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Informational role of social media: Evidence from Twitter sentiment

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This paper examines the information content of firm-specific sentiment extracted from Twitter messages. We find that Twitter sentiment predicts stock returns without subsequent reversals. This finding is consistent with the view that tweets provide information not already reflected in stock prices. We investigate possible sources of return predictability with Twitter sentiment. The results show that Twitter sentiment provides new information about analyst recommendations, analyst price targets and quarterly earnings. This information explains about one third of the predictive ability of Twitter sentiment for stock returns. Taken together, our findings shed new light on whether and why social media content has predictive value for stock returns.

1. Introduction

Social media, such as Facebook and Twitter, has become an important part of our everyday lives. Investors also increasingly rely on information from social media when making trading decisions. For example, on June 13, 2016 the American Diabetes Association (ADA) announced the results of a clinical trial of Victoza, a new diabetes drug produced by Novo Nordisk. The announcement was made through a presentation in a crowded convention hall. Although the ADA asked the attendees to keep the information confidential before its official release, within minutes several Twitter accounts posted pictures of presentation slides showing key results of the clinical trial. When the stock market opened the following morning, Novo's stock price fell by about 5.6% because Victoza appeared less effective than previously expected. Skeptics may argue that such cases are rare. Unlike traditional business columnists and financial analysts, who may have access to relevant information, most individual social media users are uninformed. Their posts may be driven by rumors and contain more noise than information relevant for predicting stock price movements. On the other hand, many firms have adopted social media to communicate with investors and customers. Since April 2013, the SEC has allowed public firms to disseminate important news, such as quarterly earnings, to the public via Twitter. Many famous investors (for example, Warren Buffett and Carl Icahn) have also started to use social media to communicate with their followers.

The aim of this paper is to provide insights into the informational role of social media and enhance our understanding of how social media can best be employed as part of an investment strategy. Bollen et al. (2011) provide evidence that the public mood extracted from Twitter predicts daily aggregate stock returns. However, we still know little about information content of firm-specific Twitter sentiment. Our study attempts to shed new light on this issue.

The main challenge faced by researchers who investigate the impact of firm-level Twitter sentiment on financial markets is that discovering and analyzing all relevant tweets is difficult, if not impossible. Existing studies mainly investigate tweets around a specific type of events and perform textual analysis using existing word classifications use the relative frequency of terms "bullish"

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and "bearish" in tweets to measure investor sentiment. Although straightforward, lexicon-based methodologies are subject to significant measurement errors (Loughran and McDonald, 2011).[2] This is especially true for analysis of posts on social media. The content of Twitter messages is likely to be quite different from that of newspapers and corporate documents.

We use Bloomberg's firm-specific Twitter sentiment calculated using tweets from the overall Twitter and StockTwits that Bloomberg classifies as being about a given company.[3] Bloomberg uses supervised machine learning algorithms that, for example, identify financial tweets about Apple, determine if the particular tweet is positive, negative or neutral, and assign it a confidence score. A firm's daily Twitter sentiment is derived from its story-level sentiment and associated confidence scores in the last 24 h. The sentiment values are released every morning before the stock market's open. Using Bloomberg's Twitter sentiment data allows us to contribute to the literature on the informational content of Twitter messages without doing daunting and potentially subjective analysis of tweet content. This makes it feasible to examine the predictive content of Twitter sentiment for a large number of individual firms over a long sample period. In addition, using Bloomberg's Twitter sentiment makes our study replicable and transparent.

Using Fama-MacBeth type regression, we find that Twitter sentiment positively predicts abnormal stock returns. This predictability is not subsumed by traditional return predictors such as past returns, abnormal volume and volatility, or by news sentiment, whose ability to predict returns has been documented in the previous literature (e.g., Tetlock et al., 2008). On average, returns of firms with the most positive sentiment are 0.27% higher than returns of firms with the most negative sentiment over the next 24 h. A simple daily long-short strategy using Twitter sentiment would have earned an annualized Sharpe ratio of 3.17 and an average annual excess return of about 24 percent before transaction costs.

Existing studies have separately examined the ability of sentiment extracted from news stories and of Twitter sentiment to forecast stock returns. However, to the best of our knowledge, no study has looked at the two types of sentiment together. It is important to control for news sentiment when testing the predictive ability of Twitter sentiment. Estimating predictive regressions with both news sentiment and Twitter sentiment allows us to examine whether sentiment extracted from social media content provides incremental predictive power for future stock returns relative to that contained in news sentiment. We find that the predictive content of Twitter sentiment for stock returns is not subsumed by news sentiment. This suggests that social media reveals information useful to traders.

Our results for stock returns may be explained by two possible mechanisms. One mechanism is that Twitter sentiment contains no relevant information but temporarily shifts the demand for stock. In this scenario, changes in Twitter sentiment should produce short-term changes in stock prices followed by reversals. The other mechanism is that Twitter sentiment conveys valuable private signals about prospects of the firms. In this case, Twitter sentiment should have a permanent impact on stock prices. Therefore, a possible way to distinguish between the two mechanisms is to test for return reversals. We find that abnormal stock returns associated with Twitter sentiment are not subsequently reversed. This finding suggests that Twitter sentiment does not simply reflect sentiment of uninformed traders. Instead, Twitter sentiment contains relevant information that is incorporated into stock prices with one-day delay. We also find that Twitter sentiment contains more information about firms with limited analyst coverage. This finding lends further support to the conclusion that firm-level Twitter sentiment plays an informational role.

In further analysis, we examine possible sources of the return predictability with Twitter sentiment. Most studies in this area focus on specific events. For example, Bartov et al. (2018) examine Twitter sentiment around quarterly earnings announcements. We examine the informational role of Twitter sentiment by looking at three types of value-relevant events: analyst recommendation releases, analyst target price changes and quarterly earnings announcements. The following findings are documented. First, we find that high Twitter sentiment predicts analyst recommendation upgrades, target price increases and higher firm earnings. Second, the pre-event Twitter sentiment predicts announcement day returns. This indicates that the information contained in Twitter sentiment is not fully reflected in stock prices before these announcements. Finally, we show that information beyond the three types of events discussed above accounts for about two thirds of the predictive ability of Twitter sentiment. Together, these findings show that messages posted on Twitter contain new information about firm fundamentals. This information drives the return predictability with Twitter sentiment.

Existing literature on Twitter sentiment can be divided into two strands. The first strand analyzes tweets that discuss broad stock markets (Bollen et al., 2011; Mao et al., 2015). The second strand examines the informational role of Twitter sentiment around specific events. For example, Bartov et al. (2018) show that tweets contain information about quarterly earnings. Azar and Lo (2016) focus on the Federal Open Market Committee (FOMC) announcements. They show that the content of tweets predicts returns on the FOMC announcement days. In contrast to these studies, we examine the general effect of firm-level Twitter sentiment on stock prices. In our analysis of informational events, we show that, in addition to the information about quarterly earnings, Twitter sentiment contains information about changes in analyst recommendations, target price changes and IPO opening prices.

Due to rapid development of textual analysis techniques, a growing literature attempts to directly measure investor sentiment by analyzing communications of those who are commenting on stocks.[4] Most studies in this area focus on traditional media and investigate aggregate stock markets. For example, Tetlock (2007) and Garcia (2013) find that the market level news sentiment predicts stock index returns with subsequent reversals. In contrast, we find that firm level Twitter sentiment affects stock returns by conveying value relevant information. The different findings are due to two reasons. First, stock indices and individual stocks have different information environments. Individual firm stock prices are usually less efficient than stock index values. Firm level information may take more time to be incorporated into stock prices than market level information, which possibly leads to longer-term return predictive ability of firm level me-

[2] Word-count methods may lead to large measurement errors because lexicons identify emotional polarity of a word without taking context into account. Some sentiment analysis methods use machine learning to analyze qualitative information. For example, Antweiler and Frank (2004) and Das and Chen (2007) use algorithms, such as Bayesian Classifier and Vector Distance Classifier, to extract investor sentiment from Internet chat room messages.

[3] StockTwits is a communications platform for the financial and investing community. Today, more than 300,000 investors, market professionals and public companies share information and ideas about the market and individual stocks using StockTwits, producing messages that are viewed by an audience of over 40 million.

[4] Besides textual analysis, there are several other ways to measure investor sentiment. Baker and Wurgler (2006) propose a sentiment proxy constructed from historical stock market data. Da et al. (2015) measure market-wide sentiment using Internet search activity data. Survey-based sentiment measures, such as the University of Michigan Consumer Sentiment and the American Association of Individual Investors (AAII) investor sentiment, are also widely used (e.g., Kurov, 2010; Stambaugh, Yu and Yuan, 2012).

dia content. Second, with the advent of high-speed Internet, social media has become an important tool for individuals and institutions to share information. In contrast to traditional media, social media, such as Twitter, allows investors instantaneously post their opinions about stocks or financial markets. Therefore, information from social media is timelier than information from traditional media and is more likely to be value relevant.

Sentiment is generally considered to be a driver of irrational noise trading. However, Tetlock et al. (2008), Bollen et al. (2011), and Bartov et al. (2018) find that qualitative information-based investor sentiment contains relevant information about stocks. Following this strand of literature, we use the term "Twitter sentiment" in this paper. This term is also used by Bloomberg, the data provider. In essence, this "sentiment" variable captures qualitative information about the firm. If this variable captures primarily irrational beliefs, Twitter sentiment should behave like a traditional sentiment variable. On the other hand, if the qualitative information is mostly rational, Twitter sentiment should be value relevant. Our findings are consistent with the second scenario.

