and from

0.0013 to 0.0008 when we use risk-adjusted returns). Precisely, fundamental information that is subsequently reflected in analysts' target prices and earnings forecasts explains about 38% ((0.0013-0.0008)/0.0013) of the predictive power of divergent opinions for risk-adjusted returns. The magnitude of the decline is statistically significant. Further, the coefficient of $Twitter_{i,t-1}^{Divergent}$ for risk-adjusted returns is no longer significant after controlling for the mediation effects. These results suggest that return predictability with divergent opinions is grounded in the fundamental information contained in their opinions, supporting H4.

Meanwhile, no significant decline is observed for the coefficient of $Twitter_{i,t-1}^{Mean}$, which drops by only approximately 12% (when we use risk-adjusted returns) and the coefficients remain statistically significant. Return predictability with a consensus opinion on Twitter is not significantly grounded in information on firm fundamentals. This might result in a strong reversal of the abnormal returns associated with consensus opinions on Twitter.

[Table 5]

4.4. Interaction Effect

Table 6 shows the results of the interaction effect, that is, the regression results of the regression models (6), (7), and (8) estimated using the Fama–MacBeth approach. Table 6(a) reveals that the coefficient of $Twitter_{i,t-1}^{Divergent} * Announcement[t-1,t]_i$ is not significant, indicating that predictive power is not significantly stronger around the earnings announcement. We also find that $Twitter_{i,t-1}^{Divergent}$ and an absolute value of demeaned $Twitter_{i,t-1}^{Divergent}$ (a proxy of the extremeness of $Twitter_{i,t-1}^{Divergent}$) are not significantly associated with $Announcement[t-1,t]_i$; that is, divergent opinions are irrelevant to the earnings announcement. Thus, the predictive power of $Twitter_{i,t-1}^{Divergent}$ is irrelevant to earnings announcements. Bartov et al. (2018) show the informational value of the consensus opinion around earnings announcements. By contrast, we show that the informativeness of divergent opinions on Twitter can be observed outside earnings announcement periods.

Tables 7(b) and 7(c) reveal that the coefficients of $Twitter_{i,t-1}^{Divergent} * ROA_{i,t-1}$ and $Twitter_{i,t-1}^{Divergent} * SUE\_P_{i,t-1}$ are not significant, indicating that predictive power is irrelevant to the firm's past performance.

[Table 6]

5. Direction of Opinions

Our divergent opinion measure $Twitter_{i,t}^{Divergent}$ includes both positive and negative opinions. In this section, we separately analyze the informational value of their positive and negative opinions. The negative opinions on Twitter for each firm might have more informational value than the positive opinions for several reasons. First, owing to short-sale constraints, negative rather than positive information remains unincorporated into stock prices. Second, managers disseminate good news as quickly as possible, but are less forthcoming on bad news (Miller, 2002; Kothari et al., 2009). This asymmetric disclosure by managers implies that the market is more likely to have advanced knowledge of favorable content in tweets than unfavorable content. Therefore, social media could be more important for propagating bad news than good news. In other words, negative opinions rather than positive ones are unlikely to be reflected in prices. Hence, we predict that divergent opinions play important informational roles especially when their opinions are negative.

5.1. Predictive Power for Stock Returns

As argued in Section 3.2., the highest and lowest intraday sentiments ($Twitter_{i,t}^{Highest}$ and $Twitter_{i,t}^{Lowest}$) could be an estimator of the positivity and negativity of divergent opinions, respectively. Thus, to test our prediction, we first separately analyze the market reaction to $Twitter_{i,t}^{Highest}$ and $Twitter_{i,t}^{Lowest}$. To this end, we run the following regression model for

$Ret_{i,t}$:

$$Ret_{i,t} = \alpha + \beta_1 Twitter_{i,t-1}^{Highest} + \beta_2 Twitter_{i,t-1}^{Lowest} + \beta_3 Twitter_{i,t-1}^{Mean} + (Controls) + \varepsilon_{i,t} \quad (9)$$

The same control variables are included as in Equation (2). Then, the coefficient of $Twitter_{i,t-1}^{Highest}$ is compared with that of $Twitter_{i,t-1}^{Lowest}$. Specifically, we examine whether the coefficient of $Twitter_{i,t-1}^{Lowest}$ is more significant than that of $Twitter_{i,t-1}^{Highest}$.

