Can Social Media Inform Corporate Decisions? Evidence from Merger Withdrawals*

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Abstract

This paper studies whether social media sentiment can predict merger withdrawals. We find that a standard deviation increase in social media sentiment after a merger announcement is associated with a 0.64 percentage points lower probability of withdrawal (16.6% of the average). This effect is unexplained by abnormal price reactions, traditional news, and analyst recommendations. Consistent with manager learning, the informativeness of social media strengthens after firms start corporate Twitter accounts. The informativeness is driven by longer acquisition-related tweets by fundamental investors, rather than memes and price trend tweets. These findings suggest that social media signals can be important for corporate decisions.

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1 Introduction

The rapid expansion of new data sources and increasing adoption of financial technology have transformed the way investors interact with markets. Today, investors share opinions and investment ideas on social media platforms (Bradley, Hanousek Jr, Jame, and Xiao, 2021), mobile apps allow investors to access financial information from anywhere via their smartphones (Kalda, Loos, Previtero, and Hackethal, 2021), and sophisticated investors like hedge funds rely on real-time trading signals extracted from social media (Grennan and Michaely, 2021).[1] At the same time, investors' use of social platforms was at the center of recent trading frenzies (Pedersen, 2021), sparking concerns about how these platforms shape and maintain investor attention (Barber, Huang, Odean, and Schwarz, 2022). Though there is debate about whether social media benefits investors, the literature paints a clear picture that investor behavior is influenced by social media.

In this paper, we investigate an important related question: does social media influence corporate decisions of firm managers? This is a natural question given that external information, like prices or traditional news sources, has been shown to shape the decision-making of firm management (Edmans, Goldstein, and Jiang, 2012). However, given that social media is often a source of noise, it is not obvious *ex ante* that firm managers should learn from social media, unlike, for example, traditional news. If social media is a useful signal for firm managers, this would be novel evidence that social media matters for corporate information environments, not just investors and markets.

Our paper shows that social media can be a valuable input to firm decision-making. We study an important class of corporate investment decisions, Mergers & Acquisitions (or M&A), which are among the most consequential investments that firms make (Andrade, Mitchell, and Stafford, 2001; Renneboog and Vansteenkiste, 2019). Our empirical tests investigate how the decision to withdraw an acquisition depends on the social media reaction to the acquisition's announcement. Our core finding is that a negative social media reaction significantly increases the likelihood that an announced merger is withdrawn. Our tests control for other reasons for merger withdrawals, such as learning from market reactions, traditional news, or analyst recommendation changes. In fact,

[1] See for example: `https://www.wsj.com/articles/tweets-give-birds-eye-view-of-stocks-1436128047`. A growing literature in finance has studied the role of social media for financial markets, focusing on investor disagreement (Cookson and Niessner, 2020), 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).

controlling for these alternative external signals does little to influence the estimated magnitude on the social media reaction.

Identifying an effect of social media on corporate decisions is empirically challenging for several reasons. First, corporate decisions affect social media directly, raising the possibility of reverse causation. Indeed, recent work has highlighted how firms use financial technologies to disclose information and communicate with investors (Blankespoor, Miller, and White, 2014; Elliott, Grant, and Hodge, 2018). Second, it is challenging to observe *firm-specific* social media sentiment across a broad cross-section of firms. Third, even with such information available, traditional investment proxies, like CAPX, are only available quarterly at best, which does not facilitate showing a compelling link to social media information, which arrives at high frequency.

Our empirical setting overcomes these challenges. First, we construct a firm-specific daily measure of social media sentiment using the investor social platform StockTwits. Like Twitter, StockTwits users share short messages (henceforth 'tweets') with their followers. However, unlike Twitter, StockTwits users primarily discuss financial markets and individual stocks. Users use 'cashtags' followed by a ticker (e.g., $AAPL for Apple stock) to tweet about a specific firm.[2] Using this information, we measure social media sentiment for a broad cross-section of firms by aggregating tweet-level sentiment to the stock-day level. Second, M&A transactions are useful because they allow us to observe the precise merger announcement date *and* the ultimate outcome of the transaction (deal completion or withdrawal). Building on Luo (2005), the intuition for our main test is simple: as long as announced acquisitions reflect genuine intentions of firm management to proceed with the takeover, the decision to withdraw an announced merger reflects an update in the firm manager's beliefs. If the social media reaction to the merger announcement predicts merger outcomes, holding constant other signals that matter for merger withdrawals, we interpret this as evidence that social media sentiment is a useful input for corporate decisions. In fact, this evidence suggests that firm managers may have learned from social media itself as in similar tests by Liu and McConnell (2013) who study information feedback from traditional media.

[2]By 2020, StockTwits had over 2 million unique users, including roughly 400,000 who post regularly (Cookson, Engelberg, and Mullins, 2022). Many of the most active users are professional traders and investors (Bartov et al., 2018; Cookson and Niessner, 2020). Further, since 2011 tweets and sentiment measures provided by 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. Figure 1 presents several examples of these firm-specific tweets in the wake of Adobe's recent announcement of their intention to acquire Figma.

We implement this empirical strategy using a comprehensive sample of acquisition announcements of public and private targets over the period from 2010 to 2021. We estimate that a standard deviation decrease in abnormal StockTwits sentiment increases the likelihood of a merger withdrawal by 0.64 percentage points or 16.6% of the unconditional likelihood of a merger withdrawal. This estimated coefficient is robust to the inclusion of other signals (e.g., acquisition announcement CARs as in Luo, 2005, traditional news sentiment as in Liu and McConnell, 2013, and analyst recommendation changes as in Becher, Cohn, and Juergens, 2015), deal characteristics, acquirer firm controls, and industry and year-by-quarter fixed effects. None of these controls diminish the estimated magnitude, increasing our confidence that the negative estimated coefficient is not driven by an omitted characteristic (e.g., Oster, 2019). Further, we find a similar negative relation between abnormal social media sentiment and merger withdrawals when we measure social media sentiment using data from Twitter rather than StockTwits. Our findings are also robust to using two alternative machine learning sentiment classifications, to focusing on public firms and large firms, and to only examining serial acquirers while adding firm fixed effects.

Next, we shed empirical light into the nature of the information contained in the social media signal. First, we find that the informativeness of social media sentiment is strongest after firms register a corporate Twitter account, especially if the account is active, which provides a conduit for firms to listen to investor commentary about the M&A announcement. Second, we find that the informativeness of social media sentiment is driven by the tweets of fundamental investors, and is not explained by the abnormal sentiment emanating from technical investors who primarily rely upon charts of past volume and returns, not fundamental information. Similarly, we find that the informativeness of social media is driven by longer tweets that likely contain more detailed analysis, not short tweets that merely convey sentiment. Third, using a topic model (biterm modeling, BTM, which works well for short messages like tweets), we decompose the social media signal into tweets about different topics that are informative of fundamental information (company discussions, discussion of deal terms, etc.) versus discussions that are not (meme tweets, and technical tweets). Consistent with the fundamental component of the signal driving its informativeness, we estimate that these fundamental topics are more tightly related to merger withdrawals, whereas memes and technical tweets are not. Fourth, social media sentiment predicts merger withdrawals most strongly when the associated analyst conference call uses a high fraction of constraining and negative terms. Consistent with a feedback mechanism whereby management learns from external sources, this difference emerges from the Q&A portion of the conference call, not the scripted presentation portion.[3]

Overall, this evidence paints a consistent picture that social media helps shape the corporate decision to withdraw or proceed with a merger. This evidence provides a systematic empirical rationale for why 'Social Media Monitoring' (SMM) has emerged as a new industry with companies such as Hootsuite, Sprout Social, TweetReach, Falcon.IO, and Keyhole who now offer continuous monitoring and analysis of online content to help inform managers.

Although these findings are consistent with a learning channel, our evidence of learning, like in much of the literature, is indirect. Consequently, there are two other potential interpretations of the main result. First, social media might not lead managers to update their evaluation of the merger, but could act as an external governance mechanism as in Liu and McConnell (2013) who study traditional media's influence on merger withdrawals. In this view, empire-building managers learn from social media whether their actions are being monitored, and thus whether they will be held to account by investors. A negative social media reaction is informative to managers because it checks their ability to extract private benefits. A second alternative interpretation is that social media is informative about the final outcome of the deal, not because managers pay attention and learn from the social media signal, but because social media correlates with unmeasured factors that predict merger withdrawals. Consistent with this channel driving part of the main result, we estimate a significant negative relation between social media sentiment and merger withdrawals for deals blocked by regulators and deals rejected by the target. Though significant, this estimate is only one third of the magnitude of our main result. Indeed, consistent with the learning channel, we find that social media's effect on merger withdrawals strengthens after the firm adopts a Twitter account. We thus interpret our evidence as implying that much of the variation is driven by manager learning. Even in cases where manager learning cannot influence the outcome, our results still imply that social media is *informative* and that managers could learn something from social media feedback.

[3]The paper includes several other robustness exercises. For example, we verify that our use of a linear probability model instead of a logistic regression is inconsequential. We also perform a propensity score matching exercise, and obtain similar findings to our main approach of OLS regression with controls. We also observe that the results are strongest for deals where the social media signal contains more tweets. Lastly, we see that the effect is largest in periods with greater economic and financial volatility; it is also larger for more complex deals and for deals where the acquirer uses stock as a method of payment. These are precisely the time periods and kinds of deals in which management can benefit most from learning.

Our paper makes several contributions to the literature on how firms and markets are influenced by financial technology, which is a growing area of interest in financial economics (Philippon, 2016). Our analysis provides a novel perspective on the informativeness of FinTech by showing that social media sentiment is a valuable signal of the likelihood of merger withdrawal. The literature is divided on whether the introduction of financial technologies that increase access to data, like social media platforms, leads to more or less informativeness. On one side, social media is thought to amplify behavioral biases (Heimer, 2016), reflect inefficient patterns of attention (Barber et al., 2022; Cookson et al., 2022), generate trading frenzies (Pedersen, 2021), and lead to inefficient information processing (Bradley et al., 2021).[4] On the other side, firms devote significant resources to social media engagement (Blankespoor et al., 2014), subscribe to services that provide social media analytics, and in normal times, social media signals have been found to contain valuable information content (Bartov et al., 2018; Farrell, Green, Jame, and Markov, 2022). Our results contribute to this literature in two ways. First, our results support the perspective that social media signals can be informative. Second, unlike most of this literature, which examines investor and financial market responses to social media signals, we show that social media can be informative for *firms* as they make consequential investment decisions.

In linking social media signals to real decisions by firms, our findings ought to be of interest to the literature at the intersection of financial markets and corporate decisions (e.g., Chen, Goldstein, and Jiang, 2006, Foucault and Frésard, 2012, 2014, Edmans, Jayaraman, and Schneemeier, 2017, Bond, Edmans, and Goldstein, 2012, and Goldstein, 2022), which has been a topic of interest for decades (Morck, Shleifer, Vishny, Shapiro, and Poterba, 1990). This literature has shown that stock market reactions help inform corporate decisions across a variety of contexts, including M&As, SEOs and management earnings forecasts (Luo, 2005; Kau, Linck, and Rubin, 2008; Giammarino, Heinkel, Hollifield, and Li, 2004; Zuo, 2016). Relative to this literature, our results show that non-price signals from social media contribute meaningfully to the firm information environment beyond the well-documented price feedback effects. In this respect, our findings relate closely

[4]There is a related literature that studies the indirect effect of FinTech and social media on price informativeness. Recent work in this vein offers a similar tension to the literature on social media informativeness: 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. These results provide a contemporary counterpoint to the classic perspective in financial economics that price informativeness declines as information becomes cheaper to access (Grossman and Stiglitz, 1980; Verrecchia, 1982).

to Liu and McConnell (2013) who study the informativeness of traditional media sentiment for M&As. Although we empirically confirm that both price feedback and feedback from traditional news media are important determinants of merger withdrawals, we highlight that social media is an important and distinct non-traditional source of information that has a similar weight in management decision-making.

Our paper also contributes to the literature on financial technology and firms' decision-making. In the context of wealth management companies, previous research has examined the uptake of robo-advising, stressing its challenges as a new technology (D'Acunto, Prabhala, and Rossi, 2019). In a similar vein, recent work has examined the implications of mobile apps and other financial platforms, emphasizing their uptake by consumers (Olafsson and Pagel, 2018; Benartzi and Levi, 2020). This research implies tangible benefits to firms, particularly financial firms, adopting financial technologies to serve their customers. Unlike much of this literature on financial technology, our research shows an impact of financial technology beyond the financial firms that employ it as a business strategy. In this respect, our paper is closely related to research that examines the use of social media as a channel for strategic information disclosure and investor relations management (e.g., Jung, Naughton, Tahoun, and Wang, 2017, Blankespoor et al., 2014, and Elliott et al., 2018). We complement this emerging line of research by showing that social media is not merely a tool for disclosure, but can be a source of information for firms. Our findings imply that this information is a valuable input to important corporate decisions: social media does not merely lead to market fluctuations, but it can drive firm investment decisions as well.

2 Data and Descriptive Statistics

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

2.1 Financial Social Media

Our main data source for social media sentiment is the financial social media network StockTwits. StockTwits users post tweets with a limited number of characters, similar to Twitter, but in contrast to Twitter, StockTwits is primarily focused on financial markets. Upon logging in, the user sees a newsfeed of the most recent tweets about stocks they are interested in or tweets by users they are currently following. By including a so-called 'cashtag', a dollar sign ($), followed by a ticker symbol, StockTwits users can specify that their post refers to a specific firm or security. For example, if a StockTwits user wanted to express a positive opinion about Apple Inc. on the platform, they could say "$AAPL is making a great acquisition, you should buy!" Using cashtags, we can unambiguously identify which companies are discussed across a large sample of tweets. In addition, StockTwits allows users to attach an optional sentiment tag to their tweet indicating if their tweet reflects "bullish" or "bearish" sentiment.

Since its launch in 2008, the StockTwits platform has grown rapidly. In 2020, users generated over 6.5 million tweets per month. The StockTwits newsfeed is integrated in many online platforms used by finance professionals, 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 onto StockTwits website or app. Owing to this broad integration with other tools, StockTwits has become popular among financial market participants and professionals including asset and investment managers, news letter writers, and financial journalists (Cookson and Niessner, 2020).

We obtain the time-stamp, raw-text, and user-provided sentiment tags (when available) of every message posted to StockTwits between January 2010 and December 2021, in total over 260 million individual tweets. We retain tweets that include at most two cashtags ("$" + Ticker Symbol) about any publicly listed U.S. company. The vast majority of the tweets in our sample (90.33%) include exactly one cashtag. This ensures that we are able to link a tweet to a specific stock and reduces ambiguity in interpreting tweets, as users frequently include multiple popular cashtags (e.g. $FB, $GOOG, $AAPL) to generate attention or share their opinion on a sector or industry.

Our data also include a sentiment score for each tweet, which is calculated and provided by StockTwits based on a proprietary text classification algorithm called MarketLex. According to StockTwits, this methodology uses lexical and semantic rules based on a custom-built lexicon for social finance, constructed from a combination of words and phrases from 4 million messages with user-provided bullish or bearish tags and manual human supervision. The final sentiment score for each tweet is a continuous measure that is normalized to be between -1 (extremely bearish) to +1 (extremely bullish).

Figure 1 presents several tweets about the recent acquisition announcement by Adobe of Figma, a company that developed a web application for interface design. These select tweets convey the range of information that is posted by users to StockTwits. For example, many users post fundamental information in support of their views (see Panel 1a), while other users adopt technical strategies (see Panel 1b). Thus, within StockTwits, different kinds of messages ought to provide different amounts of information to managers. In the mechanisms section, we exploit these differences to shed insight into what information matters for firm managers.

To provide further confidence in our estimates, in addition to the sentiment scores provided by StockTwits, we calculate our own sentiment scores based on the content of each tweet. Specifically, we apply the Maximum Entropy and Naive Bayes classifier algorithms to the raw text content to classify tweet sentiment, following Antweiler and Frank (2004), Cookson and Niessner (2020), and others. Section A.I in the Appendix provides details on the procedure and a verification exercise demonstrating that our text classification approach reliably classifies tweet sentiment.

While our main measure of social media feedback relies on StockTwits tweets and data, we also include social media sentiment based on Twitter provided by the social media data provider "Social Market Analytics" (SMA). SMA uses Natural Language Processing, Topic Modeling, and Source Rating to identify posts related to firms and financial content, and constructs measures of social media sentiment, post volume, and social media "buzz" from individual messages posted to Twitter. SMA aggregates Twitter information for each stock in their coverage at the daily frequency, starting in 2012.

2.2 Mergers & Acquisitions

Next, we construct a sample of M&A deals using data from SDC Platinum. We obtain all mergers announced during the sample period from 2010 to 2021 with a minimum deal value of $25 Million. To be able to match M&A deals with StockTwits sentiment, we limit the sample to deals where the acquiring firm is publicly listed on a U.S. exchange, a total of 7,726 unique M&A deals. In addition to key deal characteristics such as the announcement date, deal value, and percentage of shares sought, we collect data on whether an announced deal was ultimately completed or withdrawn, as well as the withdrawal date. We retain only deals with a disclosed dollar value that were either completed or withdrawn, and drop pending and intended deals.

Following the literature (e.g. Bates and Lemmon, 2003; Luo, 2005; Boone and Mulherin, 2007; Betton, Eckbo, Thompson, and Thorburn, 2014; Jacobsen, 2014), we further obtain data on deal characteristics that have been shown in the literature to be related to merger withdrawals, such as the deal payment form (cash vs. stock), the presence of a white knight, anti-takeover provisions, and the presence of rumors prior to deal announcement as controls in the sample. A detailed description of all deal characteristics obtained from SDC Platinum is available in Appendix Table A.12.

In addition, we compute Cumulative Abnormal Returns (CARs) for both the acquiring and target firms for several event windows around each M&A announcement, using the Fama-French 3-Factor model and stock return data from the Center for Research in Security Prices (CRSP). We use an estimation period of 100 days with a minimum of 70 observations with a gap of 10 days between the end of the estimation period and the event period to compute expected and abnormal returns. Since many target firms are private, stock return data are unavailable and CARs cannot be computed for these targets. We obtain standard financial and accounting data from Compustat North America. Each variable (market capitalization, cash holdings, leverage) is winsorized at the 5% level within the full Compustat universe. We further obtain data on analyst recommendations from IBES, and construct changes in analyst recommendations following Becher et al. (2015).

2.3 Other Data Sources

2.3.1 Traditional News Media

We additionally obtain sentiment measures for traditional news media related to the M&A deals in our sample from RavenPack. We rely on the latest available version of RavenPack (i.e., RPA 1.0), which includes coverage of premium newswires (such as Dow Jones, Benzinga, MT Newswires, Alliance News, FX Street, The Fly), many providers of regulatory news and press releases, and over 22,000 web publications. For each acquirer and target firm in our sample, we 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 and older stories. To alleviate concerns that media reports during this window are reflecting news other than the M&A announcement, we retain only articles and stories related to "mergers/acquisitions" as categorized by RavenPack.[5]

[5]In addition to the 'ESS' measure, we construct an alternative news media sentiment measure following Gao, Parsons, and Shen (2017): we classify each news article as positive (negative) if 'ESS' is in the upper (lower) tercile of

2.3.2 Analyst Conference Call Transcripts

We obtain analyst conference call transcripts from Refinitiv's "Transcripts and Briefs" data set, formerly known as StateStreet, from 2010 to 2021. We focus on the transcripts that are tagged as "M&A Calls/Presentations." We identify the sections of the analyst conference call transcripts related to the management's scripted presentation and the analyst questions & answers, and construct measures of text content and sentiment for each section. Specifically, we calculate the proportion of 'constrained,' 'negative,' and 'positive' words in the presentation section and the Q&A section of the transcript, respectively, as defined in Loughran and McDonald (2016) and Bodnaruk, Loughran, and McDonald (2015), using the 2022 version of the Loughran and McDonald (2011) Master Dictionary. We further calculate the average word length, number of words, and number of unique words (i.e., 'vocabulary') of the two sections for each transcript as control variables.

2.4 Tweets about M&A deals

To construct our final sample, we merge the M&A deals from SDC Platinum with StockTwits social media sentiment using StockTwits cashtags + ticker, and add news media sentiment data from RavenPack, conference call transcript data from Refinitiv, and financial and accounting data from CRSP and Compustat. We begin by plotting the daily number of tweets about the acquirer and target firms in Figure 2 to provide additional confidence that StockTwits users indeed discuss M&A deals in their tweets. As shown, the number of tweets about either type of firm is stable leading up to the M&A announcement day and increases sharply on days $t = 0$ and $t = 1$, indicating that the merger announcement is not anticipated by social media users and creates a significant increase in social media activity.

Figure 3 further confirms that the increase in tweets documented in Figure 2 is directly related to the merger announcements, by documenting the number of tweets about the acquirer firm that include the 'cashtag' + ticker of the target firm before and after the merger announcement. In the 'pre' period before the merger announcement, the average number of tweets about the acquirer that also mention the target firm is indistinguishable from zero. In the 'post' period, this number increases from zero to approximately 20, a margin similar to the increase in the total number of

all news articles in the sample, and calculate M&A-related news media sentiment over the announcement window as the number of 'positive' minus 'negative' newspaper articles, scaled by the total number of news articles.

tweets documented in Figure 2.

Figure 4 further supports the interpretation that social media users actively discuss the deal after a merger announcement. For both the acquirer (Fig. 4a) and the target (Fig. 4b), we plot the proportion of tweets that mention M&A related words (i.e., "merger", "acquisition", "m&a", "takeover", "acquirer", "target"). As shown in Figure 4, the proportion of tweets containing these M&A words more than quadruples on the day of the merger announcement, and stays elevated for at least 10 days.

2.5 Variable Construction and Summary Statistics

We next provide summary statistics for the merged sample in Table 1, splitting the sample into completed and withdrawn M&A deals.

[Insert Table 1 here.]

The final sample of M&A announcements with available StockTwits sentiment data for the acquiring firms contains 6,438 unique M&A deals, out of which 6,187 were eventually completed and 251 were eventually withdrawn. This is a deal withdrawal rate of approximately 3.9%, consistent prior literature (e.g. Luo, 2005).

Summary statistics for the full set of variables in the paper are presented in Appendix Table A.2. Most M&A transactions in the sample are full takeovers, the median percentage of shares sought is 100% (mean of 96.71% for completed and 95.91% for withdrawn deals).

The sample split in Table 1a is consistent with existing work on what correlates with M&A completion. For example, acquirer CARs and traditional news sentiment are greater for completed deals than for withdrawn deals as in Luo (2005) and in Liu and McConnell (2013), respectively. Turning to the social media signal, there is significant information contained in social media around announcements of both completed and withdrawn mergers. As seen in Table 1a, the average number of tweets about the acquiring firm around the M&A announcement date is 193.32 (148.04) for completed (withdrawn) mergers. Though there is more initial posting activity around eventually completed mergers, this difference is not statistically significant.