2. Data and sample selection

2.1. Twitter sentiment measure

Bloomberg uses a suite of supervised machine learning methods for social media sentiment analysis. First, Bloomberg lets human experts manually process a large set of tweets. Experts examine the language in a given tweet about a company to determine if the tweet is positive, negative or neutral. The labeling is based on the question "If an investor having a long position in the security mentioned were to read this news or tweet, would he/she be bullish, bearish or neutral on his/her holdings?" Bloomberg then feeds the manually classified tweets into machine-learning models that are trained to mimic language experts in analyzing textual information.[5]

Once model training is completed, the models are used to analyze new tweets tagged with company tickers in search of sentiment signals distinctive to business and finance. Each tweet is assigned a story-level sentiment score and associated confidence. The score has three possible values: 1, −1 and 0, which can be viewed as positive, negative and neutral, respectively. Confidence ranges from 0 to 100% and indicates the probability of sentiment being positive, negative or neutral. Hence, the story-level sentiment varies from −1 to 1, with −1 representing the most negative sentiment and +1 representing the most positive sentiment. The analysis is done in real time.

Bloomberg computes firm-level daily Twitter sentiment using the confidence-weighted average of the past 24 hours' story-level sentiment scores as follows:

$$Twitter_{i,t} = \frac{\sum_{k\in P(i,T)} S_i^k C_i^k}{N_{i,T}}, \qquad T \in [t-24h, t] \tag{1}$$

where S_i^k is the sentiment polarity score of tweet k that references firm i. C_i^k is the confidence of tweet k that references firm i. $P(i,T)$ is the set of all non-neutral Twitter feeds that reference firm i in the 24-hour period T. $N_{i,T}$ is firm i's total number of positive or negative tweets during period T. Daily sentiment is scaled to range from −1 to 1, similar to story-level sentiment.[6]

Bloomberg updates daily Twitter sentiment data for all U.S. stocks every morning about 10 min before the U.S. stock market open.[7] The calculation is based on the 24-hour period from 9:20 a.m. on the previous day to 9:20 a.m. on the current day. Thus, for example, Twitter sentiment released on Friday morning is based on tweets sent from 9:20 a.m. Thursday to 9:20 a.m. Friday. For interpretational convenience, in the following sections we use $Twitter_{i,t}$ to represent stock i's Twitter sentiment between 9:20 a.m. on day t and 9:20 a.m. on day $t+1$. To measure the persistence of $Twitter_{i,t}$, we estimate an AR(1) model for Twitter sentiment of each firm and then average across firms.[8] The resulting average of the AR(1) coefficient estimates is 0.22 and statistically significant. This indicates that Twitter sentiment is not very persistent.

2.2. Other variables

Besides Twitter sentiment data, we also construct return, volatility, trading volume, market capitalization and the bid-ask spread using data from Bloomberg. We use the Rogers and Satchell (1991) extreme value volatility estimator to measure daily volatility. The estimator is computed as follows:

$$Volatility_{i,t} = (H_{i,t} - C_{i,t})(H_{i,t} - O_{i,t}) + (L_{i,t} - C_{i,t})(L_{i,t} - O_{i,t}), \tag{2}$$

where $H_{i,t}$, $L_{i,t}$, $O_{i,t}$ and $C_{i,t}$ are the log-transformed highest, lowest, opening and closing prices of stock i on day t. This approach is widely used in the finance literature and is very efficient when asset prices follow a geometric Brownian motion with a drift (e.g., Vipul and Jacob, 2007).

We use the abnormal trading volume in order to make volume comparable across firms. We compute the abnormal trading volume ($Volume_{i,t}$) by dividing the difference between trading volume for stock i on day t and the mean volume for stock i across the sample period by the mean volume for stock i across the period. Thus, a positive (negative) $Volume_{i,t}$ indicates that the trading in stock i is more (less) active compared to the sample average. Both abnormal volume and volatility are expressed in percentage points.

The daily spread (expressed in dollars) is the average of the bid-ask spread within a trading day. This variable is used to control for the effect of liquidity.[9] Firm capitalization is also an important determinant of stock returns. In regressions below, we express this variable in millions of dollars and take the natural log to make our results easier to interpret.

Values of Twitter sentiment are released in the morning right before the stock market open. These values include the after-hours and pre-opening session. Barclay and Hendershott (2003) find that low trading activity after hours generates significant price discovery. To avoid this time overlap between the return and the sentiment measures in predictive regressions, we calculate holding period return, $Return_{i,t}$, from stock i's opening price on day t to the open price on day $t+1$. This approach also theoretically allows one to trade at the 9:30 a.m. market open after observing the Twitter sentiment for the previous day released at 9:20 a.m. and to rebalance his/her holdings at the open on the next trading day when the new value of Twitter sentiment is released.

2.3. Sample selection and summary statistics

We analyze Twitter sentiment for the Russell 3000 component stocks. These stocks account for about 99 percent of the total market capitalization of the U.S. equity market. Bloomberg integrated

[5] The models used to measure Twitter sentiment are developed by a team using years of Twitter history applied to financial markets. Bloomberg does not disclose details of the models due to their proprietary nature.

[6] Bloomberg does not provide story-level sentiment to subscribers.

[7] For companies based in the U.K. and Japan, Bloomberg uses the London and Tokyo opening times, respectively. All other securities are grouped in one of the three categories above based on which time zone they are closer to.

[8] In this estimation, we remove observations with missing values of Twitter sentiment.

[9] The results are very similar if the bid-ask spread is expressed in percentage terms.

Table 1
Summary statistics.

Panel A. Summary statistics					
	Mean	Median	Std	P10	P90
Twitter	0.063	0.033	0.246	−0.180	0.367
Open-to-open return	0.046	0.031	2.943	−2.624	2.664
Volume	7.793	−12.446	111.614	−53.034	75.370
Volatility	1.892	1.399	1.649	0.618	3.645
Capitalization	17,021	3352	46,718	429	36,883
Bid-ask Spread	0.241	0.109	0.896	0.029	0.487

Panel B. Sample averages conditioned on Twitter sentiment		
	$Twitter_{10\%}$	$Twitter_{90\%}$
Open-to-open return	−0.862	0.670
Volume	20.286	13.485
Volatility	2.141	1.918
Capitalization	11,235	10,103
Bid-ask Spread	0.252	0.232

Panel A reports summary statistics for daily Twitter sentiment, return (in percent), abnormal volume (in percent), volatility (in percent). Capitalization (in millions of dollars) and the bid-ask spread (in dollars) for Russell 3000 component stocks for the period from January 2015 to February 2017. The abnormal volume is computed by dividing the difference between trading volume for stock i on day t and the mean volume for stock i in the sample period by the mean of volume for stock i in the sample period. Daily volatility is estimated using the approach of Rogers and Satchell (1991). Daily spread is the average of all bid-ask spread within a trading day. P10 contains observations with selected variables in the bottom decile for a given trading day, and P90 includes observations with selected variables in the top decile for a given day.
Panel B provides the sample means conditioned on daily twitter sentiment. $Twitter_{10\%}$ contains stocks with Twitter sentiment in the bottom decile (most negative) for every trading day. $Twitter_{90\%}$ contains stocks with Twitter sentiment in the top decile (most positive) for every trading day.

Twitter feeds into its platform in April 2013 and started releasing Twitter sentiment data in January 2015. Our sample period is from January 2015 to February 2017 and contains 537 trading days. In total, we have 1,496,048 stock-day observations and 645,505 non-missing observations of firm-specific Twitter sentiment.[10]

In Panel A of Table 1, we present summary statistics for our full sample. The panel shows that the average Twitter sentiment is 0.063, indicating that on average the content of tweets concerning members of the Russell 3000 index is slightly positive. The mean open-to-open return is about 4.6 basis points, consistent with the general upward trend in the stock market during our sample period. The mean values of abnormal volume, volatility, market capitalization and the bid-ask spread are 7.79%, 1.89%, 17,021 million and 0.241 dollars, respectively.[11] All variables show large variation.

Panel B of Table 1 presents sample averages of returns, abnormal volume and volatility conditioning on Twitter sentiment. Subsample $Twitter_{10\%}$ contains observations with Twitter sentiment in the bottom decile (most negative) every trading day. Subsample $Twitter_{90\%}$ includes observations with Twitter sentiment in the top decile (most positive) for a given day. The panel indicates that positive sentiment is associated with positive stock returns, whereas negative sentiment is related to negative returns.[12] Panel B also shows that stock trading volume and volatility in the extreme sentiment deciles are larger than in the full sample. Interestingly, $Twitter_{10\%}$ has higher average volatility, abnormal volume, bid-ask spread and firm size than $Twitter_{90\%}$, although the absolute value of $Twitter_{10\%}$ reported in Panel A is smaller than that of $Twitter_{90\%}$. This suggests that negative tweets are associated with higher contemporaneous volume, volatility, spread and firm size than positive tweets. This is consistent with the well documented finding that bad news tends to have a larger effect on stock return volatility than does good news (e.g., Engle and Ng, 1993).

3. Empirical results

3.1. Predicting stock returns using Twitter sentiment

To investigate the impact of Twitter sentiment on stock returns, we use daily cross-sectional regressions similar to those in Fama and MacBeth (1973). Specifically, 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. The t-statistics are robust to heteroskedasticity and autocorrelation. Tetlock (2011) uses a similar method to investigate the impact of firm-specific news on stock returns. The regression specification is:

$$Return_{i,t} = a + bTwitter_{i,t-1} + \sum_{k=1}^{5} c_k Return_{i,t-k} + \sum_{k=1}^{5} d_k Volume_{i,t-k} + \sum_{k=1}^{5} f_k Volatility_{i,t-k} + \sum_{k=1}^{5} g_k Size_{i,t-k} + \sum_{k=1}^{5} h_k Spread_{i,t-k} + \varepsilon_{i,t}, \quad (3)$$

where $Return_{i,\,t}$ is the holding period return of stock i from market open on day t to the open on the next trading day. $Twitter_{i,t-1}$ is the Twitter sentiment of stock i on day t − 1. As discussed above, $Twitter_{i,t-1}$ measures the sentiment between 9:20 a.m. on day t − 1 to 9:20 a.m. on day t. The coefficient of $Twitter_{i,t-1}$ is our main parameter of interest.