Next, we examine whether the abnormal returns associated with $Twitter_{i,t-1}^{Lowest}$ reverse in subsequent days. To this end, we run the following regression model:

$$Ret_{i,t} = \alpha + \sum_{k=1}^{5} \beta_{1,k} Twitter_{i,t-k}^{Highest} + \sum_{k=1}^{5} \beta_{2,k} Twitter_{i,t-k}^{Lowest} + \sum_{k=1}^{5} \beta_{3,k} Twitter_{i,t-k}^{Mean} + (Controls) + \varepsilon_{i,t} \quad (10)$$

The same control variables are included as in Equation (3). As argued in Section 3.3, if tweets contain incremental fundamental information on a firm's stock valuation, their effect on returns should be long-lasting. Thus, we examine whether the abnormal returns associated with $Twitter_{i,t-1}^{Lowest}$ are temporary or long-lasting by analyzing whether the coefficients of the four lagged most negative intraday sentiments ($Twitter_{i,t-k}^{Lowest}$: *k*=2, 3, 4, and 5) are significantly negative.

Table 7(a) shows that even after controlling for $Twitter_{i,t-k}^{Highest}$ and $Twitter_{i,t-k}^{Mean}$ (*k*=1, 2, 3, 4, and 5), the coefficient of $Twitter_{i,t-1}^{Lowest}$ remains significantly positive. $Twitter_{i,t-1}^{Lowest}$ have significant predictive power for subsequent returns. Table 7(b) shows the results of the predictive power of the four lags of the most negative intraday sentiments ($Twitter_{i,t-k}^{Lowest}$: *k*=2, 3, 4, and 5). It shows that these four lags have little effect on $Ret_{i,t}$, suggesting that abnormal returns with $Twitter_{i,t-1}^{Lowest}$ do not reverse subsequently.

On the contrary, the statistical significance is much weaker for the coefficient of $Twitter_{i,t-1}^{Highest}$. The coefficient in regression model (9) is not significant (see Table 7(a)). On average, a one standard deviation increase in $Twitter_{i,t-1}^{Highest}$ raises the risk-adjusted return

($Ret_{i,t}$) by 0.5 basis points, whereas the same increase in $Twitter_{i,t-1}^{Lowest}$ raises the return by 1.3 basis points. The price impact of $Twitter_{i,t-1}^{Highest}$ is much less than that of $Twitter_{i,t-1}^{Lowest}$. These results indicate that the predictive power of divergent opinions for subsequent returns is more substantial especially when the opinions are negative. In other words, the negativity of divergent opinion identified by $Twitter_{i,t-1}^{Lowest}$ contain incremental negative information on stock valuation.

[Table 7]

5.2. Information on Firm Fundamentals

We next examine whether divergent opinions likely contain incremental information on firm fundamentals especially when the opinions are negative. Further, we analyze whether strong return predictability with $Twitter_{i,t-1}^{Lowest}$ is attributed to the fundamental information contained in $Twitter_{i,t-1}^{Lowest}$. To this end, as in the analysis in Section 3.4., we first examine whether $Twitter_{i,t-1}^{Highest}$ and $Twitter_{i,t-1}^{Lowest}$ have predictive power for subsequent revisions to analysts' earnings forecasts and target prices. We regress these two indicators as:

$$y_{i,t} = \alpha + \beta_1 Twitter_{i,t-1}^{Highest} + \beta_2 Twitter_{i,t-1}^{Lowest} + \beta_3 Twitter_{i,t-1}^{Mean} + (Controls) + \varepsilon_{i,t} \qquad (11)$$

where $y_{i,t}$ is either $\Delta \mathrm{TP}_{i,t}$ or $\Delta \mathrm{Earnings}_{i,t}$. The other control variables are the same as in Equation (4).