Our interest is in evaluating if differences in social media *sentiment* are informative of deal completion. In this case, simply considering the StockTwits sentiment at announcement in the cross-section might be misleading, as the average *level* of sentiment varies significantly across stocks. Indeed, in the raw data, users are more likely to be positive than negative in their tweets; the mean sentiment score obtained from StockTwits following an M&A announcement is 0.125 (0.110), with an inter-quartile range of 0.218 (0.181).[6] To address this issue, we construct the abnormal sentiment around M&A announcements as follows:

$$\text{AbnSent}_i = \left(\frac{1}{|J_{i,[0,3]}|} \sum_{j \in J_{i,[0,3]}} Sentiment_{i,j(t)} \right) - \left(\frac{1}{|J_{i,[-13,-7]}|} \sum_{j \in J_{i,[-13,-7]}} Sentiment_{i,j(t)} \right) \quad (1)$$

$Sentiment_{i,j(t)}$ is the social media sentiment of tweet j about acquiring firm i, which occurs on day t relative to the merger announcement date ($t = 0$). The set of tweets about firm i between date t_1 and t_2 is denoted as $J_{i,[t_1,t_2]}$, and the $|\cdot|$ operator counts the number of tweets in such a set. Thus, the first summation is the tweet-level average sentiment of tweets posted on days $t = 0$ through $t = 3$ relative to the merger announcement date, and the second summation is the tweet-level average sentiment of tweets posted in a reference period that occurs 7 to 13 days prior to the merger announcement, following Da, Engelberg, and Gao (2011). Constructed this way, $AbnSent_i$ captures the change in average tweet-level sentiment during the announcement period relative to a similar period before the M&A announcement became public. To address concerns about information leakage, the estimation period for average stock-specific sentiment during 'normal' times ends 7 days before the M&A announcement. In our baseline estimations, we use the tweet-level sentiment scores provided by StockTwits as $Sentiment_{i,j(t)}$ with a four-day announcement period, i.e., $T = 3$. This time window matches the pattern in Figure 2, which shows the number of M&A-related tweets is elevated on days $t = 0$ to $t = 3$ relative to the announcement. In robustness tests, our results are similar using sentiment measures based on the Maximum Entropy and Naive Bayes classifier algorithms and alternative event period definitions.

The summary statistics in Table 1a indicate that using abnormal sentiment scores successfully removes differences in the level of sentiment around M&A announcements. $Abnormal\ Sentiment_i$ based on sentiment scores obtained from StockTwits is centered around an average (median) of

[6] The mean sentiment score using the Maximum Entropy or Naive Bayes Classifier is similarly positive with an average of 0.834 and 0.780, respectively. Note that the Maximum Entropy and Naive Bayes sentiment scores are distributed over the [0,1] interval and the StockTwits sentiment is between -1 and 1. Thus, these average sentiment numbers are not as different as they appear.

0.022 (0.016) with an inter-quartile range of -0.121 to 0.174 for completed mergers (Panel A.2a) and an average (median) of -0.030 (0.000) for withdrawn deals (Panel A.2b). By focusing on *abnormal* sentiment, the average M&A announcement reaction is similarly centered around zero when using Maximum Entropy and Naive Bayes classifier-based sentiment scores instead, with average (median) values of 0.038 (0.027) and 0.018 (0.013) for completed mergers, and -0.009 (-0.015) and -0.012 (-0.013) for withdrawn deals.

The social media signal is distinct from other notable signals. In Table 1b, we present several cross-tabulations that provide insight into whether the abnormal sentiment from StockTwits differs from the signals from equity markets (CAR), traditional news media, and analyst recommendations. We split all four signals into positive (negative) if the signal is above (below) 0. The table contrasts *AbnSent* with the other three signals. There is significant dispersion of abnormal StockTwits sentiment within both positive and negative values of other signals (CAR of the acquirer, news sentiment, and analyst recommendations). For example, conditional on a positive CAR, the StockTwits signal is only *somewhat* more likely to be positive than negative: 55% of positive CAR deals have positive *AbnSent* versus 45% with negative *AbnSent*. Thus, a positive social media sentiment reaction to the merger announcement is not simply a reflection of the market reaction. The same broad conclusion holds for traditional news sentiment and analyst recommendations. These cross-tabulations imply that there is unique variation in abnormal StockTwits sentiment, distinct from market reactions, news sentiment, and analyst recommendation changes.

3 Results

3.1 Information from Social Media and M&A Withdrawals

This section presents several results on how merger withdrawals relate to the content of social media following the announcement of the merger. We evaluate whether social media contains *unique information* that is useful for predicting the likelihood of merger withdrawal that is unavailable from other public signals that firm managers are known to rely upon − e.g., the market reaction to the merger announcement, traditional news media, and analyst recommendations (Luo, 2005; Kau et al., 2008; Liu and McConnell, 2013), and seek to quantify how important it is relative to these traditional sources of feedback.

Using deal-level information, we estimate the following linear probability model:[7]

$$Deal\ Withdrawn_i = \beta_1 \times AbnSent_i + \beta_2 \times CAR_i + \Gamma \cdot \mathbf{X_i} + \alpha_\mathbf{t} + \gamma_\mathbf{j} + \epsilon_\mathbf{i} \tag{2}$$

where $Deal\ Withdrawn_i$ is an indicator variable that takes the value of one if the announced M&A deal i was subsequently withdrawn and zero otherwise. For ease of interpretation, we multiply the dependent variable by 100 in all regressions. The main coefficient of interest is β_1, which captures how responsive deal withdrawals are to changes in abnormal social media sentiment about the deal ($AbnSent_i$). We control for the Cumulative Abnormal Return following the M&A announcement (CAR_i) to both ensure that $AbnSent_i$ does not merely reflect market information and to benchmark the importance of social media feedback against market feedback. The specification also includes a rich set of controls ($\mathbf{X_i}$) that are known to influence M&A outcomes,[8] as well as year-by-quarter fixed effects (α_t) to control for time trends such as merger waves, and acquirer industry (GIC 2-digit) fixed effects (γ_j) to account for industry differences in M&A withdrawals. Standard errors are clustered at the year-by-quarter level.

[Insert Table 2 here]

The results from estimating Equation (2) are summarized in Panel (a) of Table 2. Our core finding is that abnormal social media sentiment exhibits a significant negative relation to the likelihood of deal withdrawal. To avoid potential issues of bad controls that can bias the estimate of β_1 (Angrist and Pischke, 2008), we first estimate Equation (2) without including control variables or fixed effects. The estimate in column 1 indicates that a standard deviation *decrease* in $AbnSent_i$ is associated with a 0.64 percentage point *increase* in the likelihood of merger withdrawal. This estimated magnitude reflects an increase of 16.6% of the baseline rate of merger withdrawals (3.89% of mergers are withdrawn in our sample). In column 2, when we enrich the specification by employing time (year-by-quarter) and industry (GIC2) fixed effects, as well as several high level deal and acquirer controls, we obtain a slightly larger estimate of 0.77. For ease of interpretation, we standardize all variables of interest to have mean zero and standard deviation of one.

[7]In the appendix, Table A.3, we present the estimates from a fixed-effects logit model, which delivers a similarly significant and negative relation between abnormal social media sentiment and the likelihood of deal withdrawal.

[8]The controls include the acquirer firm's market capitalization, the dollar value of deal i, and 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

Next, we sequentially enrich the specification with other market signals (i.e., $CAR[-5,-1]$ and $CAR[1,10]$), news media sentiment from RavenPack, analyst recommendation changes, other deal-level controls, and fixed effects. As shown in columns 2 through 6, the coefficient magnitude on $AbnSent_i$ is quite stable, despite the inclusion of additional controls increasing the R^2 from 7.1% (column 2) to 21.6% (column 6). This coefficient stability places a high bar on the criticism that an important omitted variable could be driving the connection between social media sentiment and merger withdrawal (e.g., see Oster, 2019).

Examining these other estimated coefficients, the coefficient on $CAR[-1,10]$ highlights the importance of market feedback. We estimate a negative and significant coefficient on the market M&A announcement return, which implies that a more positive market reaction at the time of the merger announcement is associated with a lower likelihood of merger withdrawal. Beyond confirming the results in Luo (2005) for our sample of M&A transactions from 2010 to 2021, this result provides a useful quantitative benchmark for our main result. A standard deviation increase in $CAR[-1,10]$ is associated with roughly a 0.88 percentage point reduction in the likelihood that the merger is withdrawn, which is similar to the implied reduction in merger withdrawals when abnormal social media sentiment increases by a standard deviation. Further, neither estimated effect is sensitive to the inclusion of the other, suggesting that these two signals capture distinct information.

In column 5, we include news media sentiment from RavenPack. We find that a standard deviation increase in news sentiment is associated with a 1.02 percentage point decline in the likelihood of a merger withdrawal, consistent with Liu and McConnell (2013) who use negative words from the Loughran and McDonald (2011) dictionary. As with the market reaction terms, the magnitude on news sentiment is similar to the social media sentiment, and its inclusion does not meaningfully change the estimate on $AbnSent_i$. Further, this specification also controls for the amount of media attention by including the number of news articles and the number of tweets about the acquiring firm around the announcement, which reduces the concern that attention to the deal and not the sentiment drives the main result.

Finally, in column 6, we also control for analyst recommendation changes around the announcement of the merger. Following Becher et al. (2015), we construct this variable as the sum of analyst recommendation upgrades and coverage initiations with a 'strong buy' recommendation, minus the sum of analyst downgrades and coverage initiations with a '(strong) sell' recommendation.[9] Consistent with Becher et al. (2015), we find that a standard deviation increase in analyst recommendation changes is associated with approximately one percentage point reduction in the likelihood of merger withdrawal. However, the inclusion of analyst recommendation changes does not meaningfully affect our estimated coefficient on $AbnSent_i$. This specification also controls for the number of analyst recommendations, which accounts for differences in analyst attention.

3.1.1 Measurement of Social Media Sentiment

A natural question regarding the main result is whether the abnormal sentiment from StockTwits is distinctive, or if sentiment from other social media sites (e.g., Twitter) would paint the same picture. To evaluate this, we obtain firm-day Twitter sentiment scores from Social Market Analytics (SMA), a firm that provides sentiment information to professional investors. To evaluate whether the Twitter signal matters for merger withdrawals, we construct a similar abnormal Twitter sentiment measure around the merger announcements from SMA's sentiment data for our sample time period. SMA data are only available starting from 2012. Thus, we are only able to construct this measure on the subset of merger announcements from 2012 onward. However, as we show in column 1, of Table 2 Panel (b), the coefficient estimate on the StockTwits abnormal sentiment measure (-0.706) is quite similar to the estimate we obtain in the full sample.

Next, column 2 presents result from estimating the specification using abnormal Twitter sentiment. Consistent with our findings from the StockTwits signal, we estimate a strong negative relation between abnormal Twitter sentiment and merger withdrawal likelihood: A standard deviation decrease in Twitter sentiment is associated with 1.075 percentage points greater likelihood of merger withdrawal. This finding suggests that social media is more broadly related to merger withdrawal.

Finally, in column 3, we present the estimates from a specification that includes both abnormal sentiment measures (StockTwits and Twitter). Strikingly, both signals remain highly statistically significant and negatively related to merger withdrawals *even after holding constant the other abnormal sentiment measure.* The fact that both signals have distinctive content suggests that different social media signals contain slightly different information regarding the likelihood of merger withdrawal. This finding makes sense given that the sentiment signal from StockTwits and Twitter

[9] Becher et al. (2015) construct this variable over the entire window between merger announcement and resolution. To be consistent with their approach, we construct our measure in a similar way, with a maximum of 100 days between announcement and resolution.

are distinct from one another (Cookson, Lu, Mullins, and Niessner, 2022). For example, StockTwits users are specifically focused on discussing investment topics, whereas Twitter investors might discuss a wider array of topics relating to firms.

Another issue with employing sentiment measures is that measuring social media sentiment is an inherently noisy enterprise. In this respect, both SMA's Twitter sentiment and StockTwits sentiment scores are a black box. To alleviate concerns that these black box measures were constructed in a way that leads to the correlation with merger withdrawals, we next examine whether the main results are robust to alternative measurement of social media sentiment that we construct ourselves. Specifically, we employ our own textual classification: we train two alternative classifiers (a Maximum Entropy classifier and a Bayesian classifier), and use each of them to impute the sentiment of unclassified tweets.[10] We aggregate the sentiment from these alternative classifications to the stock-day level, and then use this modified sentiment index to construct measures of abnormal social media sentiment, following the same procedure we use for the main measure as detailed in Section 2.5.

Columns 1 and 2 in Panel (a) of Table 3 present the estimates using these alternative measures of social media M&A announcement reaction. A standard deviation increase in these alternative measures is associated with a 0.427 to 0.584 percentage points lower likelihood of merger withdrawal, which is 11.3% to 15.4% of the mean rate of M&A deal withdrawal. This magnitude is somewhat smaller than the magnitudes we estimated with StockTwits' primary sentiment measure, but the qualitative conclusion is the same: a more negative social media reaction to deal announcement is associated with a greater likelihood of merger withdrawal. It makes sense that the signal using StockTwits' own algorithm or SMA's algorithm has more predictive power. Managers might buy social media signals about their own firm either from StockTwits directly or from vendors like SMA. In that case, they would be learning from those signals, rather than our self-classified versions. Therefore, for the rest of the paper, we use the sentiment measure provided to use by StockTwits.

[10] Section A.I in the Appendix explains in detail how we construct sentiment scores using the Maximum Entropy and Naive Bayes classifier. Further, in Appendix Table A.1 we compare the sentiment scores across 20 samples with randomly drawn training samples. As shown, considering both abnormal sentiment around M&A announcements (Panel A.1a) and sentiment in the overall sample period (Panel A.1b), the correlation across samples is between 0.85 to 0.90, indicating that our Maximum Entropy and Bayesian classifiers consistently measure sentiment.

3.2 Robustness

In this section, we present several robustness exercises and subsample tests that highlight the pervasiveness and robustness of the relationship between social media sentiment and merger withdrawals. Table 3 presents the estimates from these robustness exercises.

[Insert Table 3 here]

3.2.1 Public Targets and Target Sentiment

First, we evaluate the subset of deals with public targets. Public targets represent a minority of the mergers in our sample − only 880 mergers with public targets out of 6,306 in the full sample − however, these mergers account for most of the aggregate deal value and they attract significant scrutiny from investors and outsized media coverage (both traditional and social). In column 3, we present estimates from a specification that restricts the sample to deals with public targets. We also control for the market reaction for the target stock, both target $CAR[-5,-1]$ and $CAR[-1,10]$. We obtain an estimated magnitude that is much larger than our main estimates in Table 2: a standard deviation decrease in abnormal sentiment is associated with a 2.13 percentage point increase in the likelihood of merger withdrawal. This represents approximately 53% of the baseline likelihood of merger withdrawals for the sample of public merger announcements.

Within this subset of public targets, we can also construct an abnormal sentiment measure based on the tweets about the target firm. Columns 4 and 5 present estimates from a specification that additionally controls for abnormal sentiment about the target ticker. The correlation between the abnormal sentiment about the acquirer and the target is 0.9. However, despite this high correlation, controlling for the abnormal sentiment about the target does not change the estimated impact of acquirer abnormal sentiment much, and the inclusion of the target's abnormal sentiment does not explain merger withdrawals beyond the acquirer's abnormal sentiment. Column 5 additionally controls for the target's market reaction to the deal announcement, which does not meaningfully influence the estimate on the abnormal sentiment term.

In column 6 we additionally include the target spread – i.e., the percentage difference between the offer price and the target stock price 2 days after the merger announcement – as a market-based proxy of the likelihood of deal completion. In line with the idea that a larger spread between offer price and target stock price indicates a higher chance that the deal falls through, we estimate a significant positive coefficient on the target spread. However, the inclusion of the target spread term does not materially affect our estimated coefficient on $AbnSent_i$. That is, the social media term does not merely reflect the market evaluation of the likelihood of the deal going through, but contains unique information about the likelihood of deal completion.

3.2.2 Small Deals and Serial Acquirers

Next, we evaluate whether the main finding is driven by small deals that do not matter much economically in the merger market. To do this, we re-estimate the main specification after dropping small deals (i.e., deals in the bottom quartile of our sample with respect to deal value). In column 7, we see that in this subsample there is a slightly larger sensitivity of merger withdrawals to social media sentiment: a standard deviation increase in abnormal social media sentiment is associated with a 1.171 percentage point decline in the likelihood of a merger withdrawal.

Finally, we address the concern that firm-specific unobservable characteristics drive the relation between social media sentiment and merger withdrawal. To do this, in column 8, we estimate Equation (2) with acquirer fixed effects as in Golubov, Yawson, and Zhang (2015). This specification purely relies on within-acquirer variation in merger withdrawals and social media sentiment, and therefore can only be estimated for the subset of acquirers that make at least two acquisition announcements in our sample period. Despite the stringency of this test, we estimate a very similar magnitude relationship between social media sentiment and merger withdrawal after accounting for acquirer fixed effects.

3.2.3 Reasons for Merger Withdrawal

One issue with interpreting our main result as evidence of learning by management is that some merger withdrawal decisions are made by entities outside of the acquiring firm, and therefore, cannot reflect learning by managers from the information in social media. In this case, social media is useful as a *prediction* for eventual merger withdrawal, but it is not used as a source of feedback. To understand how much this mechanism contributes to our results, we use the "deal history" field in SDC Platinum to restrict our sample to withdrawn mergers for regulatory reasons and by the target shareholders or board.

Panel 3b of Table 3 presents the estimated coefficients after restricting our sample only to deals that were withdrawn for external reasons. For the regulator-withdrawn mergers, the estimated coefficient is -0.202 while the estimated coefficient for target-withdrawn mergers is -0.150. Though the *AbnSent* coefficient estimate is statistically significant at the 5% level for regulator-withdrawn mergers, the magnitude is less than one-third of the magnitude in our main tests (and is insignificant for target-withdrawn mergers). That is, much of the relationship of social media sentiment and merger withdrawal likelihood goes away when we focus on cases in which social media plays purely a predictive role.

3.2.4 Evidence from Propensity Score Matching

In this section, we describe a complementary propensity score matching (PSM) exercise. Angrist and Pischke (2008) show that PSM approaches can be thought to be equivalent to flexibly controlling for covariates in an OLS estimation of the same specification. However, PSM can more transparently show how matching helps to restore balance on observable characteristics. We perform a propensity score match ($k = 10$ nearest neighbor matching with replacement) on the full set of deal and acquirer controls, as well as matching within year and within industry (GIC2). Figure A.3 shows that, without matching, the withdrawn versus completed mergers are quite different on a number of observable dimensions, including propensity score distance, deal size, and several types of the deal characteristics (e.g., competing bidder deals, rumored deals, and hostile deals). After matching, the matched control sample of completed deals is statistically indistinguishable from the sample of withdrawn deals along all of these dimensions.

Table A.4 presents the estimates of Equation (2) on the matched sample, which yields a *stronger* negative and significant estimate than the result without matching. A standard deviation increase in abnormal social media sentiment is associated with a 3.198 percentage point reduction in the likelihood of merger withdrawal. This magnitude is larger only partly because the matched sample is more likely to have merger withdrawals than the full sample. The estimated magnitude is 21.67% of the baseline rate of merger withdrawals (average is 14.76% in the matched sample), which is slightly larger than the main specification without matching. These findings further alleviate omitted variable concerns.

3.3 Social Media Sentiment and Post-Announcement Returns

A natural question based on our previous main result is whether abnormal social media sentiment provides useful information about stock return performance following the announcement of the merger. To address this question, we study the relationship between the social media reaction to the deal announcement, the ultimate outcome of the deal, and the acquirer's stock returns between the announcement and the conclusion of the merger. Specifically, we compute the buy-and-hold abnormal returns (BHAR) for the event window $[11; T_{conclusion}]$ starting 11 days after the merger announcement up until the date of the deal *conclusion* ($T_{conclusion}$), i.e., either the completion date or withdrawal date of the deal.

We explicitly focus on the entire window from deal announcement to eventual conclusion for this exercise, because information about the eventual withdrawal often occurs well before the deal conclusion. Thus, for this exercise, we take the return over the entire interim period ($BHAR_{[11;T_{conclusion}]}$) to be the dependent variable in a regression that relates the initial abnormal sentiment reaction to the merger announcement to the subsequent stock returns, while conditioning on deal outcome. Specifically, we estimate the following specification:

$$\begin{aligned} BHAR_{i,[11;T_{conclusion}]} &= \beta_1 \times \mathbb{1}(Deal\ Withdrawn)_i + \beta_2 \times AbnSent_i \\ &\quad + \beta_3 \times \mathbb{1}(Deal\ Withdrawn)_i \times AbnSent_i + \Gamma \cdot \mathbf{X_i} + \epsilon_\mathbf{i} \end{aligned} \tag{3}$$

where the dependent variable is $BHAR_{i,[11;T_{conclusion}]}$, the accumulated buy-and-hold abnormal return from 11 days after the merger announcement until the deal conclusion (withdrawal or completion), $\mathbb{1}(Deal\ Withdrawn)_i$ is an indicator variable that equals one for withdrawn mergers and zero for completed mergers, and $AbnSent_i$ is the StockTwits abnormal sentiment around the merger *announcement* date. We include the same set of industry (GIC2) and time (year-by-quarter) fixed effects, as well as deal and firm controls as in earlier specifications. Critically, we include interactions between the $\mathbb{1}(Deal\ Withdrawn)_i$ indicator and the other proxies for market and media feedback − i.e., deal announcement CARs and news sentiment. The main coefficient of interest is the coefficient on the interaction β_3, which captures how useful the initial social media sentiment reaction is for predicting how investors react to the eventual withdrawal versus completion of the merger. For example, a negative coefficient on β_3 means that an initially negative social media reaction predicts that the market will eventually respond positively to a merger withdrawal.

[Insert Table 4 here]

We estimate Equation (3) on the subset of deals that have an interim period that lasts longer than 25 days (75 days) to ensure that the merger's prospects are not already understood by the market at the time of the merger announcement. Table 4 presents the estimates from this specification. Across specifications, we estimate a negative and significant coefficient on $\mathbb{1}(Deal\ Withdrawn)_i \times AbnSent_i$. This finding implies that the market eventually celebrates the withdrawal of an announced merger that engenders a negative social media reaction at the announcement. Specifically, if a merger announcement saw a standard deviation lower sentiment reaction, our estimates imply that the withdrawal of the merger (rather than its completion) leads to between 10.09% and 15.28% higher returns from 11 days after the merger announcement until its conclusion.

4 Heterogeneity and Mechanisms

In this section, we present several tests that provide sharper insight into the nature of information contained in abnormal social media sentiment, as well as how it is potentially used by managers to inform their merger withdrawal decisions.

4.1 Acquirers' Social Media Engagement

Our main tests draw a robust connection between abnormal social media sentiment and the likelihood of merger withdrawal. The social media sentiment reaction could be informative of merger withdrawal decisions because it correlates with another information source that managers use, or because social media is a source of information unto itself. To shed light into the relative weight of these two channels, we assemble a comprehensive dataset of corporate Twitter accounts for the acquirer firms in our sample. From the profile information, we observe the account registration date, number of followers, and whether the account is a verified account.[11]

[11] Our observation of verified accounts precedes Twitter's policy change that allowed users to purchase verified status. That is, *verified* in our data constitutes external verification by Twitter that the account is indeed an official account associated with the company.

