Are Managers listening to Twitter? Evidence from Mergers & Acquisitions*

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Abstract

This paper studies the feedback effects of social media on corporate investment decisions. Using a comprehensive sample of millions of tweets from a popular social media network, I show that negative social media feedback around the announcement of a corporate acquisition increases the likelihood that the M&A deal is subsequently withdrawn, especially when the relevant tweets have a higher prominence and visibility, and when the acquiring firm's stock has low price informativeness. This effect is not subsumed by the announcement returns of the acquiring and target firm or the reaction to the M&A announcement in traditional news media. Managers use feedback from social media as a substitute for other sources of information to help guide their investment decisions.

Keywords: Social Media, FinTech, Feedback Effects, Capital Allocation, M&A

JEL Codes: F30; F36; G38; Q50

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1 Introduction

The rapidly increasing adoption of financial technology and the availability of new data sources have transformed the way market participants form their beliefs. Today, investors share opinions and investment ideas on social media platforms (Antweiler and Frank, 2004; Chen, De, Hu, and Hwang, 2014), activist short-sellers use blogs to promote their campaigns (Zhao, 2019), and FinTech startups provide real-time trading signals based on social media content to hedge-funds[1] and other sophisticated investors (Grennan and Michaely, 2018).[2]

As managers realize the importance of new FinTech platforms, they increasingly use social media networks for information dissemination and communication with markets. For example, since the SEC officially permitted the use of social media for announcing key information in compliance with Regulation-FD in 2013[3], firms have relied on social media as a channel to strategically disclose information (Jung, Naughton, Tahoun, and Wang, 2017) and manage investor relations (Blankespoor, Miller, and White, 2014; Elliott, Grant, and Hodge, 2018).

While the literature has extensively studied how firms use social media platforms to address customers and financial markets, academic research has been silent on the reverse direction: the influence of social media on firms and managers. In contrast, anecdotal evidence suggests that companies closely monitor social media postings and sentiment (Bartov et al., 2018) to gather user feedback and guide corporate decisions (Zhang, Kang, Jiang, and Pei, 2018). In fact, 'Social Media Monitoring' (SMM) has emerged as a new industry with companies such as Hootsuite, TweetReach, If This Then That (IFTTT), and Brandwatch Analytics now offering continuous monitoring and analysis of online content to help inform managers.

This raises the important question if managers are sensitive to social media when forming their beliefs. Hence, I study how user feedback in a financial social media network affects firm investment decisions in this paper. I focus on one particular type of corporate investment decision – Mergers & Acquisitions – since M&A deals are among the largest and most consequential investments that firms ever make (Loughran and Vijh, 1997; Rau and Vermaelen, 1998; Andrade, Mitchell, and

[1] See for example: `https://www.wsj.com/articles/tweets-give-birds-eye-view-of-stocks-1436128047`.

[2] A growing literature in finance has studied the role of social media for financial markets, focusing on investor disagreement (Cookson and Niessner, 2019), trading volume and the convergence of investor opinions (Giannini, Irvine, and Shu, 2019), and the ability of tweets to predict returns (Giannini, Irvine, and Shu, 2017) and earnings surprises (Bartov, Faurel, and Mohanram, 2018).

[3] See: `https://www.sec.gov/news/press-release/2013-2013-51htm`.

Stafford, 2001).[4]

Corporate acquisitions provide an ideal setting for studying investment decisions and the formation of managers' beliefs. In contrast to standard investment proxies from financial statements such as CAPX, the timing (announcement date), project characteristics (deal volume, method of payment), and ultimate outcome (deal completed or withdrawn) of a corporate acquisition are observable to the econometrician. Building on Luo (2005), the intuition for the main empirical approach in this paper is simple: assuming that the managers of the acquiring firm use all available information to evaluate a prospective M&A transaction before announcing the deal, they have little incentive to subsequently withdraw the transaction after announcement, unless outside feedback changes their assessment of the deal.[5] Therefore, the sensitivity of deal completion to outside feedback immediately following the announcement can be interpreted as 'management learning' from outsiders.

Based on the idea that financial markets incorporate the information of millions of investors[6], previous research has shown that stock market announcement returns help inform corporate decisions, including M&As (Luo, 2005; Kau, Linck, and Rubin, 2008), SEOs (Giammarino, Heinkel, Hollifield, and Li, 2004), and management earnings forecasts (Zuo, 2016). However, stock prices can be strategically manipulated (Goldstein and Guembel, 2008), are subject to trading frenzies (Goldstein, Ozdenoren, and Yuan, 2013), and can be plagued with noise, leading to misinterpretation by managers (Dessaint, Foucault, Frésard, and Matray, 2018). In contrast, short messages and tweets by investors and market observers on social media, *verbalizing* the 'wisdom of the crowd', are potentially easier to interpret by managers.

To test this intuition, I combine a comprehensive sample of U.S. acquisitions of public and private firms over the period from 2010 to 2014 with over 35 million time-stamped posts from a social media investing platform called StockTwits. StockTwits is similar to Twitter in that it allows users to share short messages (henceforth 'tweets') of up to 140 characters with their followers. However, unlike Twitter, StockTwits is specifically geared towards the discussion of financial markets

[4]Consequently, firms often rely on the advice and guidance of outside lawyers (Krishnan and Masulis, 2013) and investment bankers during the M&A process (Bao and Edmans, 2011), especially when the acquisition is complex (Servaes and Zenner, 1996) and highly scrutinized (Golubov, Petmezas, and Travlos, 2012).

[5]Of course, their 'assessment' includes both value maximization for their firm as well as potential private benefits.

[6]See for example Chen, Goldstein, and Jiang (2006); Foucault and Frésard (2012, 2014); Edmans, Jayaraman, and Schneemeier (2017), and Bond, Edmans, and Goldstein (2012) for a survey of the literature.

and individual stocks. The use of so-called 'cashtags' – a dollar sign in front of a firm's ticker symbol – allows for the precise association of a given tweet with the corresponding firm. By 2014, StockTwits had approximately 1.3 million unique views, many of them professional traders and investors (Bartov et al., 2018; Cookson and Niessner, 2019), generating about 1.5 million tweets per month. Further, since 2011 tweets and sentiment measures based on StockTwits have been integrated in many of the online platforms used by finance professionals including S&P Capital IQ, Yahoo! Finance, CNN Money, and Reuters.

Using machine learning and textual analysis techniques I generate a time-series of firm-specific daily investor sentiment for each acquiring firm in the sample. I then measure the social media reaction to an acquisition announcement as the 'abnormal acquirer sentiment' in the days around the M&A announcement. Consistent with the idea that managers are sensitive to social media feedback, I find that abnormal acquirer-firm sentiment following an M&A announcement significantly predicts the likelihood that an announced acquisition is subsequently completed. A change in social media reaction from positive (top quartile of abnormal sentiment) to negative (bottom quartile) is associated with a decrease in the likelihood of M&A completion of 3 percentage points, statistically significant at the 1% level. Given the unconditional sample average that a deal is withdrawn of 6.2%, this effect is economically meaningful. The finding persists after controlling for the announcement returns of the acquirer and target firm, a host of deal and firm characteristics, as well as time fixed effects. The results are also robust to using an alternative algorithm for measuring social media sentiment, and to implementing the main test as a logit regression instead of a linear probability model.

Next, I implement my tests using social media sentiment data from an alternative data source to alleviate concerns that the results are due to my text classification algorithm. I obtain firm-specific daily social media scores from Psychsignal, a social data and sentiment analysis API & platform (Argarwal, Azar, Lo, and Singh, 2018). An important advantage of Psychsignal is that their scores are constructed using Twitter messages in addition to StockTwits, which has a much larger user base and engagement than StockTwits.[7] I document two findings. First, I confirm that the sentiment estimated from StockTwits tweets is similar to Twitter sentiment. The average correlation between

[7]However, Psychsignal uses a proprietary scoring algorithm which deters me from using it as the main measure of firm-specific sentiment in this paper.

my daily sentiment score based on StockTwits data and the score obtained from Psychsignal based on Twitter data is approximately 0.93 across all stocks. Second, I show that my main findings on the sensitivity of M&A deal completion to social media feedback remain robust when using Psychsignal sentiment, controlling for acquirer and target announcement return, news media tone and coverage, and deal characteristics.

Liu and McConnell (2013) show that the completion of announced acquisitions can be sensitive to traditional news media. Managers are concerned about their reputation and news media coverage can hence discipline managers to withdraw value-reducing corporate acquisitions. Further, Jiao, Veiga, and Walther (2018) suggest that social media content is often generated by repeating and discussing (e.g. re-tweeting) existing news, as news media are a leading indicator for social media in their sample. Hence, to determine if my results are driven by the overlap between social media and news media, I control directly for news media tone and coverage in my next tests. Following Gao, Parsons, and Shen (2017), I use Ravenpack news article sentiment around the announcement and the number of articles written specifically about the M&A deal to capture the role of traditional news media. Consistent with Liu and McConnell (2013), I find that both news media tone and coverage predict the completion of an announced acquisition, and partially crowd out the feedback effect of stock price reactions on M&A completion. However, the coefficient estimate on social media announcement reaction is unaffected by the inclusion of newspaper controls, suggesting that traditional news media are not driving my results.

The detailed user information in the StockTwits data further allows me to examine the role of managerial reputation and information in social media tweets. In the cross-section, I find that the effect of abnormal social media sentiment on deal completion increases with the number of tweets about the acquirer, the average number of 'likes' received by the tweets about the acquiring firm, and the number of followers and official user profiles involved in the social media discussion. This is consistent with the interpretation in Liu and McConnell (2013), who suggest that managers are more concerned with their reputation when the media attention to a given deal is high, and Golubov et al. (2012), who show that investment banking advice is particularly valuable when a deal is highly scrutinized.

The result is also consistent with the notion that users with official, verified accounts and a higher number of followers have more information that is new to managers and helps them guide their investment decisions. To examine this notion further, I next study the effect of stock price informativeness on the sensitivity of acquisition completion to social media reaction. If noisy stock prices can mislead managers who rely on stock prices for investment guidance (Dessaint et al., 2018), the feedback effect from social media responses to M&A completion should be stronger when the acquirer firm's price informativeness is lower, as managers can interpret the information in tweets and social media posts more easily. Using price non-synchronicity and the probability of privately informed trading as in Chen et al. (2006), and the absolute value of the M&A announcement return as measures of acquirer price informativeness, I indeed find a negative effect of stock price information content on the sensitivity of acquisition completion to social media feedback. This result holds using both StockTwits and Psychsignal data, and persists when controlling for announcement returns, deal and firm controls, and time fixed effects.

By showing that firms' investment allocations are sensitive to social media feedback, this paper contributes to the growing literature on FinTech (Philippon, 2016) in several ways. First, to the best of my knowledge, this is the first paper to examine the role of non-traditional media for corporate investment decisions. My findings parallel the research on the role of traditional media for capital allocations (e.g. Liu and McConnell, 2013), and complement the literature on feedback effects for corporate decision making (Luo, 2005; Bond et al., 2012) and the role of social media in financial markets (e.g. Bartov et al., 2018; Cookson and Niessner, 2019). The results in this paper are consistent with recent research showing that investors use FinTechs as a substitute for traditional information sources (Grennan and Michaely, 2018). In contrast to Jiao et al. (2018), I document that social media are not simply an echo-chamber for news media but contain a distinct signal, consistent with Azar and Lo (2016), that affects managers' investment decisions.