Then, we analyze whether the predictive power of $Twitter_{i,t-1}^{Lowest}$ for $Ret_{i,t}$ is attributed to the predictive power of $Twitter_{i,t-1}^{Lowest}$ 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:

$$Ret_{i,t} = \alpha + \beta_1 Twitter_{i,t-1}^{Highest} + \beta_2 Twitter_{i,t-1}^{Lowest} + \beta_3 Twitter_{i,t-1}^{Mean} + \beta_4 \Delta \mathrm{TP}_{i,t} + \beta_5 \Delta \mathrm{Earnings}_{i,t} + (Controls) + \varepsilon_{i,t} \qquad (12)$$

In this model, $\Delta \mathrm{TP}_{i,t}$ and $\Delta \mathrm{Earnings}_{i,t}$ are included as control variables to analyze the mediation effect. The other control variables are the same as in Equation (5). We first analyze whether the coefficients of $\Delta\text{TP}_{i,t}$ and $\Delta\text{Earnings}_{i,t}$ (β_4 and β_5 in Equation (12)) are significantly positive. Then, we examine whether the coefficients of $Twitter_{i,t-1}^{Lowest}$ are significantly reduced by adding $\Delta\text{TP}_{i,t}$ and $\Delta\text{Earnings}_{i,t}$; in other words, the estimated β_2 in Equation (12) is significantly lower than the estimated $\beta_2$in Equation (9).

Table 8 shows the regression results of regression model (11). The results reveal that $Twitter_{i,t-1}^{Lowest}$ is significantly associated with $\Delta\text{TP}_{i,t}$ and $\Delta\text{Earnings}_{i,t}$. This result indicates that the negativity of divergent opinions identified by the most negative intraday sentiments contains incremental information on firm fundamentals.

[Table 8]

Table 9 shows the regression results of regression model (12), that is, the results of the mediation effect. The significant coefficients of $\Delta\text{TP}_{i,t}$ and $\Delta\text{Earnings}_{i,t}$ on $Ret_{i,t}$ indicate that revisions to analysts' target prices and earnings forecasts have a significant impact on stock prices. Further, the magnitude and statistical significance of the coefficient of $Twitter_{i,t-1}^{Lowest}$ are significantly reduced by adding $\Delta\text{TP}_{i,t}$ and $\Delta\text{Earnings}_{i,t}$. Tables 8 and 10 show that the coefficient of $Twitter_{i,t-1}^{Lowest}$ for risk-adjusted returns is no longer statistically significant after considering the mediation effect. The coefficient declines by approximately 66% (from 0.0009 to 0.0003 when we use risk-adjusted returns). We find that the magnitude of the decline is statistically significant. These results suggest that return predictability with the negativity of divergent opinions ($Twitter_{i,t-1}^{Lowest}$) is mediated by the fundamental information contained in the negativity.

[Table 9]

6. Conclusion

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

Our empirical analysis reveals that not only consensus opinions but also divergent opinions, specifically the negative ones, have predictive power for cross-sectional returns. Furthermore, the abnormal returns associated with divergent opinions do not significantly reverse, whereas those associated with consensus opinions do significantly reverse on a subsequent day. These findings support the view that divergent opinions on Twitter contain incremental information on firm valuation, but they cast doubt on whether consensus opinions have sufficient informational value.

In addition, we find that the divergent opinions, specifically negative ones, predict subsequent revisions to analysts' target prices and earnings forecasts, suggesting that they contain information on firm fundamentals. Moreover, return predictability with the divergent opinions can be explained by their predictive power for revisions to analysts' target prices and earnings forecasts. In sum, our findings suggest that divergent opinions on Twitter contain incremental information on firm fundamentals and valuation.

Our results support the view that there are informative opinions on firm valuation on social media. Studies have focused on consensus opinions on social media and show mixed results on their informational value. In this study, we provide robust evidence on the existence of informed opinions on social media by focusing on divergent opinions.

References

Almatarneh, S., Gamallo, P., 2018. A lexicon based method to search for extreme opinions. *PLoS ONE* 13(5).

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.

Brav, A., and Lehavy, R., 2003, An empirical analysis of analysts' target prices: Short term informativeness and long-term dynamics, *Journal of Finance*, 58, 1933–1967.

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.

Das, 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.

Francis, J., and Soffer, L., 1997. The Relative Informativeness of Analysts' Stock Recommendations and Earnings Forecast Revisions. *Journal of Accounting Research*, 35, 193–211.

Garcia, D., 2012. Sentiment during recessions. *Journal of Finance*, 68(3), 1267–1300.

Gervais, S., Kaniel, R., and Mingelgrin, H. D., 2001. The high-volume return premium. *Journal of Finance*, 56, 877–919.

Gu, C., and Kurov, A., 2020. Informational role of social media: Evidence from Twitter sentiment, *Journal of Banking and Finance*, forthcoming.