Regression controls include firm i's five lags of the daily return, volatility, abnormal trading volume, market capitalization and the bid-ask spread. It is important to control for return momentum, since return autocorrelation in conjunction with contemporaneous correlation of returns and sentiment can generate spurious evidence of lead-lag relation (e.g., Chordia and Swaminathan, 2000; Rapach et al., 2013). The abnormal trading volume is included to control for the high-volume return premium of Gervais et al. (2001). Following Tetlock (2011), the regression also controls for volatility. Market capitalization and the bid-ask spread are used to control for firm size and liquidity in the analysis of information content of Twitter sentiment.

Panel A of Table 2 reports the regression estimates. As discussed above, the return is computed from 9:30 a.m. on the current day to 9:30 a.m. on the following day. As seen in column 1, the coefficient estimate on $Twitter_{i,t-1}$ is positive and statistically significant. On average, the stock return over the next 24 h for firms with most positive Twitter sentiment ($Twitter = 1$) is about 27.2 basis points higher than the return for firms with most negative Twitter sentiment ($Twitter = -1$).

One may argue that this positive relation between Twitter sentiment and subsequent stock returns may be driven by systematic risks. For example, if small firms unconditionally have higher Twitter sentiment than large firms, the predictive power of Twitter sentiment could be driven by the size factor. To address this concern, we re-estimate the regression above using abnormal returns, defined as the residuals of the Fama-French-Carhart four-factor model. In other words, we risk-adjust the returns using the market factor, the size factor, the value factor and the momentum factor.[13] If the return predictability with Twitter sentiment is re-

[10] The relatively short sample period is determined by availability of the Twitter sentiment data. For comparison, Bollen et al. (2011) use Twitter data for a ten-month period in 2008. Mao et al. (2015) use data from 2010 to 2012.

[11] The positive value of the average abnormal volume for days with non-missing Twitter sentiment is reasonable. Stocks tend to be actively traded when they attract investor attention on social media.

[12] The contemporaneous correlation of Twitter sentiment with stock returns is about 0.14 on average across stocks and statistically significant at 1% level.

[13] Daily risk factors in the Ken French's data library are based on close-to-close returns. Using these factors to risk-adjust open-to-open returns may lead to biased

Table 2
Predicting stock returns using Twitter sentiment.

	Raw return (1)	Risk-adjusted return (2)
Panel A: all Russell 3000 stocks, equal weighted		
Intercept	0.121 (1.75)*	0.034 (0.70)
$Twitter_{i,t-1}$	0.136 (8.06)***	0.143 (8.55)***
Controls	Yes	Yes
N	645,505	645,505
R^2 (%)	14.0	10.8
Panel B: all Russell 3000 stocks, value weighted		
Intercept	0.053 (0.70)	0.011 (0.15)
$Twitter_{i,t-1}$	0.048 (2.69)***	0.063 (3.43)***
Controls	Yes	Yes
N	645,505	645,505
R^2 (%)	19.0	15.6
Panel C: Russell 3000 stocks listed on NYSE, equal weighted		
Intercept	0.099 (1.33)	0.005 (0.09)
$Twitter_{i,t-1}$	0.099 (5.17)***	0.102 (5.44)***
Controls	Yes	Yes
N	344,802	344,802
R^2 (%)	20.5	16.7
Panel D: Russell 3000 stocks listed on NYSE, value weighted		
Intercept	0.098 (1.31)	0.048 (0.70)
$Twitter_{i,t-1}$	0.066 (3.26)***	0.075 (3.70)***
Controls	Yes	Yes
N	344,802	344,802
R^2 (%)	24.1	20.5

The table presents results for the following regression estimated using the Fama-MacBeth approach:
$Return_{i,t} = a + bTwitter_{i,t-1} + \sum_{k=1}^{5} c_k Return_{i,t-k} + \sum_{k=1}^{5} d_k Volume_{i,t-k} + \sum_{k=1}^{5} f_k Volatility_{i,t-k} + \sum_{k=1}^{5} g_k Size_{i,t-k} + \sum_{k=1}^{5} h_k Spread_{i,t-k} + \varepsilon_{i,t}$,
where $Return_{i,\,t}$ is the raw holding period return or risk-adjusted return from the open on day t to the open on day $t+1$. Risk-adjusted returns are computed as the residuals from the Fama-French-Carhart four-factor model. We compute risk factors based on open-open returns. $Twitter_{i,t-1}$ is stock i's Twitter sentiment on day $t-1$, released on day t before the market open. Control variables include daily return, abnormal volume, volatility, firm size and the bid-ask spread during the previous five trading days. The abnormal volume is computed by dividing the difference between trading volume for stock i on day t and the mean volume for stock i in the sample period by the mean of volume for stock i in the sample period. Daily volatility is estimated using the approach of Rogers and Satchell (1991). Daily firm size is the natural log of the market value in millions of dollars. Daily spread is the average of all bid-ask spreads during a trading day. The sample period is from January 2015 to February 2017. t-statistics based on Newey-West standard errors are shown in parentheses. *, **, *** indicate statistical significance at 10%, 5%, and 1% levels, respectively.

lated to any of these factors, the coefficient estimate on $Twitter_{i,t-1}$ should become smaller, if not insignificant.

The regression results for the abnormal returns are shown in Column 2 of Panel A. The coefficient estimate of Twitter sentiment remains positive and significant at the 1% level. The value of this coefficient estimate is very close to that reported in Column 1 of Panel A. This suggests that the predictive value of Twitter sentiment for stock returns is largely independent of the commonly used risk factors.

In Panel A, we run Fama-MacBeth regressions for Russell 3000 stocks using equal weights. This method could lead to results being driven by microcaps (Hou et al., 2020). It other words, our finding of return predictability with Twitter sentiment may be driven by small firms. To examine this possibility, we first estimate our regressions with weighted least squares using firm market value weights. We then exclude small firms by focusing on Russell 3000

excess returns as stock prices move between the market close and the next-day open. To overcome the timing mismatch between the daily returns and the risk factors, we reconstruct the Fama-French factors and the momentum factor following the methodologies of Fama and French (1993) and Jegadeesh and Titman (1993).

Table 3
Predicting stock returns using lagged Twitter sentiment.

	Raw return (1)	Risk-adjusted return (2)
Intercept	0.011 (0.34)	−0.064 (−0.97)
$Twitter_{i,t-1}$	0.100 (4.33)***	0.109 (4.72)***
$Twitter_{i,t-2}$	−0.001 (−0.07)	−0.003 (−0.15)
$Twitter_{i,t-3}$	0.020 (0.90)	0.028 (1.30)
$Twitter_{i,t-4}$	0.009 (0.45)	0.003 (0.14)
$Twitter_{i,t-5}$	−0.024 (−1.07)	−0.022 (−1.05)
Controls	Yes	Yes
N	247,698	247,698
R^2 (%)	24.9	21.4

The table presents results for the following regression estimated using the Fama-MacBeth approach:
$Return_{i,t} = a + \sum_{k=1}^{5} b_k Twitter_{i,t-k} + \sum_{k=1}^{5} c_k Return_{i,t-k} + \sum_{k=1}^{5} d_k Volume_{i,t-k} + \sum_{k=1}^{5} f_k Volatility_{i,t-k} + \sum_{k=1}^{5} g_k Size_{i,t-k} + \sum_{k=1}^{5} h_k Spread_{i,t-k} + \varepsilon_{i,t}$,
where $Return_{i,\,t}$ is the raw holding period return or risk-adjusted return from the open on day t to the open on day $t+1$. Risk-adjusted returns are computed as the residuals from the Fama-French-Carhart four-factor model. The risk factors are computed using open-to-open returns. $Twitter_{i,t-1}$ is stock i's Twitter sentiment on day $t-1$, released on day t before the market open. Control variables include daily return, abnormal trading volume, volatility, firm size and the bid-ask spread during the previous five trading days. The abnormal volume is computed by dividing the difference between trading volume for stock i on day t and the mean volume for stock i in the sample period by the mean of volume for stock i in the sample period. Daily volatility is estimated using the approach of Rogers and Satchell (1991). Firm size is the natural log of the market value in millions of dollars. Daily spread is the average of all bid-ask spreads during a trading day. The sample period is from January 2015 to February 2017. t-statistics based on Newey-West standard errors are shown in parentheses. *, **, *** indicate statistical significance at 10%, 5%, and 1% levels, respectively.

stocks listed on the NYSE. Panel B reports the weighted least square regression results for raw returns and risk adjusted returns. As seen in the panel, the effect of Twitter sentiment on next-day returns is significant at 1% level, but the size of the coefficient estimate on Twitter sentiment is much smaller than that based on equal-weighted portfolios reported in Panel A. This indicates that Twitter sentiment does have more predictive power for returns of small firms relative to large firms. Panel C and D document the predictive power of Twitter sentiment for NYSE firms with equal weights and with value weights, respectively. The coefficient estimates reported in these two panels again suggest that Twitter sentiment is a better predictor of returns of small firms compared to large firms.