Second, I contribute to the literature on social media as a communication device for firms. Jung et al. (2017), Blankespoor et al. (2014), and Elliott et al. (2018) document that firms use social media networks as a channel for strategic information disclosure and investor relations management, respectively. By examining the feedback from social media reactions to corporate M&A deals I show that social media act as a channel for the transmission of signals in both directions: from firms to the market, and from the market to firms.

Third, this paper also adds to the growing literature on the relation of FinTech and price informativeness. In line with the idea that prices should become more informative as as information acquisition becomes cheaper and easier (Grossman and Stiglitz, 1980; Verrecchia, 1982), Bai, Philippon, and Savov (2016) document that price informativeness has increased for large firms over the last five decades. On the other hand, Dugast and Foucault (2018) argue that a decline in the cost of raw, low-quality data can have a negative effect on price informativeness if it reduces the demand for processed high-quality data. Indeed, Farboodi, Matray, and Veldkamp (2018) find a decrease in price informativeness for smaller firms. This paper provides a new perspective on this relationship by documenting that in addition to the indirect effect of FinTechs on firms through price informativeness, firms are directly affected by FinTechs and non-traditional information sources such as social media.

2 Data and Descriptive Statistics

This section describes the data sources used in this paper, outlines the methodology to construct my main variables of interest, and provides summary statistics of the key dependent and independent variables.

2.1 StockTwits – A Financial Social Media Network

2.1.1 Financial Social Media Data

The main data source for social media feedback in this paper is the financial social media network called 'StockTwits'. Similar to Twitter, StockTwits allows users to publicly post short messages with a limited number of characters. In contrast to Twitter, StockTwits is specifically focused on financial markets. When logging into the platform, the user sees a continuous stream of the most recent posts about stocks they are interested in or tweets by users they are currently "following", similar to the Twitter or Facebook homepage. By including a so-called 'cashtag' – a dollar sign ($) plus ticker symbol – StockTwits users can share a post referring to a specific firm or security with their followers and the StockTwits community. For example, if a StockTwits user wanted to express their positive opinion about Apple Inc. on the platform, they would say "$AAPL is a great firm, you should buy!". The cashtag system provides a mechanism for attributing each post to a company with a high level of accuracy.

Since its launch in 2008, the StockTwits platform has grown rapdly. In 2014, users generated over 1.5 million tweets per month. The StockTwits newsfeed is integrated in many (online) platforms frequently used by finance professional and investors, including S&P Capital IQ, Yahoo! Finance, CNN Money, and Reuters, allowing market participants to share their comments and thoughts directly without having to log on to StockTwits website or app. As illustrated by Figure 3, financial information platforms such as Bloomberg now track Twitter engagement and sentiment with respect to individual firms, and financial market professionals are paying close attention to social media sentiment.[8]

I obtain the raw text and time-stamp of every message posted to StockTwits between January 2010 and December 2014, a total of over 35 million individual 'tweets'. In addition, the data includes a plethora of related information, including the 'cashtags' indicating which security a given tweet is referring to and whether this cashtag is currently trending, the username, corporate affiliation, and geo-location of the account who sent the tweet, an indicator if the account is officially verified (e.g. official company public & investor relations accounts), as well as self-identified financial market experience (beginner, intermediate, or professional) and investment strategy[9], the user's relationship with other users (i.e. their number of "followers", the number of accounts they follow, etc.), and user interactions with the tweet such as 'likes' and replies. Although anybody can sign up and post on StockTwits, in practice a large proportion of users are financial market participants and professionals including news letter writers, investment managers, and financial journalists (Cookson and Niessner, 2019). Additionally, StockTwits users can choose to attach a tag to their tweet indicating if their tweet reflects "bullish" or "bearish" sentiment.

From the StockTwits dataset I retain every tweet that includes exactly one cashtag ("$" + Ticker Symbol). This ensures that I am able to attribute a tweet to a specific stock and reduces ambiguity in interpreting tweet messages, as users frequently include multiple popular cashtags (e.g. $FB, $GOOG, $AAPL) to generate attention or share their opinion on a sector or industry. I further retain only tweets for which the tweet date or account name are clearly identifiable, English language tweets without foreign characters, and tweets that contain a cashtag associated with a

[8]For instance, the author of the tweet shown in Figure 3, Joe Weisenthal, is the executive editor of news for Bloomberg Digital and the co-anchor of "What'd You Miss?" on Bloomberg Television. Reflecting this trend, Chen, Hwang, and Liu (2019) suggest that the Twitter activity of company executives can enhance a firm's information environment and improve stock liquidity, while Chen et al. (2014) show that sentiment from the social media site Seeking Alpha predicts future price performance.

[9]This includes asset classes (bonds, stocks, commodities, etc.) and trading strategy (macro trends, technical analysis, momentum, etc.). See Cookson and Niessner (2019) for more information.

publicly listed, U.S. company since many cashtags refer to other securities and assets such as gold, stock indices, and foreign firms. After applying these filters, the dataset contains 21.07 million unique, English-language tweets about individual U.S. firms from January 2010 to December 2014.

Figures 1 and 2 present summary statistics on the number of tweets per hour of the day, day of the week, and over the sample period after applying the above data filters. As shown in Figure 2a, the total number of tweets posted on StockTwits per month has increased from approximately 25,000 in 2010 to over 500,000 in 2014, in line with the overall growth in the user base of the platform during this time period. Figure 2b further documents usage of the StockTwits platform per hour of the day. Most of the activity on StockTwits occurs between 1pm and 5pm EST on a given day, indicating that StockTwits users are most active during business hours when markets are open. Consistent with this interpretation and the pattern documented in Cookson and Niessner (2019), Figure 1 shows that most tweets are posted on workdays from Monday to Friday. As documented in Figure 1a, the average number of tweets per stock posted on StockTwits is between 7.35 (Monday) and 8.41 (Thursday) during workdays, and 3.51 (Saturday) and 3.15 (Sunday) on the weekend. While the most actively discussed firms on StockTwits are typically large firms such as Apple Inc ($AAPL) with an average of 540.17 tweets per day, Blackberry ($BBRY, 212.35 tweets per day), Facebook ($FB, 198.10), and Tesla ($TSLA, 156.55), small firms such as GoPro ($GPRO, average of 187.46 tweets per day) and iBioPharma Inc. ($IBIO, 78.47) are receiving considerable user attention as well, especially around important information events.

2.1.2 Content Classification and Social Media Sentiment

To classify the content of each StockTwits post I rely primarily on the Maximum Entropy (ME) approach used by Cookson and Niessner (2019) and Giannini et al. (2019), among others. Maximum Entropy is a general technique for estimating probability distributions from data. The underlying 'Principle of Maximum Entropy' states that when nothing is known about the distribution, it should be as uniform as possible, i.e. have maximum entropy. Due to the minimal assumptions made by the Maximum Entropy classification approach, it is commonly used for language detection, topic classification, and sentiment analysis.

Previous research using text classification has often used techniques such as the Naive Bayes classifier which assume conditional independence of the features in a given text, which can lead to misclassification. For example, while the word "fool" in the sequence "You would be a fool to sell $FB" has a negative connotation, the statement as a whole is clearly positive. Maximum Entropy is considered the most robust approach to information classification as it accounts for the conditional dependence of words and text features (see e.g. Nigam, Lafferty, and McCallum, 1999).

Additionally, ME also alleviates concerns with alternative approaches that rely on counting the frequency of positive or negative key-words in a given word sequence. As highlighted by Loughran and McDonald (2011), the majority of negative words in corporate 10-K filings following the commonly used Harvard Dictionary do not have a negative connotation in a financial context (e.g. liability, tax, board, etc.). Further, since previous research has found little incremental information in positive word lists, many studies rely only on the negative words in commonly used dictionaries. The Maximum Entropy classifier addresses these concern directly as it identifies key text features for classifying text purely from the underlying data of the training sample.

Maximum Entropy (ME) classification estimates the conditional probabilities of a given category (e.g. positive/neutral/negative) of a document, provided the content (e.g. words and expressions) of the document. Based on labeled training data, ME derives a set of constraints – represented as expected values of the document's "features" (e.g. the occurrence of key words) – for the model and then selects a probability distribution that is as close to uniform as possible, while satisfying the constraints.[10]

For the purpose of tweet classification in this paper, I use Maximum Entropy to estimate the conditional distribution of the tweet category given the features of the tweet. Let $W = (w_1, ..., w_M)$ be a set of words or expressions that can appear in any given tweet x_i[11], and let y_i be the category (either "bullish" or "bearish") that tweet x_i is assigned to. The training sample is then represented by a set of tweet-category combinations $((\mathcal{X}, \mathcal{Y}) = (x_1, y_1), ..., (x_N, y_N))$. For each combination of

[10] The basic intuition behind ME can be illustrated with an example. Assume that a sample of tweets can belong to one of three categories, positive, neutral, and negative, and that 50% of all tweets with the expression "vacation" are in the positive category. When presented with a tweet that has the word "vacation" in it, we would intuitively say that it has a 50% chance of being positive, and a 25% of being neutral or negative, respectively. This distribution is as close to uniform as possible while satisfying the one given constraint, i.e. maximum entropy.

[11] w_m could for example be a single word like "optimistic" or a combination of words such as "fool to sell".

word w_m and category y, I can then define the following feature function:

$$f_m(x, y(x)) = \begin{cases} \frac{N(w,x)}{N(w)} & \text{if } w_m \in x \text{ and } x \text{ is classified as } y \\ 0 & \text{otherwise} \end{cases} \tag{1}$$

where $N(w, x)$ is the number of times word w_m appears in tweet x and $N(w)$ is the number of words in x. I drop index i here to simplify notation. $f_m(x, y(x))$ is called a "joint feaure", determining which weight the word-category pair (m, y) receives in the ME constrained optimization procedure. For example, if "fool to sell" occurs often in the category "bullish", the weight for ("fool to sell", "bullish") will be higher than for the expression combined with "bearish".

Maximum Entropy uses the training data to establish constraints on the model which the learned distribution has to conform to, based on the features of the documents. Specifically, the expected value of the model distribution for each feature has to match the feature as estimated from the training data, $(\mathcal{X}, \mathcal{Y})$. Following Nigam et al. (1999), the learned conditional distribution $p(y|x)$ must therefore satisfy the following constraints:

$$\frac{1}{|\mathcal{X}|} \sum_{x \in \mathcal{X}} f_m(x, y(x)) = \frac{1}{|\mathcal{X}|} \sum_{x \in \mathcal{X}} \sum_{y \in \mathcal{Y}} p(y|x) f_m(x, y) \tag{2}$$

$$p(y|x) \geq 0 \text{ for all } x, y \tag{3}$$

$$\sum_{y} p(y|x) = 1 \text{ for all } x. \tag{4}$$

The above set of constraints can be satisfied by an infinite number of models $p(y|x)$. The Maximum Entropy classifier selects the model $p^*(y|x)$ that is as close to uniform as possible, i.e.:

$$p^*(y|x) = \underset{p(y|x) \in \mathcal{P}}{\operatorname{argmax}} H(p(y|x)) = \underset{p(y|x) \in \mathcal{P}}{\operatorname{argmax}} \sum_{x \in \mathcal{X}} p(y|x) log \left(\frac{1}{p(y|x)} \right) \tag{5}$$

where $\mathcal{P}$ is the collection of all probability distributions that satisfy the above constraints. Introducing Lagrangian multipliers λ_m to solve this optimization problem, it can be shown (Della Pietra, Della Pietra, and Lafferty, 1997) that:

$$p^*(y|x) = \frac{exp\left(\sum_m \lambda_m f_m(x,y)\right)}{\sum_{y \in \mathcal{Y}} exp\left(\sum_m \lambda_m f_m(x,y)\right)} \tag{6}$$

where $\lambda_{m,y}$ is the weighting parameter that determines the relative strength of each of the features m contained in a document. For example, if the value of $\lambda_{\text{fool to sell,positive}}$ is large, then the feature "fool to sell" is strong for category "bullish". After estimating the $\lambda_{m,y}$ parameter values on the training sample, I lastly obtain the probability of being in a given category y (i.e. "bullish" or "bearish") for every tweet based on its word content. More details on this methodology are provided in Nigam et al. (1999).