Huang, A., Zang, A., and Zheng, R., 2014. Evidence on the Information Content of Text in Analyst Reports. *The Accounting Review*, 89, 2151–2180.

Jegadeesh, N., 1990, Evidence of predictable behavior of security returns, *Journal of Finance*, 45, 881–898.

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.

Li, Y., He, J., Xiao, M., 2019. Risk Disclosure in Annual Reports and Corporate Investment Efficiency. *International Review of Economics & Finance*, 63, 138–151.

Lehmann, B., 1990. Fads, martingales and market efficiency, *Quarterly Journal of Economics*, 105, 1–28.

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.

Miwa, K., 2021. Language Barriers in Analyst Reports. *International Review of Economics & Finance*, 75, 223–236.

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.

Table 1

Descriptive Statistics and Correlations

Panel (a) reports the descriptive statistics of the dependent variables and Panel (b) shows the Pearson correlations between the dependent and independent variables. Each value is the time-series average. In Panel (a), the "Mean" column shows the average values. "Std" shows the standard deviations. "Median" shows the median values. "Max" and "Min" show the maximum and minimum values, respectively.

(a) Descriptive Statistics

	Mean	Std	Median	Max	Min
$Twitter^{Divergent}$	0.021	0.089	0.01	0.425	-0.414
$Twitter^{Mean}$	0.034	0.171	0.003	0.854	-0.841
$Twitter^{Highest}$	0.138	0.149	0.107	0.927	-0.042
$Twitter^{Lowest}$	-0.096	0.135	-0.059	0.061	-0.933
Ret	0.001	0.024	0	0.233	-0.2
ΔTP	0	0.012	0	0.2	-0.164
ΔEarnings	0	0.001	0	0.01	-0.014

(b) Correlations

	$Twitter^{Mean}$	$Twitter^{Highest}$	$Twitter^{Lowest}$	News	Ret	Volume
$Twitter^{Divergent}$	0.64	0.67	0.57	0.22	0.15	0.02
$Twitter^{Mean}$		0.44	0.35	0.19	0.14	0.01
$Twitter^{Highest}$			-0.22	0.27	0.09	0.13
$Twitter^{Lowest}$				-0.01	0.09	-0.12
News					0.10	0.07
Ret						0.04

	Volatlity	Value	Size	Momentum	ΔTP	ΔEarnings
$Twitter^{Divergent}$	-0.01	-0.04	-0.01	0.07	0.11	0.04
$Twitter^{Mean}$	-0.01	-0.03	-0.02	0.06	0.11	0.04
$Twitter^{Highest}$	0.00	-0.04	0.20	0.04	0.08	0.00
$Twitter^{Lowest}$	-0.01	0.00	-0.24	0.04	0.06	0.05
News	-0.03	-0.04	0.10	0.02	0.10	0.01
Ret	-0.01	0.00	-0.01	0.01	0.13	0.03
Volume	0.02	0.00	-0.02	0.01	0.00	-0.08
Volatlity		0.18	-0.12	-0.05	-0.02	-0.01
Value			-0.09	-0.20	-0.03	-0.03
Size				0.01	0.00	0.01
Momentum					0.11	0.03
ΔTP						0.17

Table 2

Return Predictability with Divergent Opinions

The table presents the results from regression model (2) $Ret_{i,t} = \alpha + \beta_1 Twitter_{i,t-1}^{Divergence} + (Controls) + \varepsilon_{i,t}$. Column "Raw" shows the results when we regress raw open-to-open returns. Column "Risk-adjusted" shows the results when we regress risk-adjusted open-to-open returns. The t-statistics based on Newey–West standard errors are shown in parentheses. ** and *** indicate statistical significance at the 5% and 1% levels, respectively.