If firms use social media as an information source, the estimated coefficient on *AbnSent* should be larger for the subset of acquisitions in which the acquirer is engaged with social media, either because those firms are more likely to see posts about their firms, or because the managers are more likely to be open to purchasing social media signals from vendors. Indeed, this is what we find: in the Appendix, Table A.5 presents the results from a sample split, which highlights that acquirers that have a Twitter presence at the time of the merger announcement exhibit a much stronger link between *AbnSent* and the likelihood of merger withdrawal.

To formalize this relationship, we construct a test that uses the timing when the corporate Twitter account was registered. Specifically, we estimate the following specification:

$$Deal\ Withdrawn_i = \beta_1 \times AbnSent_i + \beta_2 \times AbnSent_i \cdot Post_{i,t} + \beta_3 \times Post_{i,t} + \Gamma \cdot \mathbf{X_i} + \alpha_\mathbf{t} + \gamma_\mathbf{j} + \epsilon_\mathbf{i} \quad (4)$$

Relative to the baseline specification in Equation (2), this specification includes the $Post_{i,t}$ indicator variable that equals 1 for acquisitions by firm i that take place after firm i registers its Twitter account. In addition, the specification employs the same set of controls—including CAR_i, which is subsumed into the $\mathbf{X_i}$ term for brevity.

[Insert Table 5 here]

Table 5 presents the results from estimating Equation (4). Columns 1 and 2 estimate how the sensitivity of merger withdrawal to *AbnSent* changes after the formation of *any* corporate Twitter account. The subsequent columns require the Twitter account to have above-median number of followers (columns 3 and 4) or to be verified by Twitter (columns 5 and 6). Across all specifications, we estimate a negative β_2 coefficient on the interaction. This indicates that the sensitivity of merger withdrawal likelihoods increases after an acquirer forms a presence on Twitter.

The coefficient estimates in columns 1 and 2 (any Twitter account) are not statistically significant, but their magnitude is similar to the baseline *AbnSent* coefficient. As some firms open a Twitter account, but almost never use it, we focus on firms with a high degree of social media engagement (high follows or verified Twitter) in columns 3 to 6. For high-engagement firms, the interaction coefficient increases in magnitude and becomes highly statistically significant. This result holds even after including acquirer firm-fixed effects to absorb any time-invariant firm characteristics.

As shown in columns 2, 4, and 6, we find a similar magnitude and statistical significance for the coefficient estimates for $AbnSent_i \times Post_{i,t}$ as in the other specifications. For example, from column 4, a standard deviation decrease in *AbnSent* after an acquirer has an active Twitter account predicts an increase of merger withdrawal likelihood by 0.956 percentage points more than acquisitions announced *when the same firm was not active on Twitter*.

4.2 Nature of Social Media Content

If acquirers use social media to inform corporate decisions, a natural question is whether acquirers are listening to noise or informed analysis. To investigate this question, we present four complementary tests. First, we employ a prominent feature of StockTwits—that many of the investors are technical traders who trade on price patterns rather than fundamental information. Second, we split the social media signal into the signal from short messages versus longer messages that are more likely to contain in-depth analysis. Third, we focus on tweets that talk about M&A related topics, as determined by a Biterm Topic Model. Finally, we split tweets into before and after the GameStop episode of January 2021.

Many users on StockTwits select an investment philosophy in their profile. For users who do not, we construct a textual classifier to classify the tweets into technical ones versus those that rely upon more fundamental information.[12] Consistent with technical investors mostly ignoring fundamental information, Figure 5 shows that the number of tweets by technical investors does not spike around the merger announcement, whereas the fundamental investor tweets increase significantly. This becomes especially evident in Figures 5a and 5b, which specifically show that the number of tweets that discuss M&A-related content or mention the target firm remains flat for technical investors but spikes significantly for fundamental StockTwits users around the merger announcement.

We use this split of users to construct a separate *AbnSent* signal for technical investors and for fundamental investors. To relate this information to merger withdrawal likelihood, we include both signals in a specification like our baseline specification in Equation (2).

[12] Specifically, we classify each StockTwits tweet as 'technical' or not (a category we call 'fundamental'), using a Maximum Entropy classifier trained on the tweets of users who declare themselves as 'technical traders' (i.e., chart formations and patterns, etc.) in their profile.

[Insert Table 6 here]

Table 6 presents the results from estimating this specification. Consistent with managers reacting to fundamental information, we find that *AbnSent* from the fundamental users exhibits a strong negative relation to merger withdrawals, whereas the signal from technical investors does not. Specifically, a standard deviation increase in fundamental sentiment is associated with a 1.08 percentage point reduction in merger withdrawal likelihood. The analogous coefficient on *AbnSent* from technical investors is only -0.274 and is statistically insignificant.

As a complement to the technical versus fundamental split, we investigate whether the social media signal is stronger if it comes from longer messages. Longer messages are more likely to contain in-depth analysis versus short tweets, which tend to contain mostly sentiment and little fundamental information, as seen in Figure 1. To do this, we construct separate *AbnSent* signals based on the subset of messages with below-median tweet length and messages with above-median tweet length. As in the technical versus fundamental tests, we include both of these signals in the same specification.

Columns 3 and 4 of Table 6 present the results from estimating this specification. We find that merger withdrawal likelihood bears a strong negative relation to the abnormal sentiment of longer tweets while bearing no relation to shorter tweets.

Next, we perform a contextual analysis of the tweet topics, and relate different-context tweets to merger withdrawals. To classify tweets into different topics, we train a Biterm Topic Model (BTM) to the StockTwits tweet corpus. We employ BTM because it outperforms alternative topic models (e.g., Latent Dirichlet Allocation) when the corpus is populated by many short texts, such as tweets (Yan, Guo, Lan, and Cheng, 2013).[13] We estimate the BTM with 8 topics on the sample all tweets from the $[0, 3]$ window around merger announcements, and focus our analysis on six of the identified topics that contain meaningful content relevant to the merger announcement, which we label "Company/Business," "Disclosure," "Deal Terms," "Trading,", "Technical," and "Memes." These topics highlight conceptually distinct discussions on StockTwits. For instance, the Trading topic is dominated by discussions of specific positions (buy, sell), the Disclosure topic includes discussions of M&A-specific filings (file, report), the Meme topic most commonly features emojis

[13] Details on the estimation procedure are provided in Appendix Section A.II.

(face, rocket), and the Technical topic features discussions of technical indicators (price, volume, chart). The top 20 words from these topics are presented in Figure A.4 in the appendix.

Using the BTM to classify each tweet into its predominant topic, we next construct separate abnormal sentiment signals for each of these categories, and we relate them to the likelihood of merger withdrawal by including them as in our main specification. The most populated topic is the "Trading" topic, which comprises 42.4% of tweets, and thus all specifications include the abnormal sentiment term based on "Trading" tweets. Then, we include separately the other topics' sentiment terms. Table 6b presents the results from estimating these specifications. Consistent with the abnormal sentiment from discussions of fundamental topics like "M&A Business/Company", "Disclosure", and "Deal Terms" driving the result, we estimate a negative and significant coefficient on each of these terms, but little impact on the baseline "Trading" term, nor any impact on sentiment drawn from "Meme" tweets nor "Technical" tweets. These findings reinforce our main interpretation that the sentiment effect is driven by fundamentally-oriented discussions on social media.

As a complement to these cross-sectional tests, we also perform a test that relies on a sharp change in the informativeness of investor social media sentiment − the rise of meme stock conversations after the GameStop (GME) short squeeze. Bradley et al. (2021) show that, after the GME event in January 2021, Reddit became less informative as a predictor of future returns, while Cookson et al. (2022) show that StockTwits, Twitter, and Seeking Alpha saw a similar decline in informativeness. Based on this logic, we consider the interaction between $AbnSent$ and a post-GME indicator in Appendix Table A.6. Consistent with meme discussions offering less information, we estimate that social media sentiment after January 2021 becomes uninformative for whether a merger is withdrawn. Further, we do not see a similar decline in informativeness of market signals (i.e., we estimate an insignificant interaction between post-GME and CAR), which uniquely pins our evidence to the quality of the social media signal.

Taken together, the evidence in this section suggests that social media is informative insofar as it contains in-depth analysis beyond pure expressions of sentiment about the firm.

4.3 Other Information Sources

Next, we test whether a higher quality of the StockTwits signal carries more information. We proxy for information quality with how many messages (articles) are on StockTwits (traditional media). Table 7 presents a sample split based on how much information there is on social media (columns 1 and 2) versus in traditional media (columns 3 and 4). Consistent with greater information quality in a signal with many tweets, we see that the estimated coefficient is much stronger in the high-number-of-tweets subsample than it is in the low-number-of-tweets subsample. However, the same does not apply to traditional news media: there is a small and insignificant difference between the estimated coefficients in columns 3 and 4 where we split by there being many news articles versus few. Apart from highlighting the quality of the social media signal, these tests also enhance our confidence that the findings are not driven by the volume of traditional news coverage (more so than our main specifications, which control for news sentiment and news volume).[14]

[Insert Table 7 here]

Additionally, we study whether our main effect is driven by times when the social media signal and other signals are closer to one another, or by situations when they disagree. To evaluate this, we compute the absolute value of the difference between the abnormal social media sentiment measure and each of the traditional signals, and split the sample at the median into *high* and *low* disagreement relative to the median.[15] As shown in Appendix Table A.7, the relationship between abnormal social media sentiment and the likelihood of deal withdrawal is driven mostly by the deals where abnormal social media sentiment disagrees with the two traditional signals, i.e. market reaction (column 2) and the sentiment of news media (column 4).

4.4 Information from M&A Conference Calls

Next, we analyze the content of M&A-related conference calls with analysts, which are available for one-third of the merger announcements in our sample. We use the textual corpus from the conference call transcripts in three ways. First, we construct sentiment indexes from the analyst calls themselves to control more finely for the information environment surrounding firm managers and financial analysts of the firm. Second, we consider sample splits of our main tests to evaluate

[14] The ordering of the coefficients for social media goes the opposite direction of the ordering for news sentiment. Comparing the coefficient on *News Sentiment Acq.* in columns 3 and 4, the feedback from traditional news seems to be stronger in the subsample of deals that have a *low* number of news articles written about them.

[15] Abnormal Stocktwits sentiment, CAR and news sentiment are all standardized to be on a common scale between -1 and 1 for this exercise. Consequently, the minimum disagreement is 0, when both abnormal StockTwits and CAR/News Sentiment are equal, and the maximum disagreement is 2 (e.g., example when abnormal social media sentiment -1 and CAR or News Sentiment is +1).

whether the social media signal is more important when there are more negative and constraining words used in these conference calls. Third, we separately examine the textual content of the scripted portion versus the Q&A portion. This split helps disentangle a social media feedback channel from other explanations for the link between social media and deal withdrawals.

We first consider robustness to controlling for the content of conference calls. To do this, we construct *% Positive words* and *% Negative words* as the percentage of positive and negative words using the 2022 version of the Loughran and McDonald (2011) Master Dictionary. Similarly, *% Constrained words* is the percentage of words related to financial constraints as in Bodnaruk et al. (2015). We also compute the average word length, the number of words, and the vocabulary (i.e., number of distinct words used) of the conference call transcript. Not all merger announcements also have a conference call: in our sample, about 5/6 of merger announcements cannot be matched to a conference call (4,928) whereas 1/6 of announcements have a conference call (1,004).

[Insert Table 8 here]

The first three columns of Panel 8a of Table 8 show the difference in the relationship between the abnormal social media sentiment and the likelihood of merger withdrawals for announcements that have a conference call (about 2.56 percentage points higher if there is conference call, see column 1), and the difference in sensitivity of social media sentiment for merger announcements without a conference call (column 2) versus with a conference call (column 3). We estimate a slightly stronger relationship between abnormal social media sentiment and likelihood of merger withdrawals in the conference call sample, but it is not statistically different (p-value of 0.252). Further, in column 4, we control for the textual content of the conference call, obtaining a very similar coefficient estimate for $AbnSent_i$, which changes from -1.288 to -1.305 with the inclusion of textual controls. This finding indicates that abnormal social media sentiment does not merely reflect information contained in conference calls, either disclosed by mangers or discussed by analysts.

In Panel 8b, we consider separate sample splits of *% Constrained Words* and *% Negative words* for the presentation portion of the conference call versus the Q&A portion of the conference call. Interestingly, we see no significant differences in the use of constrained and negative words in the presentation portion but striking differences in the Q&A portion. As the content of the presentation portion is almost exclusively driven by the firm's management, this finding strengthens our view that abnormal social media sentiment's impact on deal withdrawals does not reflect the private intentions or information of management at the time of the conference call. Rather, this result indicates that the social media sentiment is stronger when there is a more contentious give and take between firm management and analysts (or other market observers). This finding is consistent with a social media feedback channel.

4.5 Other Mechanisms and Heterogeneity

Social media feedback into corporate decisions ought to be more valuable when there is greater complexity to the M&A deal, there is more information asymmetry, and the overall market is more volatile. In this section, we present several sample splits that confirm these intuitions using measures constructed in the literature.

4.5.1 Cash versus Stock Acquisitions

The literature has noted that acquisitions that are mostly stock transactions are more sensitive to feedback during the interim period between the merger announcement and eventual deal conclusion (e.g., Bhagwat, Dam, and Harford, 2016). One rationale for this additional sensitivity is that deals where a higher proportion of the acquirer's stock is used are more likely to require a vote by the acquirer shareholders, which may be an important channel for social media sentiment to influence the likelihood of deal completion. Among others, Bates and Lemmon (2003) further argue that the costs of deal negotiation, including price discovery, are higher in stock deals compared to cash deals.

In Appendix Table A.8, we therefore present sample splits based on whether the transaction was a cash deal ($\geq 90\%$ cash) or a stock deal ($\geq 25\%$ stock).[16] In either split, we estimate that stock deals are significantly more sensitive to abnormal social media sentiment than deals that are mostly cash transactions.

4.5.2 Deal Complexity

Social media feedback ought to be strongest if the proposed deal is more complex. To evaluate this, in Table A.9, we present sample splits by complexity of the deal. Following Cohen and Lou

[16] Mergers also include other or unknown sources in the data fields, so these two cuts at the data are not purely the flip side of each other.

(2012) and Aktas, De Bodt, and Roll (2013), we first include the number of SIC (3-digit) industries the target firm operates in as a measure of target firm complexity in columns 1 and 2. Second, Humphery-Jenner (2014) uses the standard deviation in one-period ahead analyst earnings forecasts to define 'hard-to-value' firms, i.e. firms with assets that are difficult to value and quantify. Following this idea, we calculate the average standard deviation of analyst earnings forecasts at the SIC (4-digit) industry level as a measure of information asymmetry, since most private target firms in our sample do not have analyst coverage. Third, Aktas et al. (2013) and Francis, Hasan, Sun, and Waisman (2014) suggest that cross-border mergers involve a higher degree of complexity and hence have a higher potential for management learning and Kang and Kim (2008) document greater information asymmetries for more remote block acquirers. To test this conjecture, we construct an indicator variable for domestic vs. cross-country deals (columns 3 and 4), and split the sample along these dimensions. Forth, Servaes and Zenner (1996) and Bates and Lemmon (2003) argue that deal complexity is positively related to the use of costly M&A advisory and investment banking services. We therefore also include the number of M&A advisors hired by the acquirer and split on the median across deals.

Across these different measures, we consistently estimate a greater sensitivity of deal withdrawal to abnormal social media sentiment for mergers with higher deal complexity, as shown in Appendix Table A.9. The differences across sample splits are significant at the 5% level across three of four tests. Further, while the estimated difference across domestic- and cross-border mergers is marginally insignificant (p-value of 0.139), the consistency of these differences across sample splits paints a reliable picture that the value of the social media signal is stronger in more complex mergers.

In a related vein, we consider whether the social media signal is heterogeneous with respect to the cost of deal withdrawal. If a deal is effectively committed to going through, there may be no opportunity for feedback from social media reactions. To proxy for this, we consider a sample split by whether the merger has a definitive agreement, which essentially commits the management to go through with the deals. We present this sample split evidence in Appendix Table A.10. Consistent with the motivating intuition, we estimate a stronger relationship between abnormal social media sentiment for deals without definitive agreements.

4.5.3 Economic and Market Uncertainty

Following the literature (e.g. Bonaime, Gulen, and Ion, 2018; Cao, Li, and Liu, 2019), we further expect that a more uncertain market environment can make alternative and informative signals, like the social media signal, more valuable. To capture this notion, we consider sample splits based on the S&P500's Volatility Index (VIX), the Baker, Bloom, and Davis (2016) Economic Policy Uncertainty (EPU) Index and the Baker et al. (2016) Equity Market-related Economic Uncertainty. Appendix Table A.11 presents the results from these sample splits, which confirm that the social media signal is most valuable in high economic and financial uncertainty and high volatility times.

5 Conclusion

Social media has rising importance and prominence in today's society. Beyond entertainment and personal connections, social media is increasingly relied upon as a source of *news*. In this paper, we show that social media is also informative for firm managers for the corporate decision about whether to proceed with an announced acquisition of a target firm, a major corporate event. Our tests reveal that the signal from social media is not subsumed by traditional signals that firms are known to use − e.g., merger announcement returns, traditional news media coverage, and analyst forecasts. In fact, the signal value of social media sentiment is strongest when the value of external non-market signals is greatest, such as when deals are more complex and the market is more volatile.

There has been growing concern about the effects of social platforms on markets and investors, particularly as more investors use social media to share investment ideas. However, these concerns would just be a "sideshow" if these "market inefficiencies would merely redistribute wealth between smart investors and noise traders," echoing Morck et al. (1990)'s classic insight from three decades ago. Just as financial markets have been shown to have real effects, our results imply that social media is not a sideshow but is becoming an important part of firms' information environments. As social media becomes more integrated into the social fabric, we anticipate the importance to investors and firms to grow even further. Future research would do well to understand these connections.

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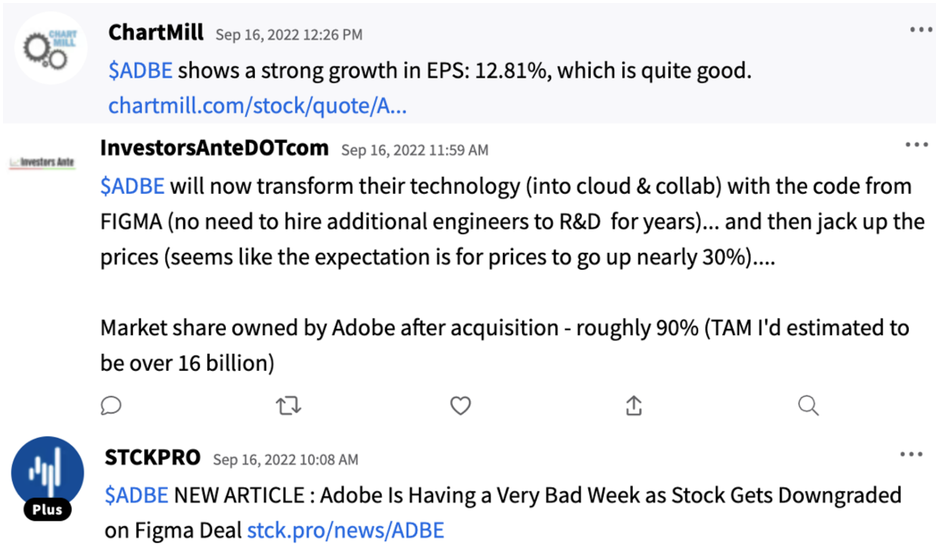
Figure 1: Examples of Tweets about M&A on StockTwits

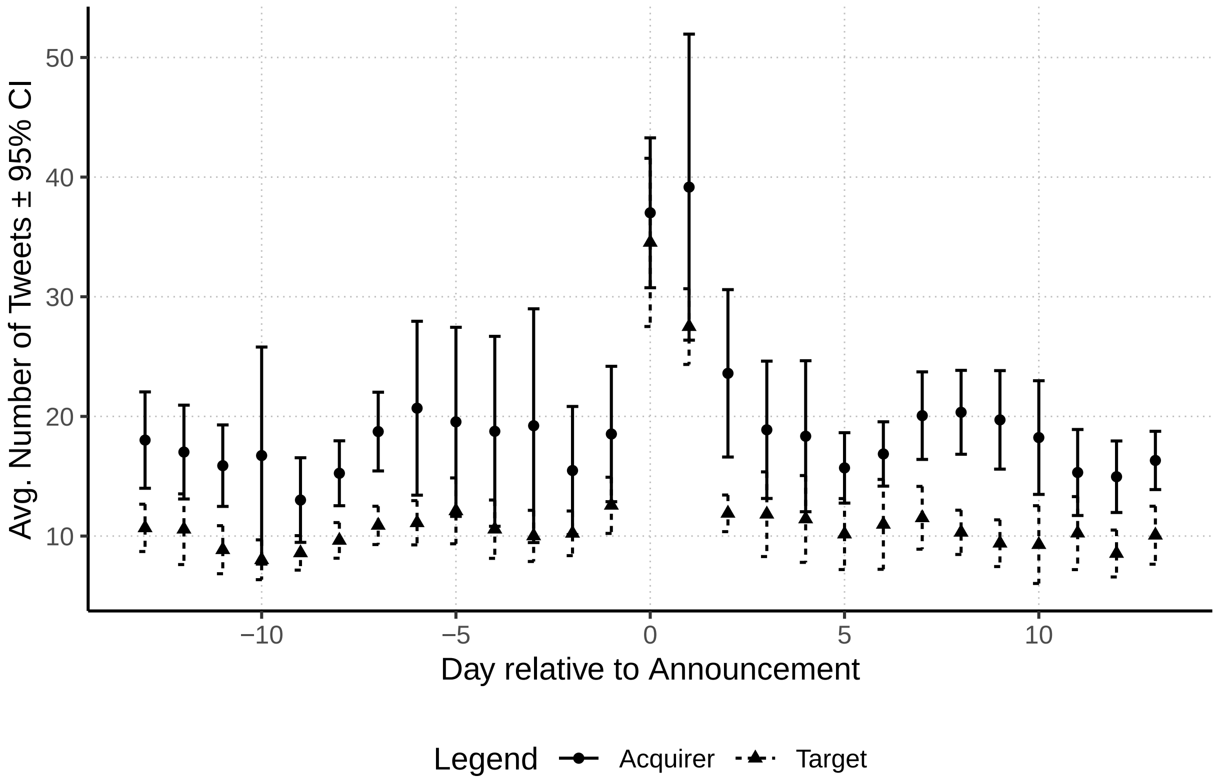


(a) Fundamental Tweets about Merger

(b) Technical and Short Tweets about Merger

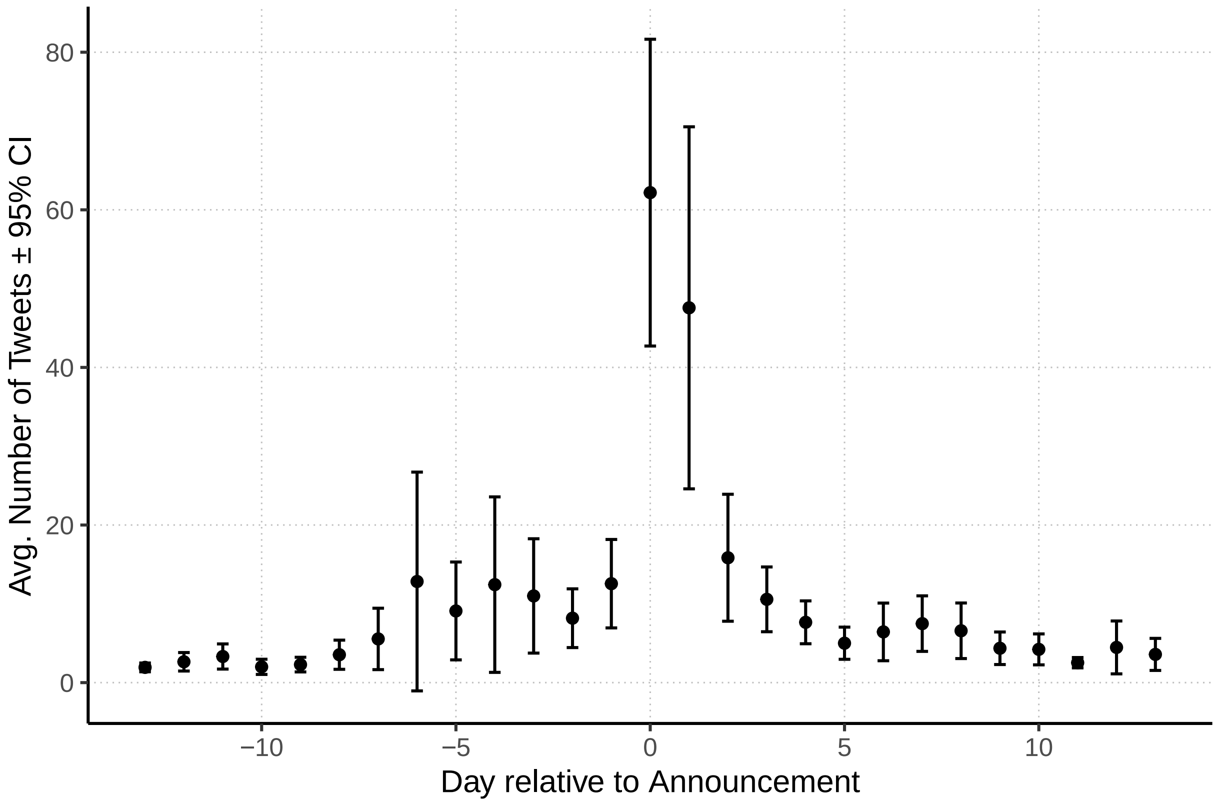
Notes: This figure presents several example tweets about Adobe ($ADBE) on September 16, 2022, which is the day after Adobe announced its intention to acquire the company Figma. Figma is a company that developed a collaborative web application for interface design. Panel (a) presents a selection of fundamentally oriented tweets, whereas Panel (b) presents a selection of short or technically oriented tweets.

