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

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Abstract

This paper examines the role of social media in informing corporate decision-making by studying the decision of firm management to withdraw an announced merger. A standard deviation decline in abnormal social media sentiment following a merger announcement predicts a 0.73 percentage point increase in the likelihood of merger withdrawal (18.9% of the baseline rate). The informativeness of social media for merger withdrawals is not explained by abnormal price reactions or news sentiment, and in fact, it is stronger when these other signals disagree. Consistent with learning from external information, we find that the social media signal is most informative for complex mergers in which analyst conference calls take a negative tone, driven by the Q&A portion of the call. Overall, these findings imply that social media is not a sideshow, but an important aspect of firm information environment.

Keywords: Social Media, Social Finance, FinTech, Capital Allocation, M&A

JEL Codes: F30; F36; G38; Q50

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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, 2021). 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 news, shapes 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. 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 firm management withdraws from an announced merger. Our tests control for other reasons that firm managers change their minds, such as learning from market reactions or news. In fact, management's

[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).

responsiveness to a negative social media signal is strongest when it disagrees with signals from other sources, i.e., when other signals are positive.

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 yearly or quarterly, which does not facilitate showing a compelling link to social media information that arrives at high frequency.

Our empirical setting overcomes each of 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 is geared towards a discussion of financial markets and individual stocks. Users use 'cashtags' followed by a ticker (e.g., $AAPL for Apple stock) to precisely associate a tweet with a specific firm.[2] Using this information, as well as the tweet sentiment provided by StockTwits, we construct a stock-day measure of social media sentiment for a broad cross-section of firms. Second, M&A transactions are a useful setting for studying how corporate investments are influenced by social media, as they allow us to observe the precise merger announcement date *and* the ultimate outcome of the transaction (deal completed or withdrawn). Building on Luo (2005), the intuition for our main test is simple: as long as announced acquisitions reflect genuine intentions of firm management, 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 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.

We implement this empirical strategy using a comprehensive sample of acquisition announce-

[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.

ments of public and private targets over the period from 2010 to 2020. We estimate that a standard deviation decrease in abnormal StockTwits sentiment increases the likelihood of a merger withdrawal by 0.73 percentage points or 18.9% 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) and news sentiment as in Liu and McConnell, 2013), 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., see Oster, 2019). Further, we find a similar negative relation between abnormal social media sentiment and merger withdrawals when we measure the sentiment of tweets using two alternative machine learning classifications, when we focus on public firms and large firms, for different subperiods, and when we exclude different kinds of mergers that were withdrawn for regulatory reasons or because of votes by the target board or shareholders.

Next, we perform several tests to understand the nature of the information contained in the social media signal. First, we find that negative abnormal social media sentiment following a merger announcement is a stronger predictor of merger withdrawals when either the stock price or news reactions is positive, implying that social media contains more information when it is more distinct from other sources of information. Second, 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. Third, in a falsification test, we see the opposite relation when we perform a similar analysis of completed and withdrawn share repurchases. Fourth, 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.[3]

Overall, this evidence paints a consistent picture that social media helps shape the corporate decision to withdraw or proceed with a merger. Information from social media informs firm managers,

[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.

allowing them to revise their original expectations. Moreover, social media is distinct from traditional sources of external feedback, and this signal is more useful for deals in which the potential gain from learning is greatest. 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 themselves to update, 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. However, even if our results were mostly driven by this predictive channel, it still suggests that social media is *informative*. In either of these interpretations, managers learn or could learn something from social media feedback. Our finding that social media's effects are most pronounced when learning is most valuable suggest a traditional learning channel explains at least part of our findings.

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, like social media platforms, that increase access to data lead 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., 2021; 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, 2021). 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) and Bond, Edmans, and Goldstein (2012)), 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&A, 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 to Liu and McConnell (2013) who study the informativeness of traditional media sentiment for M&A. 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 similar weight in management decision-making.

Our paper also contributes to the literature on financial technology and firm 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

[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).

platforms, emphasizing their uptake by consumers and informativeness (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 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 feedback is the financial social media network StockTwits. Similar to Twitter, StockTwits allows users to publicly post short messages (henceforth 'tweets') with a limited number of characters. In contrast to Twitter, StockTwits is primarily focused on financial markets. Upon login, 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 ($) followed by a ticker symbol, StockTwits users can specify that their post refers to a specific firm or security with their followers and the StockTwits community. For example, if a StockTwits user wanted to express a positive opinion about Apple Inc. on the platform, they could say "$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 a 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 on to 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 (if available) of every message posted to StockTwits between January 2010 and December 2020, 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).

To provide further confidence in our estimates, we also calculate our own sentiment scores based on the content of each tweet in addition to the sentiment scores provided by StockTwits. 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.

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 2020 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.6. Figure 1 plots the total number of mergers per year throughout our sample period.

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).[5] Since many target firms are private, stock return data are unavailable and CARs cannot be computed for this subsample. We further 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.

2.3 Other Data Sources

2.3.1 Traditional News Media

We additionally obtain sentiment measures for traditional news media reports related to the M&A deals in our sample from RavenPack News Analytics (RPNA). We rely on the Dow Jones Edition

[5]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.

package of RavenPack, which analyzes all articles and reports published on Dow Jones Newswires, regional editions of the Wall Street Journal, Barron's and MarketWatch. For each acquirer and target firm in 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.

Following Gao, Parsons, and Shen (2017), we classify each news article as positive if the corresponding Event Sentiment Score (ESS) provided by RavenPack is in the upper tercile of all news articles in the sample, and categorize each news article as negative, if the ESS is in the lower tercile. We then calculate the overall 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 newspaper articles about the M&A deal, as in Gao et al. (2017).

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 2020. 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, 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 the number 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 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 announcement by documenting the number of tweets about the acquirer firm that include the 'cashtag' (i.e. 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 figure increases from zero to approximately 20, a margin similar to the increase in the total number of 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 with such M&A words approximately doubles following the announcement of a merger.

2.5 Variable Construction and Summary Statistics

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

[Insert Table 1 here.]

The final sample of M&A announcements with available StockTwits sentiment data for the acquiring firms contains 5,631 unique M&A deals, out of which 5,417 were eventually completed (Panel 1a) and 214 were eventually withdrawn (Panel 1b). This is a deal withdrawal rate of approximately 3.8%, consistent prior literature (e.g. Luo, 2005). Most M&A transactions in the sample are full takeovers, the median percentage of shares sought is 100% (mean of 96.68% for completed and 95.75% for withdrawn deals).

Consistent with prior literature, there is a large positive abnormal announcement return for the publicly listed *target* firms in the sample. For example, the mean Cumulative Abnormal Return (CAR) for M&A targets is 0.246 during the $[-1; 10]$ day event window around the announcement for mergers that are eventually completed, and 0.173 for deals that are eventually withdrawn. In contrast, the mean CAR for acquirer firms in the sample is closer to zero, with means (medians) of 0.008 (0.005) and -0.015 (-0.009), respectively. Further, in line with recent research (e.g. Betton, Eckbo, and Thorburn, 2009), toeholds are relatively rare and small in our data. The median (mean) percentage of target shares held by the acquirer prior to the merger announcement is 0.000% (2.194%) for completed and 0.000% (3.081%) for eventually withdrawn deals.