	Raw		Risk Adjusted	
$Twitter_{i,t-1}^{Divergent}$	0.0014 ***	(3.33)	0.0013 ***	(2.82)
$Twitter_{i,t-1}^{Mean}$	0.0009 ***	(4.77)	0.0011 ***	(4.64)
$News_{i,t-1}$	0.0013 ***	(7.18)	0.0014 ***	(7.21)
$Ret_{i,t-1}$	-0.0192 ***	(6.18)	-0.0226 ***	(6.61)
$Ret_{i,t-2}$	-0.0040	(1.68)	-0.0043	(1.34)
$Ret_{i,t-3}$	0.0008	(0.39)	-0.0010	(0.40)
$Ret_{i,t-4}$	-0.0031	(1.41)	-0.0059 **	(2.12)
$Ret_{i,t-5}$	-0.0042	(1.90)	-0.0042	(1.50)
$Volume_{i,t-1}$	0.0001	(0.94)	0.0000	(0.33)
$Volume_{i,t-2}$	0.0000	(0.08)	0.0000	(0.29)
$Volume_{i,t-3}$	0.0000	(0.47)	0.0000	(0.08)
$Volume_{i,t-4}$	0.0000	(0.26)	0.0001	(0.61)
$Volume_{i,t-5}$	0.0000	(0.36)	0.0000	(0.27)
$Volatility_{i,t-1}$	-0.0541	(0.94)	0.0303	(0.43)
$Volatility_{i,t-2}$	-0.0085	(0.15)	-0.1043	(1.46)
$Volatility_{i,t-3}$	0.0256	(0.45)	0.0198	(0.31)
$Volatility_{i,t-4}$	0.0691	(1.22)	0.1344	(1.68)
$Volatility_{i,t-5}$	0.0274	(0.49)	0.0760	(1.22)
$Value_{i,t-1}$	0.0000	(0.30)	0.0003	(1.61)
$Size_{i,t-1}$	-0.0001 ***	(3.51)	-0.0001	(1.39)
$Momentum_{i,t-1}$	-0.0003	(0.98)	-0.0004	(1.25)
R2	10.47%		12.16%	

Table 3

Return Predictability with Lagged Divergent opinions

The table presents the results from regression model (3) $Ret_{i,t} = \alpha + \sum_{k=1}^{5} \beta_{1,k} Twitter_{i,t-k}^{Extreme} + \sum_{k=1}^{5} \beta_{2,k} Twitter_{i,t-k}^{Mean*} + (Controls) + \varepsilon_{i,t}$. Column “Raw” shows the results when we regress raw open-to-open returns. Column “Risk-adjusted” shows the results when we regress risk-adjusted open-to-open returns. The t-statistics based on Newey–West standard errors are shown in parentheses. *** indicates statistical significance at the 1% level.

	Raw	Risk-adjusted
$Twitter_{i,t-1}^{Divergent}$	0.0016 ***	0.0017 ***
	(3.88)	(4.21)
$Twitter_{i,t-2}^{Divergent}$	-0.0004	-0.0004
	(0.96)	(0.83)
$Twitter_{i,t-3}^{Divergent}$	-0.0001	-0.0001
	(0.36)	(0.18)
$Twitter_{i,t-4}^{Divergent}$	0.0000	-0.0004
	(0.09)	(0.90)
$Twitter_{i,t-5}^{Divergent}$	0.0001	-0.0001
	(0.28)	(0.36)
$Twitter_{i,t-1}^{Mean}$	0.0008 ***	0.0009 ***
	(4.24)	(3.89)
$Twitter_{i,t-2}^{Mean}$	-0.0007 ***	-0.0007 ***
	(2.80)	(2.94)
$Twitter_{i,t-3}^{Mean}$	-0.0002	-0.0002
	(0.95)	(0.77)
$Twitter_{i,t-4}^{Mean}$	-0.0003	-0.0003
	(1.25)	(1.25)
$Twitter_{i,t-5}^{Mean}$	0.0003	0.0002
	(1.24)	(0.85)
Controls	Yes	Yes
R2	9.1%	7.8%

Table 4

Fundamentals of Divergent opinions

The table presents the results from regression model (4) $y_{i,t} = \alpha + \beta_1 Twitter_{i,t-1}^{Extreme} + \beta_2 Twitter_{i,t-1}^{Mean} + \beta_3 \Delta \mathrm{TP}_{i,t-1} + \beta_4 \Delta \mathrm{Earnings}_{i,t-1} + (Controls) + \varepsilon_{i,t}$. Column "Earnings Forecast" shows the results when the dependent variable is analysts' earnings forecast revisions. Column "Target Price" shows the results when the dependent variable is a change in analysts' target price. The values in the two rows report 1,000 times the time-series average of the coefficients. The t-statistics based on Newey–West standard errors are shown in parentheses. ** and *** indicate statistical significance at the 5% and 1% levels, respectively.