One key advantage of using StockTwits data is that users can attach a tag to their tweet indicating if they are "bullish' or "bearish" about the stock they are tweeting about. This mechanism provides a very large, user generated training sample for the ME algorithm. In contrast, most previous research (e.g. Antweiler and Frank, 2004 and Giannini et al., 2019) constructs a training sample by manually classifying a small number of tweets as positive and negative. By relying on a user-classified training sample I avoid the subjectivity of this approach.

In total, 3.11 million tweets posted on StockTwits (approximately 14.75% of the total sample) have a user-assigned sentiment ("bullish", "bearish"). I rely on the first 33% of this set of tweets (approximately 1.04 million messages) as a training sample to infer the sentiment of all posts, using the Improved Iterative Scaling (IIS) procedure with 25 iterations to solve the Maximum Likelihood optimization problem for ME classification.[12] In undocumented tests I find that the Maximum Entropy classifier is highly accurate in detecting the sentiment of a given tweet: using the training sample of 1.04 million tweets with a user-provided sentiment, the algorithm is able to correctly identify positive and negative messages with an accuracy of 90.90% in the remaining test sample of tweets with a user-provided "bullish" or "bearish" tag.

In addition to the Maximum Entropy (ME) Classification approach I also use the popular "Naive Bayes" classification approach as an additional robustness test, following for example Antweiler and Frank (2004) and Bartov et al. (2018). In contrast to Maximum Entropy, Naive Bayes assumes

[12]Specifically, I use the Python package NLTK for Natural Language Processing (NLP) to implement Maximum Entropy and Naive Bayes Classification.

conditional independence of the words in a given document. Similar to ME, the Naive Bayes classifier relies on a training sample of tweets x with assigned classes y ("bullish", "bearish"). The probability that a tweet belongs to a certain class, given its content, is determined by first estimating the probability $p(y)$ of each class $y \in \mathcal{Y}$ by dividing the number of words in tweets that belong to class y by the total number of words in the total sample of tweets. Second, the algorithm estimates the empirical probability distribution $p(w|y)$ for all words $w = w_1, ..., w_M$ and classes y from the sample of tweets with class y. Third, to score a tweet x for class y, we calculate:

$$score(x, y) \equiv p(y) \times \prod_{m=1}^{M} p(w_m|y). \tag{7}$$

Finally, the probability that a tweet is positive or negative is obtained as:

$$p(y|x) \equiv \frac{score(x, y)}{\sum\limits_{y' \in \mathcal{Y}} score(x, y)}. \tag{8}$$

Similar to the ME classification approach, I rely on the sub-sample of tweets tagged as "bullish" or "bearish" as the training sample to execute the Naive Bayes Algorithm.

2.2 Mergers & Acquisitions

Next, I construct a sample of M&A transactions using data from SDC Platinum. Following prior literature, I obtain all Mergers & Acquisitions announced during the sample period from 2010 to 2014 with a minimum deal value of $25 Million. I limit the sample to transactions where the acquiring firms are publicly listed on a U.S. stock exchange. In addition to key deal characteristics such as the announcement date, deal value, and percentage of shares sought, I collect data on whether an announced deal was ultimately completed or withdrawn, as well as the withdrawal date. I drop observations where the M&A announcement date and deal withdrawal date are less than 10 days apart to eliminate M&A transactions that were withdrawn for technical or procedural reasons. Following Luo (2005), I further include deal features that have been shown in the literature to be closely related to M&A completion, such as the deal payment form (cash vs. stock), the presence of a white knight, anti-takeover provisions such as poison pills, and the presence of rumors prior to deal announcement as controls in the sample.

In addition, I compute Cumulative Abnormal Returns (CARs) for both the acquiring and target firms for several event windows around the M&A announcements, using a standard Fama-French 3-Factor model[13] and stock return data from the Center for Research in Security Prices (CRSP). Since many target firms are private firms, stock return data are unavailable and CARs cannot be computed for this subsample.

[Insert Table 1 here.]

Table 1 presents summary statistics for the sample M&A deal characteristics (Panel A) and M&A announcement returns (Panel B). The sample comprises 4,495 M&A announcements between January 2010 and December 2014 with an average deal value of $0.858 Billion. As shown in Panel A, 93.8% of all announced deals are eventually completed, consistent with Luo (2005). Most M&A transactions in the sample are full takeovers, the median (mean) percentage of shares sought is 100% (93.35%), and the majority of deals (86.04%) are cash offers.

Consistent with prior literature, I find a large positive abnormal return for the publicly listed target firms in my sample around the M&A announcement date. For example, the mean Cumulative Abnormal Return for M&A targets is 0.15 during the $[-1;1]$ day event window around the announcement, with a standard deviation of 0.224. In contrast, the mean Cumulative Abnormal Return for acquirer firms in the sample is closer to zero, with a mean (median) of 0.00 (0.011) and a standard deviation of 0.064.

2.3 Other Data Sources

2.3.1 Psychsignal

The main data source for social media feedback and sentiment in this paper is StockTwits, since the high granularity of information and availability of raw text messages allows for various cross-sectional and sub-sample tests. In addition, I also obtain social media sentiment data from Psychsignal to complement the StockTwits sample. Psychsignal is a financial technology company providing hedge funds and other sophisticated investors with trading signals based on social media content. Importantly, Psychsignal sentiment scores are based on tweets posted on *both* Twitter and StockTwits.

[13] I use an estimation period of 100 days with a minimum of 70 observations with a gap of 50 days between the end of the estimation period and the event period to compute expected and abnormal returns.

Twitter has a much larger user base than StockTwits and might therefore incorporate additional M&A announcement feedback not captured by StockTwits. For each stock covered by Psychsignal, their proprietary sentiment algorithm generates a 'bullish' and 'bearish' measure by counting the number of posts with an overall positive or negative sentiment in a given day. I generate a measure of social media sentiment based on Psychsignal data by taking the ratio of bearish over bullish number of tweets about a firm in a given day (i.e. *Ratio Bullish/Bearish*).

Figure 1b shows a similar pattern for the average number of Tweets per weekday captured by Psychsignal (using both Twitter and StockTwits) as documented in Figure 1a, which is based on StockTwits data only. Most 'Finance Twitter' activity occurs between Monday and Friday, with an average of 18.43 tweets per day per firm recorded on Wednesdays. Twitter activity is considerably lower on Saturdays (8.24 tweets) and Sundays (8.36).

2.3.2 Traditional News Media

Further, I obtain sentiment scores for traditional news media reports from Ravenpack News Analytics (RPNA). I rely on the Dow Jones Edition package of Ravenpack, which analyzes all articles and reports published on Dow Jones Newswires, regional editions of the Wall Street Journal, Barron's and MarketWatch. For each acquirer and target firm in my sample, I obtain the "Event Sentiment Score" (ESS) of all news articles and reports published during a four day window (i.e. [-1;+2]) around the M&A announcement, excluding reposted, older stories. To alleviate concerns that media reports during this window are reflecting news other than the M&A announcement, I retain only articles and stories related to "mergers/acquisitions" as categorized by Ravenpack.

Following Gao et al. (2017), I classify each news article as positive if the corresponding Event Sentiment Score (ESS) provided by Ravenpack is in the upper tercile of all news articles in the sample, and categorize each news article as negative, if the ESS is in the lower tercile. I then calculate the overall M&A related news media sentiment over the M&A announcement window follows:

$$RPNA\ Sentiment = \frac{\sum Positive\ articles - \sum Negative\ articles}{Total\ number\ of\ articles}. \tag{9}$$

2.4 Variable Construction and Summary Statistics

Finally, I merge the M&A announcement sample from SDC with StockTwits, Psychsignal, and Ravenpack (social) media sentiment data based on the cashtags provided in the StockTwits messages and the standard firm identifiers in the Psychsignal and Ravenpack data. For each M&A announcement, I consider the StockTwits, Psychsignal, and Ravenpack (social) media sentiment during the seven-day window ([0;6]) and four day window ([-1;2]), respectively, around the M&A announcement date. Table 2 provides summary statistics for the merged sample.

[Insert Table 2 here.]

The final sample of M&A announcements with available StockTwits (Psychsignal) sentiment data for the acquiring firm contains 2,743 (4,056) observations. The average number of StockTwits (Psychsignal) posts about the acquiring firm around the M&A announcement date is 36.98 (184.12). On average, users are more likely to be positive than negative in their tweets, the mean probability of a "bullish" sentiment using the Maximum Entropy classification is 0.79. Similarly, the mean bullish/bearish ratio in Psychsignal tweets around M&A announcements is 0.724.

When evaluating the impact of social media feedback on firm investment decisions, simply considering the Twitter sentiment at announcement in the cross-section might therefore be misleading, as the average level of "positive sentiment" varies significantly across stocks. Hence, I construct a measure of 'social media feedback' as the abnormal sentiment around M&A announcements following Engelberg and Gao (2011) as follows:

$$\text{Abnormal Sentiment}_i = \left(\frac{1}{T}\sum_{t=0}^{T=6} Sentiment_{i,t}\right) - \left(\frac{1}{T}\sum_{t=-13}^{T=-7} Sentiment_{i,t}\right) \tag{10}$$

where $Sentiment_{i,t}$ is the StockTwits sentiment (average probability that a message is 'bullish' from Maximum Entropy and Naive Bayes classification) or Psychsignal sentiment (ratio of bullish to bearish messages) for M&A transaction i on announcement date t, respectively. Essentially, Abnormal Sentiment$_i$ captures the change in sentiment during the seven-day announcement period relative to a similar period before the M&A announcement became public. To alleviate concerns about information leakage the estimation period for average stock-specific sentiment during 'normal' times ends 7 days before the M&A announcement.

As documented in Panels A and B of Table 2, the average StockTwits and Twitter activity is considerably higher following M&A announcements than during 'normal' times. The average *abnormal* number of posts about the acquiring firm on StockTwits (Psychsignal) is 25.06 (102.82) during the announcement period, compared to 11.92 (81.29) during a seven-day period before the announcement. As illustrated in Figures 4a and 4b, most of the heightened activity is concentrated in the [0;2] window around the announcement. Further, the mean (median) Abnormal Sentiment$_i$ is close to zero, i.e. 0.02 (0.00) for Maximum Entropy classification, 0.02 (0.01) for Naive Bayes, and 0.41 (0.00) for Psychsignal bullish/bearish ratio, consistent with the objective of capturing the social media feedback rather than overall stock-specific level sentiment.

A considerable portion of tweets, approximately 16%, are sent by users with officially verified profiles. The average number of followers per user who tweeted during the announcement period is 7,620 and the average number of tweet received 0.03 likes. These numbers are very similar during the announcement and pre-announcement periods, the abnormal mean official users, followers, and likes are 0.01, 0.15, and 0.00, respectively.