3.2. Does information in Twitter sentiment have a permanent effect on stock returns?

The predictive power of Twitter sentiment for individual stock returns may be explained by its information content. If Twitter sentiment contains useful fundamental information about stocks, its effect on returns should be permanent. Mao et al. (2015) find that the effect of market-wide Twitter sentiment on stock indices is permanent. On the other hand, if Twitter sentiment simply reflects sentiment of uninformed traders, the impact of Twitter sentiment on stock returns should be reversed over the next few trading days. We test whether the positive influence of Twitter sentiment on returns is temporary or permanent by including four additional lags of Twitter sentiment in the model in Eq. (3).[14] We run regressions for both raw returns and risk-adjusted returns. Table 3 shows that controlling for lags of Twitter sentiment has little effect on the predictive value of Twitter sentiment for stock returns.[15]

[14] The results are not sensitive to the number of lags.

[15] For this subsection only, we only keep observations with non-missing Twitter sentiment in the previous five consecutive trading days. This adjustment decreases

Moreover, the coefficient estimates on lags of Twitter sentiment are small and statistically insignificant. These findings are consistent with the notion that Twitter sentiment contains some fundamental information that has not been incorporated into stock prices.

3.3. Does information environment influence the informativeness of Twitter sentiment?

So far, our results suggest that Twitter sentiment contains new value-relevant information. However, this information content varies across firms of different sizes. Twitter sentiment predicts returns of small firms more strongly than returns of large firms. This finding may be related to differences in pricing efficiency of small and large stocks. Small firms are usually in a weaker information environment than large firms. Therefore, Twitter content may play a more important informational role for small firms, leading to stronger return predictability. To test this conjecture, we use the number of analysts from IBES as a proxy for information environment and run the following Fama-MacBeth regression:

$$\begin{aligned} Return_{i,t} &= a_0 + a_1 HAC_{i,t} + b_1 Twitter_{i,t-1} + b_2 HAC_{i,t} Twitter_{i,t-1} \\ &\quad + \sum_{k=1}^{5} c_k Return_{i,t-k} + \sum_{k=1}^{5} d_k Volume_{i,t-k} + \sum_{k=1}^{5} f_k Volatility_{i,t-k} \\ &\quad + \sum_{k=1}^{5} g_k Size_{i,t-k} + \sum_{k=1}^{5} h_k Spread_{i,t-k} + \varepsilon_{i,t} \end{aligned} \tag{4}$$

where $HAC_{i,t}$ is a dummy variable equal to one if the number of analysts for firm i on day t is greater than the cross-sectional median. Thus, the coefficient b_1 captures the information content of Twitter sentiment for firms in a relatively weak information environment, while b_2 measures the incremental information content for firms in a relatively strong information environment.

Panel A of Table 4 reports the regression results for raw returns and risk adjusted returns. As seen in the panel, Twitter sentiment has a statistically significant predictive power for stock returns of firms, although the predictive power is weaker for firms followed by a larger number of analysts. This suggests that Twitter content plays a larger informational role for firms in weak information environments.

Small firms tend to have less analyst coverage. To control for the effect of firm size, we follow Hong et al. (2000) and estimate residual analyst coverage by regressing the natural log of the number of analysts on the natural log of the firm's market capitalization. We then use the median value of this residual to divide firms into subsamples with high and low residual analyst coverage. The results in Panel B of Table 4 are similar to those in Panel A of the table. Specifically, the information content of Twitter sentiment for future returns is weaker for firms with higher residual analyst coverage. Overall, the results in Table 4 indicate that information in Twitter messages is more relevant for future returns of stocks that are less likely to be efficiently priced.

3.4. Twitter sentiment vs. news sentiment

Tetlock et al. (2008) find that the firm-level news sentiment predicts stock returns. Specifically, there is a significant negative relation between the percentage of negative words in firm-specific news reported by the Dow Jones News Service and next day stock returns. In this subsection, we test whether Twitter sentiment has predictive value for stock returns incremental to that of news sentiment. We do so by adding news sentiment as an additional regressor to Eq. (3). This specification allows us to compare the predictive ability of Twitter sentiment to that of news sentiment. If fundamental information diffuses from traditional media to social media, we should expect the predictive power of Twitter sentiment for stock returns to disappear after controlling for news sentiment.

We obtain firm-specific news sentiment from Bloomberg. It is measured by following the same procedure as the one used to calculate Twitter sentiment, and is based on all news published on Bloomberg. The value of news sentiment ranges from +1 to −1 and is updated before the market open every trading day. The regression results are reported in Table 5. [16] Columns (1) and (3) show that the news sentiment has predictive value for raw and excess returns. Consistent with Tetlock et al. (2008), we find that firm-level news sentiment predicts future returns. Ignoring transaction costs, one would be able to earn a return of 19.4 basis points ($9.7 \times 2 = 19.4$) over the next 24 h by buying stocks with the most positive news sentiment and selling stocks with the most negative news sentiment at the market open.

Columns (2) and (4) show results for regressions including both Twitter sentiment and news sentiment. As seen in the columns, the predictive power of Twitter sentiment is not subsumed by that of news sentiment and vice versa. Combined with low correlation between news sentiment and Twitter sentiment, this finding suggests that social media contains value-relevant information that is different from the information in traditional news media.[17]

Overall, the above three subsections show that Twitter sentiment predicts stock returns over the next 24 h without subsequent reversals. This indicates that Twitter sentiment contains value-relevant information. In addition, we provide evidence that information in Twitter messages is incremental to that contained in traditional news media.

3.5. Economic significance of return predictability

The positive relation between Twitter sentiment and subsequent returns suggests that a simple long-short trading strategy could earn positive risk-adjusted returns. In this subsection, we examine this possibility by estimating trading profits of a simple trading strategy using Twitter sentiment. Specifically, we form two equally-weighted portfolios at the market open right after Twitter sentiment release. The long portfolio includes all firms with Twitter sentiment in the top decile. The short portfolio contains all firms with Twitter sentiment in the bottom decile. We hold both portfolios for 24 h and rebalance at the beginning of the next trading day.

The performance of the trading strategy is reported in Table 6. Column 1 shows that, ignoring transaction costs, the daily average raw return of this long-short strategy is 8.6 basis points. This translates into average annual raw return of approximately 21.5 percent. The strategy produces an annualized Sharpe ratio of 3.17.[18]

Columns 2, 3 and 4 in Table 6 report risk-adjusted excess returns of this daily trading strategy based on Twitter sentiment. We use the CAPM, the Fama-French (1993) three-factor and

our sample size to 247,698. The results are similar if we replace missing values of Twitter sentiment with the last available non-missing values.

[16] In this subsection, we remove observations with missing Twitter sentiment or news sentiment and omit days with less than 50 non-missing observations to avoid possible issues caused by days with a small number of observations. The results based on dropping days with fewer than 10, 100 or 200 observations are similar to the reported results and are available upon request. The results are also similar if we replace missing values of Twitter sentiment and news sentiment with the last available non-missing values.

[17] The correlation between news sentiment and Twitter sentiment is about 0.20 and statistically significant.

[18] The annualized Sharpe ratio is calculated by multiplying the daily Sharpe ratio by the square root of the number of trading days per year.

Table 4
Predicting stock returns using Twitter sentiment, conditioned on analyst coverage.

	Raw return (1)	Risk-adjusted return (2)
Panel A: conditioning on analyst coverage		
Intercept	0.121 (1.65)	0.037 (0.69)
$HAC_{i,t}\,(a_1)$	0.028 (1.96)*	0.026 (2.21)**
$Twitter_{i,t-1}\ (b_1)$	0.241 (8.86)***	0.249 (8.81)***
$HAC_{i,t} * Twitter_{i,t-1}\ (b_2)$	−0.197 (−6.41)***	−0.197 (6.39)***
Controls	Yes	Yes
N	645,505	645,505
R^2 (%)	14.5	11.2
Panel B: conditioning on residual analyst coverage		
Intercept	0.103 (1.41)	0.016 (0.30)
$HAC_{i,t}\,(a_1)$	0.027 (1.96)*	0.027 (2.28)**
$Twitter_{i,t-1}\ (b_1)$	0.238 (8.81)***	0.246 (8.73)***
$HAC_{i,t} * Twitter_{i,t-1}\ (b_2)$	−0.191 (−6.32)***	−0.192 (−6.31)***
Controls	Yes	Yes
N	645,505	645,505
R^2 (%)	14.7	11.3

The table presents results for the following regression estimated using the Fama-MacBeth approach:
$Return_{i,t} = a_0 + a_1 HAC_{i,t} + b_1 Twitter_{i,t-1} + b_2 HAC_{i,t} Twitter_{i,t-1} + \sum_{k=1}^{5} c_k Return_{i,t-k} + \sum_{k=1}^{5} d_k Volume_{i,t-k} + \sum_{k=1}^{5} f_k Volatility_{i,t-k} + \sum_{k=1}^{5} g_k Size_{i,t-k} + \sum_{k=1}^{5} h_k Spread_{i,t-k} + \varepsilon_{i,t}$,
where $Return_{i,\,t}$ is the raw holding period return or risk-adjusted return from the open on day t to the open on day $t+1$. Risk-adjusted returns are computed as the residuals from the Fama-French-Carhart four-factor model. The risk factors are computed using open-to-open returns. In Panel A, $HAC_{i,t}$ is a dummy variable equal to one for firms with the number of analysts greater than the cross sectional median on day t. In Panel B, $HAC_{i,t}$ is a dummy variable equal to one for firms with the residual number of analysts (obtained from regressing the log of the number of analysts on the log of the firm's market capitalization) greater than the cross sectional median. $Twitter_{i,t-1}$ is stock i's Twitter sentiment on day $t-1$, released on day t before the market open. Control variables include the daily return, abnormal volume, volatility, firm size and the bid-ask spread during the previous five trading days. The abnormal volume is computed by dividing the difference between the trading volume for stock i on day t and the mean volume for stock i in the sample period by the mean of volume for stock i in the sample period. Daily volatility is estimated using the approach of Rogers and Satchell (1991). Daily size is the natural log of market value in millions of dollars. Daily spread is the average of all bid-ask spreads during a trading day. The sample period is from January 2015 to February 2017. t-statistics based on Newey-West standard errors are shown in parentheses. *, **, *** indicate statistical significance at 10%, 5%, and 1% levels, respectively.