	Earnings Forecast (x1000)		Target Price (x1000)	
$Twitter_{i,t-1}^{Divergent}$	0.0400 ***	(2.65)	0.8756 ***	(4.63)
$Twitter_{i,t-1}^{Mean}$	0.0104	(1.24)	0.2512 **	(2.47)
$\Delta TP_{i,t-1}$	0.2558	(1.40)	8.9972 ***	(3.51)
$\Delta Earnings_{i,t-1}$	24.5069 ***	(4.82)	79.9960	(1.56)
Controls	Yes		Yes	
R2	4.89%		5.23%	

Table 5

Mediation Analysis for Divergent opinions

The table presents the results from regression model (5) $Ret_{i,t} = \alpha + \beta_1 Twitter_{i,t-1}^{Extreme} + \beta_2 Twitter_{i,t-1}^{Mean}$ $+\beta_3 \Delta\text{TP}_{i,t} + \beta_4 \Delta\text{Earnings}_{i,t} + (Controls) + \varepsilon_{i,t}$. Column "Raw" shows the results when we regress raw open-to-open returns. Column "Risk-adjusted" shows the results when we regress risk-adjusted open-to-open returns. The t-statistics based on Newey–West standard errors are shown in parentheses. ** and *** indicate statistical significance at the 5% and 1% levels, respectively.

	Raw		Risk Adjusted	
$Twitter_{i,t-1}^{Divergent}$	0.0011 ***	(2.68)	0.0008	(1.77)
$\Delta Earnings_{i,t}$	1.5104 ***	(3.06)	1.5513 **	(2.46)
$\Delta TP_{i,t}$	0.3183 ***	(28.84)	0.3072 ***	(26.20)
$Twitter_{i,t-1}^{Mean}$	0.0007 ***	(3.87)	0.0009 ***	(4.16)
Controls	Yes		Yes	
R2	15.12%		16.23%	

Table 6

Interaction Effects

Panels (a), (b), and (c) present the results from regression models (6), (7), and (8), respectively. Column "Raw" shows the results when we regress raw open-to-open returns. Column "Risk-adjusted" shows the results when we regress risk-adjusted open-to-open returns. The t-statistics based on Newey–West standard errors are shown in parentheses. ** and *** indicate statistical significance at the 5% and 1% levels, respectively.

(a) Interaction with Earnings Announcement

	Raw		Risk Adjusted	
$Twitter_{i,t-1}^{Divergent}$ X $Announcement$	1.4529	(1.19)	0.6439	(1.43)
$Twitter_{i,t-1}^{Divergent}$	0.0009 ***	(4.71)	0.0010 ***	(4.33)
$Twitter_{i,t-1}^{Mean}$	0.0020 ***	(4.28)	0.0020 ***	(3.91)
Controls	Yes		Yes	
R2	10.47%		12.16%	

(b) Interaction with ROA

	Raw		Risk Adjusted	
$Twitter_{i,t-1}^{Divergent}$ X ROA	-0.0046	(1.50)	-0.0099	(1.58)
$Twitter_{i,t-1}^{Divergent}$	0.0010 ***	(5.06)	0.0011 ***	(4.62)
$Twitter_{i,t-1}^{Mean}$	0.0019 ***	(4.12)	0.0019 ***	(3.78)
Controls	Yes		Yes	
R2	10.67%		12.32%	

(c) Interaction with SUE.

	Raw		Risk Adjusted	
$Twitter_{i,t-1}^{Divergent}$ X SUE_P	0.0003	(1.55)	0.0005 **	(2.23)
$Twitter_{i,t-1}^{Divergent}$	0.0010 ***	(4.89)	0.0011 ***	(4.61)
$Twitter_{i,t-1}^{Mean}$	0.0019 ***	(4.11)	0.0018 ***	(3.76)
Controls	Yes		Yes	
R2	10.67%		12.32%	

Table 7

Return Predictability with Positive and Negative Opinions

Panels (a) and (b) present the results from regression models (9) and (10), respectively. The t-statistics based on Newey–West standard errors are shown in parentheses. *** indicates statistical significance at the 1% level.