The average number of tweets about the acquiring firm around the M&A announcement date is 146.8 (97.5) for completed (withdrawn) mergers. On average, 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). 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.[6]

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

$$\text{AbnSent}_i = \left(\frac{1}{T} \sum_{t=0}^{T} Sentiment_{i,t} \right) - \left(\frac{1}{T} \sum_{n=-13}^{N=-7} Sentiment_{i,t} \right) \tag{1}$$

$Sentiment_{i,t}$ is the social media sentiment for M&A transaction i on day t relative to the merger announcement date ($t = 0$). Hence, $AbnSent_i$ captures the change in 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

[6]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.

estimations, we use the sentiment scores provided by StockTwits as $Sentiment_{i,t}$ with a four-day announcement period, i.e. $T = 3$. This time window matches the pattern in Figure 2, which shows a sharp increase in the number of M&A related tweets on days $t = 0$ to $t = 3$ relative to the announcement. In robustness tests, we confirm that 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 1 indicate that this procedure 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 0.014 (0.016) with an inter-quartile range of -0.136 to 0.172 for completed mergers (Panel 1a) and an average (median) of -0.029 (0.000) for withdrawn M&A deals (Panel 1b). 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 0.016 (0.009) and 0.022 (0.007) for completed mergers, and -0.012 (-0.016) and -0.008 (-0.008) for withdrawn deals.

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 around the announcement of the merger. Our aim is to 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, and traditional news media (Luo, 2005; Kau et al., 2008; Liu and McConnell, 2013). If it does contain useful information beyond these traditional sources, we also 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]

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

[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.

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. The main coefficient of interest is β_1, which captures how responsive deal withdrawals are to changes in a firm's abnormal social media sentiment ($AbnSent_i$). 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 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 0.7320 percentage point *increase* in the likelihood of merger withdrawal. This estimated magnitude is quite large, reflecting an increase of 18.9% of the baseline rate of merger withdrawals (3.870% 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 0.86.

Next, we sequentially enrich the specification with other market signals (i.e., $CAR[-5,-1]$ and $CAR[1,10]$), news media sentiment from RavenPack, other deal-level controls, and fixed effects. As shown in columns 2 through 5, the coefficient magnitude on $AbnSent_i$ is quite stable, despite the inclusion of additional controls increasing the R^2 from 6.73% (column 2) to 21.05% (column 5). 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,

[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

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 2020, this result provides a useful quantitative benchmark for our main result. A standard deviation increase in $CAR[-1, 10]$ is associated with roughly a 0.9 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 1.14 percentage point decline in the likelihood of a merger withdrawal, consistent with Liu and McConnell (2013). As with the market reaction terms, the magnitude on news sentiment is similar to the social media sentiment, and its individual inclusion does not meaningfully change the estimate on $AbnSent_i$. Further, this specification also controls for the amount of attention by including the number of news articles and the number of tweets about the acquiring firm around the announcement. The inclusion of these controls reduces concerns that attention to the firm on social media or traditional media drives the connection between $AbnSent_i$ and merger withdrawals.

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 withdrawal outcomes. Table 3 presents the estimates from these robustness exercises.

[Insert Table 3 here]

3.2.1 Measurement of Social Media Sentiment

First, we consider robustness to alternative measurement of social media sentiment. One concern is that corporate decision makers are not attuned to the precise social media signal we employ − the firm-day sentiment score from StockTwits. To alleviate this concern, 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.[9] 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 (3a) 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 0.4239 to 0.5887 percentage points lower likelihood of merger withdrawal, which is 11.4% to 15.8% 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.

3.2.2 Important Subsamples

Next, we evaluate the subset of deals with public targets. Public targets represent a minority of the mergers in our sample − only 776 mergers with public targets out of 5,289 in the full sample − however, these mergers account for most of aggregate deal value and they attract significant scrutiny from investors and outsized coverage in media (both traditional or 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 2.55 percentage point increase in the

[9] 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.

likelihood of merger withdrawal. This represents approximately 53% of the baseline likelihood of merger withdrawals for the sample of public merger announcements.

In column 4 and 5, we separately estimate the specification for the first five years of our sample period (2010-2014) versus for the last five years of the sample period (2015-2020). Both subsamples deliver a similar estimate, alleviating a potential concern that the result arises from a particular time period. In a similar spirit, we re-estimate the specification in column 6 after dropping small deals, i.e. deals in the bottom quartile of our sample with respect to deal value. In this subsample, we see a slightly larger sensitivity of merger withdrawals to social media sentiment: A standard deviation increase in abnormal social media is associated with a 1.171 percentage point decline in the likelihood of a merger withdrawal. Together, these subsample tests show that the relationship of merger withdrawals to social media sentiment is not driven by smaller deals, nor particular time periods.

Finally, we address the concern that a firm-specific unobservable characteristic drives the relation between social media sentiment and merger withdrawal. To do this, in column 7, 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 depends only 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 concern with interpreting our main result is that some merger withdrawal decisions are made by entities outside of acquiring firm, and therefore, cannot reflect learning from the information in social media. To alleviate the concern that these mergers drive the result, we extract classify the reasons for merger withdrawals into six categories using the "deal history" field in SDC Platinum : regulator, acquirer shareholders, target shareholders, acquirer board, target board and other.

Using these stated reasons for merger withdrawal, we re-estimate the main specification but drop the observations that correspond to each of these major categories (except for "other") one at a time. Panel (3b) of Table 3 presents the estimated coefficients for each of these subsamples.

Regardless of the subset of merger announcements dropped, we estimate that abnormal social media sentiment has a significant negative relationship with the likelihood of merger withdrawal. The estimated coefficient ranges from -0.6205 to -0.7653, reflecting a high degree of stability. These results suggest that the content of social media is useful to predict the likelihood of deal withdrawal, irrespective of the type of merger withdrawal.

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.1 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 3.89 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 27.01% of the baseline rate of merger withdrawals (average is 14.39% in the matched sample), which is moderately larger than the main specification without matching. In addition to the coefficient stability argument for the main table of results, these findings further alleviate omitted variable concerns.

3.2.5 Market Reactions to Deal Outcome

As supplemental evidence, we evaluate whether abnormal social media sentiment provides useful information about the ultimate valuation of the deal. In particular, we study whether abnormal social media sentiment helps forecast the market's reaction to the conclusion of the deal. Specifically, we compute CARs for a 3-day window $[-1, +1]$ around the deal *conclusion*, i.e., either the completion date or withdrawal date of the deal. Then, using deal-level information, we estimate a specification of the following form:

$$\begin{aligned} CAR_i = \beta_1 \times \mathbb{1}(Deal\ Withdrawn)_i + \beta_2 \times AbnSent_i \\ + \beta_3 \times \mathbb{1}(Deal\ Withdrawn)_i \cdot AbnSent_i + \Gamma \cdot \mathbf{X_i} + \epsilon_\mathbf{i} \end{aligned} \tag{3}$$

where the dependent variable is $CAR[-1, +1]$ from the 3-day window around the conclusion of the merger (either completion or withdrawal), $\mathbb{1}(Deal\ Withdrawn)_i$ 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. In addition, 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 respond positively to a merger withdrawal.