3 Results

3.1 M&A completion and Social Media Feedback

The main goal of this paper is to evaluate if firm investment decisions are affected by social media feedback. The basic idea for the following tests builds on Luo (2005): assuming that the managers of the acquiring firm use all available information to evaluate a prospective corporate acquisition before announcing the deal, they have no incentive to subsequently withdraw the transaction after announcement, unless outside feedback changes their assessment of the deal. Of course, assessment of the deal by the acquiring firm's managers includes both the value created for the firm itself as well as any private benefits (e.g. such as empire building). Therefore, the sensitivity of deal completion to outside feedback immediately following the announcement can be interpreted as 'management listening' to outsiders, i.e. Twitter feedback. In line with this intuition I estimate the following linear probability model:

$$Deal\ Completed_i = \alpha + \beta_1 \times CAR_i + \beta_2 \times AbnSent_i + \text{Firm \& Deal Controls} + \text{Time FE} + \epsilon_i \quad (11)$$

where *Deal Completed*$_i$ is an indicator variable that takes the value of one if the announced M&A deal i was subsequently completed and zero otherwise, and $AbnSent_i$ and CAR_i are the acquirer firm's abnormal social media sentiment and Cumulative Abnormal Return following the M&A announcement, respectively. The controls include the acquirer firm's market capitalization, the dollar value of deal i, as well as indicator variables capturing if the acquirer is a white knight, the involvement of a hedge fund, a challenged deal, a privatization, if the deal was rumored, if the target is public, if the deal is hostile, and the percentage of shares sought. Additionally I also include year-by-quarter fixed effects to control for time trends such as merger waves. Standard errors are clustered at the year-by-quarter level.

[Insert Table 4 here.]

The results for Equation (11), summarized in Table 4, provide three main insights. First, the findings confirm the results in Luo (2005) for my sample of M&A transactions from 2010 to 2014. The M&A announcement return (CAR [-1;1]) for the acquiring firm positively predicts the likelihood that the M&A transaction is subsequently completed. The estimated effect is both statistically significant in the specifications in columns 1 to 4 and economically meaningful. For example, the coefficient estimate of $\hat{\beta}_1 = 0.288$ (t-statistic of 2.54) in column 4 indicates that a one standard deviation (0.43) increase in acquirer CAR_i is associated with a 1.238 percentage point ($= 0.043 \times 0.288$) increase in the likelihood that the M&A deal will subsequently be completed. Given the sample average that a deal will be withdrawn of 6.2%, this effect is substantial.[14]

Second, the abnormal returns of the acquiring firm before the M&A announcement have no predictive power for the subsequent completion of the M&A transaction. The coefficient estimate on the pre-announcement acquirer CAR, using an event window of [-5;-1], is small (0.0217) and statistically indistinguishable from zero, as shown in column 1. This is consistent with the idea that managers consider all available information before announcing an M&A transaction and pre-announcement stock returns therefore do not contain incremental information about the likelihood of deal completion.

Third, and most importantly, my results show a robust positive relationship between social media feedback, measured as abnormal acquirer tweet sentiment, and the likelihood of M&A deal

[14] In undocumented robustness tests, I find qualitatively similar results using alternative event windows for the M&A announcement CARs.

completion. As documented in columns 3 to 5, a one standard deviation increase in 'Abnormal Bullish (Maximum Entropy)' of 0.17 is associated with a 2.074 percentage point increase in the likelihood of subsequent deal completion. This estimate is statistically significant at the 1% level (t-statistic of 3.64 in column 5) and robust to the inclusion of firm and deal controls.

Importantly, the effect of social media feedback on M&A completion is *not* subsumed by the acquirers' abnormal stock returns. The coefficient estimate for $\hat{\beta}_2$ remains almost unchanged and highly significant when including CAR_i and various controls in Equation 11. This indicates that the effect of social media feedback on M&A completion cannot be fully explained by a potential overlap between the information and sentiment driving both stock return and social media posts. If the messages posted to StockTwits simply followed stock market returns, we would not expect the relationship of deal completion and acquirer tweet sentiment to remain unchanged when including acquirer stock returns.

In the following sections I conduct additional robustness checks and tests to provide confidence that this main result is indeed due to a feedback effect from social media to firm decision making, and to shed additional light on the channels driving this effect.

3.2 Robustness

3.2.1 Traditional news media and subsample tests

Liu and McConnell (2013) show that the feedback from traditional news media can affect the completion of announced M&A transactions, as executives are concerned about their reputation, and newspaper coverage can hence discipline firms to withdraw value-reducing corporate acquisitions. Further, Jiao et al. (2018) present evidence suggesting that in some settings social media acts primarily as an 'echo chamber' for traditional news media, amplifying and repeating information that first became public in traditional news outlets. Therefore, one interpretation consistent with the findings in Section 3.1 is that StockTwits-based acquirer sentiment is a reflection of the feedback to the M&A announcement published by traditional media.

To distinguish between the feedback effect of traditional news media and social media content for corporate investment decisions I control directly for newspaper coverage and content in this paper. Following Liu and McConnell (2013), I use the number and sentiment of articles published in common news outlets, which specifically cover a given M&A transaction. The data is obtained from Ravenpack as described in detail in Section 2.3.2. I then estimate a model similar to Equation 11 adding variables capturing newspaper sentiment and the number of articles published.

[Insert Table 5 here.]

Column 1 of Table 5 presents the results. In line with Liu and McConnell (2013), I find a strong, positive relationship between newspaper sentiment and M&A completion. A one standard deviation increase in newspaper sentiment, using the measure introduced in Gao et al. (2017), is associated with a 3.05 percentage point increase in the likelihood that an M&A transaction is completed after its announcement. This estimate is statistically significant at the 1% level.

If the sensitivity of M&A completion to social media feedback was indeed driven by a social media 'echo' effect, we would expect the inclusion of a newspaper sentiment measure to subsume or at least attenuate the effect of social media sentiment on M&A completion. However, the results are not consistent with this interpretation. The coefficient estimate for 'Abnormal Bullish' in column 1 is virtually unchanged (t-statistic of 4.29) compared to the main specifications in Table 4 when including newspaper sentiment and content proxies, indicating that social media feedback is providing a signal to managers that is distinct from both the stock price reaction and traditional news media.

In column 2, I replace the main measure for acquiring firm sentiment based on the Maximum Entropy classifier with a similar measure constructed using the Naive Bayes classifier, as outlined in Section 2.1.2, to alleviate concerns that the main result is due to the specific text classification methodology. As shown in column 2 of Table 5, the results are very similar. The coefficient estimate for $\hat{\beta}_2$ of 0.109 indicates that a one standard deviation increase in StockTwits-based M&A announcement feedback is associated with a 1.74 percentage point increase in the likelihood of M&A completion, in line with the results using the Maximum Entropy classification approach.

One potential concern with the set of tests up to this point is that they do not account for stock market participants' evaluation of the announced M&A transaction for the *target* firm. For this reason I additionally include the CAR ([-1;1]) of the target firm around the announcement date in column 3. Of course, this reduces the sample size considerably, since I can only include M&A deals with public target firms and available stock return data.[15] The results, summarized in column 3 of Table 5 are consistent with my previous findings and prior literature: the announcement CAR of the target firm has strong predictive power for subsequent deal completion, consistent with Luo (2005). For a one standard deviation increase in target CAR, the likelihood of deal completion increases by 11.75 percentage points (t-statistic of 5.74). However, the effect of social media feedback (abnormal bullishness using maximum entropy) remains significant (t-statistic of 2.34) despite the smaller sample size and even increases slightly in magnitude. This again suggests that the social media feedback effect is not subsumed by the stock market reaction to the M&A announcement.

In column 4, I restrict the sample to those M&A announcements with at least 15 posts about the acquiring firm on StockTwits during the event window. If the documented sensitivity of M&A completion to social media feedback is indeed due to the content of the postings, we would expect to find a stronger and more precisely estimated relationship when users are more active, as a larger number of postings would allow me to estimate social media feedback from postings with higher precision. The result, documented in column 4 of Table 5, is consistent with this interpretation. The coefficient estimate on 'Abnormal Sentiment' based on this subsample is almost twice as large (t-statistic of 3.14) as the estimate in column 4 of Table 4, using a similar specification.[16] The coefficient for CAR_i remains significant and similar in size as in Table 4.

Lastly, I estimate the model in Equation (11) using a conditional logit model as an alternative to the linear probability model used in the main specification. The results, documented in column 5 of Table 5, confirm the previous finding that the likelihood of M&A completion is strongly positively related to StockTwits social media feedback. The coefficient estimate of 4.00 indicates that a unit increase in 'Abnormal Bullish' around the M&A announcement makes it 55 times (i.e. 0.982/0.0180, $54.598 = exp(4)$) as likely for the deal to be completed than not to be completed. Given the standard deviation in abnormal acquirer sentiment of 0.17, a one SD increase in 'Abnormal Bullish' is related to an odds ratio of 9.282 (i.e. 0.903/0.097)).

[15] This reduction in sample size is the primary reason I refrain from including target CAR in my main tests.

[16] Again, restricting the sample in this way reduces the sample size by more than 500 observations. For this reason I focus on the full sample in my main specification.

3.2.2 Psychsignal Social Sentiment

One potential concern with feedback effects based on StockTwits social media data is that StockTwits as a social media platform has a relatively small user base compared to more popular and widely used platforms such as Twitter. It could be argued that firms and managers looking for investment feedback and guidance from social media signals would primarily consider Twitter, since many companies have official Twitter accounts to engage with investors and the public, and since Twitter sentiment measures are tracked by financial news platforms such as Bloomberg.

I hence repeat the analysis from the previous section using social media sentiment provided by Psychsignal, as outlined in Section 2.3.1. Psychsignal constructs their sentiment measures based on both Twitter and StockTwits, thus capturing a larger group of users and opinions. The main variable of interest is "Abnormal Bullish/Bearish Ratio", capturing the ratio of tweets rated as 'bullish' over tweets classified as 'bearish' by the Psychsignal algorithm during the event period, compared to a 7-day period before the M&A announcement. Details of the variable construction are provided in Section 2.4. I then estimate regressions as specified in Equation 11.

[Insert Table 6 here.]

Table 6 summarizes the results. Column 1 provides the main results based on the full sample of abnormal Psychsignal-based sentiment. Compared to the tests summarized in Tables 4 and 5, the sample size is significantly larger since Psychsignal extracts user sentiment from both Twitter and StockTwits, therefore covering a greater number of firms and M&A deals.

First, consistent with Luo (2005), Liu and McConnell (2013), and the findings from Tables 4 and 5, I find a strong positive relation between both news media sentiment, stock market reaction, and subsequent M&A completion. Newspaper sentiment from Ravenpack and abnormal acquirer CAR around the M&A announcement date are positive and statistically significant, and comparable in economic magnitude to the previous results reported in Tables 4 and 5. Additionally, I also find a positive effect of news media coverage on the likelihood of M&A completion in this larger sample, in line with Liu and McConnell (2013).

Second, and more importantly, the results confirm the findings in the previous section, documenting a positive effect of social media feedback during the announcement period on the subsequent completion of M&A deals. The coefficient estimate for $Abnormal\ bullish/bearish_i$ of 0.00324 (t-statistic of 2.44), based on Psychsignal sentiment data, indicates an increase in the likelihood of M&A deal completion of 0.460 percentage points. Compared to the results reported in Tables 4 and 5 this effect is economically smaller, but still meaningful in relation to the average likelihood of a deal withdrawal of 6.20% in the overall sample. The controls variables have similar signs and magnitude as in the main results in Tables 4 and 5. For example, as documented in the literature, the deal volume in dollar terms is negatively associated with the likelihood of deal completion.