Figure 2: Number of Tweets around Merger Announcements



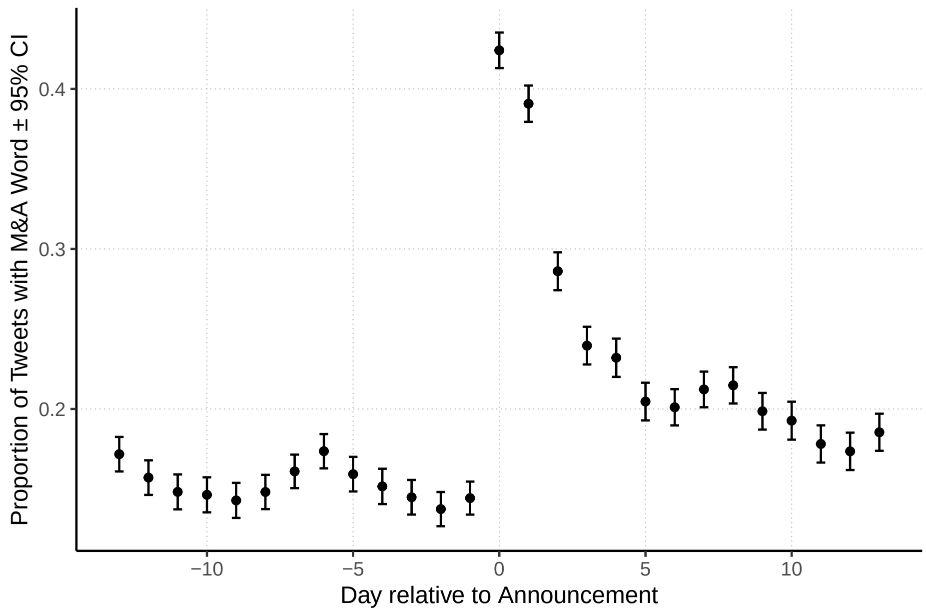
Notes: This figure shows the average and 95% confidence interval of the number of tweets posted to StockTwits around the announcement of an M&A deal that mention the acquiring and target firm, respectively. The solid line displays the numbers for the acquirer firm, the dashed line represents the target firm. The number of tweets about the target firm is only available when the target firm is public, i.e., in StockTwits.

Figure 3: Tweets about Acquirer that include Target Ticker

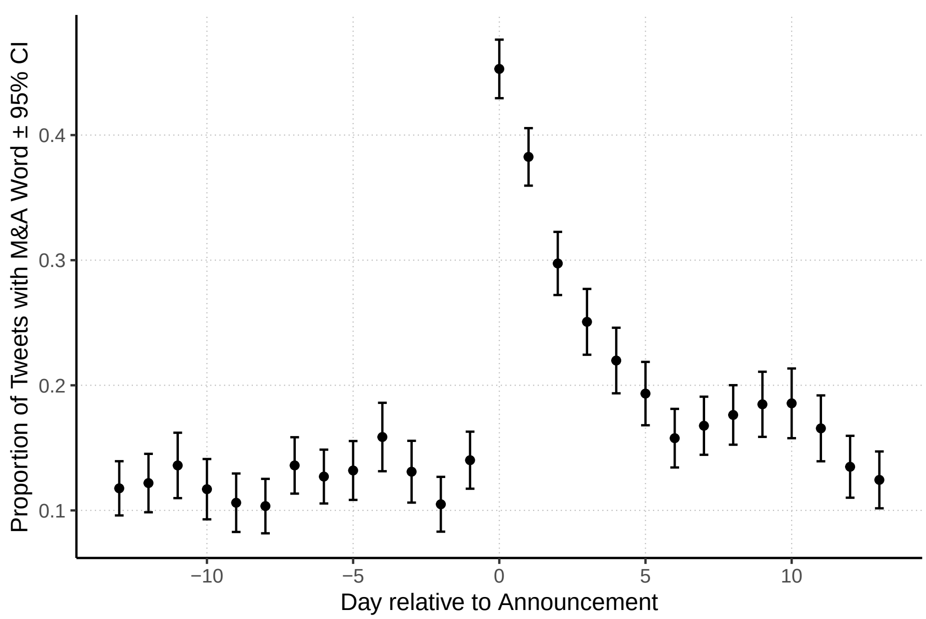


Notes: This figure shows the average and 95% confidence interval of the number of tweets about the acquiring firm posted to StockTwits around the announcement of an M&A deal that also include the ticker of the target firm, relative to the deal announcement date. The sample underlying this figure includes only deals with publicly listed target firms, as private firms do not have a 'cashtag' in StockTwits.

Figure 4: M&A Words in Tweets



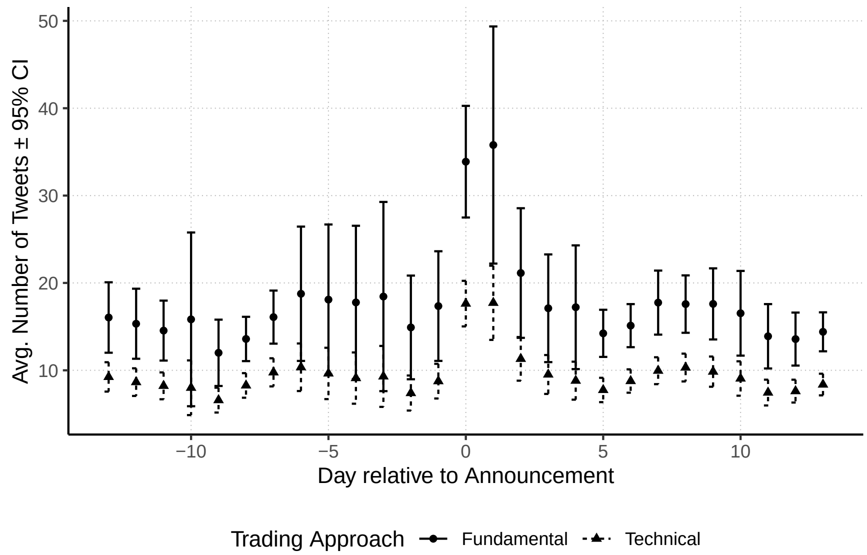
(a) Tweets about Acquirer



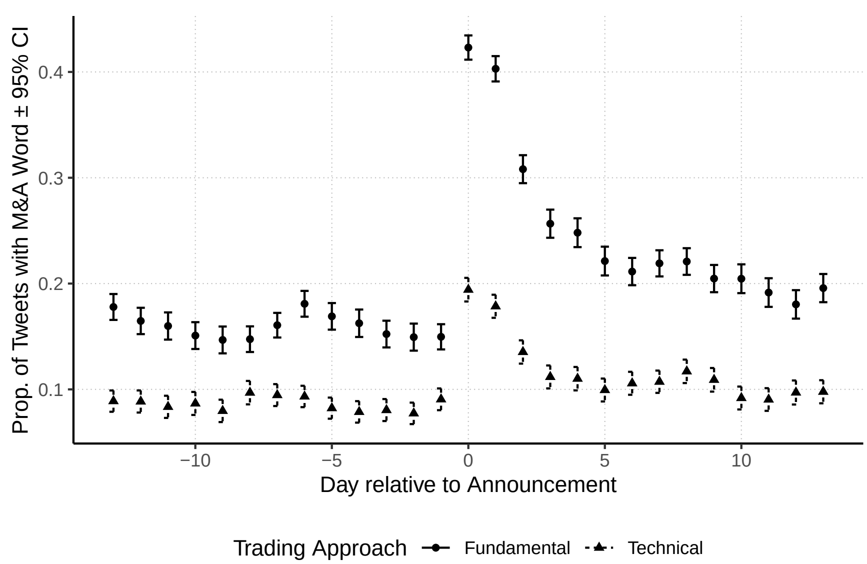
(b) Tweets about Target

Notes: This figure shows the proportion of tweets that include M&A-related words (relative to the total number of tweets) around the announcement of an M&A deal about the acquirer (Fig. 4a) and target firm (Fig. 4b). Figure 4a displays the average and 95% confidence interval of the proportion of tweets posted to StockTwits that include at least one word related to mergers and acquisitions (i.e., “merger”, “acquisition”, “m&a”, “takeover”, “acquirer”, “target”). Figure 4b plots the corresponding numbers for the target firm.

Figure 5: Tweets by (Non)-Technical Traders



(a) Tweets by Technical and Non-Technical Traders



(b) Tweets about Acquirer that include M&A-related words

Notes: This figure shows the dynamics of StockTwits posts around M&A announcements for technical and fundamental StockTwits users. We classify individual tweets posted to StockTwits into "technical" and "fundamental" (i.e., non-technical) tweets, using a Maximum Entropy classifier trained on the messages of users who declare that they use a "technical approach" to trading. Figure 5a shows the average and 95% confidence interval of the number of tweets around the M&A announcement. Figure 5b shows the average proportion and 95% confidence interval of tweets that contain words related to mergers and acquisitions (relative to the total number of tweets), similar to Figure 4. Each figure plots the dynamics separately for 'technical' and 'other' (i.e., non-technical) posts.

Table 1: Summary Statistics

This table presents summary statistics for the main variables in our sample. Table 1a compares the variables across completed mergers and withdrawn mergers. The last three columns of the table present the average difference, standard error, and corresponding p-value of the average difference. All variables are defined as detailed in Section 2 and Appendix Table A.12. All M&A deal characteristics are obtained from SDC Platinum, all accounting variables are obtained from Compustat NA and winsorized at the 5% within the full Compustat universe. Stock returns and cumulative abnormal returns are constructed using data from CRSP and the Fama-French 3-factor model as detailed in Section 2.2. News media sentiment and coverage data are from RavenPack. The sample covers all M&A deals with U.S. acquiring firms over the period from 2010 to 2021 with a minimum deal volume of $25M. Panel 1b cross-tabulates positive (i.e., greater than zero) and negative Abnormal Sentiment around M&A announcements with positive and negative stock market reactions (CAR), news sentiment reactions, and analyst recommendation changes. Summary statistics for the full set of variables in the paper are presented in Appendix Table A.2.

(a) Completed vs. Withdrawn Mergers

	Completed (N=6187)		Withdrawn (N=251)				
Variable	Mean	SD	Mean	SD	Diff.	SE	p-Value
Abn. Sent (StTw)	0.022	0.305	-0.030	0.271	-0.052	0.018	0.003
Abn. Sent (MaxE)	0.038	0.166	-0.009	0.151	-0.047	0.010	0.000
Abn. Sent (SMA-Tw)	0.297	0.590	0.350	0.623	0.053	0.047	0.255
CAR Acq. [-1,10]	0.008	0.090	-0.016	0.093	-0.024	0.006	0.000
News Sent. Acq.	0.007	0.997	-0.181	1.046	-0.189	0.067	0.005
N Tweets	193.316	1961.903	148.036	519.080	-45.280	41.178	0.272
N News Articles	4.500	17.014	8.888	18.126	4.389	1.164	0.000
Deal Delay	80.350	106.566	179.649	187.172	99.299	11.892	0.000
Deal Value (B. USD)	1.028	2.517	4.466	6.030	3.438	0.382	0.000
Pct. Held Prior	2.157	10.867	2.921	11.471	0.765	0.737	0.301
Acq. White Knight (0/1)	0.001	0.025	0.012	0.109	0.011	0.007	0.102
Competing Bidder (0/1)	0.008	0.088	0.211	0.409	0.203	0.026	0.000
Challenged Deal (0/1)	0.009	0.096	0.275	0.447	0.266	0.028	0.000
Rumored Deal (0/1)	0.093	0.291	0.207	0.406	0.114	0.026	0.000
Target Private (0/1)	0.419	0.494	0.120	0.325	-0.300	0.021	0.000
Hostile Deal (0/1)	0.000	0.013	0.064	0.245	0.064	0.015	0.000
Pct. Shares Sought	96.714	13.018	95.906	14.497	-0.807	0.941	0.392
Target Termination Fee	15.564	101.350	37.422	172.388	21.858	10.957	0.047

... continued

(b) Cross-tabulation of positive and negative M&A announcement reactions

	AbnSent	
	Negative	Positive
CAR Acq.		
Negative	1,383 (49%)	1,423 (51%)
Positive	1,413 (45%)	1,713 (55%)

	AbnSent	
	Negative	Positive
News Sent.		
Negative	459 (49%)	472 (51%)
Positive	2,337 (47%)	2,664 (53%)

	AbnSent	
	Negative	Positive
Analyst Recd.		
Negative	2,293 (48%)	2,507 (52%)
Positive	503 (44%)	629 (56%)

Table 2: Social Media Feedback and M&A Outcomes

This table presents linear probability model estimates for the effect of social media feedback on the likelihood of M&A deal withdrawal. In both Panels 2a and 2b, the dependent variable is an indicator variable taking the value of one if the announced M&A transaction was subsequently withdrawn, and zero otherwise. For legibility we multiply the dependent variable by 100 in all regressions. 'Abn. Sentiment (z) (StTw)' is the social media feedback from StockTwits, constructed as the difference between average StockTwits sentiment around the M&A deal announcement ($[0;3]$) and a benchmark period before the announcement. 'Abn. Sentiment (z) (SMA-Tw)' is constructed similarly using Twitter sentiment data provided by SMA. All variables denoted with '(z)' are standardized to have mean zero and standard deviation of one. 'CAR Acq. (z) [-1;10] ([-5;-1])' are the cumulative abnormal returns of the acquiring firm in the $[-1;10]$ and $[-5;-1]$ window around the M&A announcement. 'News Sentiment Acq. (z)' and 'N News Articles' are the news media sentiment and the number of news articles published about the M&A deal, respectively, both obtained from RavenPack. 'Analyst Rec. Changes' and 'N Analyst Rec.' are the net changes and the number of analyst recommendations, and 'N Tweets' is the number of StockTwits tweets around the deal announcement. All other M&A deal characteristics are from SDC Platinum, detailed variable definitions are provided in Appendix Table A.12. 'Mean(LHS)' is the average of the dependent variable in the given regression. Acquiring firm-level controls (firm size, leverage, and cash holdings) are included as indicated. All regressions include year-by-quarter and acquiring firm industry (GIC 2-digit) fixed effects. Standard errors are clustered at the year-by-quarter level and reported in parentheses. *, ** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

(a) Baseline effect

	$\mathbb{1}$(Deal Withdrawn)					
	(1)	(2)	(3)	(4)	(5)	(6)
Abn. Sentiment (z) (StTw)	-0.6434***	-0.7712***	-0.7153***	-0.7165***	-0.7294***	-0.7110***
	(0.2185)	(0.2167)	(0.2165)	(0.2066)	(0.2067)	(0.2099)
CAR Acq. (z) [-1;10]			-0.8760***	-0.9090***	-0.9259***	-0.8353***
			(0.2620)	(0.2562)	(0.2563)	(0.2689)
CAR Acq. (z) [-5;-1]			0.6584**	0.4687*	0.4713*	0.4688*
			(0.2601)	(0.2614)	(0.2663)	(0.2630)
News Sentiment Acq. (z)					-1.024***	-1.019***
					(0.2633)	(0.2578)
Analyst Rec. Changes (z)						-0.9653***
						(0.3246)
N Analyst Rec.						0.0986
						(0.1898)
N News Articles					0.0092	0.0094
					(0.0102)	(0.0101)
Log Deal Value ($B)		8.275***	8.262***	7.795***	8.009***	8.115***
		(0.7574)	(0.7667)	(0.8927)	(0.9041)	(0.9721)
% Shares Held Prior		0.0350	0.0324	0.0434*	0.0380	0.0385
		(0.0228)	(0.0236)	(0.0228)	(0.0232)	(0.0232)
Acq. White Knight (0/1)				0.5101	0.2363	-0.2203
				(16.27)	(16.21)	(16.29)
Competing Bidder (0/1)				43.02***	42.89***	42.77***
				(5.341)	(5.340)	(5.296)
Rumored Deal (0/1)				-1.196	-1.174	-1.196
				(1.144)	(1.151)	(1.136)
Hostile Deal (0/1)				76.96***	76.16***	76.16***
				(6.683)	(6.530)	(6.448)
Termination Fee Target ($M)				-0.0167***	-0.0171***	-0.0165***
				(0.0045)	(0.0045)	(0.0044)
N Tweets					-0.0002***	-0.0002***
					(0.00004)	(0.00004)
Mean(LHS)	3.885	3.763	3.776	3.776	3.776	3.776
Observations	6,306	5,979	5,932	5,932	5,932	5,932
R^2	0.0011	0.0710	0.0738	0.2107	0.2137	0.2161
Firm Controls		✓	✓	✓	✓	✓
Year-by-Quarter FE		✓	✓	✓	✓	✓
Acq. Industry (GIC2) FE		✓	✓	✓	✓	✓

... continued

(b) StockTwits vs. Twitter Sentiment

	$\mathbb{1}$(Deal Withdrawn)		
	(1)	(2)	(3)
Abn. Sentiment (z) (StTw)	-0.7060**		-0.5925**
	(0.2796)		(0.2839)
Abn. Sentiment (z) (SMA-Tw)		-1.075***	-0.9981***
		(0.2705)	(0.2804)
CAR Acq. (z) [-1;10]	-1.145***	-0.9775***	-0.9609***
	(0.2713)	(0.2748)	(0.2706)
CAR Acq. (z) [-5;-1]	0.4592	0.4610	0.4504
	(0.3158)	(0.3125)	(0.3117)
News Sentiment Acq. (z)	-1.330***	-1.253***	-1.266***
	(0.2969)	(0.2955)	(0.2948)
Log Deal Value ($B)	7.672***	8.176***	8.151***
	(0.9369)	(0.9439)	(0.9433)
% Shares Held Prior	0.0346	0.0322	0.0326
	(0.0335)	(0.0331)	(0.0329)
Acq. White Knight (0/1)	-8.539	-9.037	-8.838
	(16.50)	(16.28)	(16.37)
Competing Bidder (0/1)	42.64***	42.62***	42.62***
	(6.074)	(6.029)	(6.036)
Rumored Deal (0/1)	-0.6059	-0.5472	-0.5514
	(1.410)	(1.431)	(1.423)
Hostile Deal (0/1)	79.80***	78.95***	79.07***
	(5.116)	(5.265)	(5.284)
Termination Fee Target ($M)	-0.0150***	-0.0145***	-0.0145***
	(0.0045)	(0.0044)	(0.0045)
N Tweets	-0.0002	-0.0001	-0.0002
	(0.0003)	(0.0003)	(0.0003)
N News Articles	0.0023	0.0024	0.0023
	(0.0082)	(0.0080)	(0.0079)
Mean(LHS)	3.864	3.885	3.756
Observations	4,553	4,553	4,553
R^2	0.2203	0.2215	0.2223
Firm Controls	✓	✓	✓
Year-by-Quarter FE	✓	✓	✓
Acq. Industry (GIC2) FE	✓	✓	✓

Table 3: Robustness – Social Media Feedback and M&A Outcomes

This table presents linear probability model estimates for the effect of social media feedback on the likelihood of M&A deal withdrawal, analogous to Table 2. The dependent variable is a dummy variable indicating whether or not an announced M&A transaction was subsequently withdrawn, multiplied by 100. In Panel 3a, 'Abn. Sentiment (z) (MaxE)' and 'Abn. Sentiment (z) (Bayes)' are the social media feedback from StockTwits using the Maximum Entropy and Naive Bayes classifier, respectively, constructed similarly as 'Abn. Sentiment (z) (StTw)' in Table 2. 'Abn. Sent. Target (z) (StTw)' is the corresponding social media feedback for the target firm, constructed using StockTwits sentiment data. 'CAR Target (z) [-1;10] ([-5;-1])' are the cumulative abnormal returns of the target firm in the $[-1; 10]$ and $[-5; -1]$ window around the M&A announcement. In Panel 3b, we include only M&A deals that were either completed, or that were withdrawn for the indicated reason, i.e., due to regulators in column (1) and due to target shareholders or the target firm board in column (2). All other variables are similar as in Table 2. Each regression includes similar deal and firm-level controls as Table 2 and year-by-quarter and acquiring firm industry (GIC 2-digit) fixed effects as indicated. Standard errors are clustered at the year-by-quarter level and reported in parentheses. *, ** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