[Insert Table 4 here]

Table 4 presents the estimates from Equation (3). We estimate a negative coefficient on the interactive term $\mathbb{1}(Deal\ Withdrawn)_i \cdot AbnSent_i$ in all specifications, which is significant and large in magnitude if we include acquirer firm fixed effects. Further, we obtain similar estimates, irrespective of whether we also include the interaction between merger announcement CARs and $\mathbb{1}(Deal\ Withdrawn)_i$. Interpreting the most stringent interaction, we estimate that the market reaction to a withdrawn merger is 0.9592 percentage points higher for each standard deviation decrease in the initial social media reaction (measured by $AbnSent_i$). That is, the market eventually celebrates the withdrawal of mergers that initially generated a negative social media reactions at deal announcement, consistent with social media containing useful information about the eventual value of completing such mergers. In line with the idea that stock market reactions to M&A announcements contain relevant information (Luo, 2005; Kau et al., 2008), we estimate a similar effect of comparable magnitude for the interaction term of $\mathbb{1}(Deal\ Withdrawn)_i$ and deal announcement CAR.

4 Heterogeneity and Mechanisms

In this section, we present several sample splits 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. Most of the tests in this section are conducted by taking the median split on a firm or deal characteristic, and re-estimating our baseline Equation (2) for each subsample.

4.1 Other Information Sources

Our main result establishes that abnormal social media sentiment conveys useful information above and beyond other well-known sources of information feedback to firms: the market reaction (e.g., CARs) and news sentiment. Given this main finding, it is natural to examine whether this relationship 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, i.e., either CAR or news sentiment, all standardized to be on a common scale between -1 and 1. 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). We say that the two signals have *high disagreement* if the magnitude of this difference is above the median in our sample, and *low disagreement* if it is below median. We re-estimate Equation (2) separately for these high- and low-disagreement subsamples.

[Insert Table 5 here]

Panel 5a of Table 5 presents the estimates from these sample-split regressions. For both traditional signals, 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 market reaction (column 2) or when it disagrees with the sentiment of news media (column 4). When these signals are more similar (columns 1 and 3), we estimate a small and statistically insignificant coefficient on $AbnSent_i$. Moreover, the difference between the estimated coefficients on $AbnSent_i$ is statistically significant at 10% (5%) for the CAR sample split (new media sample split). These findings indicate that the social media signal is most informative when it disagrees with other well-known signals.

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). Panel 5b of Table 5 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).[10]

4.2 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

[10] 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.

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 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 using the Bodnaruk et al. (2015) dictionary. 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 2/3 of merger announcements cannot be matched to a conference call (2,852) whereas 1/3 of announcements have a conference call (963).

[Insert Table 6 here]

The first three columns of Panel 6a of Table 6 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 2.79 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 0.167). Further, in column 4, we control for the textual content of the conference call, obtaining a very similar estimated coefficient on $AbnSent_i$, which changes from -1.430 to -1.469 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 6b, 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.

4.3 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.

4.3.1 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.

[Insert Table 8 here]

In Table 8, we therefore present sample splits based on whether the transaction was a cash deal ($\geq 80\%$ cash) or a stock deal ($\geq 25\%$ stock).[11] In either split, we estimate that stock deals are significantly more sensitive to abnormal social media sentiment than deals that are mostly cash transactions.

[11] 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.

4.3.2 Deal Complexity

Social media feedback ought to be strongest if the proposed deal is more complex. To evaluate this, in Table 9, we present sample splits by complexity of the deal. Following Cohen and Lou (2012) and Aktas, De Bodt, and Roll (2013), we first include the number of SIC (4-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 both an indicator variable for domestic vs. cross-country deals (columns 3 and 4) and the geographic distance (in miles) between the target and acquiring firm headquarters (columns 5 and 6), and split the sample along these dimensions.

[Insert Table 9 here]

Consistently across different measures, we estimate a greater sensitivity of deal withdrawal likelihood to abnormal social media sentiment. Though the estimated differences across sample splits are marginal in their statistical significance (p-values ranging from 0.083 to 0.145), 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 Table A.5. Consistent with the motivating intuition, we estimate a stronger relationship between abnormal social media sentiment for deals without definitive agreements.

4.3.3 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 Baker, Bloom, and Davis (2016) Economic Policy Uncertainty Index and the S&P500's Volatility Index (VIX). Table 10 presents the results from these sample splits, which confirm that the social media signal is most valuable in high economic uncertainty and high volatility times.

[Insert Table 10 here]

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 can also be 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 and traditional news media coverage. In fact, the signal value of social media sentiment is strongest when the social media reaction to a merger announcement disagrees with the market reactions or the sentiment of traditional news coverage.

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 as well. Future research would do well to understand these connections.

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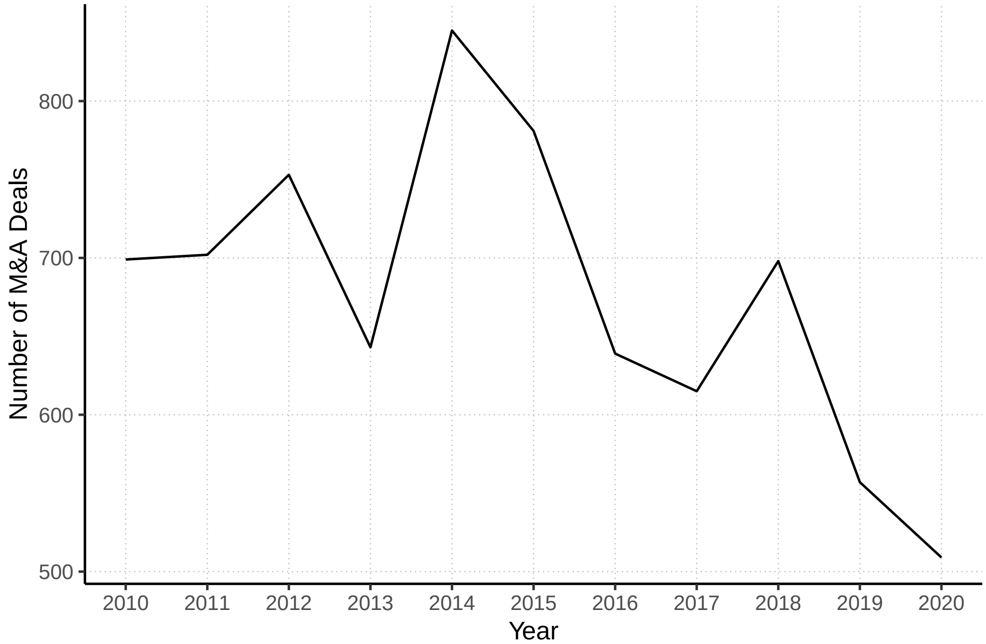
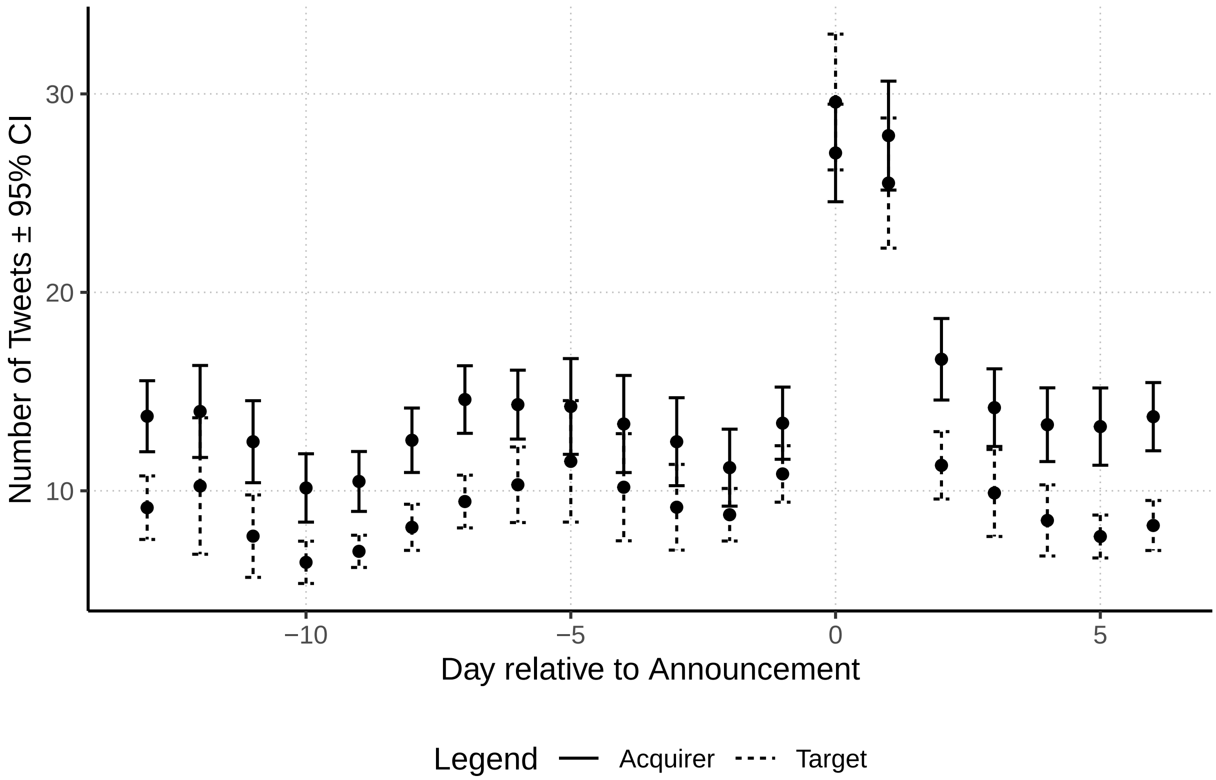
Figure 1: M&As over Time