(a) Associations with the Most Recent Measures

	Raw		Risk Adjusted	
$Twitter_{i,t-1}^{Lowest}$	0.0009 ***	(2.93)	0.0009 ***	(3.17)
$Twitter_{i,t-1}^{Highest}$	0.0005	(1.94)	0.0003	(1.15)
$Twitter_{i,t-1}^{Mean}$	0.0009 ***	(4.77)	0.0011 ***	(4.61)
Controls	Yes		Yes	
R2	10.52%		12.22%	

(b) Associations with the Five Lags

	Raw	Risk-adjusted
$Twitter_{i,t-1}^{Lowest}$	0.0010 *** (2.82)	0.0011 *** (3.26)
$Twitter_{i,t-2}^{Lowest}$	0.0001 (0.24)	0.0000 (0.13)
$Twitter_{i,t-3}^{Lowest}$	-0.0003 (1.05)	-0.0005 (1.48)
$Twitter_{i,t-4}^{Lowest}$	0.0002 (0.79)	-0.0001 (0.18)
$Twitter_{i,t-5}^{Lowest}$	0.0003 (1.14)	0.0002 (0.83)
$Twitter_{i,t-1}^{Highest}$	0.0007 *** (2.88)	0.0007 *** (2.69)
$Twitter_{i,t-2}^{Highest}$	-0.0002 (0.97)	-0.0003 (0.90)
$Twitter_{i,t-3}^{Highest}$	0.0001 (0.54)	0.0002 (0.82)
$Twitter_{i,t-4}^{Highest}$	-0.0001 (0.66)	-0.0003 (1.35)
$Twitter_{i,t-5}^{Highest}$	0.0000 (0.01)	-0.0004 (1.36)
Controls	Yes	Yes
R2	9.3%	8.3%

Table 8

Fundamentals Contained in Positive and Negative Opinions

The table presents the results from regression model (11): $y_{i,t} = \alpha + \beta_1 Twitter_{i,t-1}^{Highest} + \beta_2 Twitter_{i,t-1}^{Lowest} + \beta_3 Twitter_{i,t-1}^{Mean} + (Controls) + \varepsilon_{i,t}$. Column "Earnings Forecast" shows the results when the dependent variable is analysts' earnings forecast revisions. Column "Target Price" shows the results when the dependent variable is a change in analysts' target price. The values in the two rows report 1,000 times the time-series average of the coefficients. The t-statistics based on Newey–West standard errors are shown in parentheses. ** and *** indicate statistical significance at the 5% and 1% levels, respectively.

	Earnings Forecast (x1000)		Target Price (x1000)	
$Twitter_{i,t-1}^{Lowest}$	0.0748 ***	(6.23)	0.6580 ***	(5.38)
$Twitter_{i,t-1}^{Highest}$	-0.0303 ***	(3.39)	0.2502 **	(2.12)
$Twitter_{i,t-1}^{Mean}$	0.0121	(1.42)	0.2608 **	(2.58)
$\Delta TP_{i,t-1}$	0.2556	(1.40)	8.9506 ***	(3.50)
$\Delta Earnings_{i,t-1}$	8.7512	(0.54)	72.2570	(1.43)
Controls	Yes		Yes	
R2	4.92%		5.24%	

Table 9

Mediation Analysis for Positive and Negative Opinions

The table presents the results from regression model (12) $Ret_{i,t} = \alpha + \beta_1 Twitter_{i,t-1}^{Highest} + \beta_2 Twitter_{i,t-1}^{Lowest} + \beta_3 Twitter_{i,t-1}^{Mean} + \beta_4 \Delta \mathrm{TP}_{i,t} + \beta_5 \Delta \mathrm{Earnings}_{i,t} + (Controls) + \varepsilon_{i,t}$. Column "Raw" shows the results when we regress raw open-to-open returns. Column "Risk-adjusted" shows the results when we regress risk-adjusted open-to-open returns. The t-statistics based on Newey–West standard errors are shown in parentheses. ** and *** indicate statistical significance at the 5% and 1% levels, respectively.