(a) Alternative measures and specifications

	𝟙(Deal Withdrawn)							
Specification	MaxEnt	Bayes	Public Targets				Drop Small	Acq. FE
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Abn. Sentiment (z) (MaxE)	-0.5835***							
	(0.1971)							
Abn. Sentiment (z) (Bayes)		-0.4268**						
		(0.2053)						
Abn. Sentiment (z) (StTw)			-2.133**	-2.962**	-2.804*	-2.607*	-1.170***	-0.8011**
			(0.9750)	(1.438)	(1.447)	(1.492)	(0.2785)	(0.3337)
Abn. Sent. Target (z) (StTw)				0.1704	0.0286	0.0228		
				(1.119)	(1.160)	(1.167)		
CAR Acq. (z) [-1;10]	-0.9461***	-0.9609***	-1.443	-2.042*	-1.949	-1.129	-1.315***	-1.278***
	(0.2501)	(0.2560)	(1.178)	(1.213)	(1.189)	(1.240)	(0.2813)	(0.3612)
CAR Acq. (z) [-5;-1]	0.5323**	0.5319**	1.064	0.7762	1.176	0.9680	0.6810**	0.7815**
	(0.2598)	(0.2593)	(1.154)	(1.280)	(1.328)	(1.421)	(0.3218)	(0.3277)
CAR Target (z) [-1;10]			-1.230		-1.571	-1.921		
			(1.148)		(1.245)	(1.440)		
CAR Target (z) [-5;-1]			-0.7008		-0.5146	-0.7775		
			(1.146)		(1.183)	(1.121)		
News Sentiment Acq. (z)	-1.007***	-1.004***	-3.932**	-4.022***	-4.036***	-2.440*	-1.612***	-1.049***
	(0.2566)	(0.2579)	(1.500)	(1.433)	(1.461)	(1.381)	(0.3662)	(0.3757)
N Tweets	-0.0002***	-0.0002***	-0.0006	-0.0008*	-0.0007	-0.0013***	-0.0002***	0.0002
	(0.00004)	(0.00004)	(0.0005)	(0.0004)	(0.0004)	(0.0005)	(0.00004)	(0.0006)
N News Articles	0.0087	0.0089	0.0551	0.0272	0.0353	0.0112	0.0102	0.0129
	(0.0102)	(0.0103)	(0.0636)	(0.0585)	(0.0566)	(0.0461)	(0.0103)	(0.0120)
Target Spread						20.23*		
						(11.54)		
Mean(LHS)	3.791	3.791	4.139	11.57	11.63	10.91	3.914	3.825
Observations	5,988	5,988	880	683	679	605	4,445	5,896
R^2	0.2117	0.2113	0.3372	0.3523	0.3567	0.3639	0.2344	0.5536
Deal Controls	✓	✓	✓	✓	✓	✓	✓	✓
Firm Controls	✓	✓	✓	✓	✓	✓	✓	✓
Year-by-Quarter FE	✓	✓	✓	✓	✓	✓	✓	✓
Acq. Industry (GIC2) FE	✓	✓	✓	✓	✓	✓	✓	✓
Acq. Firm FE								✓

... continued

(b) Deal rejection reasons

	$\mathbb{1}$(Deal Withdrawn)	
Deal Rejected by:	Regulator	Target
	(1)	(2)
Abn. Sentiment (z) (StTw)	-0.2020**	-0.1504
	(0.0883)	(0.1219)
CAR Acq. (z) [-1;10]	-0.0226	-0.2921***
	(0.0725)	(0.0974)
CAR Acq. (z) [-5;-1]	0.2586**	0.0806
	(0.1139)	(0.1168)
News Sentiment Acq. (z)	-0.2009*	-0.8442***
	(0.1141)	(0.2059)
N Tweets	$-3.81 \times 10^{-5**}$	$-7.73 \times 10^{-5***}$
	(1.48×10^{-5})	(1.88×10^{-5})
N News Articles	0.0041	0.0038
	(0.0080)	(0.0060)
N Deals Withdr.	30	74
Observations	5,734	5,776
R^2	0.0564	0.2790
Deal Controls	✓	✓
Firm Controls	✓	✓
Year-by-Quarter FE	✓	✓
Acq. Industry (GIC2) FE	✓	✓

Table 4: Social Media Feedback and Deal BHARs

This table summarizes OLS regressions of the Buy-and-hold Abnormal Returns (BHAR) from M&A deal announcement to deal conclusion on the initial social media and stock market feedback, the eventual deal outcome (i.e., either completion or withdrawal), and their interactions. The dependent variable, $Acq.\ BHAR[11; T_{conclusion}]$, is constructed over the event window from 11 days after the deal announcement until deal conclusion ($T_{conclusion}$), using abnormal returns with respect to the Fama-French 3-Factor model. As before, 'Abn. Sentiment (z) (StTw)' is the social media feedback from StockTwits, and 'CAR Acq. (z) [-1;10] ([-5;-1])' are the cumulative abnormal returns of the acquiring firm in the $[-1; 10]$ and $[-5; -1]$ window around the M&A announcement. $1(Deal\ Withdr.)$ is an indicator variable that takes the value of one if the deal was ultimately withdrawn and zero if it was completed. To avoid an overlap between the event window around the deal announcement and the deal conclusion columns (1)–(2) retain only deals with a minimum delay between announcement and conclusion of at least 25 days, and columns (3)–(4) retain only deals with a delay of more than 75 days. In all regressions we exclude deals that were rejected by the target firm. All other variables are similar as in Table 2. Each regression includes similar deal and firm-level controls as Table 2 and year-by-quarter and acquiring firm industry (GIC 2-digit) fixed effects as indicated. Standard errors are clustered at the year-by-quarter level and reported in parentheses. *, ** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

	BHAR Acq. [+11; Deal Conclusion]			
	Delay>25 days		Delay>75 days	
	(1)	(2)	(3)	(4)
Abn. Sentiment (z) (StTw) × 𝟙(Deal Withdr.)	-0.1009**	-0.1087**	-0.1427***	-0.1528***
	(0.0390)	(0.0423)	(0.0309)	(0.0357)
Abn. Sentiment (z) (StTw)	-0.0078	-0.0074	-0.0154*	-0.0150
	(0.0050)	(0.0050)	(0.0090)	(0.0090)
𝟙(Deal Withdr.) × CAR Acq. (z) [-1;10]		0.1505		0.1710
		(0.1018)		(0.1347)
𝟙(Deal Withdr.) × CAR Acq. (z) [-5;-1]		0.0212		0.0319
		(0.0449)		(0.0558)
𝟙(Deal Withdr.)	-0.0608	-0.0242	-0.0715	-0.0328
	(0.0622)	(0.0785)	(0.0820)	(0.1018)
CAR Acq. (z) [-1;10]	0.0389***	0.0324***	0.0624***	0.0519***
	(0.0114)	(0.0100)	(0.0204)	(0.0181)
CAR Acq. (z) [-5;-1]	0.0116	0.0096	0.0211	0.0175
	(0.0118)	(0.0116)	(0.0218)	(0.0218)
News Sentiment Acq. (z)	0.0115**	0.0118**	0.0233**	0.0226**
	(0.0051)	(0.0051)	(0.0096)	(0.0093)
Mean(LHS)	3.857	3.857	3.890	3.890
Observations	3,343	3,343	1,784	1,784
R^2	0.0444	0.0523	0.0781	0.0864
(Soc) Media Controls	✓	✓	✓	✓
Deal Controls	✓	✓	✓	✓
Firm Controls	✓	✓	✓	✓
Year-by-Quarter FE	✓	✓	✓	✓
Acq. Industry (GIC2) FE	✓	✓	✓	✓

Table 5: Acquirers' Social Media Engagement

This table presents linear probability model estimates on the effect of Corporate Social Media engagement on the relationship between M&A deal completion and social media feedback around M&A deal announcement. Similar to Table 2, the dependent variable is an indicator that takes the value of one if the previously announced M&A deal is ultimately withdrawn, and zero otherwise and 'Abn. Sentiment (z) (StTw)' is the social media feedback from StockTwits. $1(Acq. Twitter)$ is an indicator variable that takes the value of one for firms that have a corporate Twitter account that was registered and activated before the announcement of the M&A deal, and zero otherwise. Similarly, $1(Acq. HighFollow)$ and $1(Acq. Verified)$ are indicator variables that take the value of one if at the time of deal announcement the acquiring firm had a corporate Twitter account with an above-median number of followers and with "verified account" (i.e., blue check-mark) status, respectively. All other variables are similar as in Table 2. Each regression includes similar deal and firm-level controls as Table 2 and year-by-quarter and acquiring firm industry (GIC 2-digit) fixed effects as indicated. Standard errors are clustered at the year-by-quarter level and reported in parentheses. *, ** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

	1(Deal Withdrawn)					
	(1)	(2)	(3)	(4)	(5)	(6)
Abn. Sentiment (z) (StTw) × 1(Acq. Twitter)	-0.4711	-0.4472				
	(0.4025)	(0.4206)				
Abn. Sentiment (z) (StTw) × 1(Acq. HighFollow)			-0.9646**	-0.9559**		
			(0.4352)	(0.4608)		
Abn. Sentiment (z) (StTw) × 1(Acq. Verified)					-1.301**	-0.9259*
					(0.5019)	(0.5262)
Abn. Sentiment (z) (StTw)	-0.4356*	-0.4998	-0.3400*	-0.3764	-0.4000**	-0.5430
	(0.2495)	(0.3752)	(0.2002)	(0.3025)	(0.1981)	(0.3277)
1(Acq. Twitter)	0.4215	-0.8588				
	(0.5940)	(1.766)				
1(Acq. HighFollow)			0.4742	-1.722		
			(0.6047)	(3.602)		
1(Acq. Verified)					0.7672	-3.835
					(0.6698)	(3.799)
Mean(LHS)	3.776	3.776	3.776	3.776	3.776	3.776
Observations	5,932	5,932	5,932	5,932	5,932	5,932
R^2	0.2139	0.5538	0.2144	0.5541	0.2148	0.5542
Deal Controls	✓	✓	✓	✓	✓	✓
Firm Controls	✓	✓	✓	✓	✓	✓
(Social) Media Controls	✓	✓	✓	✓	✓	✓
CAR Controls	✓	✓	✓	✓	✓	✓
Year-by-Quarter FE	✓	✓	✓	✓	✓	✓
Acq. Industry (GIC2) FE	✓	✓	✓	✓	✓	✓
Acq. Firm FE		✓		✓		✓

Table 6: Nature of StockTwits Content

This table presents linear probability model estimates on the effect of social media feedback on M&A deal completion focusing on the nature of the content of the tweets posted to StockTwits. Table 6a focuses on technical posts and tweet length: to construct 'Abn. Sent (z) Technical=N' and 'Abn. Sent (z) Technical=Y' in columns (1)–(2), we classify each StockTwits post as 'technical' or 'non-technical' content using a Maximum Entropy classifier trained on the tweets of users who declare themselves as 'technical traders' (i.e., chart formations and patterns, etc.). We then aggregate the tweets across these two subgroups and construct "Abn. Sentiment" as before. Similarly, 'Abn. Sent (z) Long=Y' ('Abn. Sent (z) Long=N') are constructed by separately estimating abnormal sentiment around merger announcement for tweets with above and below median number of words (i.e., seven words) in the tweet. Table 6b focuses on abnormal sentiment from subsamples of tweets based on the topic of the tweet. We use a Biterm-topic-modeling (BTM) approach to identify the topic of a given tweet and construct AbnSent for each subset of tweets individually, similar to Table 6a. All variables denoted with '(z)' are standardized to have mean zero and standard deviation of one. All other variables are similar as in Table 2. Each regression includes similar deal and firm-level controls as Table 2 and year-by-quarter and acquiring firm industry (GIC 2-digit) fixed effects as indicated. Standard errors are clustered at the year-by-quarter level and reported in parentheses. *, ** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

(a) Abnormal Sentiment by tweet type and length

	$\mathbb{1}$(Deal Withdrawn)			
	Technical Traders		Tweet Length	
	(1)	(2)	(3)	(4)
Abn. Sent (z) Technical=N	-1.105***	-1.080***		
	(0.2905)	(0.2884)		
Abn. Sent (z) Technical=Y	-0.3497	-0.2744		
	(0.3095)	(0.3010)		
Abn. Sent (z) Long=Y			-1.214***	-1.222***
			(0.3033)	(0.2983)
Abn. Sent (z) Long=N			-0.0525	0.0140
			(0.2664)	(0.2616)
CAR Acq. (z) [-1;10]		-1.023***		-0.8895***
		(0.3024)		(0.2837)
CAR Acq. (z) [-5;-1]		0.3161		0.4885
		(0.2983)		(0.2914)
News Sentiment Acq. (z)		-1.191***		-1.202***
		(0.3365)		(0.3239)
Mean(LHS)	4.239	4.247	3.909	3.920
Observations	3,680	3,650	4,042	4,005
R^2	0.2331	0.2430	0.2272	0.2361
(Soc) Media Controls		✓		✓
Deal Controls	✓	✓	✓	✓
Firm Controls	✓	✓	✓	✓
Year-by-Quarter FE	✓	✓	✓	✓
Acq. Industry (GIC2) FE	✓	✓	✓	✓

... continued

(b) Abnormal Sentiment by tweet topic

	𝟙(Deal Withdrawn)				
	(1)	(2)	(3)	(4)	(5)
Abn. Sent (z) Company/Business	-1.202***				
	(0.3160)				
Abn. Sent (z) Deal-Terms		-1.139***			
		(0.2983)			
Abn. Sent (z) Disclosure			-0.8675**		
			(0.3987)		
Abn. Sent (z) Meme				-0.2804	
				(0.6155)	
Abn. Sent (z) Technical					-0.4872
					(0.3391)
Abn. Sent (z) Trading	0.1189	0.1649	0.5371	-1.082	-0.3840
	(0.2733)	(0.2771)	(0.3953)	(0.7547)	(0.3508)
CAR Acq. (z) [-1;10]	-1.091***	-0.8503***	-0.9082***	-1.159***	-0.9557***
	(0.2858)	(0.2869)	(0.3209)	(0.3449)	(0.2714)
CAR Acq. (z) [-5;-1]	0.5760*	0.4322	0.4014	-0.0846	0.7333**
	(0.3007)	(0.3320)	(0.4072)	(0.4911)	(0.3166)
News Sentiment Acq. (z)	-0.9505**	-1.366***	-1.158***	-0.4856	-1.419***
	(0.3645)	(0.3482)	(0.4149)	(0.6599)	(0.3654)
Mean(LHS)	4.339	4.202	4.030	4.103	4.333
Observations	3,941	4,117	3,151	1,121	3,600
R^2	0.2450	0.2531	0.2480	0.2345	0.2546
(Soc) Media Controls	✓	✓	✓	✓	✓
Deal Controls	✓	✓	✓	✓	✓
Firm Controls	✓	✓	✓	✓	✓
Year-by-Quarter FE	✓	✓	✓	✓	✓
Acq. Industry (GIC2) FE	✓	✓	✓	✓	✓

Table 7: Other Information Sources – Stock Market and News Media

This table presents linear probability model estimates for the effect of social media feedback on the likelihood of M&A deal withdrawal, focusing on the relationship of Social Media with other sources of information. Similar to Table 2, the dependent variable is a dummy variable indicating whether or not an announced M&A transaction was subsequently withdrawn, multiplied by 100. All explanatory variables are defined similarly as in Table 2. We split the sample into observations with above and below median number of tweets posted on StockTwits (columns 1 and 2), the number of news articles about the M&A deal (columns 3 and 4), and the absolute value of the acquirer's M&A annoucement returns (columns 5 and 6), respectively. Each regression includes similar deal and firm-level controls as Table 2 and year-by-quarter and acquiring firm industry (GIC 2-digit) fixed effects as indicated. Standard errors are clustered at the year-by-quarter level and reported in parentheses. *, ** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

	$\mathbb{1}$(Deal Withdrawn)					
Sample Split	N Tweets		N News Articles		Abs(CAR)	
	Low	High	Low	High	Low	High
	(1)	(2)	(3)	(4)	(5)	(6)
Abn. Sentiment (z) (StTw)	-0.5157*	-2.030***	-0.6450**	-0.8438*	-0.3169	-1.202***
	(0.2560)	(0.6128)	(0.2692)	(0.4818)	(0.2307)	(0.3090)
CAR Acq. (z) [-1;10]	-0.8590*	-1.100***	-0.5859	-1.726***	0.2068	-0.9857***
	(0.4697)	(0.2573)	(0.3725)	(0.4473)	(1.291)	(0.2653)
CAR Acq. (z) [-5;-1]	0.3030	0.6596*	0.5017	0.8547	0.1316	0.6140
	(0.4102)	(0.3391)	(0.3540)	(0.5448)	(0.3046)	(0.3889)
News Sentiment Acq. (z)	-0.4724	-1.968***	-1.554*	-9.080***	-0.8905**	-1.161**
	(0.3206)	(0.5284)	(0.9126)	(1.788)	(0.3697)	(0.4376)
N Tweets	-0.0103	-0.0002	-0.0005**	-0.0001**	-0.0003	-0.0002***
	(0.0405)	(0.0002)	(0.0002)	(0.00005)	(0.0004)	(0.00004)
N News Articles	0.1226	0.0119	0.4044	0.0088	0.0031	0.0301
	(0.0853)	(0.0113)	(0.3160)	(0.0110)	(0.0086)	(0.0419)
Mean(LHS)	3.449	3.144	3.453	3.016	3.323	3.793
Coef. Diff. *t*-Stat. (p-Value)	2.279	(0.023)	0.360	(0.719)	2.295	(0.022)
Observations	2,957	2,322	2,838	2,188	2,979	2,953
R^2	0.1621	0.2755	0.1622	0.2673	0.2472	0.2124
Deal Controls	✓	✓	✓	✓	✓	✓
Firm Controls	✓	✓	✓	✓	✓	✓
Year-by-Quarter FE	✓	✓	✓	✓	✓	✓
Acq. Industry (GIC2) FE	✓	✓	✓	✓	✓	✓

Table 8: Analyst Conference Calls

This table presents linear probability estimates on the relationship between M&A-related analyst conference calls and the effect of social media reactions on M&A deal withdrawals. The dependent variable is a dummy variable indicating whether or not an announced M&A transaction was subsequently withdrawn, multiplied by 100. In addition to the same explanatory variables as in Table 2, column (1) in Panel 8a includes the indicator variable 'Has Conf. Call (0/1)' which takes the value of one if the acquiring firm held an analyst conference call related to the M&A announcement, and zero otherwise. In column (2) and columns (3) and (4) we split the sample into M&A deals without and with M&A-related analyst conference calls. Column (4) additionally includes measures about the content of the Q&A section of the respective conference call. '% Positive Words', '% Negative Words', and '% Constraining Words' are defined as in Loughran and McDonald (2016) and Bodnaruk et al. (2015), using the 2022 version of the Loughran and McDonald (2011) Master Dictionary. 'Avg. Word Length', 'N Words', and 'Vocabulary' are defined as the average number of letters per word, the number of words, and the number of unique words spoken in the Q&A section of the conference call, respectively. Panel 8b splits the sample by observations with above and below median percentage of 'Constrained Words' (columns 1 through 4), and 'Negative Words' (columns 5 through 8). Panel 8b additionally distinguishes between words spoken in the presentation (columns 1–2, 5–6) and the Q&A section (columns 3–4, 7–8) of the confernence calls. Each regression includes similar deal and firm-level controls as Table 2 and year-by-quarter and acquiring firm industry (GIC 2-digit) fixed effects as indicated. 'Mean(LHS)' is the average of the dependent variable in the given regression, 'Coef. Diff. t-Stat (p-Value)' provides the t-Statistic and corresponding p-Value testing the hypothesis that the coefficient estimates on our main variable of interest, 'Abn. Sentiment (z) (StTw)', are equal across both regressions. Standard errors are clustered at the year-by-quarter level and reported in parentheses. *, ** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

(a) Analyst conference calls and deal completion

	$\mathbb{1}$(Deal Withdrawn)			
Sample Split	Full Sample	Conf. Call (0/1)		
		No	Yes	
	(1)	(2)	(3)	(4)
Abn. Sentiment (z) (StTw)	-0.7425***	-0.5738**	-1.288**	-1.303**
	(0.2410)	(0.2144)	(0.5848)	(0.5867)
Has Conf. Call (0/1)	-2.563***			
	(0.6202)			
% Positive Words (Q&A)				0.8393
				(1.062)
% Negative Words (Q&A)				-0.1196
				(2.451)
% Constraining Words (Q&A)				8.473
				(6.859)
Avg. Word Length (Q&A)				4.339
				(5.457)
N Words (Q&A)				-0.0002
				(0.0017)
Vocabulary (Q&A)				-0.0008
				(0.0127)
Mean(LHS)	3.704	3.612	3.287	3.785
Coef. Diff. t-Stat (p-Value)		1.147	(0.252)	
Observations	3,834	4,928	1,004	1,004
R^2	0.2173	0.2357	0.2059	0.2091
Firm and Deal Controls	✓	✓	✓	✓
Stock Return and Media Controls	✓	✓	✓	✓
Year-by-Quarter FE	✓	✓	✓	✓
Acq. Industry (GIC2) FE	✓	✓	✓	✓

... continued

(b) Conference Calls: Presentation vs. Q&A

	$\mathbb{1}$(Deal Withdrawn)							
Sample Split	% Constrained Words				% Negative Words			
	Presentation		Q&A		Presentation		Q&A	
	Low	High	Low	High	Low	High	Low	High
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Abn. Sentiment (z) (StTw)	-1.242	-1.447*	0.3123	-2.067**	-1.880	-0.7685	0.4652	-2.310**
	(0.9231)	(0.8030)	(0.5131)	(0.9696)	(1.142)	(0.4897)	(0.4602)	(0.8673)
Mean(LHS)	2.970	2.806	3.006	2.772	3.400	2.381	3.808	1.980
Coef. Diff. t-Stat (p-Value)	0.168	(0.867)	2.169	(0.030)	0.895	(0.371)	2.826	(0.005)
Observations	505	499	499	505	500	504	499	505
R^2	0.2055	0.3400	0.2344	0.3163	0.2637	0.3250	0.2461	0.3325
Deal Controls	✓	✓	✓	✓	✓	✓	✓	✓
Firm Controls	✓	✓	✓	✓	✓	✓	✓	✓
Social & News Media Controls	✓	✓	✓	✓	✓	✓	✓	✓
Stock Return Controls	✓	✓	✓	✓	✓	✓	✓	✓
Conf. Call Controls	✓	✓	✓	✓	✓	✓	✓	✓
Year-by-Quarter FE	✓	✓	✓	✓	✓	✓	✓	✓
Acq. Industry (GIC2) FE	✓	✓	✓	✓	✓	✓	✓	✓

Appendix

A.I Content Classification and Social Media Sentiment

As our main measure of social media reactions to M&A announcements we rely on tweet-level sentiment scores provided by StockTwits, as these scores are published in real-time on the StockTwits website and app and can easily be viewed by market participants and corporate decision makers. As an additional robustness and validity test, we also compute StockTwits sentiment scores based on the text content of individual tweets by using two different approaches. Specifically, we apply the Maximum Entropy (ME) classifier and Naive Bayes classifier to categorize the content of each StockTwits post, following Cookson and Niessner (2020) and Giannini et al. (2019), among others.