Table 5
Predicting stock returns using Twitter sentiment and news sentiment.

	Raw return		Risk-adjusted return	
	(1)	(2)	(3)	(4)
Intercept	0.165 (1.66)*	0.145 (1.45)	0.089 (1.10)	0.061 (0.77)
$Twitter_{i,t-1}\ (b_1)$		0.149 (5.57)***		0.160 (5.90)***
$News_{i,t-1}\ (b_2)$	0.097 (4.34)***	0.066 (3.04)***	0.115 (5.83)***	0.083 (4.33)***
Controls	Yes	Yes	Yes	Yes
N	293,396	293,396	293,396	293,396
R^2 (%)	23.0	23.3	20.3	20.6

The table presents results for the following regression estimated using the Fama-MacBeth approach:
$Return_{i,t} = a + b_1 Twitter_{i,t-1} + b_2 News_{i,t-1} + \sum_{k=1}^{5} c_k Return_{i,t-k} + \sum_{k=1}^{5} d_k Volume_{i,t-k} + \sum_{k=1}^{5} f_k Volatility_{i,t-k} + \sum_{k=1}^{5} g_k Size_{i,t-k} + \sum_{k=1}^{5} h_k Spread_{i,t-k} + \varepsilon_{i,t}$,
where $Return_{i,\,t}$ is the raw holding period return or risk-adjusted return from the open on day t to the open on day $t+1$ Risk-adjusted returns are computed as the residuals from the Fama-French-Carhart four-factor model. The risk factors are computed using open-to-open returns. $Twitter_{i,t-1}$ is stock i's Twitter sentiment on day $t-1$, released on day t before the market open. $News_{i,t-1}$ is stock i's news sentiment on day $t-1$, released on day t before the market open. We set missing values of Twitter sentiment and news sentiment equal to zero. Control variables include daily return, abnormal volume, volatility, size and spread during previous five trading days. The abnormal volume is computed by dividing the difference between trading volume for stock i on day t and the mean volume for stock i in the sample period by the mean of volume for stock i in the sample period. Daily volatility is estimated using the approach of Rogers and Satchell (1991). Firm size is the natural log of the market value in millions of dollars. Daily spread is the average of all bid-ask spreads during a trading day. The sample period is from January 2015 to February 2017. t-statistics based on Newey-West standard errors are shown in parentheses. *, **, *** indicate statistical significance at 10%, 5%, and 1% levels, respectively.

Carhart (1997) four-factor models and regress the raw portfolio returns on the contemporaneous factor returns. The intercepts of the regressions represent the portfolio alphas, or the average risk-adjusted excess returns.

Similar to the raw returns in Column 1, the excess returns reported in the other three columns are positive and statistically significant. This suggests that, ignoring transaction costs, the daily Twitter-based trading strategy would generate positive risk-adjusted returns. Specifically, CAPM, three-factor and four-factor

Table 6
Returns of Twitter-Based Trading Strategy.

	(1)	(2)	(3)	(4)
Raw Return	0.086 (4.65)***			
Alpha		0.087 (4.68)***	0.093 (5.21)***	0.096 (5.65)***
Market		-0.022 (-0.94)	-0.028 (-1.26)	-0.007 (-0.33)
SMB			-0.030 (-0.91)	0.028 (0.87)
HML			-0.202 (-6.81)***	-0.110 (-3.59)***
UMD				0.096 (7.73)***
Trading Days	537	537	537	537
R^2 (%)		0.16	8.16	17.44
Sharpe Ratio	3.17			

This table shows the daily returns of a Twitter-based trading strategy. We assemble the portfolio for the trading strategy at the beginning of each trading day. We form two equal-weighted portfolios based on each firm's recent Twitter sentiment. The long portfolio includes all firms with Twitter sentiment in the top decile (most positive). The short portfolio contains all firms with Twitter sentiment in the bottom decile (most negative). We hold both the long and the short portfolios for 24 hours and rebalance at the beginning of the next trading day. We use the CAPM, Fama-French (1993) three-factor model and Carhart (1997) four-factor model, respectively, to adjust the trading strategy returns for the impact of contemporaneous market (*Market*), size (*SMB*), book-to-market (*HML*), and momentum (*UMD*) factors. The risk factors are computed using open-to-open returns. Sharpe ratio is the annualized Sharpe ratio. The sample period is from January 2015 to February 2017. *t*-statistics computed using the White (1980) heteroskedasticity-consistent covariance matrix are in parentheses. *, **, *** indicate statistical significance at 10%, 5%, and 1% levels, respectively.

alphas are 8.7, 9.3, and 9.6 basis points, respectively. These risk-adjusted returns are close to the raw returns. Interestingly, the return from Twitter-based trading is strongly related to the value and momentum factors. The positive loading on the momentum factor indicates that past stock returns influence current Twitter sentiment. This suggests that the predictive ability of Twitter sentiment is likely driven by the market's sluggish reaction to information contained in Twitter content. The negative loading on the value factor indicates that the strategy based on Twitter sentiment is more effective for growth stocks than for value stocks. The non-trivial regression R^2 estimates show that some of the risk of the Twitter-based long-short trading strategy is not firm-specific. This finding suggests that firm-specific tweets are partly based on market-level information.[19]

Table 6 shows that the average returns of a simple hypothetical trading strategy based on Twitter sentiment are substantial. However, the high profitability may be driven by extremely high returns earned in a few good months. To address this concern, we measure monthly returns of our trading strategy. Fig. 1 depicts the monthly returns over our sample period. As seen in the figure, the Twitter-based trading strategy would have earned positive returns in 22 out of 26 months in the sample period. To put this in perspective, if the unconditional likelihood of obtaining a positive trading return were 0.5, the probability of getting 22 or more positive returns in 26 independent periods would be less than 0.001. This result indicates that the Twitter sentiment based trading strategy was consistently profitable in most of our sample period.

Another result that emerges from Fig. 1 is that monthly trading returns vary significantly over time with the highest return of over 6 percent and the largest loss of over 3 percent. Although our sample period prevents us from performing a statistically meaningful time variation analysis, the monthly return pattern suggests that the predictive ability of Twitter sentiment for stock returns is not constant. Similarly, Garcia (2013) shows that the ability of news sentiment to predict returns depends on the state of the macroeconomy.

[19] Howe et al. (2009) find that analysts use industry-level and market-level information besides firm-level information when updating their recommendations. If the market-level information contains past market-wide returns, the significant predictive value of Twitter sentiment for analyst recommendation changes, which is documented in Section 4.1, provides an explanation of the significant relation between returns of the Twitter-based trading strategy and the momentum factor.

It is important to note that the trading strategy returns discussed above are computed without taking into account transaction costs. Frazzini et al. (2018) provide evidence that the average transaction costs of institutional traders are around 10 basis points. Our simple long-short trading strategy based on Twitter sentiment requires daily portfolio turnover of about 66%. With estimated daily alphas slightly below 10 basis points, it is clear that this trading strategy may be unprofitable after considering reasonable transaction costs.[20] Most of the new information from social media is likely incorporated into current day's stock prices, which may explain why the trading returns discussed above are not very large.

Although our simple long-short strategy may be unprofitable after accounting for transaction costs, skilled traders should be able to trade profitably by using information from Twitter. We use Bloomberg's measure of Twitter sentiment that is based on all tweets tagged with company tickers posted on Twitter and StockTwits. However, some Twitter feeds are more informative than others. If sophisticated traders can identify the more informative Twitter accounts, they should be able to generate higher profits. Traders may also be able to increase profits by using real-time Twitter data. Most of the new information in Twitter messages is likely incorporated into stock prices in the same day. Panel B of Table 1 shows that, when the Twitter sentiment and stock returns are measured contemporaneously, the difference in daily returns between the portfolio containing firms with Twitter sentiment in the top decile ($Twitter_{90\%}$) and the portfolio containing firms with Twitter sentiment in the bottom decile ($Twitter_{10\%}$) is about 1.5%. This suggests that intraday trading based on real-time analysis of Twitter content has potential to generate substantial returns.

4. Fundamentals reflected in Twitter sentiment

The previous section provides evidence that tweets contain some relevant information about corporate fundamentals. In this section, we investigate potential sources of this information by focusing on three important events. We find that Twitter sentiment predicts analyst recommendation changes, target price changes and quarterly earnings. This information accounts for about one third

[20] For comparison, Tetlock et al. (2008) report average daily returns of about 10 basis points (before transaction costs) from trading based on news sentiment.