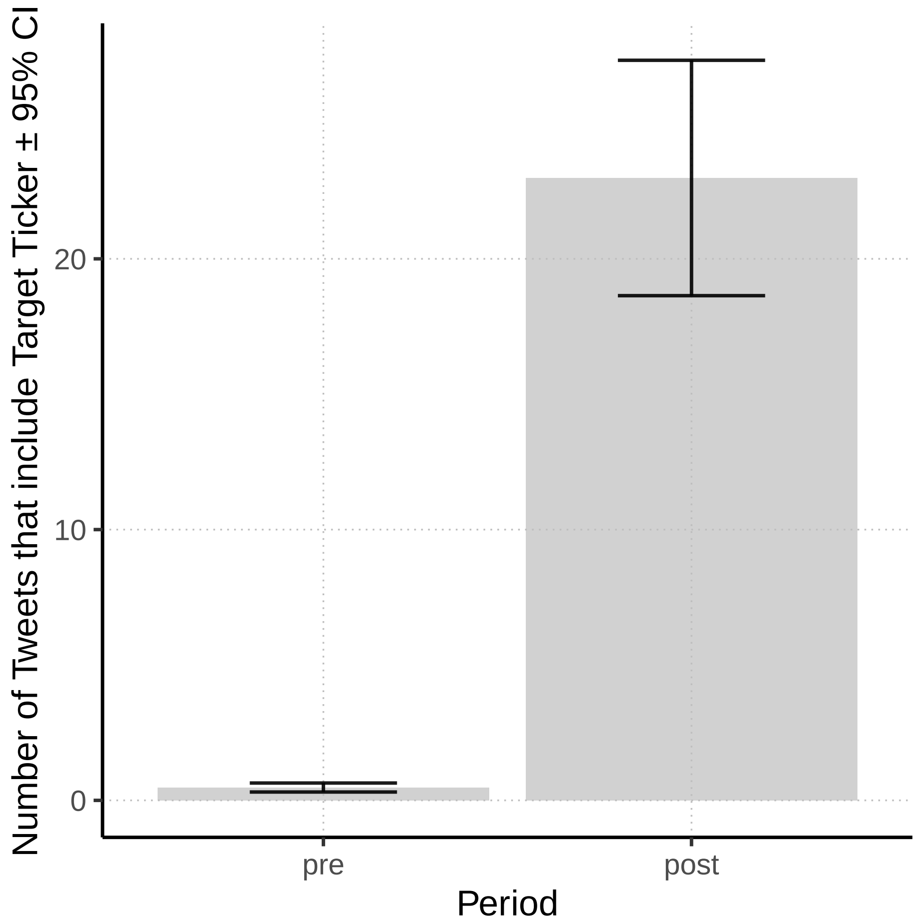
Notes: This figure plots the annual number of M&A deals in our sample over the sample period from 2010 to 2020. We include all announced mergers with U.S. acquiring firms and a minimum deal volume of at least $25M.

Figure 2: Number of Tweets over Time



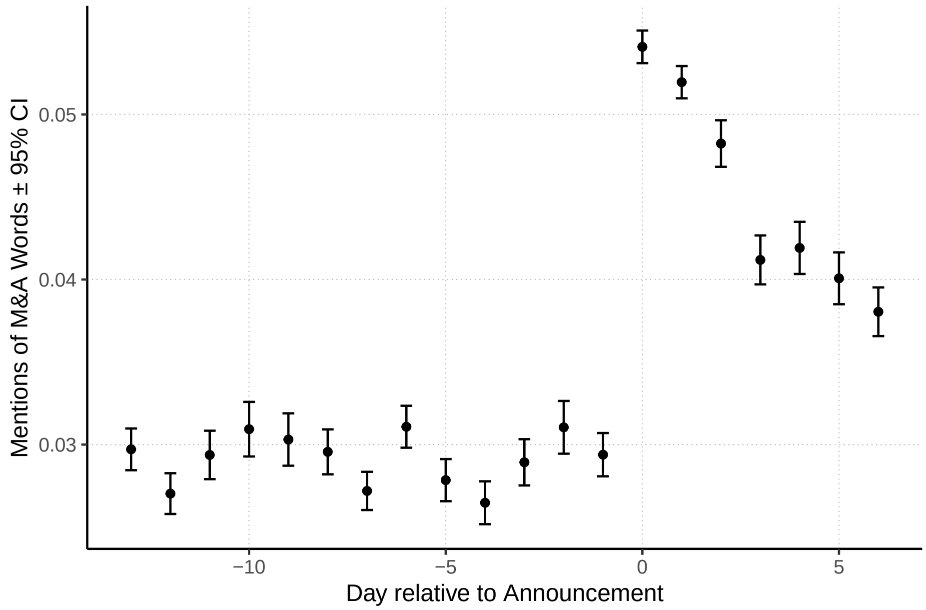
Notes: This figure shows the average and 95% confidence interval of the number of tweets posted to StockTwits around the announcement of an M&A deal mentioning the acquiring and target firm. The solid line displays the numbers for the acquirer firm, the dashed line represents the target firm.