Maximum Entropy is a commonly used 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 a 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.[1]

We use Maximum Entropy to estimate the conditional distribution of a tweet's 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[2], 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 word w_m and category y, we can then

[1] 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.

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

define the following feature function:

$$f_m(x, y(x)) = \begin{cases} \frac{N(w,x)}{N(w)} & \text{if } w_m \in x \text{ and } x \text{ is classified as } y \\ 0 & \text{otherwise} \end{cases} \tag{5}$$

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. We 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:

$$\frac{1}{|\mathcal{X}|}\sum_{x\in\mathcal{X}} f_m(x, y(x)) = \frac{1}{|\mathcal{X}|}\sum_{x\in\mathcal{X}}\sum_{y\in\mathcal{Y}} p(y|x) f_m(x, y) \tag{6}$$

$$p(y|x) \geq 0 \text{ for all } x, y \tag{7}$$

$$\sum_y p(y|x) = 1 \text{ for all } x. \tag{8}$$

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.:

$$p^*(y|x) = \underset{p(y|x)\in\mathcal{P}}{\operatorname{argmax}}\, H(p(y|x)) = \underset{p(y|x)\in\mathcal{P}}{\operatorname{argmax}} \sum_{x\in\mathcal{X}} p(y|x) log\left(\frac{1}{p(y|x)}\right) \tag{9}$$

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:

$$p^*(y|x) = \frac{exp\left(\sum\limits_m \lambda_m f_m(x, y)\right)}{\sum\limits_{y\in\mathcal{Y}} exp\left(\sum\limits_m \lambda_m f_m(x, y)\right)} \tag{10}$$

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, we 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) manually constructs a training sample by classifying a small number of tweets as positive or negative by hand. By relying on a user-classified training sample we avoid the subjectivity of this approach. In total, 77,919,074 tweets posted on StockTwits during our sample period have a user-assigned sentiment (i.e. "bullish" or "bearish"). We randomly draw 20% of these user-classified tweets 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.

In addition to the Maximum Entropy (ME) Classification approach we 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 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:

$$score(x, y) \equiv p(y) \times \prod_{m=1}^{M} p(w_m|y). \tag{11}$$

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

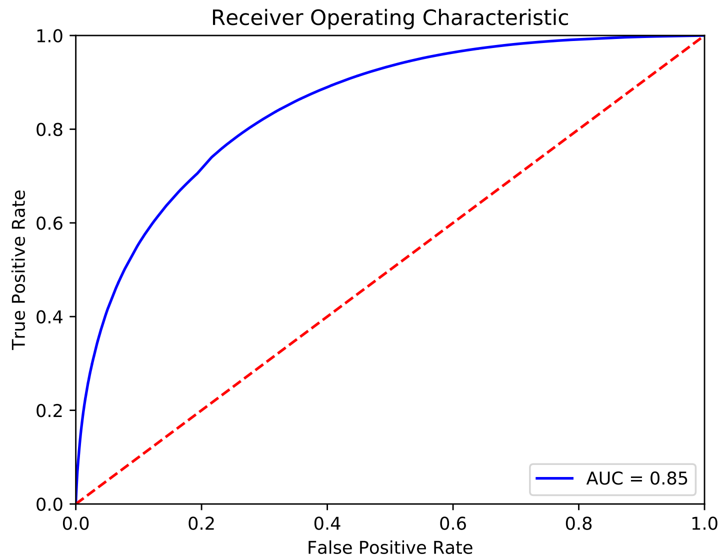
$$p(y|x) \equiv \frac{score(x, y)}{\sum\limits_{y' \in \mathcal{Y}} score(x, y)}. \tag{12}$$

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

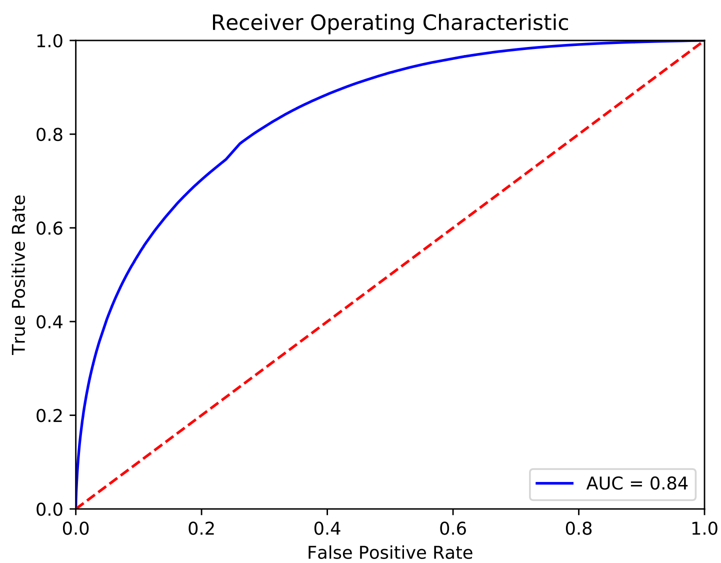
To evaluate the accuracy of our classification methodology, Figure A.1 plots the Receiver Operating Characteristic (ROC) curve for the Maximum Entropy (Fig. A.1a) and the Naive Bayes classifier (Fig. A.1b). The ROC curves plot the True Positive Rate (TPR) against the False Positive Rate (TPR) for a range of possible classification thresholds – i.e. critical values produced by the classifier algorithm above which a tweet would be classified as 'positive' rather than 'negative' sentiment. The straight, dashed red line through the origin represents the ROC curve that would result from classifying tweets randomly. Hence, the Area-Under-the-Curve (AUC) of the ROC curve can be interpreted as a measure of the classification accuracy gained using our two classifier algorithms, respectively. With AUC values of 0.85 and 0.84, respectively, the ROC curves of our Maximum Entropy and Naive Bayes classifiers show that both classifier algorithms provide a high degree of accuracy at identifying positive and negative tweets.

As an additional verification exercise, Appendix Table A.1 provides cross-correlations of sentiment scores across 20 samples generated with the Maximum Entropy and Naive Bayes classifier algorithms, using a randomly drawn training subsample from the universe of StockTwits tweets (5% of all posted messaged with a user-provided sentiment indicator) to train the Maximum Entropy and Naive Bayes classifier, respectively. As shown in Table A.1, the correlations across samples with randomly drawn training samples is consistently around 85% indicating a very high degree of overlap in the text sentiment assigned by the two classifier algorithms. The cross-correlations are similarly high for the abnormal sentiment around M&A announcement periods (Panels A.1a and A.1b) and the sentiment scores over the entire sample period (Panels A.1c and A.1d) for both algorithms, indicating that sentiment classification algorithms perform similarly well during merger announcement periods as during the overall sample period.

Figure A.1: Receiver Operating Characteristic (ROC) curve of StockTwits Classification



(a) Maximum Entropy Classifier.



(b) Naive Bayes Classifier.

Notes: This figure shows the Receiver Operating Characteristic (ROC) curve of the Maximum Entropy Classifier (Figure A.1a) and the Naive Bayes Classifier (Figure A.1b) used to classify the sentiment in individual StockTwits tweets in our sample. Both figures plot the True Positive Rate (y-axis) against the False Positive Rate in solid blue, showing the diagnostic ability of our binary classifiers across a range of classification thresholds – i.e., critical values above which a tweet would be classified as 'positive' rather than 'negative' sentiment. Hence, the Area-Under-the-Curve (AUC) represents a measure of the classification accuracy gained by using the Maximum Entropy or Naive Bayes Classifier, respectively. The dashed red line represents the ROC curve that would result from classifying tweets randomly.

Table A.1: Social Media Sentiment across Training Samples

This table presents correlations between social media sentiment scores using the Maximum Entropy (MaxEnt) classifier and the Naive Bayes classifier across 20 samples. In each of the 20 samples the StockTwits social media sentiment is constructed using a randomly drawn training subsample from the universe of StockTwits tweets (5% of all posted messaged with a user-provided sentiment indicator) to train the Maximum Entropy classifier algorithm. Panels A.1a and A.1b present correlations for the Social Media reaction constructed around M&A announcements across the 20 samples using the Maximum Entropy and Naive Bayes classifier, respectively. Panels A.1c and A.1d present the correlations of StockTwits sentiment for the full sample of Tweets across the 20 samples using the Maximum Entropy and Naive Bayes classifier, respectively.

(a) M&A announcement abnormal sentiment (MaxEnt)

S1	S2	S3	S4	S5	S6	S7	S8	S9	S10	S11	S12	S13	S14	S15	S16	S17	S18	S19	S20
1																			
0.86	1																		
0.85	0.84	1																	
0.86	0.84	0.86	1																
0.87	0.87	0.85	0.85	1															
0.86	0.86	0.84	0.85	0.88	1														
0.79	0.78	0.83	0.81	0.78	0.77	1													
0.87	0.86	0.85	0.85	0.87	0.86	0.81	1												
0.87	0.87	0.85	0.85	0.86	0.85	0.8	0.88	1											
0.85	0.84	0.86	0.87	0.85	0.84	0.86	0.86	0.86	1										
0.86	0.86	0.85	0.86	0.87	0.86	0.78	0.85	0.85	0.84	1									
0.79	0.78	0.83	0.83	0.78	0.78	0.87	0.82	0.81	0.87	0.79	1								
0.85	0.87	0.84	0.84	0.85	0.85	0.79	0.86	0.86	0.84	0.85	0.79	1							
0.85	0.84	0.86	0.86	0.84	0.84	0.85	0.86	0.85	0.88	0.83	0.86	0.85	1						
0.86	0.86	0.83	0.84	0.86	0.86	0.77	0.87	0.87	0.84	0.85	0.78	0.85	0.84	1					
0.85	0.87	0.87	0.86	0.87	0.86	0.8	0.87	0.87	0.85	0.86	0.81	0.87	0.85	0.85	1				
0.82	0.81	0.84	0.83	0.8	0.8	0.85	0.81	0.82	0.88	0.81	0.87	0.81	0.88	0.81	0.82	1			
0.83	0.82	0.85	0.84	0.82	0.82	0.76	0.83	0.83	0.81	0.82	0.77	0.82	0.82	0.81	0.85	0.78	1		
0.86	0.87	0.85	0.86	0.88	0.86	0.8	0.86	0.86	0.86	0.87	0.79	0.86	0.85	0.85	0.87	0.83	0.82	1	
0.85	0.83	0.85	0.85	0.84	0.85	0.77	0.86	0.85	0.83	0.83	0.79	0.84	0.84	0.84	0.85	0.82	0.87	0.83	1

(b) M&A announcement abnormal sentiment (Bayes)

S1	S2	S3	S4	S5	S6	S7	S8	S9	S10	S11	S12	S13	S14	S15	S16	S17	S18	S19	S20
1																			
0.86	1																		
0.85	0.84	1																	
0.86	0.84	0.86	1																
0.87	0.87	0.85	0.85	1															
0.86	0.86	0.84	0.85	0.88	1														
0.79	0.78	0.83	0.81	0.78	0.77	1													
0.87	0.86	0.85	0.85	0.87	0.86	0.81	1												
0.87	0.87	0.85	0.85	0.86	0.85	0.8	0.88	1											
0.85	0.84	0.86	0.87	0.85	0.84	0.86	0.86	0.86	1										
0.86	0.86	0.85	0.86	0.87	0.86	0.78	0.85	0.85	0.84	1									
0.79	0.78	0.83	0.83	0.78	0.78	0.87	0.82	0.81	0.87	0.79	1								
0.85	0.87	0.84	0.84	0.85	0.85	0.79	0.86	0.86	0.84	0.85	0.79	1							
0.85	0.84	0.86	0.86	0.84	0.84	0.85	0.86	0.85	0.88	0.83	0.86	0.85	1						
0.86	0.86	0.83	0.84	0.86	0.86	0.77	0.87	0.87	0.84	0.85	0.78	0.85	0.84	1					
0.85	0.87	0.87	0.86	0.87	0.86	0.8	0.87	0.87	0.85	0.86	0.81	0.87	0.85	0.85	1				
0.82	0.81	0.84	0.83	0.8	0.8	0.85	0.81	0.82	0.88	0.81	0.87	0.81	0.88	0.81	0.82	1			
0.83	0.82	0.85	0.84	0.82	0.82	0.76	0.83	0.83	0.81	0.82	0.77	0.82	0.82	0.81	0.85	0.78	1		
0.86	0.87	0.85	0.86	0.88	0.86	0.8	0.86	0.86	0.86	0.87	0.79	0.86	0.85	0.85	0.87	0.83	0.82	1	
0.85	0.83	0.85	0.85	0.84	0.85	0.77	0.86	0.85	0.83	0.83	0.79	0.84	0.84	0.84	0.85	0.82	0.87	0.83	1

... continued

(c) Full sample sentiment score (MaxEnt)

S1	S2	S3	S4	S5	S6	S7	S8	S9	S10	S11	S12	S13	S14	S15	S16	S17	S18	S19	S20
1																			
0.88	1																		
0.88	0.88	1																	
0.88	0.88	0.87	1																
0.88	0.88	0.88	0.88	1															
0.88	0.88	0.88	0.88	0.89	1														
0.85	0.86	0.85	0.86	0.85	0.86	1													
0.89	0.88	0.88	0.88	0.88	0.88	0.85	1												
0.88	0.88	0.88	0.87	0.88	0.88	0.87	0.88	1											
0.86	0.87	0.86	0.87	0.86	0.87	0.88	0.87	0.88	1										
0.88	0.88	0.88	0.88	0.88	0.88	0.85	0.88	0.88	0.87	1									
0.84	0.86	0.85	0.85	0.84	0.84	0.88	0.84	0.87	0.88	0.85	1								
0.88	0.88	0.88	0.88	0.88	0.88	0.87	0.88	0.88	0.87	0.88	0.86	1							
0.87	0.88	0.87	0.88	0.88	0.88	0.87	0.88	0.87	0.88	0.88	0.86	0.88	1						
0.88	0.89	0.88	0.88	0.88	0.89	0.86	0.88	0.88	0.87	0.88	0.85	0.88	0.88	1					
0.88	0.88	0.88	0.87	0.88	0.88	0.86	0.88	0.88	0.87	0.88	0.85	0.88	0.88	0.88	1				
0.87	0.88	0.87	0.88	0.87	0.87	0.87	0.88	0.87	0.88	0.87	0.86	0.87	0.88	0.87	0.87	1			
0.88	0.88	0.87	0.86	0.87	0.87	0.84	0.87	0.88	0.85	0.87	0.84	0.88	0.86	0.88	0.87	0.85	1		
0.88	0.88	0.88	0.88	0.88	0.88	0.85	0.88	0.87	0.86	0.88	0.83	0.88	0.87	0.88	0.88	0.87	0.87	1	
0.88	0.88	0.87	0.87	0.88	0.88	0.86	0.88	0.88	0.86	0.88	0.85	0.88	0.87	0.88	0.88	0.87	0.88	0.87	1

(d) Full sample sentiment score (Bayes)

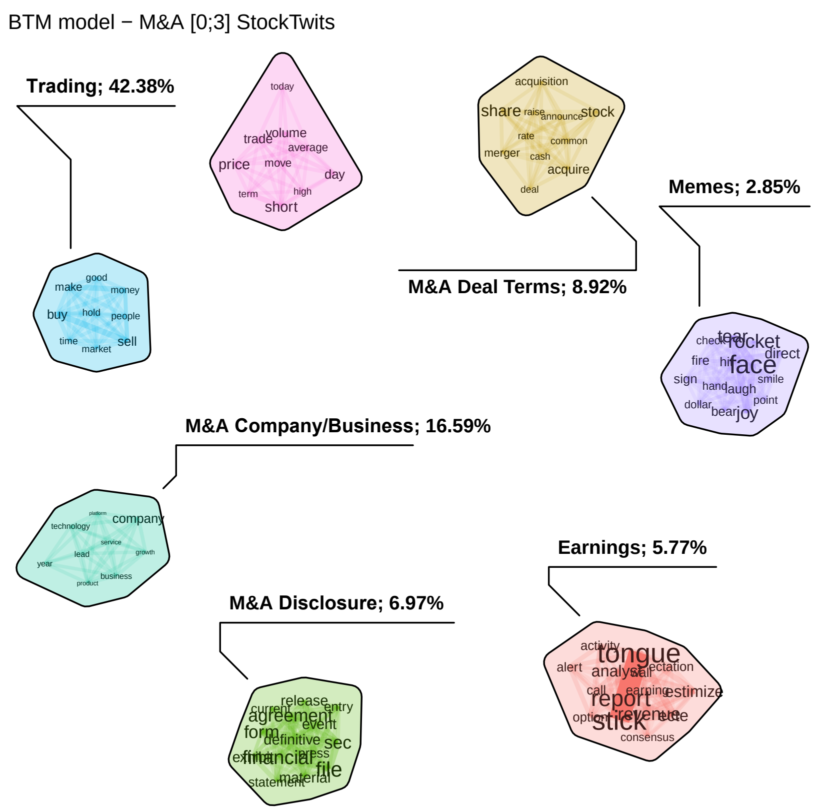
S1	S2	S3	S4	S5	S6	S7	S8	S9	S10	S11	S12	S13	S14	S15	S16	S17	S18	S19	S20
1																			
0.88	1																		
0.87	0.87	1																	
0.87	0.87	0.87	1																
0.88	0.88	0.87	0.87	1															
0.88	0.88	0.87	0.87	0.88	1														
0.85	0.85	0.86	0.86	0.84	0.84	1													
0.88	0.88	0.87	0.87	0.88	0.88	0.85	1												
0.88	0.88	0.87	0.87	0.88	0.88	0.86	0.88	1											
0.87	0.87	0.87	0.88	0.87	0.87	0.87	0.87	0.88	1										
0.88	0.88	0.87	0.87	0.88	0.88	0.84	0.87	0.87	0.87	1									
0.85	0.85	0.87	0.86	0.85	0.85	0.87	0.86	0.86	0.88	0.85	1								
0.87	0.88	0.87	0.87	0.87	0.88	0.85	0.88	0.88	0.87	0.87	0.85	1							
0.87	0.87	0.88	0.87	0.87	0.87	0.87	0.88	0.87	0.88	0.87	0.88	0.87	1						
0.88	0.88	0.87	0.87	0.88	0.88	0.84	0.88	0.88	0.87	0.88	0.85	0.88	0.87	1					
0.87	0.88	0.87	0.87	0.88	0.87	0.85	0.88	0.88	0.87	0.87	0.86	0.88	0.87	0.87	1				
0.86	0.86	0.87	0.86	0.86	0.86	0.87	0.86	0.86	0.88	0.86	0.88	0.86	0.88	0.86	0.86	1			
0.86	0.86	0.87	0.87	0.86	0.86	0.84	0.86	0.87	0.86	0.86	0.84	0.86	0.86	0.86	0.87	0.85	1		
0.88	0.88	0.87	0.87	0.88	0.88	0.85	0.88	0.87	0.87	0.88	0.85	0.88	0.87	0.88	0.87	0.86	0.86	1	
0.87	0.87	0.88	0.87	0.87	0.87	0.84	0.88	0.87	0.87	0.87	0.85	0.87	0.87	0.87	0.88	0.86	0.88	0.87	1

A.II Topic Modeling in Social Media Posts

To identify the primary topic of a given StockTwits tweet, we rely on the Biterm Topic Modeling (BTM) approach of Yan et al. (2013). BTM is based on the idea that if two words co-occur frequently, they likely belong to the same topic. Traditional topic modeling approaches, such as the Latent-Dirichlet-Algorithm (LDA) estimate co-occurrence patterns within a document to capture the latent semantic structure of a corpus implicitly by modeling the generation of *documents*. This approach suffers greatly in short texts such as Tweets. In contrast, BTM models the generation of *biterms* – i.e. the co-occurrence of words in the same text window (Tweet)– explicitly, and uses the aggregated word co-occurrence patterns in the whole corpus to identify topics.

In the BTM generation procedure, a biterm (an unordered word-pair of words) is generated by drawing two words, w_i and w_j, independently from the same topic z. In other words, the distribution of a biterm $b = (w_i, w_j)$ is defined as: $P(b) = \sum_{k=1}^{K} P(w_i|z = k) \times P(w_j|z = k) \times P(z_i = k)$ where K is the pre-defined number of topics to be extracted. We set the number of topics to $K = 8$ following the LDA diagnostics tests of Cao, Xia, Li, Zhang, and Tang (2009) and Deveaud, SanJuan, and Bellot (2014), and estimate the BTM with Gibbs sampling, using biterms of nouns, adjectives, and verbs within a 3 word distance. The model estimates in Figure A.4 indicate the probability that a word is in a given topic z, i.e. $\phi = P(w|z)$. Figure A.2 below displays the co-occurrence patterns and frequency of words within each topic.

Figure A.2: BTM topics and co-occurrences



Notes: This figure shows the most common terms and their co-occurrences within each topic z.

Table A.2: Summary Statistics M&A Sample

This table presents summary statistics for the sample of completed mergers (Panel A.2a) and withdrawn mergers (Panel A.2b). All variables are defined as detailed in Section 2 and Appendix Table A.12. All M&A deal characteristics are obtained from SDC Platinum, all accounting variables are obtained from Compustat NA and Winsorized at the 5% within the full Compustat universe. Stock Returns and cumulative abnormal returns are constructed using data from CRSP and the Fama-French 3-factor model as detailed in Section 2.2. VIX data is obtained from the CBOE. News media sentiment and coverage data are from RavenPack. The sample covers all M&A deals with U.S. acquiring firms over the period from 2010 to 2021 with a minimum deal volume of at least $25M.