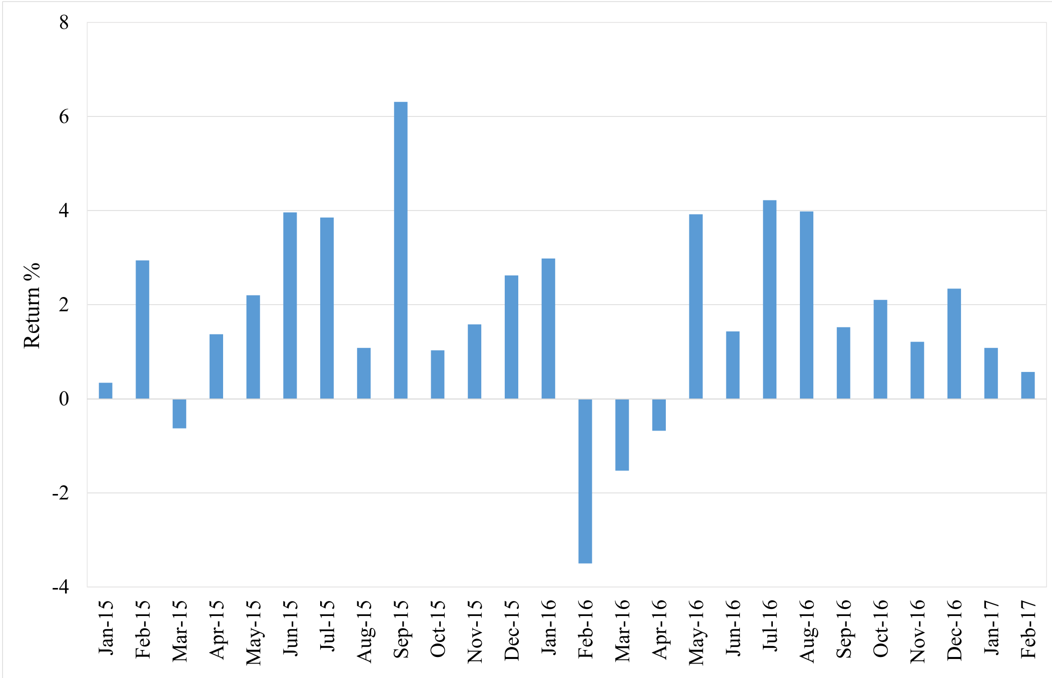

Fig. 1. Monthly returns of the trading strategy based on Twitter sentiment. The figure shows monthly returns for the trading strategy based on Twitter sentiment over our sample period. We assemble the portfolio at the beginning of each trading day. We form two equal-weighted portfolios based on each firm's recent Twitter sentiment. We include all firms with Twitter sentiment in the top decile (most positive) in the long portfolio and all firms with Twitter sentiment in the bottom decile (most negative) in the short portfolio. We hold both the long and the short portfolios for 24 h and rebalance at the beginning of the next trading day. The sample period is from January 2015 to February 2017.

of the predictive ability of Twitter sentiment. Finally, we show that pre-IPO Twitter sentiment predicts IPO underpricing.

4.1. Analyst recommendation changes

Extensive literature finds that analyst recommendations contain valuable information that moves stock prices (Womack, 1996). Howe et al. (2009) further report that in addition to firm-level information, market-level and industry-level information is also reflected in analyst recommendations. In this subsection, we examine whether Twitter sentiment contains information about analyst recommendation changes using the following regression model:

$$\begin{aligned} RecChng_{i,t} &= a + bTwitter_{i,t-2} + \sum_{k=2}^{6} c_k Return_{i,t-k} + \sum_{k=2}^{6} d_k Volume_{i,t-k} \\ &\quad + \sum_{k=2}^{6} f_k Volatility_{i,t-k} + \sum_{k=2}^{6} g_k Size_{i,t-k} \\ &\quad + \sum_{k=2}^{6} h_k Spread_{i,t-k} + \varepsilon_{i,t}, \end{aligned} \tag{5}$$

where $RecChng_{i,\,t}$ is the change in firm *i*'s consensus recommendation on day *t*. Jegadeesh et al. (2004) argue that consensus recommendation changes are more informative than the level of the consensus.[21] The consensus recommendations for Russell 3000 component stocks are obtained from Bloomberg. Bloomberg reports consensus recommendations ranging from one to five (strong sell to strong buy) that reflect the aggregate opinions of equity analysts. When an analyst upgrades (downgrades) his or her recommendation for a firm's stock, Bloomberg adjusts the firm's consensus upward (downward). Control variables included in the model are past return, abnormal volume, volatility, firm size and the bid-ask spread.

Analysts may release their recommendations before the market open.[22] Hence, it is possible that recommendations announced on day *t* could affect $Twitter_{i,t-1}$, which measures firm *i*'s Twitter sentiment from market open on day $t-1$ to market open on day *t*. To rule out such reverse causality, we use the Twitter sentiment released on day $t-1$ ($Twitter_{i,t-2}$) in the regression.[23]

Following the previous literature, we estimate the regression in Eq. (5) using pooled OLS with standard errors clustered by calendar day to account for cross-correlation between firms.[24] The results are presented in Table 7. Column 1 of Table 7 shows that Twitter sentiment positively predicts forthcoming recommendation changes. Upgraded stocks are more likely to have positive Twitter sentiment prior to the recommendation release. This suggests that tweets contain information about analyst recommendation changes.

If the information contained in Twitter sentiment is not fully incorporated into stock prices before the recommendation release, the ability of Twitter sentiment to predict the consensus recommendations should translate into its ability to predict the price reaction to the release. To test this, we regress the risk-adjusted return around the recommendation release on the pre-release Twitter sentiment. The return is measured by taking the sum of the risk-adjusted returns on day $t-1$ and on day *t*. This window cap-

[21] Jegadeesh et al. (2004) find that stock returns are significantly affected by analyst consensus recommendation changes but are not associated with the consensus recommendation levels.

[22] Furthermore, Bradley et al. (2020) show that Theflyonthewall.com, a digital publisher of financial news, leaks about half of analyst recommendation changes before the stock market opens on the recommendation release date.

[23] The results based on $Twitter_{i,t-1}$, available upon request, are qualitatively similar.

[24] See, for example, Tetlock et al. (2008) and Loh (2010).

Table 7
Predicting Analyst Recommendation Changes and Event Returns Using Twitter Sentiment.

	RecChng (t) (1)	Risk-Adjusted Announcement Return (2)
Intercept	-0.049 (-2.94)***	-0.908 (-2.22)**
$Twitter_{i,t-2}$	0.015 (3.21)***	0.363 (2.50)**
Controls	Yes	Yes
N	27,366	27,366
Clusters	537	537
R^2 (%)	0.416	0.294

Column (1) presents estimation results for the following regression:
$RecChng_{i,t} = a + bTwitter_{i,t-2} + \sum_{k=2}^{6} c_k Return_{i,t-k} + \sum_{k=2}^{6} d_k Volume_{i,t-k} + \sum_{k=2}^{6} f_k Volatility_{i,t-k} + \sum_{k=2}^{6} g_k Size_{i,t-k} + \sum_{k=2}^{6} h_k Spread_{i,t-k} + \varepsilon_{i,t}$,
Column (2) presents estimation results for the following regression:
$Return_{i,t-1:t+1} = a + bTwitter_{i,t-2} + \sum_{k=2}^{6} c_k Return_{i,t-k} + \sum_{k=2}^{6} d_k Volume_{i,t-k} + \sum_{k=2}^{6} f_k Volatility_{i,t-k} + \sum_{k=2}^{6} g_k Size_{i,t-k} + \sum_{k=2}^{6} h_k Spread_{i,t-k} + \varepsilon_{i,t}$,
where $RecChng_{i,t}$ is the change in firm i's consensus analyst recommendation on day t. $Return_{i,t-1:t+1}$ is firm i's risk-adjusted return from the market open on day $t-1$ to market open on day $t+1$. The two-day risk-adjusted returns are computed as the sum of two daily risk-adjusted returns. Risk-adjusted returns are computed as the residuals from the Fama-French-Carhart four-factor model. The risk factors are computed using open-to-open returns. $Twitter_{i,t-2}$ is stock i's Twitter sentiment on day $t-2$, released on day $t-1$ before the market open. Control variables include daily return, abnormal volume, volatility, size and spread during previous five trading days. The abnormal volume is computed by dividing the difference between trading volume for stock i on day t and the mean volume for stock i in the sample period by the mean of volume for stock i in the sample period. Daily volatility is estimated using the approach of Rogers and Satchell (1991). Firm size is the natural log of the market value in millions of dollars. Daily spread is the average of all bid-ask spreads during a trading day. The sample period is from January 2015 to February 2017. The regression is estimated with OLS using standard errors clustered by calendar day. The corresponding t-statistics are shown in parentheses. *, **, *** indicate statistical significance at 10%, 5%, and 1% levels, respectively.

tures the stock price reaction to analyst recommendations on the announcement day and the potential pre-announcement effect.[25]

Column 2 of Table 7 shows that Twitter sentiment predicts the response of stock prices to analyst recommendation changes. Higher pre-event Twitter sentiment predicts higher return in the event window. This indicates that information about analyst recommendations contained in Twitter sentiment is not fully reflected in stock prices before the recommendation release.

4.2. Analyst target price changes

Another important value-relevant information event is analyst target price revisions. Brav and Lehavy (2003) document a significant price reaction to target price announcements. In this subsection, we use Twitter sentiment to predict upcoming target price changes using a regression with clustered standard errors that is similar to that in Eq. (5). We first download target price data for Russell 3000 component stocks from Bloomberg. We then compute target price change ($TargetChng_{i,t}$) and use it as the main dependent variable. $Twitter_{i,t-2}$ is used as the main independent variable to address the possible reverse causality discussed in Section 4.1.[26]

Column 1 of Table 8 shows the regression results. The positive and significant coefficient on $Twitter_{i,t-2}$ confirms that Twitter sentiment predicts target price changes. An increase in a firm's target price is more likely to occur after Twitter users express positive views about the firm. We also estimate a similar regression where the main dependent variable is the stock return around target price changes. The results reported in Column 2 of Table 8 show that

[25] Irvine, Lipson and Puckett (2006) document informed trading before recommendation announcements.

[26] The target price change (in percentage) is computed by dividing the difference between the new target price and the previous releasing target price by the previous target price. We drop observations with zero target price changes. Including such observations has little effect on the results.

Table 8
Predicting Target Price Changes and Event returns Using Twitter Sentiment.