Figure 3: Tweets about Target Firm

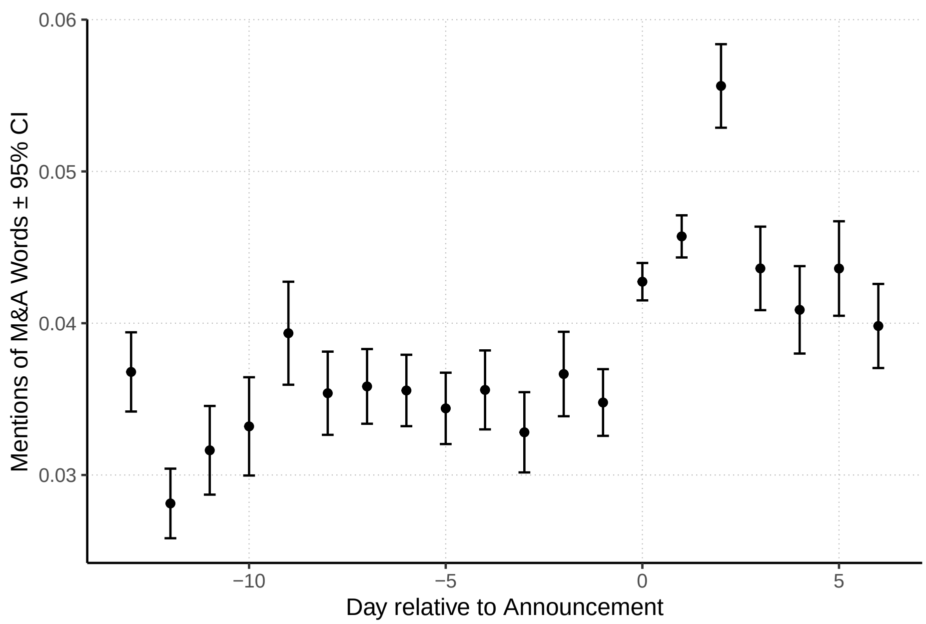


Notes: This figure shows the average and 95% confidence interval of the number of tweets about the acquiring firm posted to StockTwits around the announcement of an M&A deal that also includes the ticker of the target firm. The pre-period covers the [-13;-7] day window before the announcement of the merger. The post-period covers the [0;6] day window after the announcement of the merger.

Figure 4: M&A Words in Tweets



(a) Tweets about Acquirer



(b) Tweets about Target

Notes: This figure shows the number of times words related to M&A transactions are mentioned in tweets about the acquirer and target firm around the announcement of an M&A deal. Figure 4a displays the average and 95% confidence interval of the number of times words related to mergers and acquisitions (i.e. "merger", "acquisition", "m&a", "takeover", "acquirer", "target") are mentioned in tweets posted to StockTwits. Figure 4b plots the corresponding numbers for the target firm.

Table 1: Summary Statistics M&A Sample

This table presents summary statistics for the sample of completed mergers (Panel 1a) and withdrawn mergers (Panel 1b). All variables are defined as detailed in Section 2 and Appendix Table A.6. 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 2020 with a minimum deal volume of at least $25M.

(a) Completed Mergers

	N	Mean	SD	Min	P25	P50	P75	Max
Deal Withdrawn (0/1)	5417	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Days to Deal Conclusion	5417	78.825	105.106	0.000	12.000	48.000	108.000	1524.000
Sentiment (StockTwits)	5359	0.125	0.186	-0.904	0.000	0.114	0.218	0.972
Sentiment (MaxEnt)	5417	0.834	0.092	0.090	0.793	0.847	0.893	1.000
Sentiment (Bayes)	5417	0.780	0.081	0.175	0.737	0.784	0.830	0.998
Abn. Sentiment (StockTwits)	5329	0.014	0.298	-0.829	-0.136	0.016	0.172	0.867
Abn. Sentiment (MaxEnt)	5417	0.016	0.119	-0.286	-0.052	0.009	0.074	0.421
Abn. Sentiment (Bayes)	5417	0.022	0.144	-0.735	-0.049	0.007	0.072	0.925
CAR Acq. [-1;1]	5357	0.010	0.063	-0.174	-0.017	0.004	0.031	0.252
CAR Acq. [-1;10]	5364	0.008	0.090	-0.252	-0.036	0.005	0.048	0.326
CAR Acq. [-5;-1]	5357	0.000	0.040	-0.149	-0.020	-0.000	0.019	0.129
CAR Target [-1;1]	752	0.246	0.214	-0.170	0.089	0.207	0.365	0.722
CAR Target [-1;10]	752	0.246	0.230	-0.223	0.073	0.208	0.371	0.745
CAR Target [-5;-1]	751	0.011	0.062	-0.174	-0.023	0.003	0.038	0.171
Deal Value (B. USD)	5417	1.005	2.512	0.025	0.080	0.220	0.696	17.908
% Shares Held Prior	5417	2.194	11.053	0.000	0.000	0.000	0.000	98.000
Acq. White Knight (0/1)	5417	0.001	0.027	0.000	0.000	0.000	0.000	1.000
Hedge Fund Involed (0/1)	5417	0.002	0.043	0.000	0.000	0.000	0.000	1.000
Challenged Deal (0/1)	5417	0.010	0.100	0.000	0.000	0.000	0.000	1.000
Rumored Deal (0/1)	5417	0.095	0.293	0.000	0.000	0.000	0.000	1.000
Target Private (0/1)	5417	0.406	0.491	0.000	0.000	0.000	1.000	1.000
Hostile Deal (0/1)	5417	0.000	0.014	0.000	0.000	0.000	0.000	1.000
% Shares Sought	5351	96.681	13.154	3.400	100.000	100.000	100.000	100.000
Mcap Acq. (B. USD)	5310	22.982	62.962	0.005	1.402	4.307	16.986	1638.236
M/B Acq.	5229	3.659	8.272	0.113	1.341	2.177	3.717	221.237
Cash/AT Acq.	5223	0.100	0.110	0.000	0.024	0.067	0.138	0.967
Leverage Acq.	5301	0.249	0.199	0.000	0.103	0.201	0.357	0.978
N. Posts	5417	146.823	720.858	2.000	14.000	30.000	69.000	20416.000
News Sentiment Acq.	5417	-0.035	0.484	-1.000	0.000	0.000	0.000	1.000
N News Articles	5417	29.370	61.579	0.000	4.000	14.000	30.000	1397.000
Has Conf. Call (CC)	3887	0.245	0.430	0.000	0.000	0.000	0.000	1.000
VIX (S&P500)	5253	17.061	6.440	9.140	13.040	15.420	19.090	82.690
EPU	5417	134.256	46.431	71.262	100.207	121.965	158.562	350.460
EPU (Regulation)	5417	128.535	53.633	55.794	87.445	110.914	160.139	384.390