(a) Completed Mergers

	N	Mean	SD	P25	P50	P75
Days to Deal Conclusion	6187	80.350	106.566	11.000	48.000	112.000
Abn. Sentiment (StockTwits)	6061	0.022	0.305	-0.121	0.016	0.174
Abn. Sentiment (MaxEnt)	6118	0.038	0.166	-0.058	0.027	0.124
Abn. Sentiment (Bayes)	6118	0.018	0.139	-0.056	0.013	0.091
Abn. Sentiment (SMA-Twitter)	4645	0.297	0.590	-0.020	0.115	0.501
CAR Acq. [-1;1]	6121	0.010	0.064	-0.017	0.004	0.031
CAR Acq. [-1;10]	6129	0.008	0.090	-0.036	0.005	0.048
CAR Acq. [-5;-1]	6121	-0.000	0.041	-0.020	-0.000	0.019
CAR Target [-1;1]	821	0.247	0.218	0.087	0.205	0.368
CAR Target [-1;10]	821	0.247	0.233	0.072	0.206	0.382
CAR Target [-5;-1]	820	0.011	0.063	-0.023	0.002	0.038
Deal Value (B. USD)	6187	1.028	2.517	0.085	0.234	0.744
% Shares Held Prior	6187	2.157	10.867	0.000	0.000	0.000
Acq. White Knight (0/1)	6187	0.001	0.025	0.000	0.000	0.000
Competing Bidder (0/1)	6187	0.008	0.088	0.000	0.000	0.000
Challenged Deal (0/1)	6187	0.009	0.096	0.000	0.000	0.000
Rumored Deal (0/1)	6187	0.093	0.291	0.000	0.000	0.000
Target Private (0/1)	6187	0.419	0.494	0.000	0.000	1.000
Hostile Deal (0/1)	6187	0.000	0.013	0.000	0.000	0.000
% Shares Sought	6111	96.714	13.018	100.000	100.000	100.000
Target Termination Fee (M. USD)	6187	15.564	101.350	0.000	0.000	0.000
Mcap Acq. (B. USD)	5989	23.952	70.498	1.446	4.493	17.847
M/B Acq.	5886	3.925	12.929	1.355	2.189	3.797
Cash/AT Acq.	5893	0.102	0.117	0.025	0.066	0.137
Leverage Acq.	5978	0.248	0.198	0.102	0.199	0.356
N. Tweets	6187	193.316	1961.903	15.000	35.000	81.500
News Sentiment Acq.	6187	0.007	0.997	-0.215	0.526	0.665
N News Articles	6187	4.500	17.014	1.000	2.000	5.000
Has Conf. Call (CC)	3890	0.247	0.431	0.000	0.000	0.000
VIX (S&P500)	6009	17.385	6.202	13.280	15.990	19.610
EPU	6187	135.596	44.107	102.660	126.192	157.496
Equity-Market Uncertainty	6187	52.271	68.344	12.320	29.270	63.170

... continued

(b) Withdrawn Mergers

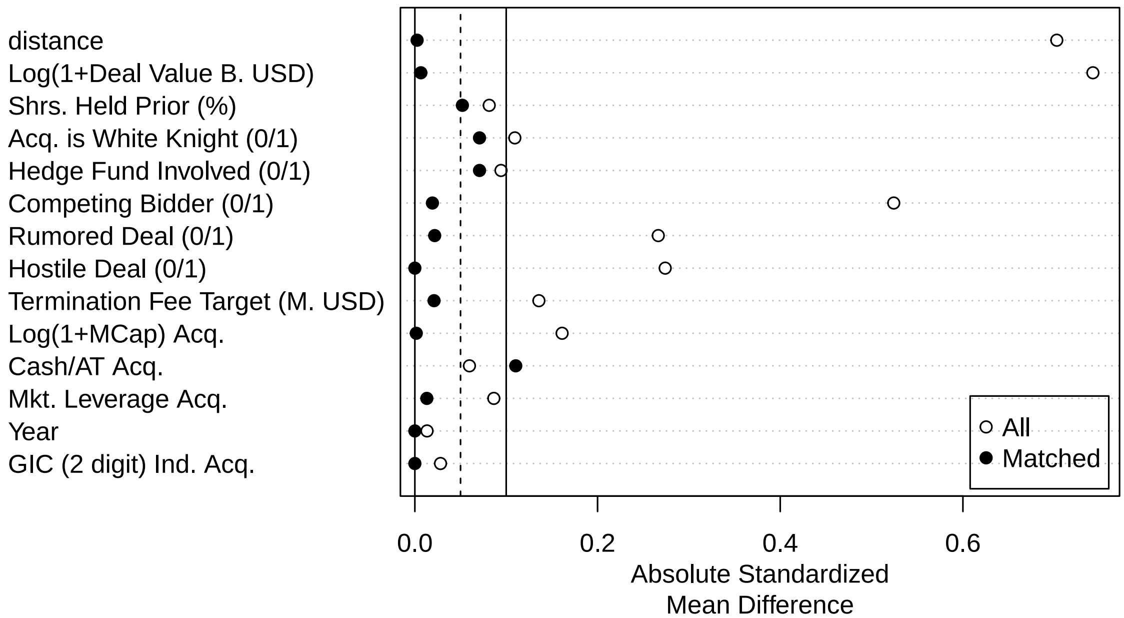
	N	Mean	SD	P25	P50	P75
Days to Deal Conclusion	251	179.649	187.172	56.000	119.000	226.500
Abn. Sentiment (StockTwits)	245	-0.030	0.271	-0.130	0.000	0.105
Abn. Sentiment (MaxEnt)	248	-0.009	0.151	-0.099	-0.015	0.074
Abn. Sentiment (Bayes)	248	-0.012	0.134	-0.086	-0.013	0.047
Abn. Sentiment (SMA-Twitter)	186	0.350	0.623	-0.025	0.157	0.723
CAR Acq. [-1;1]	247	-0.005	0.064	-0.035	-0.002	0.029
CAR Acq. [-1;10]	248	-0.016	0.093	-0.061	-0.009	0.041
CAR Acq. [-5;-1]	247	0.007	0.042	-0.015	0.003	0.024
CAR Target [-1;1]	106	0.168	0.192	0.033	0.140	0.235
CAR Target [-1;10]	107	0.170	0.223	0.017	0.125	0.261
CAR Target [-5;-1]	106	0.017	0.058	-0.012	0.008	0.041
Deal Value (B. USD)	251	4.466	6.030	0.364	1.360	6.326
% Shares Held Prior	251	2.921	11.471	0.000	0.000	0.000
Acq. White Knight (0/1)	251	0.012	0.109	0.000	0.000	0.000
Competing Bidder (0/1)	251	0.211	0.409	0.000	0.000	0.000
Challenged Deal (0/1)	251	0.275	0.447	0.000	0.000	1.000
Rumored Deal (0/1)	251	0.207	0.406	0.000	0.000	0.000
Target Private (0/1)	251	0.120	0.325	0.000	0.000	0.000
Hostile Deal (0/1)	251	0.064	0.245	0.000	0.000	0.000
% Shares Sought	245	95.906	14.497	100.000	100.000	100.000
Target Termination Fee (M. USD)	251	37.422	172.388	0.000	0.000	0.000
Mcap Acq. (B. USD)	236	31.799	55.857	1.789	9.263	33.027
M/B Acq.	231	4.291	8.483	1.369	2.188	4.059
Cash/AT Acq.	232	0.108	0.115	0.028	0.075	0.144
Leverage Acq.	236	0.267	0.214	0.108	0.208	0.376
N. Tweets	251	148.036	519.080	23.000	48.000	93.000
News Sentiment Acq.	251	-0.181	1.046	-0.923	0.365	0.625
N News Articles	251	8.888	18.126	2.000	5.000	9.000
Has Conf. Call (CC)	156	0.263	0.442	0.000	0.000	1.000
VIX (S&P500)	234	18.433	8.325	13.760	16.445	20.082
EPU	251	136.465	47.036	102.410	126.192	152.422
Equity-Market Uncertainty	251	58.205	86.725	12.570	28.580	62.260

Table A.3: Robustness – Fixed-effects GLM (Logit)

This table presents fixed effects logit (GLM) model estimates for the effect of social media feedback on the likelihood of M&A deal withdrawal, analogous to Table 2. The dependent variable is a dummy variable indicating whether or not an announced M&A transaction was subsequently withdrawn. 'Abn. Sentiment (z) (StTw)', 'Abn. Sentiment (z) (MaxE)', and 'Abn. Sentiment (z) (Bayes)' are the social media reaction from StockTwits using the sentiment score provided by StockTwits, the Maximum Entropy classifier, and the Naive Bayes classifier, respectively. The measures are constructed similarly as in Table 2. 'CAR Target (z) [-1;10] ([-5;-1])' are the cumulative abnormal returns of the target firm in the $[-1; 10]$ and $[-5; -1]$ window around the M&A announcement. 'News Sentiment Acq. (z)' and 'N News Articles' are the (standardized) news media sentiment and the number of news articles published about the M&A deal from from RavenPack, respectively. All variables denoted with '(z)' are standardized to have mean zero and standard deviation of one. All other variables are similar as in Table 2. 'Mean(LHS)' is the sample average of the dependent variable in the given regression. Each regression includes similar deal and firm-level controls as Table 2 and year-by-quarter and acquiring firm industry (GIC 2-digit) fixed effects as indicated. Standard errors are clustered at the year-by-quarter level and reported in parentheses. *, ** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

	$\mathbb{1}$(Deal Withdr.)		
	(1)	(2)	(3)
Abn. Sentiment (z) (StTw)	-0.2838***		
	(0.0730)		
Abn. Sentiment (z) (MaxE)		-0.2507***	
		(0.0792)	
Abn. Sentiment (z) (Bayes)			-0.1759**
			(0.0853)
CAR Acq. (z) [-1;10]	-0.2382***	-0.2455***	-0.2501***
	(0.0650)	(0.0617)	(0.0632)
CAR Acq. (z) [-5;-1]	0.1178	0.1421*	0.1404*
	(0.0864)	(0.0844)	(0.0850)
News Sentiment Acq. (z)	-0.2488***	-0.2469***	-0.2435***
	(0.0740)	(0.0708)	(0.0726)
N Tweets	-0.00009	-0.00010	-0.00010
	(0.0001)	(0.0001)	(0.0001)
N News Articles	0.0030	0.0029	0.0030
	(0.0020)	(0.0019)	(0.0019)
Mean(LHS)	0.0350	0.0350	0.0350
Observations	5,684	5,740	5,740
Deal Controls	✓	✓	✓
Firm Controls	✓	✓	✓
Year-by-Quarter FE	✓	✓	✓
Acq. Industry (GIC2) FE	✓	✓	✓

Figure A.3: PSM Matching Balance



Notes: This figure summarizes the covariate balance of the propensity score matching (PSM) procedure detailed in Section 3, comparing treated and matched observations (solid points) as well as treated observations and the full sample (hollow points). Observations are considered to be treated if the previously announced M&A deal was subsequently withdrawn. For each withdrawn M&A deal, we implement $k = 10$ nearest neighbor matching with replacement, by matching on the following covariates observed at the time of the M&A announcement: Log(1+Deal Value), shares held prior to the deal announcement (i.e., toehold), indicator variables for whether the acquirer is a white knight, hedge fund involvement, presence of a competing bidder, rumored deal, hostile deal, as well as the target firm termination fees and acquiring firm size (log market cap), cash holdings (cash/total assets), and market leverage. Each matched observation is required to be in the same year and GIC 2-digit industry as the acquiring firm in the withdrawn M&A transaction. Each point represents the absolute value of the standardized mean difference of the corresponding covariate in the matched or unmatched sample. 'Distance' corresponds to the Propensity Score from a logistic regression. The solid and dashed vertical lines indicate the 10% and 5% threshold, respectively.

Table A.4: Robustness – PSM Matching Estimations

This table presents linear probability model estimates analogous to Table 2, using the sample of withdrawn and completed M&A deals matched using $k = 10$ nearest-neighbor Propensity Score Matching (PSM) based on observable firm and deal characteristics as detailed in Figure A.3. The dependent variable is a dummy variable indicating whether or not an announced M&A transaction was subsequently withdrawn, multiplied by 100 for legibility. 'Abn. Sentiment (z) (StTw)', 'Abn. Sentiment (z) (MaxE)', and 'Abn. Sentiment (z) (Bayes)' are the social media reaction from StockTwits using the sentiment score provided by StockTwits, the Maximum Entropy classifier, and the Naive Bayes classifier, respectively. The measures are constructed similarly as in Table 2. 'CAR Target (z) [-1;10] ([-5;-1])' are the cumulative abnormal returns of the target firm in the $[-1; 10]$ and $[-5; -1]$ window around the M&A announcement. 'News Sentiment Acq. (z)' and 'N News Articles' are the (standardized) news media sentiment and the number of news articles published about the M&A deal from RavenPack, respectively. All variables denoted with '(z)' are standardized to have mean zero and standard deviation of one. All other variables are similar as in Table 2. 'Mean(LHS)' is the sample average of the dependent variable in the given regression. Each regression includes similar deal and firm-level controls as Table 2 and year-by-quarter and acquiring firm industry (GIC 2-digit) fixed effects as indicated. Standard errors are clustered at the year-by-quarter level and reported in parentheses. *, ** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

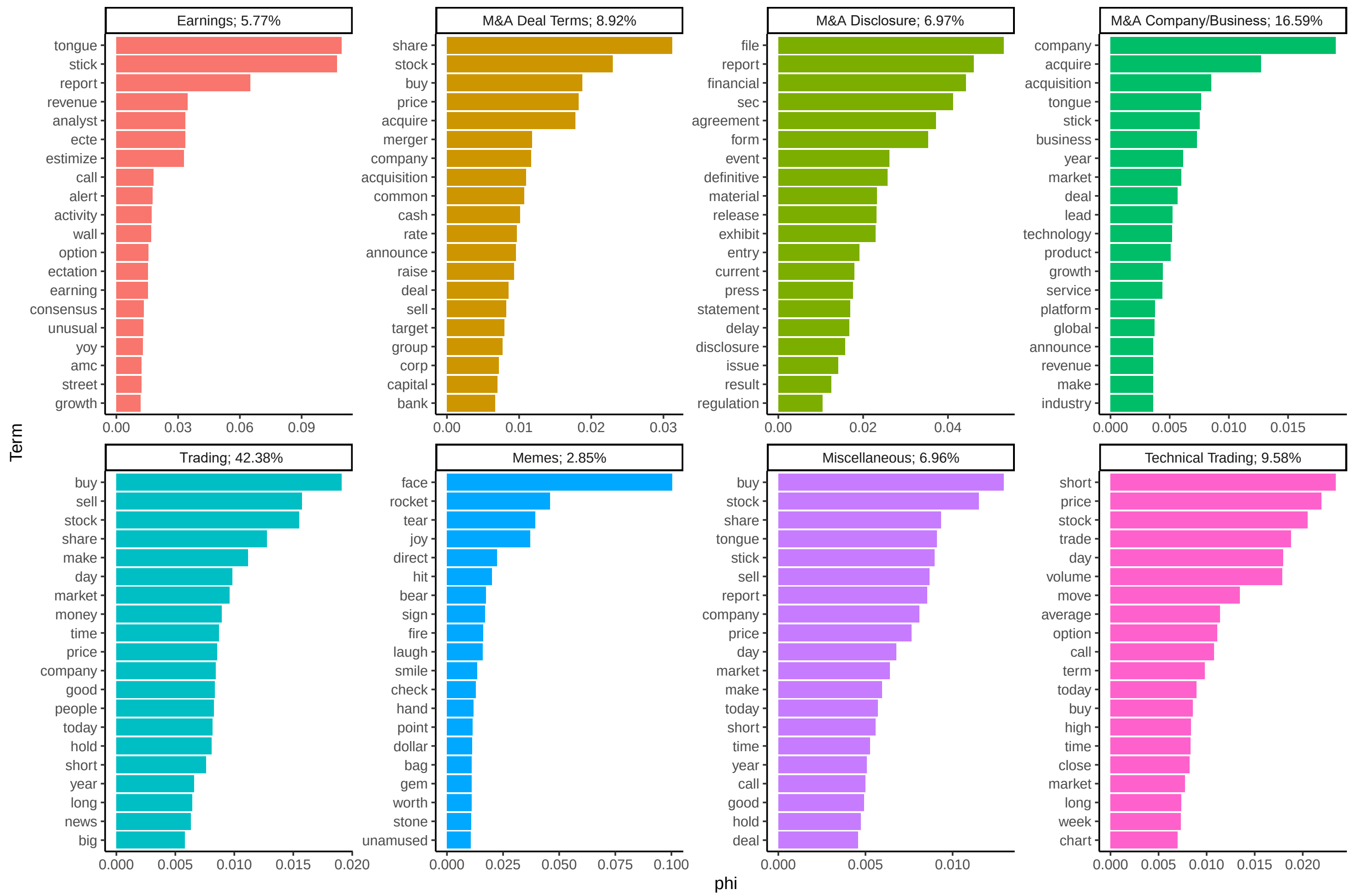
	$\mathbb{1}$(Deal Withdrawn)		
	(1)	(2)	(3)
Abn. Sentiment (z) (StTw)	-3.198***		
	(1.035)		
Abn. Sentiment (z) (MaxE)		-2.624**	
		(1.207)	
Abn. Sentiment (z) (Bayes)			-1.196
			(1.236)
CAR Acq. (z) [-1;10]	-2.386**	-2.679**	-2.723**
	(1.100)	(1.027)	(1.064)
CAR Acq. (z) [-5;-1]	0.4451	0.7436	0.7630
	(1.574)	(1.499)	(1.517)
News Sentiment Acq. (z)	-2.457**	-2.508**	-2.468*
	(1.197)	(1.222)	(1.231)
N Tweets	-0.0015	-0.0018*	-0.0017
	(0.0010)	(0.0010)	(0.0010)
N News Articles	-0.0686	-0.0578	-0.0621
	(0.0746)	(0.0749)	(0.0753)
Mean(LHS)	14.76	14.75	14.75
Observations	813	827	827
R^2	0.1328	0.1274	0.1237
Deal Controls	✓	✓	✓
Firm Controls	✓	✓	✓
Year-by-Quarter FE	✓	✓	✓
Acq. Industry (GIC2) FE	✓	✓	✓

Table A.5: Robustness – Corporate Social Media Engagement

This table presents cross-sectional evidence on the moderating effect of corporate social media engagement on the sensitivity of M&A deal withdrawal to social media feedback around M&A deal announcement. Across columns (1) through (10), we split the sample of M&A deals based on five measures of corporate social media engagement capturing whether: the firm had a corporate twitter account at any point (columns 1–2), the firm had a verified corporate twitter account at any point (columns 3–4), the firm had a corporate twitter account with an above median number of followers at any point (columns 5–6), the firm uses a 'Social Media Monitoring' service to post on Twitter (columns 7–8), the CEO had a personal twitter account at any point (columns 9–10). All other variables are similar as in Table 2. Each regression includes similar deal and firm-level controls as Table 2 and year-by-quarter and acquiring firm industry (GIC 2-digit) fixed effects as indicated. 'Mean(LHS)' is the average of the dependent variable in the given regression, 'Coef. Diff. t-Stat (p-Value)' provides the Welch t-Statistic and corresponding p-Value testing the hypothesis that the coefficient estimates on our main variable of interest, 'Abn. Sentiment (z) (StTw)', are equal across both regressions. Standard errors are clustered at the year-by-quarter level and reported in parentheses. *, ** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

	$\mathbb{1}$(Deal Withdrawn)									
Sample Split	Acq. had Twitter		Verified Account		Follower Count		Acq. uses SMM		Acq. CEO has Twitter	
	No	Yes	No	Yes	Low	High	No	Yes	No	Yes
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Abn. Sentiment (z) (StTw)	-0.4007	-0.9392***	-0.3202	-1.513***	-0.2215	-1.296***	-0.4002*	-1.159***	-0.6781***	-2.283**
	(0.2572)	(0.3130)	(0.1978)	(0.4416)	(0.2212)	(0.3630)	(0.2327)	(0.3336)	(0.2163)	(0.9169)
CAR Acq. (z) [-1;10]	-0.8678**	-0.9818***	-0.9789***	-0.7920**	-0.5969	-1.394***	-0.6921**	-1.397***	-1.005***	0.2874
	(0.4304)	(0.3567)	(0.3208)	(0.3910)	(0.3645)	(0.3846)	(0.3202)	(0.4391)	(0.2636)	(0.7820)
CAR Acq. (z) [-5;-1]	0.0940	0.7060**	0.2019	1.071**	0.2694	0.7677*	0.4006	0.6076	0.4610	0.5433
	(0.3961)	(0.3022)	(0.2720)	(0.4954)	(0.3558)	(0.3840)	(0.2979)	(0.3798)	(0.2875)	(0.7601)
News Sentiment Acq. (z)	-0.9015	-1.186***	-0.7167**	-2.026***	-1.103***	-0.8295**	-1.120***	-0.9579**	-1.095***	-0.3076
	(0.5609)	(0.3099)	(0.3031)	(0.5763)	(0.3785)	(0.3867)	(0.3633)	(0.3953)	(0.2744)	(1.111)
N Tweets	-0.00010**	-0.0004*	-0.0001***	-0.0001	-0.0001***	-0.0004	-0.0001**	-0.0012***	-0.0002***	-0.0003
	(0.00004)	(0.0003)	(0.00004)	(0.0003)	(0.00004)	(0.0003)	(0.00004)	(0.0004)	(0.00004)	(0.0004)
N News Articles	0.1099	0.0053	0.1063	0.0064	0.0262	0.0071	0.1131	-0.0002	0.0087	0.0330
	(0.1742)	(0.0096)	(0.0803)	(0.0098)	(0.1089)	(0.0104)	(0.1096)	(0.0084)	(0.0082)	(0.1715)
Mean(LHS)	3.144	3.744	3.458	3.743	3.215	3.890	3.150	3.996	3.535	3.805
Coef. Diff. t-Stat. (p-Value)	1.329	(0.184)	2.466	(0.014)	2.528	(0.012)	1.865	(0.062)	1.704	(0.088)
Observations	1,845	4,087	3,875	2,057	2,924	3,008	3,079	2,853	5,459	473
R^2	0.1635	0.2572	0.2130	0.2450	0.1936	0.2521	0.2049	0.2431	0.2167	0.2816
Deal Controls	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Firm Controls	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Year-by-Quarter FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Acq. Industry (GIC2) FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓

Figure A.4: Biterm Topic Modeling (BTM) topics and top words



Notes: This figure shows the $K = 8$ topics in StockTwits tweets during the $[0; 3]$ day window around the announcement of an M&A deal, as identified by the Biterm Topic Modeling (BTM) approach outlined in Appendix Section A.II. For each topic, the figure shows the topic label and proportion the topic represents in the overall body of StockTwits posts, along with the 20 most representative words for each topic. *phi* represents $P(w|z)$ in the BTM: the probability that a word belongs to a given topic given its co-occurrence with other words.