	TargetChng (t) (1)	Risk-Adjusted Announcement Return (2)
Intercept	0.965 (5.66)***	0.224 (0.98)
$Twitter_{i,t-2}$	0.595 (10.54)***	0.452 (6.20)***
Controls	Yes	Yes
N	106,692	106,692
Clusters	537	537
R^2 (%)	7.174	0.181

Column (1) presents results for the following regression:
$TargetChng_{i,t} = a + bTwitter_{i,t-2} + \sum_{k=2}^{6} c_k Return_{i,t-k} + \sum_{k=2}^{6} d_k Volume_{i,t-k} + \sum_{k=2}^{6} f_k Volatility_{i,t-k} + \sum_{k=2}^{6} g_k Size_{i,t-k} + \sum_{k=2}^{6} h_k Spread_{i,t-k} + \varepsilon_{i,t}$,
Column (2) presents results for the following regression:
$Return_{i,t-1:t+1} = a + bTwitter_{i,t-2} + \sum_{k=2}^{6} c_k Return_{i,t-k} + \sum_{k=2}^{6} d_k Volume_{i,t-k} + \sum_{k=2}^{6} f_k Volatility_{i,t-k} + \sum_{k=2}^{6} g_k Size_{i,t-k} + \sum_{k=2}^{6} h_k Spread_{i,t-k} + \varepsilon_{i,t}$,
where $TargetChng_{i,t}$ is the change in firm i's target price on day t. $Return_{i,t-1:t+1}$ is firm i's risk-adjusted return from the market open on day $t-1$ to market open on day $t+1$. The two-day risk-adjusted returns are computed as the sum of two daily risk-adjusted returns. Risk-adjusted returns are computed as the residuals from the Fama-French-Carhart four-factor model. The risk factors are computed using open-to-open returns. $Twitter_{i,t-2}$ is stock i's Twitter sentiment on day $t-2$, released on day $t-1$ before the market open. Control variables include daily return, abnormal volume, volatility, size and volatility during previous five trading days. The abnormal volume is computed by dividing the difference between trading volume for stock i on day t and the mean volume for stock i in the sample period by the mean of volume for stock i in the sample period. Daily volatility is estimated using the approach of Rogers and Satchell (1991). Firm size is the natural log of the market value in millions of dollars. Daily spread is the average of all bid-ask spreads during a trading day. The sample period is from January 2015 to February 2017. The regression is estimated with OLS using standard errors clustered by calendar day. The corresponding t-statistics are shown in parentheses. *, **, *** indicate statistical significance at 10%, 5%, and 1% levels, respectively.

Twitter sentiment before target price announcements helps predict returns around the announcement. We conclude that information about upcoming target price changes is another example of relevant information contained in Twitter sentiment.

4.3. Quarterly earnings

Bartov et al. (2018) use a sample period from January 2009 to December 2012 to show that Twitter sentiment predicts quarterly corporate earnings.[27] However, since recent years have seen a large increase in the amount of activity and number of users on Twitter, it is worthwhile to revisit the relation between Twitter sentiment and firms' earnings using a more recent sample period. Moreover, the results in this subsection can be viewed as a test of the quality of Twitter sentiment constructed by Bloomberg.

To measure earnings surprises, we use the standardized unexpected earnings (SUE), computed as follows:

$$SUE_{i,q} = \left(A_{i,q} - F_{i,q}\right)/\sigma_{i,q}, \tag{6}$$

where $A_{i,q}$ is the actual earnings per share reported by firm i for quarter q, $F_{i,q}$ is the I/B/E/S consensus forecast of quarterly earnings per share just prior to the earnings announcement date, and $\sigma_{i,q}$ is the cross-sectional standard deviation of analyst forecasts comprising the consensus. Following the existing literature, we estimate the regression in Eq. (5) with SUE as the dependent variable using pooled OLS with standard errors clustered by calendar quarter.

Table 9 shows that Twitter sentiment released one day before earnings reports predicts earnings surprises and is positively related to the stock price reaction to earnings releases. These findings are similar to those documented in Bartov et al. (2018), suggesting that Twitter sentiment contains information about firms' quarterly earnings.

[27] Bartov et al. (2018) measure sentiment using the proportion of negative words in each tweet.

Table 9
Predicting Earnings Surprises and Event Returns Using Twitter Sentiment.

	SUE (t) (1)	Risk-Adjusted Announcement Return (2)
Intercept	1.046 (2.70)**	0.113 (0.35)
$Twitter_{i,t-2}$	0.721 (1.94)*	0.523 (2.83)**
Controls	Yes	Yes
N	11,435	11,435
Clusters	8	8
R^2 (%)	0.752	0.523

Column (1) presents results for the following regression:
$SUE_{i,t} = a + bTwitter_{i,t-2} + \sum_{k=2}^{6} c_k Return_{i,t-k} + \sum_{k=2}^{6} d_k Volume_{i,t-k} + \sum_{k=2}^{6} f_k Volatility_{i,t-k} + \sum_{k=2}^{6} g_k Size_{i,t-k} + \sum_{k=2}^{6} h_k Spread_{i,t-k} + \varepsilon_{i,t}$,
Column (2) presents results for the following regression:
$Return_{i,t-1:t+1} = a + bTwitter_{i,t-2} + \sum_{k=2}^{6} c_k Return_{i,t-k} + \sum_{k=2}^{6} d_k Volume_{i,t-k} + \sum_{k=2}^{6} f_k Volatility_{i,t-k} + \sum_{k=2}^{6} g_k Size_{i,t-k} + \sum_{k=2}^{6} h_k Spread_{i,t-k} + \varepsilon_{i,t}$,
where $SUE_{i,t}$ is the standardized earning surprise announced on day t. $Return_{i,t-1:t+1}$ is firm i's risk-adjusted return from the market open on day $t-1$ to market open on day $t+1$. The two-day risk-adjusted returns are computed as the sum of two daily risk-adjusted returns. Risk-adjusted returns are computed as the residuals from the Fama-French-Carhart four-factor model. The risk factors are computed using open-to-open returns. $Twitter_{i,t-2}$ is stock i's Twitter sentiment on day $t-2$, released on day $t-1$ before the market open. Control variables include daily return, abnormal volume, volatility, size and spread during previous five trading days. The abnormal volume is computed by dividing the difference between trading volume for stock i on day t and the mean volume for stock i in the sample period by the mean of volume for stock i in the sample period. Daily volatility is estimated using the approach of Rogers and Satchell (1991). Firm size is the natural log of market value in millions of dollars. Daily spread is the average of all bid-ask spreads during a trading day. The sample period is from January 2015 to February 2017. The regression is estimated with OLS using standard errors clustered by calendar day. The corresponding t-statistics are shown in parentheses. *, **, *** indicate statistical significance at 10%, 5%, and 1% levels, respectively.

Table 10
Test for other value-relevant information in Twitter sentiment.

	Model (1)	Model (2)
Intercept	0.018 (0.21)	0.002 (0.02)
$Twitter_{i,t-2}$	0.163 (7.56)***	0.103 (4.89)***
$RecChng_{i,t}$		0.978 (16.35)***
$TargetChng_{i,t}$		2.597 (28.59)***
$SUE_{i,t}$		14.779 (2.27)**
Controls	Yes	Yes
N	645,431	645,431
R^2 (%)	8.70	14.3

The table presents results for the following regression estimated using the Fama-MacBeth approach:
$Return_{i,t-1:t+1} = a + b_1 Twitter_{i,t-2} + b_2 RecChng_{i,t} + b_3 TargetChng_{i,t} + b_4 SUE_{i,t} + \sum_{k=2}^{6} c_k Return_{i,t-k} + \sum_{k=2}^{6} d_k Volume_{i,t-k} + \sum_{k=2}^{6} f_k Volatility_{i,t-k} + \sum_{k=1}^{5} g_k Size_{i,t-k} + \sum_{k=1}^{5} h_k Spread_{i,t-k} + \varepsilon_{i,t}$,
where $Return_{i,t-1:t+1}$ is firm i's risk-adjusted return from the market open on day $t-1$ to market open on day $t+1$. The two-day risk-adjusted returns are computed as the sum of two daily risk-adjusted returns. The risk-adjusted returns are computed as the residuals from the Fama-French-Carhart four-factor model. The risk factors are computed using open-to-open returns. $Twitter_{i,t-2}$ is stock i's Twitter sentiment on day $t-2$, released on day $t-1$ before the market open. $RecChng_{i,t}$ is the standardized change in firm i's consensus analyst recommendation on day t. $TargetChng_{i,t}$ is the standardized change in firm i's target price on day t. $SUE_{i,t}$ is the standardized earning surprise announced on day t. Control variables include daily return, abnormal volume, volatility, size and spread during previous five trading days. The abnormal volume is computed by dividing the difference between trading volume for stock i on day t and the mean volume for stock i in the sample period by the mean of volume for stock i in the sample period. Daily volatility is estimated using the approach of Rogers and Satchell (1991). Firm size is the natural log of market value in millions of dollars. Daily spread is the average of all bid-ask spreads during a trading day. The sample period is from January 2015 to February 2017. t-statistics based on Newey-West standard errors are shown in parentheses. *, **, *** indicate statistical significance at 10%, 5%, and 1% levels, respectively.