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(b) Withdrawn Mergers

	N	Mean	SD	Min	P25	P50	P75	Max
Deal Withdrawn (0/1)	214	1.000	0.000	1.000	1.000	1.000	1.000	1.000
Days to Deal Conclusion	214	182.930	195.053	0.000	56.000	116.000	227.250	1126.000
Sentiment (StockTwits)	214	0.110	0.163	-0.383	0.006	0.106	0.187	0.582
Sentiment (MaxEnt)	214	0.816	0.100	0.209	0.783	0.841	0.873	0.967
Sentiment (Bayes)	214	0.764	0.077	0.357	0.725	0.776	0.809	0.937
Abn. Sentiment (StockTwits)	213	-0.029	0.257	-0.829	-0.144	0.000	0.104	0.791
Abn. Sentiment (MaxEnt)	214	-0.012	0.112	-0.286	-0.074	-0.016	0.042	0.421
Abn. Sentiment (Bayes)	214	-0.008	0.127	-0.536	-0.075	-0.008	0.053	0.762
CAR Acq. [-1;1]	211	-0.004	0.063	-0.174	-0.033	-0.001	0.030	0.252
CAR Acq. [-1;10]	212	-0.015	0.093	-0.252	-0.062	-0.009	0.042	0.254
CAR Acq. [-5;-1]	211	0.007	0.044	-0.132	-0.016	0.003	0.025	0.129
CAR Target [-1;1]	94	0.169	0.191	-0.141	0.036	0.133	0.221	0.722
CAR Target [-1;10]	95	0.173	0.222	-0.223	0.021	0.125	0.267	0.745
CAR Target [-5;-1]	94	0.020	0.055	-0.090	-0.011	0.009	0.043	0.171
Deal Value (B. USD)	214	4.225	6.032	0.031	0.341	1.149	5.339	17.908
% Shares Held Prior	214	3.081	11.603	0.000	0.000	0.000	0.000	80.100
Acq. White Knight (0/1)	214	0.009	0.096	0.000	0.000	0.000	0.000	1.000
Hedge Fund Involed (0/1)	214	0.014	0.118	0.000	0.000	0.000	0.000	1.000
Challenged Deal (0/1)	214	0.252	0.435	0.000	0.000	0.000	0.750	1.000
Rumored Deal (0/1)	214	0.220	0.415	0.000	0.000	0.000	0.000	1.000
Target Private (0/1)	214	0.107	0.310	0.000	0.000	0.000	0.000	1.000
Hostile Deal (0/1)	214	0.075	0.264	0.000	0.000	0.000	0.000	1.000
% Shares Sought	209	95.747	14.819	19.900	100.000	100.000	100.000	100.000
Mcap Acq. (B. USD)	204	30.569	54.523	0.005	1.373	7.298	30.027	424.736
M/B Acq.	200	3.989	7.964	0.154	1.295	2.088	3.748	85.305
Cash/AT Acq.	200	0.108	0.115	0.000	0.027	0.080	0.144	0.805
Leverage Acq.	204	0.271	0.217	0.000	0.109	0.225	0.376	0.973
N. Posts	214	97.425	159.402	3.000	17.000	43.000	77.500	862.000
News Sentiment Acq.	214	-0.281	0.678	-1.000	-1.000	0.000	0.000	1.000
N News Articles	214	52.028	95.611	0.000	5.000	22.500	50.750	696.000
Has Conf. Call (CC)	155	0.258	0.439	0.000	0.000	0.000	1.000	1.000
VIX (S&P500)	201	17.466	7.278	9.400	13.330	15.630	18.930	75.910
EPU	214	131.513	45.743	71.262	100.207	118.599	149.055	350.460
EPU (Regulation)	214	127.802	54.254	55.794	87.498	110.559	160.139	354.558

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. 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. 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 (standardized) news media sentiment and the number of news articles published about the M&A deal, respectively, both obtained from RavenPack. 'N Tweets' is the number of messages posted to StockTwits around the deal announcement. All other variables are standard M&A deal characteristics from SDC Platinum, detailed variable definitions are provided in Appendix X. '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.

	$\mathbb{1}$(Deal Withdrawn)				
	(1)	(2)	(3)	(4)	(5)
AbnSent (z) (StTw)	-0.7320***	-0.8629***	-0.7881***	-0.7487***	-0.7503***
	(0.2479)	(0.2436)	(0.2436)	(0.2312)	(0.2277)
CAR Acq. (z) [-1;10]			-0.8963***	-0.9029***	-0.9457***
			(0.2630)	(0.2562)	(0.2523)
CAR Acq. (z) [-5;-1]			0.7000**	0.4749*	0.4640*
			(0.2805)	(0.2705)	(0.2693)
News Sentiment Acq. (z)					-1.139***
					(0.3005)
Log Deal Value ($B)		7.930***	7.811***	7.052***	7.630***
		(0.8264)	(0.8401)	(0.9343)	(1.019)
% Shares Held Prior		0.0340	0.0202	0.0315	0.0174
		(0.0243)	(0.0226)	(0.0215)	(0.0209)
Acq. White Knight (0/1)				-4.655	-4.386
				(17.69)	(17.17)
Hedge Fund Involed (0/1)				12.39	12.07
				(10.38)	(10.42)
Competing Bidder (0/1)				38.93***	38.32***
				(5.080)	(5.026)
Rumored Deal (0/1)				-0.3216	-0.2136
				(1.087)	(1.117)
Hostile Deal (0/1)				78.73***	76.81***
				(6.150)	(6.150)
Termination Fee Target ($M)				-0.0154***	-0.0141***
				(0.0047)	(0.0048)
N Tweets					-0.0002
					(0.0002)
N News Articles					-0.0118
					(0.0077)
Mean(LHS)	3.870	3.765	3.740	3.740	3.740
Observations	5,478	5,259	5,214	5,214	5,214
R^2	0.0014	0.0673	0.0698	0.2060	0.2105
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. '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 sequentially drop M&A deals that were withdrawn for the indicated reason (i.e. due to regulators, acquiring shareholders, target shareholders, acquiring firm board, target firm board) in columns (1) through (5). 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	Publ. Targets	2010-2014	2015-2020	Drop Small	Acq. FE
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
AbnSent (z) (MaxE)	-0.5887***						
	(0.2080)						
AbnSent (z) (Bayes)		-0.4239**					
		(0.2023)					
AbnSent (z) (StTw)			-2.549**	-0.7906**	-0.6900**	-1.171***	-0.9278**
			(1.113)	(0.3358)	(0.3221)	(0.3095)	(0.3797)
CAR Acq. (z) [-1;10]	-0.9550***	-0.9664***	-0.7760	-0.1581	-1.345***	-1.293***	-1.115***
	(0.2398)	(0.2428)	(1.225)	(0.2209)	(0.3433)	(0.2994)	(0.4108)
CAR Acq. (z) [-5;-1]	0.4902*	0.4923*	0.8542	0.8955**	0.1772	0.6656**	0.7985**
	(0.2588)	(0.2600)	(1.209)	(0.3720)	(0.3740)	(0.3205)	(0.3035)
CAR Target (z) [-1;10]			-1.404				
			(1.275)				
CAR Target (z) [-5;-1]			-0.4736				
			(1.370)				
News Sentiment Acq. (z)	-1.146***	-1.140***	-2.574***	-0.6578	-1.390***	-1.343***	-0.6577*
	(0.2925)	(0.2923)	(0.8669)	(0.4303)	(0.3935)	(0.3411)	(0.3631)
N Tweets	-0.0002	-0.0002	-0.0004	0.0001	-0.0004*	-0.0005**	0.0007
	(0.0002)	(0.0002)	(0.0007)	(0.0004)	(0.0002)	(0.0002)	(0.0005)
N News Articles	-0.0110	-0.0111	0.0063	-0.0161	-0.0120	-0.0115	-0.0193
	(0.0075)	(0.0075)	(0.0073)	(0.0132)	(0.0088)	(0.0079)	(0.0117)
Mean(LHS)	3.706	3.706	4.720	3.825	3.828	3.883	3.700
Observations	5,289	5,289	776	2,136	3,078	3,923	5,182
R^2	0.2083	0.2078	0.3397	0.2343	0.2173	0.2332	0.5645
Deal Controls	✓	✓	✓	✓	✓	✓	✓
Firm Controls	✓	✓	✓	✓	✓	✓	✓
Year-by-Quarter FE	✓	✓	✓	✓	✓	✓	✓
Acq. Industry (GIC2) FE	✓	✓	✓	✓	✓	✓	✓
Acq. Firm FE							✓