Column 2 focuses on the subsample of M&A deals with publicly listed target firms to be able to include the stock market reaction to the M&A announcement with respect to the target. In line with the previous findings, I find a strong relationship between stock market reaction – both of the target and acquiring firm – and subsequent deal completion. A one standard deviation increase in CAR_i^{target} translates into a 9.184 percentage point increase in the likelihood of deal completion. Similar to the results in Table 5 using StockTwits data, Table 6 documents a larger, more precisely estimated effect of social media feedback on deal completion on this subsample when using Psychsignal data. A one standard deviation increase in 'abnormal bullish/bearish' is associated with a 0.863 percentage point increase in the likelihood of deal completion (t-statistic of 3.29), controlling for both stock market and news media feedback, as well as standard deal and firm characteristics and year-by-quarter fixed effects.

4 Channels of Social Media Investment Feedback

In the next sections, I explore several dimensions of cross-sectional heterogeneity in the sensitivity of M&A completion to social media reaction, to provide additional support for the proposed 'feedback' explanation and shed light on the underlying channels. Specifically, I focus on the characteristics (user type, likes, etc.) of the underlying tweets and stock price informativeness.

4.1 User and Tweet Characteristics

I first consider the role of tweet characteristics, i.e. the number of likes the tweets have received ($AvgLikes$), the number of followers ($AvgFollowers$) of the users, and if the StockTwits users have official status ($AvgOffStatus$), for the sensitivity of M&A deal completion to abnormal acquirer sentiment around the announcement event. If the previously documented effect of social media feedback is indeed due to managers gaining additional information or investment signals from the Twitter "crowd", the deal-completion-to-social-sentiment sensitivity should be stronger when the tweets are posted by more prominent users with higher visibility, clout, and attention. To test this conjecture I augment the model in Equation 11 with interaction terms as follows,

$$\begin{aligned} Deal\ Completed_i = \alpha + \beta_1 \times AbnSent_i + \beta_2 \times Tweet\ Characteristics_i \\ + \beta_3 \times (AbnSent_i \times Tweet\ Characteristics_i) \\ + \beta_4 \times CAR_i + \text{Firm \& Deal Controls} + \text{Time FE} + \epsilon_i \end{aligned} \tag{12}$$

where $Deal\ Completed_i$ is an indicator variable capturing the subsequent completion of M&A deal i, $AbnSent_i$ and CAR_i are the abnormal tweet sentiment and cumulative abnormal return around i as before, and $Tweet\ Characteristics_i$ captures several tweet characteristics. Controls and fixed effects are included similarly as in Equation 11.

[Insert Table 7 here.]

Table 7 summarizes the results. In column 1, I use the average number of 'likes' the tweets about the acquiring firm have received during the M&A announcement period as a measure of tweet visibility and prominence. If more users clicked 'like' on a given tweet, it is reasonable to assume that (a) more users were aware of the tweet and (b) more users agreed with it. Hence, social media feedback around the M&A announcement that contains a higher proportion of tweets with a higher number of likes should have a stronger effect on deal completion.

The result documented in column 1 of Table 7 is consistent with this conjecture. The main variable of interest – the interaction term of $AbnSent_i$ and $AvgLikes_i$ – is positive and statistically significant at the 5% level. At the same time, the coefficient estimates on CAR_i and $AbnSent_i$ remain positive (and significant in case of CAR_i), in line with the previous results. The coefficient estimate on $AbnSent_i \times AvgLikes_i$ of 1.316 suggests that for a one standard deviation increase in the average number of likes (0.10), deal-completion-to-social-media-feedback sensitivity (0.0938) increases by 140.30% ($= 0.10 \times 1.316/0.0938$), i.e. more than doubles.

Column 2 focuses on the abnormal number of followers of the users sending tweets during the M&A announcement period. The intuition for including this variable is similar to the number of 'likes'. If the tweets underlying the social media sentiment were posted to a larger number of followers, they generally had a higher exposure, a higher likelihood to be seen by company representatives, and potentially a higher impact. The result in column 2 is in line with this conjecture. The coefficient estimate on $AbnSent_i \times AvgFollowers_i$ is positive and statistically significant (at the 10% level), indicating a 115.28% change in deal-completion-to-social-media sensitivity for a one standard deviation increase in $AvgFollowers_i$.

In column 3, I interact $AbnSent_i$ with the abnormal average proportion of users with an officially verified account who posted tweets about the acquiring firm on StockTwits during the M&A announcement, i.e. $AvgOffStatus_i$. The intuition follows columns 1 and 2: if a higher number of relevant tweets was sent by verified accounts, i.e. accounts representing well-known individuals, institutions, or firms, the messages are likely to have a broader reach and higher likelihood of impacting firm decision making. The results, summarized in column 3 of Table 7 are consistent with the previous findings. The coefficient estimate on $AbnSent_i \times AvgFollowers_i$ is positive and statistically significant (at the 10% level), and suggests a 97.12% increase in the sensitivity of M&A deal completion to abnormal acquirer sentiment around the announcement for a one standard deviation increase in $AvgOffStatus_i$.

Taken together, the results in this section suggest that the sensitivity of M&A deal completion to social media feedback is stronger when the underlying tweets have a higher user agreement (i.e. 'likes'), visibility and reach, and credibility. This is consistent with the interpretation that managers use social media posts as investment guidance particularly in those cases where social media feedback is easily accessible, more precisely measurable, and potentially perceived to be more reliable.

4.2 Price Informativeness

In this last set of tests, I consider the effect of stock price informativeness on the sensitivity of deal completion to social media feedback. The intuition behind these tests is as follows: suppose managers have multiple sources of 'outsider information' they can consult for investment guidance, such as stock prices (Luo, 2005; Chen et al., 2006; Bond et al., 2012 and others), social media, and traditional news media (Liu and McConnell, 2013), and their ability and resources to gather and interpret these investment signals is limited, then managers will focus on those sources of outsider information which provide the best signal. As Chen et al. (2006) and others have shown, investment-to-Q sensitivity, where Tobin's Q serves as a proxy for investment opportunities, increases with stock price informativeness as the stock prices contain more valuable investment guidance for managers. However, if stock prices are highly informative and provide valuable investment signals, managers' will rely less on alternative sources of outside investment guidance. Hence, we would expect acquiring firm stock price informativeness to have a negative effect on M&A-completion-to-social-media-feedback sensitivity.

To test this conjecture I interact the baseline regression in Equation 11 with several measures of stock price informativeness commonly used in the literature as follows,

$$\begin{aligned} Deal\ Completed_i = \alpha + \beta_1 \times AbnSent_i + \beta_2 \times PI_i + \beta_3 \times (AbnSent_i \times PI_i) \\ + \beta_4 \times CAR_i + \text{Firm \& Deal Controls} + \text{Time FE} + \epsilon_i \end{aligned} \tag{13}$$

where $Deal\ Completed_i$, $AbnSent_i$, and CAR_i are defined as before, and PI_i is one of the measures of stock price informativeness. For additional robustness I consider both *AbnSent* as constructed from StockTwits posts as in Table 4 as well as from Psychsignal as in Table 6.

Following Chen et al. (2006), I use both price non-synchronicity (1-R^2), i.e. 1 minus the R^2 from a regression of a stock's daily returns on the contemporaneous market returns, and the *PIN* measure of Easley, Kiefer, and O'Hara (1996), Easley, Kiefer, O'Hara, and Paperman (1996), and Easley, Kiefer, and O'Hara (1997), capturing the Probability of Informed Trading as measures of stock price informativeness. In addition, I also consider the absolute value of the acquirer's CAR around the M&A announcement, as a small stock market reaction with abnormal returns close to zero is less likely to be a strong investment signal in either direction than a small reaction. In this case, managers might be more likely to consider investment signals from alternative outside sources like social media sentiment.

[Insert Table 8 here.]

The results, summarized in Table 8, are consistent with the prediction that stock price informativeness has a negative effect on deal-completion-to-social-media sensitivity, and in line with the previous tables. Columns 1 and 2, 3 and 4, and 5 and 6 use (1-R^2), the *PIN* measure, and $abs(CAR_i)$ as measures of price informativeness (PI_i), respectively.

First, in line with Tables 4 and 6, both CAR_i and $AbnSent_i$ are positive and statistically significant across almost all specifications. Second, price informativeness is unrelated to M&A completion. The coefficient estimate for all three measures of PI_i is close to zero and statistically insignificant at the standard levels. Third, the coefficient estimate for the main variable of interest, $AbnSent_i \times PI_i$ is negative and statistically significant across all six specifications in Table 8. For example, as shown in column 1, for a one standard deviation increase in (1-R^2) (1.435), the sensitivity of M&A deal completion to StockTwits feedback decreases by -49.07% (= $1.435 \times -0.0595/0.174$). Similarly, the sensitivity to Twitter and StockTwits, as captured by Psychsignal abnormal sentiment in column 2, decreases by 96.95% (= $1.435 \times -0.00352/0.00521$) for a one standard deviation increase in price informativeness. Both estimates are statistically at the 5% level.

The results in columns 3 to 6 are consistent with this finding. In both columns 3 and 4, and 5 and 6 I find a negative, significant effect of price informativeness, using PIN and $abs(CAR_i)$ respectively, on the sensitivity of M&A deal completion on StockTwits and Psychsignal M&A announcement feedback. The economic magnitude in both cases is comparable to the results in columns 1 and 2. Taken together, the results in this section indicate that the feedback effect from social media posts to firm investment decisions is weaker when price informativeness of the acquiring firm's stock increases. This is consistent with the idea that managers learn from social media postings when making acquisitions, especially when other important sources of investment signals such as their stock prices are less informative and provide less reliable investment guidance.

5 Conclusion

This paper examines the effect of social media feedback on corporate investment decisions. Specifically, I estimate if the subsequent completion of announced M&A transactions is sensitive to the sentiment of tweets and messages posted to Twitter and StockTwits around the M&A announcement date. For this purpose, I construct measures of the change in social media sentiment compared to normal times without any corporate announcements from the universe of raw posts on StockTwits, using Machine Learning techniques for text classification.

The results show that social media feedback has a positive effect on the likelihood of M&A deal completion, controlling for a host of deal and firm characteristics. This result remains robust after controlling directly for the stock market reaction (i.e. abnormal returns) of the acquiring and the target firm, as well as the sentiment in traditional news media with respect to the M&A deal. I find similar results using social media sentiment indicators based on StockTwits and Twitter data from Psychsignal.

Further, the effect of social media feedback on the likelihood of M&A completion is stronger when the underlying tweets received more attention, had a higher reach and visibility, and were sent by more prominent users. I also find a weaker effect when the price informativeness of the acquirer's stock returns is higher, indicating that managers use different sources of investment guidance as substitutes, in line with Grennan and Michaely (2018).

This is the first paper to document investment feedback effects from non-traditional sources of information, such as modern financial technology. My results show that not only do firms use social media to communicate with investors, markets, and the general public, but that in reverse managers also use signals and feedback from social media to help guide their corporate investment decisions.