4.4. Other value-relevant information in Twitter sentiment

In the previous subsections, we show that Twitter sentiment provides new information about upcoming revisions of analyst recommendations, target price changes and earnings surprises. A natural follow-up question is whether Twitter sentiment contains value-relevant information beyond these three types of events. To answer this question, we account for the effect of analyst recommendations, target price changes and earnings announcements on the relation between Twitter sentiment and future returns. We estimate the following regression:

$$\begin{aligned} Return_{i,t-1:t+1} &= a + b_1 Twitter_{i,t-2} + b_2 RecChng_{i,t} + b_3 TargetChng_{i,t} \\ &\quad + b_4 SUE_{i,t} + \sum_{k=2}^{6} c_k Return_{i,t-k} + \sum_{k=2}^{6} d_k Volume_{i,t-k} \\ &\quad + \sum_{k=2}^{6} f_k Volatility_{i,t-k} + \sum_{k=2}^{6} g_k Size_{i,t-k} \\ &\quad + \sum_{k=2}^{6} h_k Spread_{i,t-k} + \varepsilon_{i,t}, \end{aligned} \tag{7}$$

where $Return_{i,t-1:t+1}$ is firm i's risk-adjusted return from the market open on day t – 1 to the market open on day $t+1$. The reason for using the two-day return window is discussed in Section 4.1. We use Newey and West (1987) standard errors to account for the residual serial correlation. If information related to upcoming analyst recommendations, target price changes and earnings surprises fully explains the predictive power of Twitter sentiment, the coefficient estimate on $Twitter_{i,t-2}$ should be close to zero. Before estimating the regression, we standardize $RecChng_{i,t}$, $TargetChng_{i,t}$ and $SUE_{i,t}$. This allows comparing the relative magnitude of the market reaction to the three types of events (Thompson et al., 1987).

Column 1 of Table 10 reports the regression results without controlling for event surprises. Compared to results reported in Column 2 of Panel A of Table 2, the magnitude of the coefficient estimate of Twitter sentiment only increases by about 14%, although the return window widens from one to two days. Moreover, the comparison of model R^2 indicates that Twitter sentiment has lower explanatory power for two-day returns than for daily returns. This is not surprising as Table 3 shows that information in Twitter sentiment affects returns with only one-day delay.

The estimates reported in Column 2 of the table show whether Twitter sentiment contains information about future stock returns that is not contained in analyst recommendations, target price changes and earnings surprises. As seen in the column, the coefficient of Twitter sentiment remains positive and statistically significant, but its magnitude declines (from 0.163 to 0.103) after the three event variables are included in the model. More precisely, information about analyst recommendations, target price changes and earnings news explains about 36.8% ((0.163–0.103)/0.163) of the return predictability of Twitter sentiment. This implies that other value-relevant information accounts for about two thirds of the predictive ability of Twitter sentiment. Column 2 also shows that earnings announcements move stock prices more strongly than do analyst recommendations and target price changes. One possible explanation for this finding is that earnings reports contain more relevant information than analyst recommendations and target price changes. Another possibility is that information about upcoming recommendation revisions and target price updates often finds its way to the market before the public release.

4.5. IPO underpricing

IPO underpricing has been widely studied in finance literature. Recent studies investigate the relation between IPO initial returns and investor sentiment. Cornelli et al. (2006) find that higher pre-IPO retail investor sentiment, measured by pre-IPO market prices,

Table 11
Predicting IPO underpricing using Twitter sentiment.

	Offer to first day open		First day open to second day open	
	OLS	Robust	OLS	Robust
Intercept	23.65 (1.66)*	22.28 (2.19)**	3.93 (0.58)	−1.40 (−0.26)
$Twitter_{i,t-1}$	24.97 (2.18)**	26.51(3.23)***	−5.58 (−1.02)	−4.74 (−1.10)
$MarketReturn_{t-1:t-67}$	0.46 (0.84)	0.17 (0.42)	0.08 (0.30)	−0.05 (−0.22)
$OvernightReturn_{t-1}$	−5.02 (−0.89)	5.86 (1.38)	2.80 (1.04)	−0.34 (−0.16)
$Offer_i$	−1.25 (−0.43)	−2.71 (−0.47)	−0.50 (−0.36)	−0.17 (−0.154)
$Analysts_i$	0.24 (0.06)	3.41 (1.21)	0.78 (0.44)	2.36 (1.69)*
N	132	132	132	132
R^2 (%)	5.51	5.23	2.30	2.19

The table presents results for the following regression: $Return_{i,t} = a + bTwitter_{i,t-1} + c_1MarketReturn_{t-1:t-67} + c_2OvernightReturn_{t-1} + c_3Offer_i + c_4Analysts_i + \varepsilon_{i,t}$ where $Return_{i,\,t}$ is firm i's return on the first trading day. We report results for the return from the offer price to the first opening price (Offer to First Day Open) and for the return from the first opening price to the next day opening price (First Day Open to Second day Open). $Twitter_{i,t-1}$ is stock i's Twitter sentiment released before the IPO. $MarketReturn_{t-1:t-67}$ is the S&P 500 index return in the three-month period prior to the IPO. $OvernightReturn_{t-1}$ is the S&P 500 index return measured from the closing price on day $t-1$ to the opening price on day t. $Offer_i$ is the log value of firm i's offer size. $Analysts_i$ is the log value of the number of analysts before the IPO, according to IBES. The sample period is from January 2015 to February 2017. The regression is estimated using (1) OLS with the White (1980) heteroskedasticity consistent covariance matrix and (2) robust MM-estimator of Yohai (1987). The corresponding t-statistics for OLS and the Chi-square statistics for the robust regression are shown in parentheses.*, **, *** indicate statistical significance at 10%, 5%, and 1% levels, respectively.

can lead to higher first trading day returns.[28] Liu et al. (2014) document that news sentiment is related to IPO underpricing. In this subsection, we test the effect of Twitter sentiment on IPO underpricing.

Loughran and Ritter (2002) show that IPO offer prices only partially incorporate available public information. If Twitter sentiment contains relevant information not incorporated in IPO offer prices, it should have predictive value for the difference between the offer prices and the first day opening prices. To illustrate this point, suppose that an analyst, who is active on social media, estimates that the fair offer price of an upcoming IPO is $20, whereas the actual offer price is $15. The analyst would share his/her optimism about the success of the IPO on social media, such as Twitter. This would lead to a positive relation between pre-IPO sentiment and IPO underpricing. Moreover, when pre-IPO sentiment provides incremental information, we would not expect a significant price reversal after the opening.

To construct our sample of IPOs, we first obtain from Bloomberg a list of IPOs whose first trading days were between January 2015 and February 2017. We then exclude IPOs with missing Twitter sentiment before the first trading day. Finally, we remove IPOs with offer sizes of less than $50 million. The final sample consists of 132 IPOs.

To examine the relation between pre-IPO Twitter sentiment and IPO performance, we regress the return from the offer price to the first opening price and return from the first opening price to the second opening price on $Twitter_{i,t-1}$. Following Cornelli et al. (2006), the regression controls for the market index (S&P 500) return measured over the three-month period before the IPO, as Cornelli et al. (2006) argue that pre-IPO sentiment can be associated with market sentiment. We also control for the overnight market return before the IPO, the offering size and the number of analysts followings the company. These variables control for the effect of overnight market-wide information, firm size and investor attention, respectively. The analyst coverage data is obtained from IBES and shows how many analysts follow the newly publicly traded firm. The regressions are estimated using OLS with the White (1980) heteroskedasticity consistent standard errors and using the MM estimator of Yohai (1987). The MM estimator is robust to the presence of outliers.

The regression results are reported in Table 11. Both OLS and robust regression estimates show a significant positive relation between pre-IPO Twitter sentiment and the return from the offer price to the first opening price but no significant relation between pre-IPO Twitter sentiment and the return from the first opening price to the opening price on the next trading day. These findings are consistent with our hypothesis that Twitter sentiment contains information about IPO underpricing.

The above findings are also consistent with the pre-IPO Twitter sentiment merely repeating available information from other sources. This information is incorporated in the price of the stock during the opening auction. However, we believe our results cannot be explained by this rationale for two reasons. First, we repeat the analysis of returns from the offer price to the first open price but include News sentiment and Twitter sentiment two and three days prior to the first trading day in the model. The regression results, available upon request, show that the explanatory power of Twitter sentiment for the offer-to-open returns is essentially unchanged after controlling for the News sentiment and Twitter sentiment in previous days. This suggests that information in Twitter sentiment on the day before the IPO is neither from traditional media, nor from previous days' Twitter content. Second, our Twitter sentiment is based on qualitative information in tweets during the 24-hour period before the first trading day. This is during the so-called quiet period when firms are not allowed to release value relevant information. Overall, our findings are more consistent with the notion that Twitter content provides information to the stock market shortly before IPOs.

5. Conclusion

Social media has recently become one of the main communication channels for financial information. However, the role of social media in finance is still not well understood due to the challenges involved in analyzing massive amounts of social media content. This study uses firm-specific Twitter sentiment data provided by Bloomberg to investigate the impact of social media

[28] Pre-IPO (grey) markets allow investors to trade based on their expectations on stock prices of firms that are going to be listed in exchanges. Grey markets only exist in Europe, and most traders are individual investors with little capital (Cornelli et al., 2006).

on the stock market. Although most Twitter users are believed to be uninformed, our findings show that the daily firm-level Twitter sentiment contains information that is useful for predicting next day stock returns. In particular, we document that Twitter sentiment contains information about analyst recommendation changes, target price changes, quarterly earnings surprises and IPO opening prices. We also find that Twitter sentiment is a stronger predictor of returns for firms with less analyst coverage. These findings are consistent with the notion of the "wisdom of crowds" (Surowiecki, 2004).

Our findings have important implications for market participants. The predictive power of Twitter sentiment for stock returns gives traders a strong incentive to analyze social media content carefully. Such analysis may be useful in making security selection decisions. Our results are also consistent with the notion that business entities may be able to improve transparency and market efficiency by using social media.

CRediT authorship contribution statement

Chen Gu: Conceptualization, Methodology, Software, Formal analysis, Investigation, Writing - original draft, Writing - review & editing, Visualization. **Alexander Kurov:** Conceptualization, Methodology, Writing - review & editing, Visualization, Supervision, Project administration.

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