… continued

(b) Deal rejection reasons

	$\mathbb{1}$(Deal Withdrawn)				
Drop Deals Rejected by:	Regulator	Acq. ShrH.	Target ShrH.	Acq. Board	Target Board
	(1)	(2)	(3)	(4)	(5)
AbnSent (z) (StTw)	-0.6205***	-0.6849***	-0.7114***	-0.7653***	-0.7005***
	(0.2094)	(0.2287)	(0.2231)	(0.2283)	(0.2083)
CAR Acq. (z) [-1;10]	-1.001***	-0.8719***	-0.8126***	-0.9845***	-0.7573***
	(0.2414)	(0.2601)	(0.2418)	(0.2455)	(0.2587)
CAR Acq. (z) [-5;-1]	0.2602	0.4304*	0.4887*	0.4502*	0.4258*
	(0.2522)	(0.2538)	(0.2684)	(0.2654)	(0.2472)
News Sentiment Acq. (z)	-1.145***	-1.170***	-1.147***	-1.141***	-0.2927
	(0.2880)	(0.2875)	(0.3190)	(0.3010)	(0.2333)
N Tweets	2.55×10^{-5}	-0.0002	-0.0003	-0.0002	-0.0002
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
N News Articles	-0.0179***	-0.0110	-0.0100	-0.0122	-0.0016
	(0.0061)	(0.0077)	(0.0077)	(0.0078)	(0.0072)
Mean(LHS)	3.795	3.911	3.759	3.817	3.794
Observations	5,193	5,209	5,203	5,213	5,157
R^2	0.2179	0.2125	0.2065	0.2111	0.1130
Deal Controls	✓	✓	✓	✓	✓
Firm Controls	✓	✓	✓	✓	✓
Year-by-Quarter FE	✓	✓	✓	✓	✓
Acq. Industry (GIC2) FE	✓	✓	✓	✓	✓

Table 4: Reactions to Deal Outcome

This table presents OLS regression estimates for the effect of deal outcomes and deal announcement reactions on the abnormal stock returns around M&A deal conclusion. The dependent variable in all columns is the Cumulative Abnormal Return (CAR) in the $[-1;1]$ day window around the conclusion (i.e. either the withdrawal or completion) of the previously announced M&A deal. The dependent variable is multiplied by 100 for legibility. '$\mathbb{1}$(Deal Withdr.)' is a dummy variable that takes the value of one if the announced deal was withdrawn on the conclusion date, and zero if it was completed. 'Abn. Sentiment (z) (StTw)', 'CAR Acq. (z) [-1;3]', and 'News Sentiment Acq. (z)' are the standardized reaction to the M&A deal on the announcement deal, defined similarly to previous tables. The sample in each regression excludes deals with less than 10 days between the announcement and conclusion of the deal. 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.

	CAR Acq. (in %): Deal Conclusion [-1;1]			
	(1)	(2)	(3)	(4)
$\mathbb{1}$(Deal Withdrawn) × AbnSent (z) (StTw)	-0.2609	-0.2009	-1.129**	-0.9592**
	(0.4681)	(0.4379)	(0.5565)	(0.4647)
$\mathbb{1}$(Deal Withdrawn) × CAR Acq. (z) [1;3]		-1.401***		-1.317*
		(0.5007)		(0.6833)
$\mathbb{1}$(Deal Withdrawn) × News Sentiment Acq. (z)		-0.3308		-0.3538
		(0.2933)		(0.3378)
$\mathbb{1}$(Deal Withdrawn)	-0.0770	-0.5887	-0.1418	-0.5445
	(0.4704)	(0.4435)	(0.5397)	(0.5625)
AbnSent (z) (StTw)	-0.1229**	-0.1277**	-0.0012	-0.0071
	(0.0609)	(0.0607)	(0.1027)	(0.1044)
CAR Acq. (z) [1;3]	-0.2867***	-0.2238**	-0.4527***	-0.3832***
	(0.0957)	(0.0900)	(0.1292)	(0.1368)
News Sentiment Acq. (z)	0.0347	0.0508	0.0372	0.0571
	(0.0490)	(0.0523)	(0.0781)	(0.0797)
Mean(LHS)	0.1769	0.1769	0.1769	0.1769
Observations	4,001	4,001	4,001	4,001
R^2	0.0296	0.0354	0.6333	0.6356
Deal Controls	✓	✓	✓	✓
Firm Controls	✓	✓	✓	✓
Social & News Media Controls	✓	✓	✓	✓
Year-by-Quarter FE	✓	✓	✓	✓
Acq. Industry (GIC2) FE	✓	✓	✓	✓
Acq. Firm FE			✓	✓

Table 5: 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. In Panel 5a, 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 X. In Panel 5b, 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.

(a) Disagreement with stock market and news media

	$\mathbb{1}$(Deal Withdrawn)			
Sample Split	Disagr. CAR		Disagr. News Media	
	Low	High	Low	High
	(1)	(2)	(3)	(4)
AbnSent (z) (StTw)	-0.2922	-1.170***	-0.2071	-1.306***
	(0.2893)	(0.3376)	(0.2421)	(0.4113)
CAR Acq. (z) [-1;10]	-0.2356	-1.237***	-0.4955	-1.429***
	(0.4095)	(0.3388)	(0.3297)	(0.4110)
CAR Acq. (z) [-5;-1]	0.2455	0.4989	-0.3794	1.203***
	(0.4180)	(0.3774)	(0.2700)	(0.4225)
News Sentiment Acq. (z)	-0.2020	-1.970***	-0.0048	-1.204***
	(0.3727)	(0.5096)	(0.7508)	(0.3268)
N Tweets	0.00004	-0.0007*	-0.00005	-0.00006
	(0.0003)	(0.0003)	(0.0002)	(0.0004)
N News Articles	-0.0090	-0.0142	-0.0097	-0.0117
	(0.0089)	(0.0101)	(0.0066)	(0.0117)
Mean(LHS)	4.155	2.906	2.953	3.682
Coef. Diff. t-Stat (p-Value)	1.836	(0.066)	2.157	(0.031)
Observations	2,599	2,615	2,438	2,173
R^2	0.3043	0.1595	0.0442	0.2701
Deal Controls	✓	✓	✓	✓
Firm Controls	✓	✓	✓	✓
Year-by-Quarter FE	✓	✓	✓	✓
Acq. Industry (GIC2) FE	✓	✓	✓	✓