Table A.6: Robustness – Effect of the GME Episode

This table presents linear probability model estimates on the effect of the GameStop Corp. (GME) episode in early 2021 on the relationship between M&A deal completion and social media feedback around M&A deal announcement. Similar to Table 2, the dependent variable is an indicator that takes the value of one if the previously announced M&A deal is ultimately withdrawn, and zero otherwise and 'Abn. Sentiment (z) (StTw)' is the social media feedback from StockTwits. $1(PostGME)$ is an indicator variable that takes the value of one for M&A deals that were announced after the trading frenzy around GME started on January 21, 2021, and zero otherwise. All other variables are similar as in Table 2. Each regression includes similar deal and firm-level controls as Table 2 and year-by-quarter and acquiring firm industry (GIC 2-digit) fixed effects as indicated. Standard errors are clustered at the year-by-quarter level and reported in parentheses. *, ** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

	𝟙(Deal Withdrawn)	
	(1)	(2)
Abn. Sentiment (z) (StTw)	-0.7654***	-0.7625***
	(0.2203)	(0.2204)
Abn. Sentiment (z) (StTw) × 1(Post GME)	0.9349*	0.9074*
	(0.4875)	(0.4792)
CAR Acq. (z) [-1;10]	-0.8409***	-0.8890***
	(0.2684)	(0.2879)
CAR Acq. (z) [-5;-1]	0.4706*	0.4684*
	(0.2626)	(0.2629)
1(Post GME) × CAR Acq. (z) [-1;10]		0.3601
		(0.6113)
News Sentiment Acq. (z)	-1.016***	-1.016***
	(0.2588)	(0.2591)
Analyst Rec. Changes (z)	-0.9441***	-0.9425***
	(0.3278)	(0.3277)
N Analyst Rec.	0.1101	0.1087
	(0.1922)	(0.1919)
N News Articles	0.0094	0.0094
	(0.0101)	(0.0101)
N Tweets	-0.0002***	-0.0002***
	(0.00004)	(0.00004)
Mean(LHS)	3.776	3.776
Observations	5,932	5,932
R^2	0.2161	0.2161
Deal Controls	✓	✓
Firm Controls	✓	✓
Year-by-Quarter FE	✓	✓
Acq. Industry (GIC2) FE	✓	✓

Table A.7: Disagreement of Stock Market and News Media

This table presents linear probability model estimates for the effect of social media feedback on the likelihood of M&A deal withdrawal, focusing on the relationship of Social Media with other sources of information. Similar to Table 2, the dependent variable is a dummy variable indicating whether or not an announced M&A transaction was subsequently withdrawn, multiplied by 100. All explanatory variables are defined similarly as in Table 2. We split the sample into observations with above and below median disagreement between Social Media feedback from StockTwits and Acquirer announcement CAR (columns 1 and 2) and News Media sentiment (columns 3 and 4), respectively. We measure disagreement as defined in Appendix Table A.12. Each regression includes similar deal and firm-level controls as Table 2 and year-by-quarter and acquiring firm industry (GIC 2-digit) fixed effects as indicated. Standard errors are clustered at the year-by-quarter level and reported in parentheses. *, ** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

	$\mathbb{1}$(Deal Withdrawn)			
Sample Split	Disagr. CAR		Disagr. News Media	
	Low	High	Low	High
	(1)	(2)	(3)	(4)
Abn. Sentiment (z) (StTw)	-0.1747	-1.117***	-0.3595	-1.199***
	(0.3493)	(0.2739)	(0.3237)	(0.2980)
CAR Acq. (z) [-1;10]	-0.1731	-1.274***	-0.8039**	-1.191**
	(0.4974)	(0.2938)	(0.3902)	(0.4970)
CAR Acq. (z) [-5;-1]	0.5824	0.4189	1.082***	0.2693
	(0.3604)	(0.3478)	(0.3736)	(0.4847)
News Sentiment Acq. (z)	-1.892***	-0.2013	-6.403***	0.5372
	(0.4191)	(0.3384)	(1.141)	(0.7522)
N Tweets	-0.0002	-0.0002***	0.0003	-0.0002***
	(0.0003)	(0.00004)	(0.0007)	(0.00005)
N News Articles	0.0101	-0.0039	0.0019	0.0019
	(0.0120)	(0.0296)	(0.0134)	(0.0120)
Mean(LHS)	3.543	3.570	3.353	2.753
Coef. Diff. t-Stat (p-Value)	2.123	(0.034)	1.909	(0.056)
Observations	2,851	3,081	2,237	2,252
R^2	0.2792	0.1720	0.2508	0.1979
Deal Controls	✓	✓	✓	✓
Firm Controls	✓	✓	✓	✓
Year-by-Quarter FE	✓	✓	✓	✓
Acq. Industry (GIC2) FE	✓	✓	✓	✓

Table A.8: Seller's put – Cash vs. Stock Deals

This table presents linear probability estimates on the relationship between M&A deal payment form and the effect of social media reactions on M&A deal withdrawals. The dependent variable is a dummy variable indicating whether or not an announced M&A transaction was subsequently withdrawn, multiplied by 100. In columns (1) and (2) we split the sample into cash (i.e., at least 90% of transaction paid in cash) and non-cash deals. In columns (3) and (4) we split the sample into deals with and without a significant proportion of the payment in the form of stocks (i.e., at least 25%). All explanatory variables are similar as in Table 2. Each regression includes similar deal and firm-level controls as Table 2 and year-by-quarter and acquiring firm industry (GIC 2-digit) fixed effects as indicated. 'Mean(LHS)' is the average of the dependent variable in the given regression, 'Coef. Diff. t-Stat (p-Value)' provides the t-Statistic and corresponding p-Value testing the hypothesis that the coefficient estimates on our main variable of interest, 'Abn. Sentiment (z) (StTw)', are equal across both regressions. Standard errors are clustered at the year-by-quarter level and reported in parentheses. *, ** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

	$\mathbb{1}$(Deal Withdrawn)			
Sample Split	Cash Deal (≥90% cash)		Stock Deal (≥25% stock)	
	No	Yes	No	Yes
	(1)	(2)	(3)	(4)
Abn. Sentiment (z) (StTw)	-0.9903***	-0.2563	-0.3856	-2.219***
	(0.2497)	(0.3394)	(0.2369)	(0.6153)
CAR Acq. (z) [-1;10]	-0.8293**	-0.9407**	-0.6554**	-1.048*
	(0.3280)	(0.4333)	(0.2518)	(0.5414)
CAR Acq. (z) [-5;-1]	0.4564	0.5716	0.4134	0.6094
	(0.3274)	(0.4696)	(0.2511)	(0.6231)
News Sentiment Acq. (z)	-0.9373***	-1.423***	-0.7406***	-1.590*
	(0.3383)	(0.4736)	(0.2491)	(0.8734)
N Tweets	-0.0002***	-0.0002	-0.0002	-0.0002***
	(0.00004)	(0.0003)	(0.0002)	(0.00006)
N News Articles	0.1462**	-0.0072	-0.0025	0.1501*
	(0.0649)	(0.0072)	(0.0056)	(0.0798)
Mean(LHS)	3.641	3.408	3.550	3.583
Coef. Diff. t-Stat (p-Value)	1.742	(0.082)	2.780	(0.005)
Observations	3,790	2,142	4,704	1,228
R^2	0.2076	0.2689	0.1924	0.2999
Deal Controls	✓	✓	✓	✓
Firm Controls	✓	✓	✓	✓
Year-by-Quarter FE	✓	✓	✓	✓
Acq. Industry (GIC2) FE	✓	✓	✓	✓

Table A.9: M&A Deal Complexity

This table presents linear probability estimates examining cross-sectional differences in the effect of social media reactions on M&A deal withdrawals with respect to information asymmetry between the target and acquiring firm. The dependent variable is a dummy variable indicating whether or not an announced M&A transaction was subsequently withdrawn, multiplied by 100. In columns (1) and (2) we split the sample into deals with above and below median number of industries (SIC 3-digit) the target firm is actively operating in. In columns (3) and (4) we split the sample into deals where the target firm is in an industry with above and below median standard deviation in analyst earnings forecasts, following Humphery-Jenner (2014). Columns (5) and (6) distinguish between cross-border deals, i.e., M&As in which target and acquirer are located in different countries, and domestic deals, as in Francis et al. (2014), and columns (7) and (8) split the sample into observations with above and below median number of M&A advisors working for the acquiring firm, following Servaes and Zenner (1996). All other explanatory variables are similar as in Table 2. Each regression includes similar deal and firm-level controls as Table 2 and year-by-quarter and acquiring firm industry (GIC 2-digit) fixed effects as indicated. 'Mean(LHS)' is the average of the dependent variable in the given regression, 'Coef. Diff. t-Stat (p-Value)' provides the Welch t-Statistic and corresponding p-Value testing the hypothesis that the coefficient estimates on our main variable of interest, 'Abn. Sentiment (z) (StTw)', are equal across both regressions. Standard errors are clustered at the year-by-quarter level and reported in parentheses. *, ** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

	$\mathbb{1}$(Deal Withdrawn)							
Sample Split	N SIC3 Tgt.		Hard-To-Value Tgt.		Cross-Border Deal		N Advisors Acq.	
	Low	High	No	Yes	No	Yes	Low	High
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Abn. Sentiment (z) (StTw)	-0.4082**	-1.684***	-0.3631	-1.337***	-0.4682**	-1.294**	-0.3004	-1.185***
	(0.1773)	(0.5662)	(0.2467)	(0.3764)	(0.2016)	(0.5195)	(0.2353)	(0.3148)
CAR Acq. (z) [-1;10]	-0.8014***	-0.9352*	-0.1023	-1.396***	-0.9577***	-0.7281	-0.1492	-1.412***
	(0.2393)	(0.5553)	(0.3839)	(0.3870)	(0.2581)	(0.5705)	(0.3140)	(0.3988)
CAR Acq. (z) [-5;-1]	0.3417	0.8592	0.8258***	0.3717	0.3266	0.7275	0.0376	0.8090**
	(0.2523)	(0.7132)	(0.2755)	(0.4583)	(0.2883)	(0.6505)	(0.2623)	(0.3977)
News Sentiment Acq. (z)	-0.2820	-2.477***	-1.239***	-1.016**	-0.6782***	-1.329**	-0.3938	-1.875***
	(0.2281)	(0.6221)	(0.3556)	(0.4529)	(0.2510)	(0.5123)	(0.2383)	(0.5190)
Mean(LHS)	3.540	3.598	3.236	3.327	3.288	4.241	3.419	3.691
Coef. Diff. t-Stat (p-Value)	2.150	(0.032)	2.163	(0.031)	1.481	(0.139)	2.250	(0.024)
Observations	4,181	1,751	2,658	2,585	4,258	1,674	2,925	3,007
R^2	0.1389	0.3109	0.2112	0.2402	0.2098	0.2639	0.1475	0.2506
Deal Controls	✓	✓	✓	✓	✓	✓	✓	✓
Firm Controls	✓	✓	✓	✓	✓	✓	✓	✓
Social & News Media Controls	✓	✓	✓	✓	✓	✓	✓	✓
Year-by-Quarter FE	✓	✓	✓	✓	✓	✓	✓	✓
Acq. Industry (GIC2) FE	✓	✓	✓	✓	✓	✓	✓	✓

Table A.10: Cost of Deal Withdrawal

This table presents linear probability estimates examining cross-sectional differences in the effect of social media reactions on M&A deal withdrawals with respect to the costs of withdrawing the announced M&A deal. The dependent variable is a dummy variable indicating whether or not an announced M&A transaction was subsequently withdrawn, multiplied by 100. In columns (1) through (4) we split the sample into deals with and without a definitive merger agreement. All explanatory variables are similar as in Table 2. Each regression includes similar deal and firm-level controls as Table 2 and year-by-quarter and acquiring firm industry (GIC 2-digit) fixed effects as indicated. 'Mean(LHS)' is the average of the dependent variable in the given regression, 'Coef. Diff. t-Stat (p-Value)' provides the t-Statistic and corresponding p-Value testing the hypothesis that the coefficient estimates on our main variable of interest, 'Abn. Sentiment (z) (StTw)', are equal across both regressions. Standard errors are clustered at the year-by-quarter level and reported in parentheses. *, ** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

	$\mathbb{1}$(Deal Withdrawn)			
Sample Split	Definitive Agreement			
	No	Yes	No	Yes
	(1)	(2)	(3)	(4)
Abn. Sentiment (z) (StTw)	-2.276**	-0.6230***	-1.963***	-0.5795***
	(0.9292)	(0.1924)	(0.6571)	(0.1866)
Mean(LHS)	4.370	2.814	4.258	2.799
Coef. Diff. t-Stat (p-Value)	1.742	(0.082)	2.026	(0.043)
Observations	984	3,696	963	3,608
R^2	0.1900	0.0235	0.5537	0.1133
Deal Controls			✓	✓
Firm Controls			✓	✓
Social & News Media Controls			✓	✓
Stock Return Controls			✓	✓
Year-by-Quarter FE	✓	✓	✓	✓
Acq. Industry (GIC2) FE	✓	✓	✓	✓

Table A.11: Economic Uncertainty

This table presents linear probability estimates examining cross-sectional differences in the effect of social media reactions on M&A deal withdrawals with respect to economic uncertainty. The dependent variable is a dummy variable indicating whether or not an announced M&A transaction was subsequently withdrawn, multiplied by 100. In columns (1)–(2), (3)–(4), and (5)–(6) we split the sample into deals with above and below median value of the CBOE's VIX in the month of the M&A deal announcement, Economic Policy Uncertainty (EPU), and Equity Market-related Economic Uncertainty (Equ. Mkt. Unc.), both obtained from Baker et al. (2016), respectively. All explanatory variables are similar as in Table 2. Each regression includes similar deal and firm-level controls as Table 2 and year-by-quarter and acquiring firm industry (GIC 2-digit) fixed effects as indicated. 'Mean(LHS)' is the average of the dependent variable in the given regression, 'Coef. Diff. t-Stat (p-Value)' provides the t-Statistic and corresponding p-Value testing the hypothesis that the coefficient estimates on our main variable of interest, 'Abn. Sentiment (z) (StTw)', are equal across both regressions. Standard errors are clustered at the year-by-quarter level and reported in parentheses. *, ** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

	𝟙(Deal Withdrawn)					
Sample Split	VIX (S&P500)		EPU		Equ. Mkt. Unc.	
	Low	High	Low	High	Low	High
	(1)	(2)	(3)	(4)	(5)	(6)
Abn. Sentiment (z) (StTw)	-0.5464*	-1.652***	-0.5149*	-1.126***	-0.6324**	-1.304***
	(0.2712)	(0.4628)	(0.2698)	(0.3863)	(0.2874)	(0.3500)
CAR Acq. (z) [-1;10]	-0.9756***	-1.232***	-1.240***	-0.7278*	-1.042**	-1.230***
	(0.3085)	(0.4050)	(0.3705)	(0.3880)	(0.4345)	(0.3783)
CAR Acq. (z) [-5;-1]	1.013***	-0.0316	0.7350	0.4750	1.281***	0.1791
	(0.3725)	(0.4770)	(0.4368)	(0.3670)	(0.4553)	(0.4293)
News Sentiment Acq. (z)	-1.254***	-1.198**	-1.365***	-1.227**	-1.234***	-1.552***
	(0.3658)	(0.5039)	(0.4001)	(0.4496)	(0.4359)	(0.4405)
N Tweets	-0.0006**	-0.0001**	-0.0007**	-0.0002***	-0.0002***	-0.00003
	(0.0003)	(0.00007)	(0.0003)	(0.00005)	(0.00004)	(0.0004)
N News Articles	0.0132	-0.0053	0.0085	0.0218	0.0106	0.0093
	(0.0092)	(0.0422)	(0.0103)	(0.0441)	(0.0138)	(0.0188)
Mean(LHS)	3.141	3.600	3.355	3.236	3.430	3.062
Coef. Diff. t-Stat (p-Value)	2.061	(0.039)	1.297	(0.195)	1.483	(0.138)
Observations	3,407	1,750	2,623	2,534	2,507	2,417
R^2	0.2674	0.1824	0.2407	0.2188	0.2435	0.2350
Deal Controls	✓	✓	✓	✓	✓	✓
Firm Controls	✓	✓	✓	✓	✓	✓
Year-by-Quarter FE	✓	✓	✓	✓	✓	✓
Acq. Industry (GIC2) FE	✓	✓	✓	✓	✓	✓

Table A.12: Variable Definitions and Data Sources

Variable	Description
$\mathbb{1}$(Deal Withdrawn)	Indicator variable that takes the value of one if a previously announced M&A deal is subsequently withdrawn. We multiply this variable by 100 for better legibility when indicated. *Data source:* SDC Platinum.
Days to Deal Conclusion	The number of days between the announcement of the M&A deal and the conclusion, i.e. either the completion ("effective date") or the withdrawal of the merger. *Data source:* SDC Platinum.
Abn. Sentiment (StTw)	Abnormal social media sentiment estimated from tweets posted on StockTwits around the announcement of an M&A transaction. We calculate this variable as the difference between the average sentiment score of tweets about the acquiring firm posted to StockTwits in the [0;3] day window around the merger announcement and the [-13;-6] day benchmark period. Sentiment scores at the individual tweet-level are obtained directly from StockTwits and are distributed between −1 and 1. *Data source:* StockTwits.
Abn. Sentiment (MaxEnt)	This variable is constructed similarly as 'Abn. Sentiment (StTw)'. However, 'Abn. Sentiment (MaxEnt)' uses tweet-level sentiment scores obtained using the Maximum Entropy (MaxEnt) classifier algorithm to classify the text of the tweets posted to StockTwits as described in Appendix A.I. Maximum Entropy sentiment scores are distributed between −1 and 1. *Data source:* StockTwits.
Abn. Sentiment (Bayes)	This variable is constructed similarly as 'Abn. Sentiment (StTw)'. However, 'Abn. Sentiment (Bayes)' uses tweet-level sentiment scores obtained using the Naive Bayes classifier algorithm to classify the text of the tweets posted to StockTwits as described in Appendix A.I. Naive Bayes sentiment scores are distributed between −1 and 1. *Data source:* StockTwits.
Abn. Sentiment (Twitter)	This variable is constructed similarly as 'Abn. Sentiment (StTw)'. However, 'Abn. Sentiment (Twitter)' uses tweet-level sentiment scores based on Twitter data, obtained by the data provider Social Market Analytics (SMA). Twitter sentiment scores from SMA are distributed between 0 and 1. *Data source:* SMA.
CAR Acq. (Target)	The cumulative abnormal return (CAR) of the acquirer (target) firm around the announcement of an M&A deal, estimated over the event window indicated in the variable name. CARs are estimated using the Fama-French 3-factor model with a 100-day pre-event estimation window, and a 10 day distance between estimation and event window. *Data source:* CRSP and Kenneth French's website.
Deal Value (B. USD)	The total volume (i.e. transaction value) of the M&A deal in $ Billion. *Data source:* SDC Platinum.
Acq. White Knight	Indicator variable that takes the value of one if the acquiror has made a friendly offer or has reached an agreement to acquire a target that is currently the subject of a hostile or unsolicited offer by another company, i.e. acquiror is a White Knight, and zero otherwise. *Data source:* SDC Platinum.
Hedge Fund Involved	Indicator variable that takes the value of one if any party involved in the deal is a hedge fund, and zero otherwise. This includes Target, Acquiror, Seller, Investor, or any of their immediate or ultimate parents. *Data source:* SDC Platinum.

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Variable	Description
Challenged Deal	Indicator variable that takes the value of one if a third party launched an offer for the target while this original bid was pending. *Data source:* SDC Platinum.
Rumored Deal	Indicator variable that takes the value of one if the transaction is currently or originally began as a rumor, even if both parties later confirm the deal. *Data source:* SDC Platinum.
Target Private	Indicator that takes the value of one if the target firm is a private company at the time of the merger announcement (i.e. shares not traded on a public exchange). *Data source:* SDC Platinum.
Hostile Deal	Indicator variable that takes the value of one if the deal attitude is 'hostile', i.e. the target board officially rejects the offer but the acquiror persists with the takeover. *Data source:* SDC Platinum.
Definitive Agreement	Indicator variable that takes the value of one if there is a publicly filed definitive agreement for the deal, and zero otherwise. *Data source:* SDC Platinum.
Pct Cash	Percentage of consideration paid in cash: Value paid in cash divided by total value. *Data source:* SDC Platinum.
Pct Stock	Percentage of consideration paid in stock: Value paid in stock divided by total value. *Data source:* SDC Platinum.
MCap Acq.	Market capitalization (in $ Billion) of the acquiring firm in the current fiscal year. Calculated as price per share ('prcc_f') $\times$ number of shares outstanding ('csho'). *Data source:* Compustat North America.
M/B Acq.	Market-to-book ratio of the acquiring firm. Calculated as market capitalization over book equity (i.e. 'mcap/be'). *Data source:* Compustat North America.
Cash/AT Acq.	Cash holdings of the acquiring firm (i.e. 'ch'), scaled by total book value of assets ('at'). *Data source:* Compustat North America.
Leverage Acq.	Market leverage of the acquiring firm. Calculated as the sum of long and short-term debt (i.e. total debt) over the sum of total debt and market capitalization (i.e. '(dltt+dlc)/(dltt+dlc+csho*prcc_f)'). *Data source:* Compustat North America.
N Posts	The number of tweets about the acquiring firm posted to StockTwits in the event window around the M&A announcement. *Data source:* StockTwits.
News Sentiment Acq.	The aggregate sentiment of newspaper articles about the M&A deal, calculated using the Event Sentiment Score (ESS) provided by Ravenpack News Analytics (Version 1.0). We retain only articles and stories related to 'mergers / acquisitions' as categorized by Ravenpack and exclude reposted, older stories. *Data source:* Ravenpack News Analytics.
N News Articles	The number of novel, unique news articles published about the M&A deal during the event window as recorded by Ravenpack News Analytics. *Data source:* Ravenpack News Analytics.

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Variable	Description
Has Conf. Call	An indicator variable that takes the value of one if the acquiring firm held an analyst conference call in relation to the merger on the day of the merger announcement and has a conference call transcript available as provided Streetevents, and zero otherwise. We retain only analyst conference call transcripts labeled as M&A-related. *Data source:* Streetevents.
% Constrainted Words PPT (Q&A)	The percentage of 'constrained words' in the presentation section (Questions & Answers section) of the M&A-related analyst conference call transcript as defined in Loughran and McDonald (2016) and Bodnaruk et al. (2015), using the 2022 version of the Loughran and McDonald (2011) Master Dictionary. *Data source:* Streetevents.
% Negative Words PPT (Q&A)	The percentage of 'negative words' in the presentation section (Questions & Answers section) of the M&A-related analyst conference call transcript as defined in Loughran and McDonald (2016) and Bodnaruk et al. (2015), using the 2022 version of the Loughran and McDonald (2011) Master Dictionary. *Data source:* Streetevents.
VIX (S&P500)	The option-implied volatility index of the S&P500 provided by the CBOE. *Data source:* CBOE website.
EPU	The Economic Policy Uncertainty index obtained from Baker et al. (2016). *Data source:* Nick Bloom's website.
Equity Market Uncertainty	Economic uncertainty index related to equity markets, obtained from Baker et al. (2016). *Data source:* FRED Database Series WLEMUINDXD.
N SIC3	The number of 3-digit SIC industry segments the target (acquiring) firm is actively operating in. *Data source:* SDC Platinum.
Hard-to-value Target	The median standard deviation in analyst earnings forecasts by industry. *Data source:* Compustat and IBES.
Cross-border deal	Indicator variable that takes the value of one if the acquirer and target firm are in different home countries. *Data source:* SDC Platinum.
N Advisors Acq.	The number of M&A advisors hired by the acquiring firm. *Data source:* SDC Platinum.