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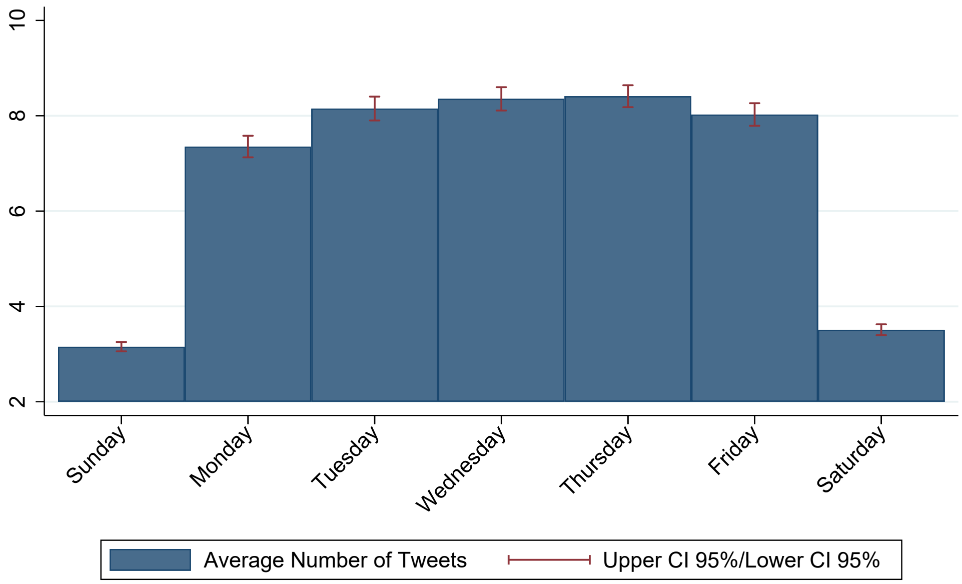
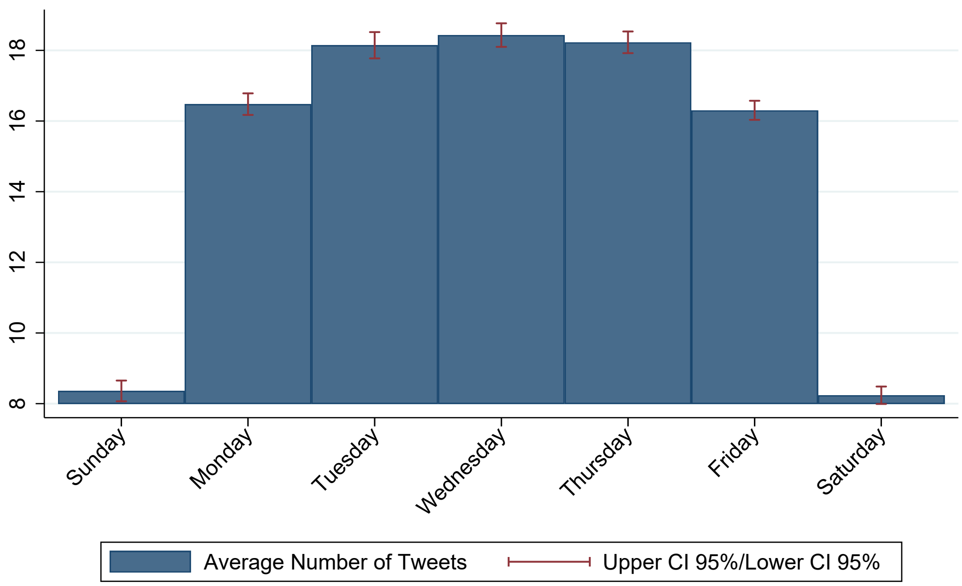
Tables and Figures



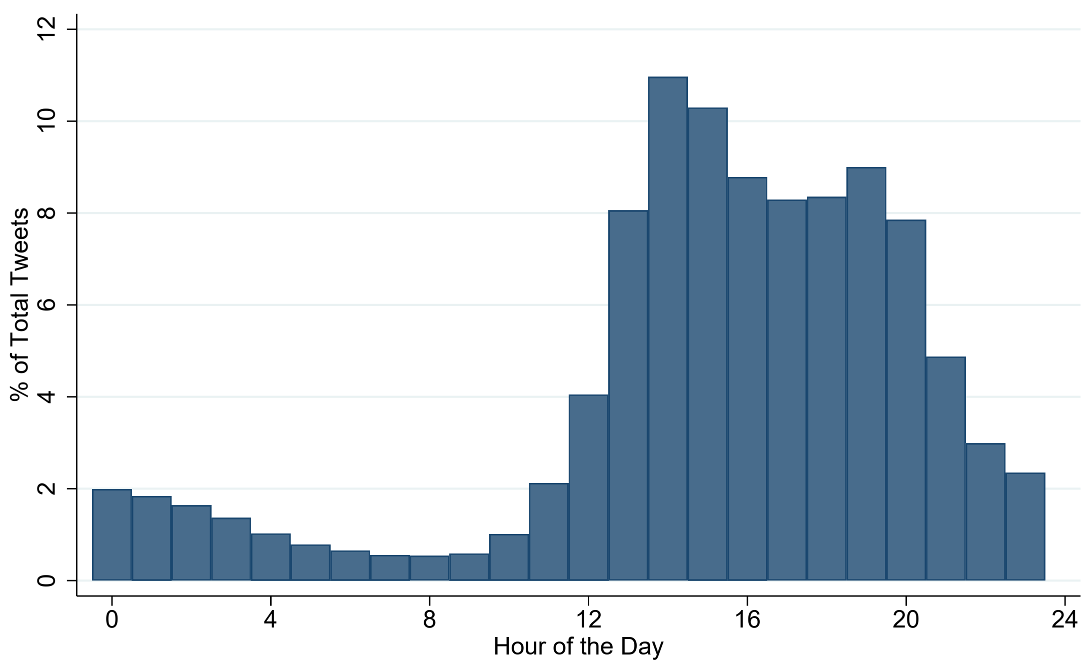
(a) StockTwits Data



(b) Psychsignal Data based on Twitter and StockTwits

Figure 1: *Notes.* This figure presents average usage statistics per security in StockTwits and Psychsignal per day of the week. Panel (a) summarizes the mean number of tweets per 'cashtag' in StockTwits, Panel (b) presents the same information across all 'cashtags' covered by Psychsignal. More details on data sources and sample construction are provided in Section 2.

(a) Monthly Number of Tweets from StockTwits



(b) Number of Tweets by Hour of the Day from StockTwits

Figure 2: *Notes.* This figure presents StockTwits usage statistics over the sample period and by hour of the day. Panel (a) summarizes the average number of tweets posted on StockTwits per month, and Panel (b) displays the average number of tweets per 'cashtag' in StockTwits per hour of the day (EST). More details on data sources and sample construction are provided in Section 2.

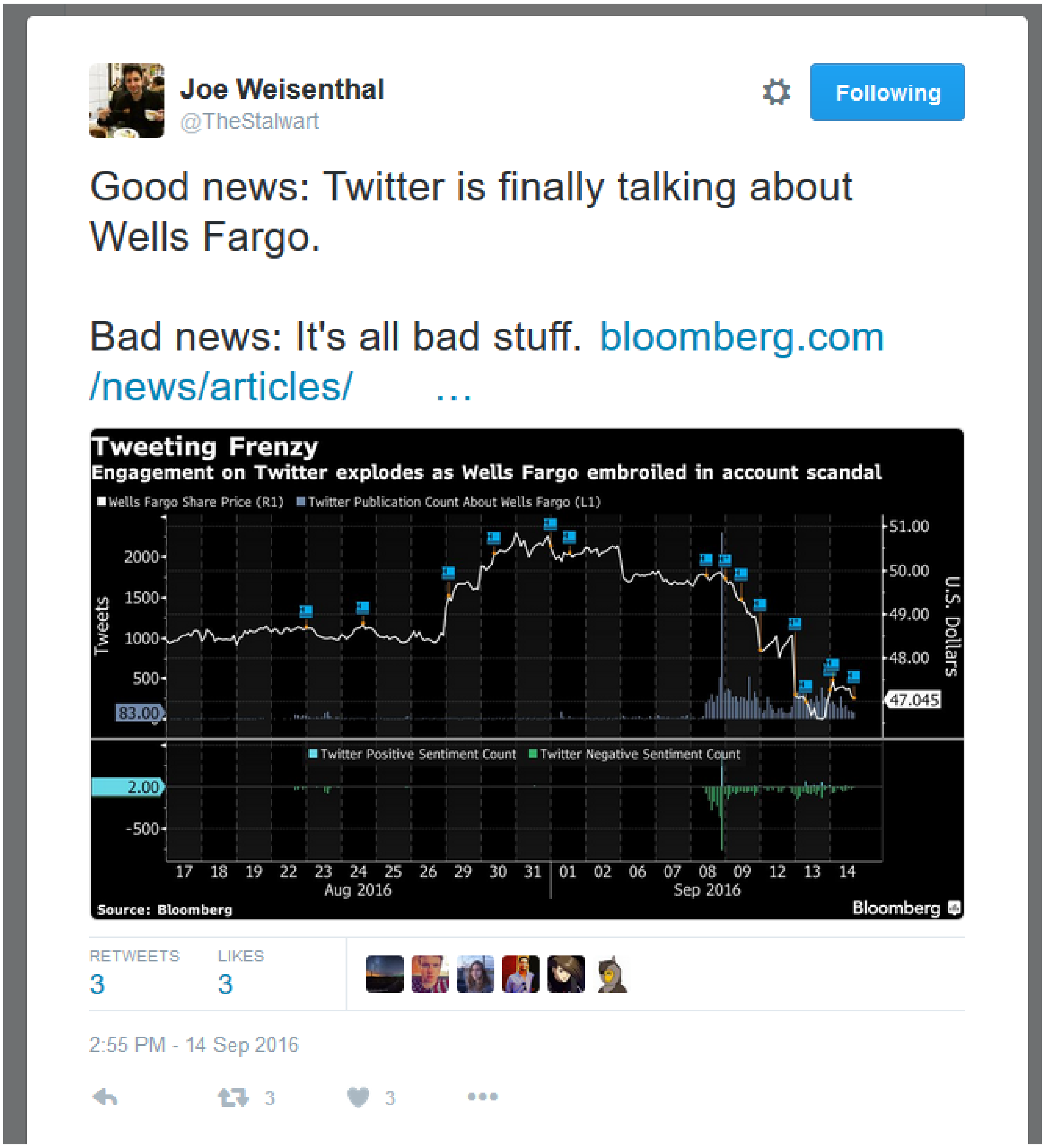
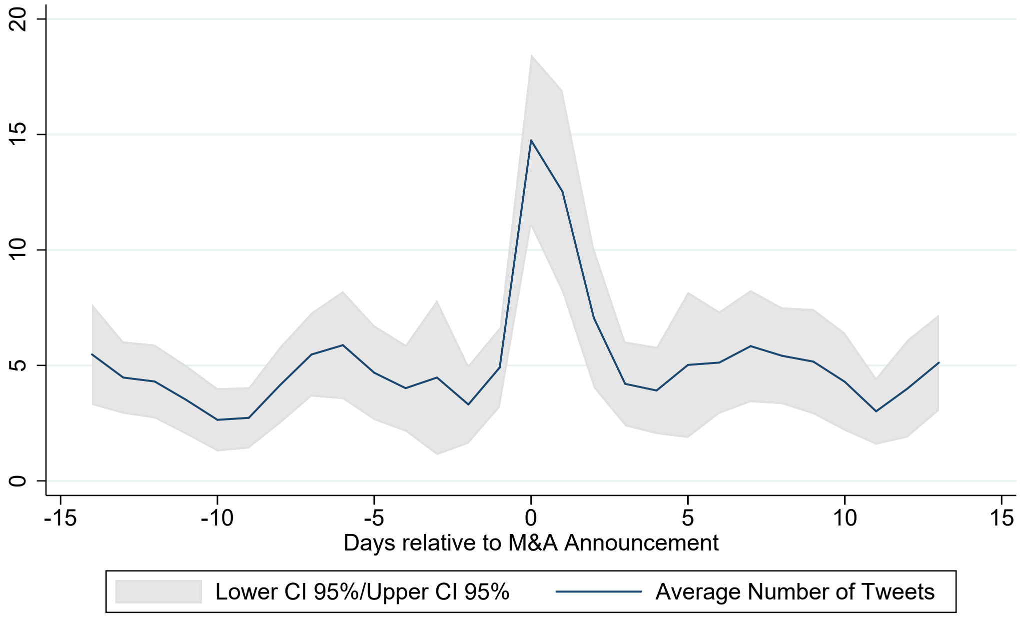
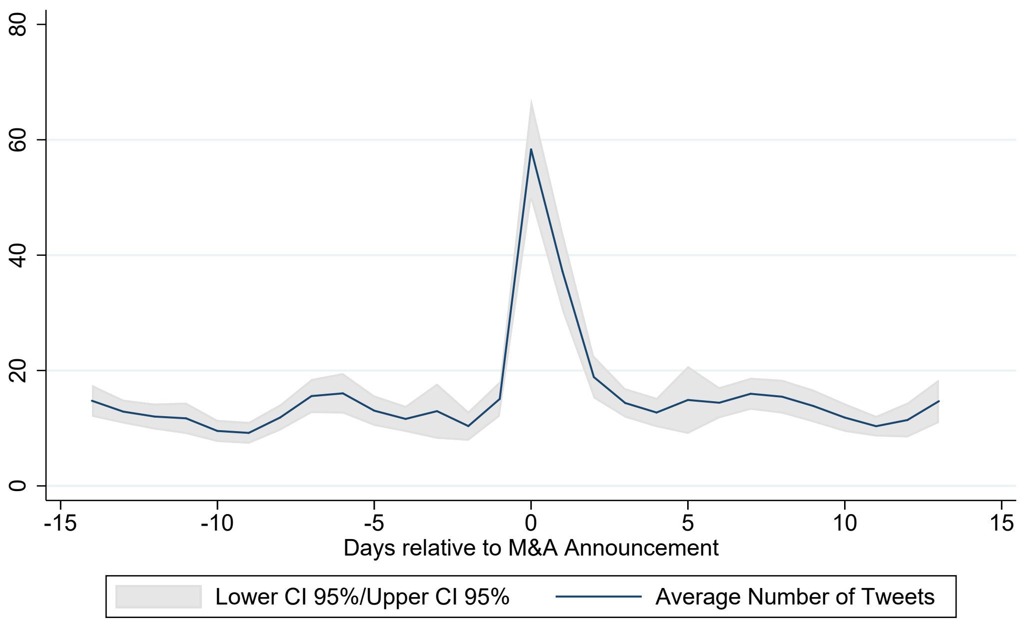