	Raw		Risk Adjusted	
$Twitter_{i,t-1}^{Lowest}$	0.0005 **	(2.11)	0.0003	(0.91)
$Twitter_{i,t-1}^{Highest}$	0.0006 **	(1.98)	0.0007 **	(2.42)
$\Delta Earnings_{i,t}$	1.5147 ***	(3.06)	1.4246 **	(2.51)
$\Delta TP_{i,t}$	0.3183 ***	(28.82)	0.3163 ***	(28.08)
$Twitter_{i,t-1}^{Mean}$	0.0007 ***	(3.86)	0.0009 ***	(3.95)
Controls	Yes		Yes	
R2	15.12%		16.19%	

a) Positive divergent opinions

b) Negative divergent opinions

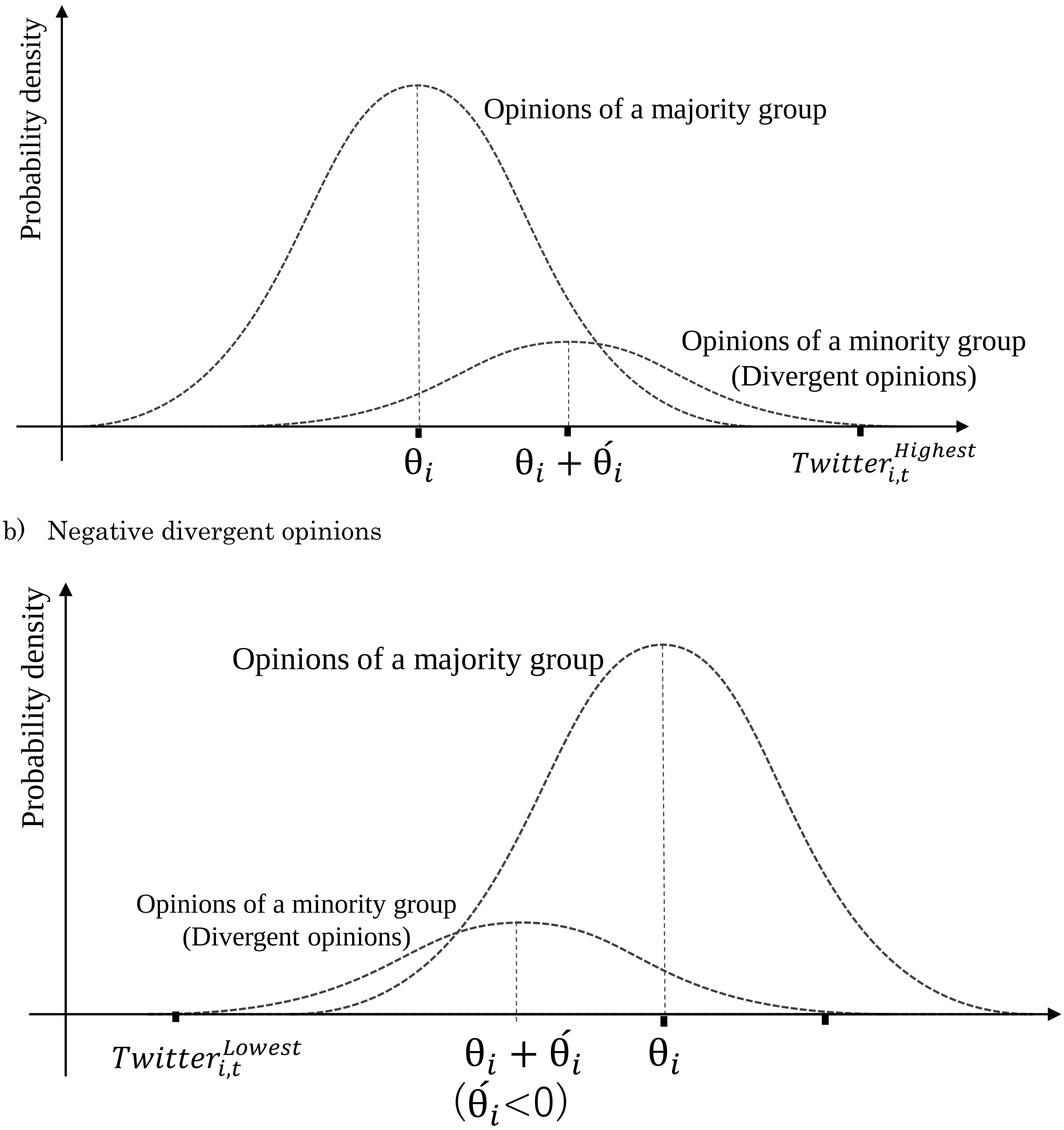

Figure 1. Distribution of Intraday Twitter Sentiments and the Information Sets