Figure 3: *Notes.* This figure presents a screenshot of a tweet posted to Twitter by user @TheStalwart (Joe Weisenthal) in September 2016. Weisenthal is the co-host of the show "What'd You Miss?" on Bloomberg Television and an editor at Bloomberg Markets.



(a) Tweets from StockTwits around M&A Announcement



(b) Tweets from Psychsignal around M&A Announcement

Figure 4: *Notes.* This figure presents the average number of tweets per day on (a) StockTwits and (b) Psychsignal (Twitter and StockTwits) about the acquiring firm during the [-15;15] day event window around an M&A announcement. In both panels, the graph shows the mean number of tweets (line) and 95% confidence interval (grey shaded area). The sample consists of all English-language tweets which include exactly one cashtag ("$" + Ticker Symbol) to ensure that tweets can be mapped to the acquiring firms in the sample with high accuracy.

Table 1: M&A Deals Summary Statistics

Notes. This table presents summary statistics of the M&A deal characteristics (Panel A), and the M&A announcement returns for both the acquiring and target firms (Panel B) in the sample, whenever available. The sample period is from January 2010 to December 2014. M&A announcement, completion, and withdrawal dates, as well as all deal characteristics summarized in Panel A are from SDC Platinum. I retain all Mergers & Acquisitions announced during the sample period from 2010 to 2014 with a minimum deal value of $25 Million, where the acquiring firm is publicly listed on a U.S. stock exchange. The M&A announcement returns are calculated using stock return data from the Center for Research in Security Prices (CRSP) and a 3-Factor Fama-French model, based on an estimation period of 100 days with a minimum of 70 observations and a gap of 50 days between the end of the estimation period and the event period.

Panel A: M&A Deal Characteristics

	N	Mean	SD	Min	p25	p50	p75	Max
Deal Completed (0/1)	4495	0.938	0.240	0.00	1.00	1.00	1.00	1.00
Deal Value (1 Bill.)	4495	0.858	3.025	0.03	0.07	0.17	0.50	48.08
% Shares Sought	4037	93.340	21.308	1.50	100.00	100.00	100.00	100.00
% Cash Offer	2938	86.038	25.431	0.24	82.44	100.00	100.00	100.00
Acq. is White Knight (0/1)	4495	0.000	0.021	0.00	0.00	0.00	0.00	1.00
Hedge Fund Involved (0/1)	4495	0.004	0.061	0.00	0.00	0.00	0.00	1.00
Challenged Deal (0/1)	4495	0.014	0.117	0.00	0.00	0.00	0.00	1.00
Poison Pill (0/1)	4495	0.003	0.054	0.00	0.00	0.00	0.00	1.00
Privatization (0/1)	4495	0.001	0.026	0.00	0.00	0.00	0.00	1.00
Target Public (0/1)	4495	0.279	0.449	0.00	0.00	0.00	1.00	1.00
Deal was Rumored (0/1)	4495	0.056	0.230	0.00	0.00	0.00	0.00	1.00
Deal Friendly (0/1)	4495	0.861	0.346	0.00	1.00	1.00	1.00	1.00

Panel B: M&A Announcement Returns

	N	Mean	SD	Min	p25	p50	p75	Max
CAR Acq. [0;0]	4282	0.007	0.043	-0.17	-0.01	0.00	0.01	0.38
CAR Acq. [0;1]	4282	0.011	0.062	-0.31	-0.01	0.00	0.03	0.59
CAR Acq. [-1;1]	4282	0.011	0.064	-0.31	-0.01	0.00	0.03	0.59
CAR Acq. [0;5]	4282	0.011	0.078	-0.36	-0.02	0.01	0.04	0.80
CAR Acq. [-5;-1]	4282	-0.001	0.040	-0.27	-0.02	-0.00	0.02	0.25
CAR Target [0;0]	1082	0.109	0.200	-0.40	-0.00	0.02	0.16	1.26
CAR Target [0;1]	1082	0.148	0.221	-0.43	0.01	0.05	0.24	1.26
CAR Target [-1;1]	1082	0.150	0.224	-0.48	0.01	0.06	0.24	1.25
CAR Target [0;5]	1082	0.150	0.227	-0.43	0.00	0.06	0.24	1.34
CAR Target [-5;-1]	1082	0.007	0.059	-0.27	-0.02	0.00	0.03	0.39
Acq. MCap. (1. Bill.)	4380	10.679	29.242	0.02	0.78	2.10	6.97	300.61

Table 2: (Social) Media Summary Statistics

Notes. This table reports summary statistics for the social media sentiment estimates from StockTwits (Panel A) and Psychsignal (Panel B), as well as newspaper coverage and sentiment scores from Ravenpack (Panel C) during the [0;6] day window around the M&A announcement events in the sample. The measures of social media sentiment in Panel A are constructed using Maximum Entropy and Naive Bayes text classification, as detailed in Section 2.1.2. 'Bullish (Max. Entr.)' and 'Bullish (Bayes)' measure the average probability that a tweet is positive (i.e. "bullish") across the tweets about the acquiring firm in the event window using the two text classifiers, respectively. Social media feedback, i.e. 'Abnormal Bullish', is constructed as the difference between 'bullish' during the announcement event window and a similar 7-day period before the event window. 'Bullish/Bearish Ratio' in Panel B is constructed as the ratio of tweets rated bullish over the number rated bearish by Psychsignal. 'Abn. Bullish/Bearish' is constructed in the same way as 'Abnormal Bullish'. 'RPNA Sentiment' in Panel C is based on the sentiment scores of M&A related, unique newspaper articles published on Dow Jones Newswires, obtained from Ravenpack. Following Gao et al. (2017), I calculate 'RPNA Sentiment' as the ratio of the difference of positive minus negative articles over the total number of articles on the subject. Details are provided in Section 2.3.2.

Panel A: StockTwits Posts

	N	Mean	SD	Min	p25	p50	p75	Max
Bullish (Max. Entr.)	2743	0.79	0.12	0.02	0.73	0.80	0.87	1.00
Bullish (Bayes)	2743	0.85	0.12	0.00	0.80	0.87	0.93	1.00
Number of Posts	2743	36.98	293.62	1.00	2.00	6.00	14.00	8339
Avg. Official Users	2743	0.16	0.25	0.00	0.00	0.04	0.22	1.00
Avg. # Followers (1000)	2743	7.62	10.00	0.00	0.60	3.90	10.45	60.86
Avg. # Likes	2743	0.03	0.10	0.00	0.00	0.00	0.00	1.94
Abn. Bullish (Max. Entr.)	1866	0.02	0.17	-0.85	-0.08	0.00	0.10	0.73
Abn. Bullish (Bayes)	1866	0.02	0.16	-0.85	-0.06	0.01	0.08	0.84
Abn. Number of Posts	1866	25.06	197.99	-483.00	0.00	3.00	12.00	5142
Abn. Avg. Official Users	1866	0.01	0.28	-1.00	-0.03	0.00	0.11	1.00
Abn. Avg. # Followers (1000)	1866	0.15	11.47	-60.50	-2.60	0.27	4.60	51.17
Abn. Avg. # Likes	1866	-0.00	0.13	-1.00	0.00	0.00	0.00	1.61

Panel B: Psychsignal Posts

	N	Mean	SD	Min	p25	p50	p75	Max
Bullish/Bearish Ratio	4056	0.724	1.42	0.00	0.00	0.00	0.86	14.66
Number of Posts	4056	184.118	981.03	1.00	14.00	38.00	111.00	34378
Abn. Bullish/Bearish Ratio	3734	0.407	1.36	-8.54	0.00	0.00	0.57	13.67
Abn. Number of Posts	3734	102.824	671.13	-2339.00	2.00	18.00	65.00	23000

Panel C: Ravenpack Newspaper Articles

	N	Mean	SD	Min	p25	p50	p75	Max
RPNA Sentiment	4495	0.005	0.33	-1.00	0.00	0.00	0.00	1.00
Number of Articles	4495	2.931	3.86	0.00	0.00	2.00	4.00	38.00

Table 3: Cross-Correlations

Notes. This table reports cross-correlations between the main variables of interest in this paper. 'Deal Completed (0/1)' is a dummy variable indicating if an announced M&A deal was subsequently completed or withdrawn. All other variables are defined as detailed in Tables 1 and 2. Standard errors are provided in parentheses.

Variables	(1)	(2)	(3)	(4)	(5)
(1) Deal Completed (0/1)	1.000				
(2) CAR Acq. [-1;1]	0.039	1.000			
	(0.011)				
(3) Abn. Bullish Sentiment (Max. Entr.)	0.056	0.032	1.000		
	(0.015)	(0.178)			
(4) Abn. Bullish Sentiment (Bayes)	0.047	0.036	0.840	1.000	
	(0.040)	(0.128)	(0.000)		
(5) Abnormal Bullish/Bearish Ratio	-0.026	0.122	0.010	0.014	1.000
	(0.112)	(0.000)	(0.657)	(0.550)	

Table 4: Social Media Sentiment and M&A Completion

Notes. This table presents linear probability model estimates of the effect of social media feedback on M&A deal completion. *CAR Acq* ([-1;1] and [-5;-1]) is the acquiring firm's Cumulative Abnormal Return for the 3-day window around and 5-day before the M&A announcement date, respectively. *AbnBullish* is the abnormal acquirer sentiment, capturing social media feedback. It is estimated using the Maximum Entropy classifier on StockTwits tweets and constructed as detailed in Section 2.4. All other variables are firm and deal controls as explained in detail in Section 2.2. All regressions include year-by-quarter fixed effects to control for time trends and seasonal effects. Standard errors are clustered at the year-by-quarter level. *, ** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

	Dependent Variable: Deal Completed (0/1)				
	(1)	(2)	(3)	(4)	(5)
CAR Acq. [-1;1]	0.288***	0.331**	0.318**	0.288**	0.0774
	(3.55)	(2.59)	(2.53)	(2.54)	(1.11)
CAR Acq. [-5;-1]	0.0217				
	(0.15)				
Abn. Bullish (Max. Entr.)			0.122***	0.105**	0.122***
			(2.95)	(2.63)	(3.64)
Deal Value (1 Bill.)	-0.0141***	-0.0127***	-0.0126***	-0.0107***	-0.0105***
	(-5.53)	(-3.47)	(-3.49)	(-4.02)	(-4.89)
MCap (1000 Bill.)	0.366***	0.231**	0.236**	0.0576	0.258**
	(3.48)	(2.15)	(2.26)	(0.49)	(2.33)
Acq. is White Knight (0/1)				0.612***	0.631***
				(4.12)	(5.00)
Hedge Fund Involved (0/1)				0.146***	0.0406***
				(33.65)	(12.40)
Challenged Deal (0/1)				-0.258***	-0.334***
				(-3.50)	(-4.56)
Privatization (0/1)				-0.817***	-0.934***
				(-56.54)	(-81.09)
Deal Rumored (0/1)				0.0935***	0.0199
				(3.32)	(0.72)
Target Private (0/1)				0.114***	0.0100
				(7.95)	(1.44)
Deal Hostile (0/1)				-0.729***	-0.777***
				(-4.80)	(-4.26)
% Shares Sought					0.00126**
					(2.57)
Year×Quarter FE	Yes	Yes	Yes	Yes	Yes
Observations	2770	1248	1248	1248	1023
R^2	0.036	0.041	0.045	0.115	0.229
Adjusted R^2	0.027	0.023	0.027	0.093	0.205

Table 5: Robustness – Social Media Sentiment and M&A Completion

Notes. This table presents robustness tests on the effect of social media feedback on the likelihood of M&A deal completion. Columns 1 to 4 presents results from linear probability models, column 5 is estimated as a conditional logit model. *AbnBullish* (*MaxEntr.*) and *AbnBullish* (*Bayes*) measure social media feedback using the Maximum Entropy and Naive Bayes classification algorithm on StockTwits data, respectively. *CAR Acq* [-1;1] and *CAR Target* [-1;1] are the acquiring and target firm's Cumulative Abnormal Return for the 3-day window around the M&A announcement date, respectively. *Newspapersentiment* and *numberofarticles* are from Ravenpack, as detailed in Section 2.3.2. All other control variables are similar as in Table 4. All regressions include year-by-quarter fixed effects to control for time trends and seasonal effects. Standard errors are clustered at the year-by-quarter level. *, ** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

	Dependent Variable: Deal Completed (0/1)				
	Newspaper Controls	Alternative Sentiment Measure	Only Public Targets	At least 15 Postings	Logit Model Estimation
	(1)	(2)	(3)	(4)	(5)
Abn. Bullish (Max. Entr.)	0.119***		0.172**	0.198***	4.000***
	(4.29)		(2.34)	(3.14)	(4.29)
Newspaper Sentiment	0.0923***				
	(3.37)				
Number of Articles	0.000460				
	(0.32)				
Abn. Bullish (Bayes)		0.109***			
		(3.22)			
CAR Acq. [-1;1]	0.0807	0.0781	0.488*	0.300*	3.304
	(1.21)	(1.10)	(1.75)	(1.84)	(1.40)
CAR Target [-1;1]			0.512***		
			(5.74)		
Firm Controls	Yes	Yes	Yes	Yes	Yes
Deal Controls	Yes	Yes	Yes	Yes	Yes
Year×Quarter FE	Yes	Yes	Yes	Yes	Yes
Observations	1023	1023	460	492	897
R^2	0.253	0.227	0.176	0.160	
Adjusted R^2	0.228	0.203	0.119	0.107	

Table 6: Psychsignal Sentiment and M&A Completion

Notes. This table presents linear probability model estimates of the effect of social media feedback on M&A deal completion, using data from Psychsignal. The main variable of interest, *Abn. Bullish/Bearish Ratio* is the ratio of tweets about the acquiring firm classified as positive over tweets classified as negative during the event window ([0;6]). Details are provided in Section 2.3.1 and 2.4. *CAR Acq* ([-1;1] and [-5;-1]) is the acquiring firm's Cumulative Abnormal Return for the 3-day window around and 5-day before the M&A announcement date, respectively. *AbnBullish* is the abnormal acquirer sentiment, capturing social media feedback. It is estimated using the Maximum Entropy classifier on StockTwits tweets and constructed as detailed in Section 2.4. *CAR Acq* [-1;1] and *CAR Target* [-1;1] are the acquiring and target firm's CAR for the 3-day window around the M&A announcement, respectively. $Newspapersentiment$ and $numberofarticles$ are from Ravenpack, as in Table 5. All other variables are firm and deal controls as explained in detail in Section 2.2. All regressions include year-by-quarter fixed effects to control for time trends and seasonal effects. Standard errors are clustered at the year-by-quarter level. *, ** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

	Dependent Variable: Deal Completed (0/1)	
	Full Sample	Only Public Targets
	(1)	(2)
Abnormal Bullish/Bearish Ratio	0.00324**	0.00608***
	(2.44)	(3.29)
CAR Acq. [-1;1]	0.161*	0.453**
	(1.99)	(2.53)
CAR Target [-1;1]		0.410***
		(7.05)
Newspaper Sentiment	0.0644***	0.0986***
	(4.14)	(2.83)
Number of Articles	0.00891***	0.00654***
	(4.68)	(2.84)
Deal Value (1 Bill.)	-0.00929***	-0.00974***
	(-3.99)	(-3.74)
MCap (1000 Bill.)	-0.0559	0.00794
	(-0.41)	(0.03)
Acq. is White Knight (0/1)	0.723***	0.738**
	(3.46)	(2.76)
Hedge Fund Involved (0/1)	0.100**	0.308***
	(2.68)	(6.29)
Challenged Deal (0/1)	-0.354***	-0.376***
	(-4.20)	(-4.42)
Deal Rumored (0/1)	0.0183	0.112*
	(1.09)	(1.97)
Deal Hostile (0/1)	-0.668***	-0.725***
	(-10.74)	(-7.38)
Target Public (0/1)	-0.168***	
	(-8.29)	
Year×Quarter FE	Yes	Yes
Observations	2373	863
R^2	0.217	0.204
Adjusted R^2	0.205	0.171

Table 7: Tweet Characteristics and Social Media Feedback

Notes. This table presents linear probability model estimates of the effect of tweet reach, visibility, and credibility on the sensitivity of M&A deal completion on social media feedback. *Avg. Likes* is the average number of likes the tweets about the acquiring firm received during the event period. Similarly, *Abn. Abg. Followers* and *Abn. Avg. Official Users* measure the average number of followers and the average number of tweets sent by users with officially verified profiles during the event period, relative to a similar period before the M&A announcement. All other variables of interest and controls are constructed similarly as in Tables 4 and 5. All regressions include year-by-quarter fixed effects to control for time trends and seasonal effects. Standard errors are clustered at the year-by-quarter level. *, ** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

	Dependent Variable: Deal Completed (0/1)		
	(1)	(2)	(3)
Abn. Bullish (Max. Entr.)	0.0938	0.0794	0.0839
	(1.64)	(1.32)	(1.36)
Abn. Bullish × Avg. Likes	1.316**		
	(2.02)		
Abn. Bullish × Abn. Avg. # Followers (1000)		0.00798*	
		(1.76)	
Abn. Bullish × Abn. Avg. Official Users			0.291*
			(1.77)
Abn. Number of Posts (1000)	0.0173	0.00110	0.00917
	(0.76)	(0.05)	(0.41)
Abn. Avg. # Followers (1000)	-0.0000888	-0.000619	-0.00000553
	(-0.09)	(-0.49)	(-0.00)
Avg. Likes	-0.213**	-0.106	-0.105
	(-1.99)	(-1.21)	(-1.22)
Abn. Avg. Official Users	0.00832	0.0450	0.0143
	(0.18)	(0.83)	(0.31)
CAR Acq. [-1;1]	0.347***	0.295**	0.297**
	(2.75)	(2.28)	(2.25)
Deal Controls	Yes	Yes	Yes
Acq. Firm Controls	Yes	Yes	Yes
Year × Quarter FE	Yes	Yes	Yes
Observations	1167	1089	1158
R^2	0.123	0.127	0.117
Adjusted R^2	0.096	0.098	0.093

Table 8: Price Informativeness and Feedback from Social Media

Notes. This table presents linear probability model estimates of the effect of stock price informativeness on the sensitivity of M&A deal completion on social media feedback. $(1-R^2)$, PIN, and $abs(CAR)$ are the price non-synchronicity, probability of informed trading (PIN), and absolute value of the M&A announcement CAR of the acquiring firm, respectively. $(1-R^2)$ and PIN are measured at the quarterly frequency, $abs(CAR)$ is measured during the [-1;1] event window around the M&A announcement. All other variables of interest and controls are constructed similarly as in Tables 4 and 5. All regressions include year-by-quarter fixed effects to control for time trends and seasonal effects. Standard errors are clustered at the year-by-quarter level. *, ** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

	Dependent Variable: Deal Completed (0/1)					
	INFO = (1-R2)		INFO = PIN		INFO = Abs(CAR Acq. [-1;1])	
	(1)	(2)	(3)	(4)	(5)	(6)
INFO	-0.00800	-0.00423	-0.0338	0.00238	-0.0954	-0.0917
	(-1.01)	(-0.71)	(-0.47)	(0.04)	(-0.49)	(-0.65)
Abn. Bullish (Max. Entr.)	0.174***		0.185***		0.185***	
	(3.47)		(2.65)		(3.70)	
Abn. Bullish × INFO	-0.0595**		-0.521*		-1.664**	
	(-2.29)		(-1.70)		(-2.48)	
Abnormal Bullish/Bearish Ratio		0.00521***		0.00584*		0.00334**
		(2.95)		(1.92)		(2.28)
Abn. Bullish/Bearish × INFO		-0.00352**		-0.0271*		-0.0453***
		(-2.32)		(-1.66)		(-3.07)
CAR Acq. [-1;1]	0.216*	0.293***	0.199*	0.188**	0.261	0.339***
	(1.98)	(3.52)	(1.92)	(2.38)	(1.68)	(2.93)
Deal Controls	Yes	Yes	Yes	Yes	Yes	Yes
Acq. Firm Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1246	2306	1248	1867	1248	2309
R^2	0.306	0.302	0.303	0.305	0.305	0.298
Adjusted R^2	0.288	0.291	0.285	0.293	0.287	0.287