... continued

(b) Attention from social media, news media, and the stock market

	𝟙(Deal Withdrawn)					
Sample Split	N Tweets		N News Articles		Abs(CAR)	
	Low	High	Low	High	Low	High
	(1)	(2)	(3)	(4)	(5)	(6)
AbnSent (z) (StTw)	-0.3731	-1.864***	-0.4445	-0.7865**	-0.2465	-1.241***
	(0.2406)	(0.5895)	(0.3195)	(0.3434)	(0.2491)	(0.3349)
CAR Acq. (z) [-1;10]	-0.7933**	-1.003***	-0.5275	-1.374***	-0.0944	-1.024***
	(0.3875)	(0.3189)	(0.3340)	(0.3981)	(1.218)	(0.2479)
CAR Acq. (z) [-5;-1]	0.2120	0.6788*	0.3788	0.3953	0.1950	0.5846
	(0.3654)	(0.3441)	(0.3024)	(0.3558)	(0.3201)	(0.4146)
News Sentiment Acq. (z)	-1.453***	-0.9818***	-2.016***	-0.9431**	-0.5994	-1.676***
	(0.4000)	(0.3571)	(0.5679)	(0.3842)	(0.4164)	(0.4922)
N Tweets	-0.0257	-0.0002	0.00002	-0.0001	0.00002	-0.0003
	(0.0462)	(0.0002)	(0.0004)	(0.0003)	(0.0002)	(0.0003)
N News Articles	-0.0623**	-0.0089	-0.1108	-0.0058	-0.0252**	-0.0026
	(0.0259)	(0.0080)	(0.0838)	(0.0087)	(0.0094)	(0.0102)
Mean(LHS)	3.324	3.735	3.296	3.297	3.684	3.371
Coef. Diff. t-Stat (p-Value)	2.605	(0.009)	0.700	(0.484)	2.081	(0.037)
Observations	2,617	2,597	1,881	2,730	2,633	2,581
R^2	0.1905	0.2496	0.1871	0.2435	0.2624	0.1983
Deal Controls	✓	✓	✓	✓	✓	✓
Firm Controls	✓	✓	✓	✓	✓	✓
Year-by-Quarter FE	✓	✓	✓	✓	✓	✓
Acq. Industry (GIC2) FE	✓	✓	✓	✓	✓	✓

Table 6: 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 6a 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 6b 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 6b 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

	𝟙(Deal Withdrawn)			
Sample Split	Full Sample	Conf. Call (0/1)		
		No	Yes	
	(1)	(2)	(3)	(4)
AbnSent (z) (StTw)	-0.7345***	-0.5451**	-1.498**	-1.522**
	(0.2268)	(0.2277)	(0.5994)	(0.6040)
Has Conf. Call (0/1)	-2.818***			
	(0.7450)			
% Positive Words (Q&A)				0.5620
				(1.181)
% Negative Words (Q&A)				0.5138
				(2.685)
% Constraining Words (Q&A)				5.605
				(7.160)
Avg. Word Length (Q&A)				9.226
				(6.262)
N Words (Q&A)				0.0003
				(0.0019)
Vocabulary (Q&A)				-0.0051
				(0.0134)
Mean(LHS)	3.740	3.425	4.051	3.935
Coef. Diff. t-Stat (p-Value)		1.340	(0.180)	
Observations	5,214	4,350	864	864
R^2	0.2132	0.2299	0.2385	0.2431
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

Sample Split	𝟙(Deal Withdrawn)							
	% 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)
AbnSent (z) (StTw)	-1.685*	-1.665**	0.0537	-2.279**	-2.321*	-1.015*	0.1596	-2.620***
	(0.9328)	(0.7430)	(0.6238)	(0.9967)	(1.251)	(0.5257)	(0.4929)	(0.8872)
Mean(LHS)	3.953	2.074	2.817	3.196	3.497	2.529	4.206	1.835
Coef. Diff. t-Stat (p-Value)	-0.014	(0.989)	1.672	(0.095)	-0.946	(0.344)	2.002	(0.045)
Observations	430	434	426	438	429	435	428	436
R^2	0.2040	0.4148	0.3166	0.3351	0.3238	0.3418	0.2939	0.3744
Deal Controls	✓	✓	✓	✓	✓	✓	✓	✓
Firm Controls	✓	✓	✓	✓	✓	✓	✓	✓
Social & News Media Controls	✓	✓	✓	✓	✓	✓	✓	✓
Stock Return Controls	✓	✓	✓	✓	✓	✓	✓	✓
Conf. Call Controls	✓	✓	✓	✓	✓	✓	✓	✓
Year-by-Quarter FE	✓	✓	✓	✓	✓	✓	✓	✓
Acq. Industry (GIC2) FE	✓	✓	✓	✓	✓	✓	✓	✓

Table 7: Falsification test — Share repurchases

This table presents linear probability model estimates analogous to Table 2, focusing on share repurchases rather than M&A deals. The sample in all regressions in Table 7 below comprises of all share repurchases from SDC Platinum with a minimum volume of $25M that were announced and either completed or withdrawn between 2010 and 2020. The dependent variable takes the value of one if the announced share repurchase was withdrawn and zero otherwise, multiplied with 100 for legibility. 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. 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)	(4)	(5)
AbnSent (z) (StTw)	3.910*	4.035*	4.112*	4.204*	1.873
	(2.156)	(2.307)	(2.334)	(2.330)	(3.719)
CAR Acq. (z) [-1;10]			-2.013	-1.788	-4.706
			(1.879)	(1.823)	(3.137)
CAR Acq. (z) [-5;-1]			-1.515	-1.644	-3.211
			(1.760)	(1.772)	(3.447)
News Sentiment Acq. (z)				0.7306	2.095
				(1.927)	(2.809)
N Tweets				-0.0012	0.0275
				(0.0023)	(0.0185)
N News Articles				-0.5829***	-1.793***
				(0.1522)	(0.5871)
Mean(LHS)	40.57	40.39	40.42	40.42	40.42
Observations	742	713	710	710	710
R^2	0.0063	0.1998	0.2020	0.2141	0.8374
Deal Controls		✓	✓	✓	✓
Firm Controls		✓	✓	✓	✓
Year-by-Quarter FE		✓	✓	✓	✓
Acq. Industry (GIC2) FE		✓	✓	✓	✓
Acq. Firm FE					✓

Table 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 80% 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 (≥80% cash)		Stock Deal (≥25% stock)	
	No	Yes	No	Yes
	(1)	(2)	(3)	(4)
AbnSent (z) (StTw)	-1.152***	-0.2283	-0.3867	-2.322***
	(0.3170)	(0.2991)	(0.2389)	(0.6950)
CAR Acq. (z) [-1;10]	-0.7621**	-1.030***	-0.6882***	-0.7985
	(0.3375)	(0.3807)	(0.2354)	(0.5574)
CAR Acq. (z) [-5;-1]	0.4884	0.3256	0.2990	0.8484
	(0.3863)	(0.3788)	(0.2464)	(0.7257)
News Sentiment Acq. (z)	-1.065***	-1.504***	-1.371***	-1.260*
	(0.3845)	(0.4549)	(0.3920)	(0.6374)
N Tweets	-0.0002	0.0001	0.0002	-0.0005
	(0.0003)	(0.0003)	(0.0002)	(0.0004)
N News Articles	-0.0025	-0.0185*	-0.0161*	-0.0007
	(0.0116)	(0.0095)	(0.0088)	(0.0121)
Mean(LHS)	3.519	3.544	3.501	3.640
Coef. Diff. t-Stat (p-Value)	-1.917	(0.055)	2.394	(0.017)
Observations	3,126	2,088	4,170	1,044
R^2	0.2086	0.2590	0.1964	0.2910
Deal Controls	✓	✓	✓	✓
Firm Controls	✓	✓	✓	✓
Year-by-Quarter FE	✓	✓	✓	✓
Acq. Industry (GIC2) FE	✓	✓	✓	✓

Table 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 4-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, and columns (7) and (8) split the sample into observations with above and below median geographical distance between the target and acquiring firm headquarters (HQ). 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 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 SIC4 Tgt.		Hard-To-Value Tgt.		Cross-Border Deal		Distance HQ	
	Low	High	No	Yes	No	Yes	Low	High
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
AbnSent (z) (StTw)	-0.4146**	-1.532**	-0.3947	-1.280***	-0.4761**	-1.365**	-0.3064	-1.075***
	(0.1827)	(0.6703)	(0.2749)	(0.3737)	(0.2306)	(0.5439)	(0.3117)	(0.3770)
CAR Acq. (z) [-1;10]	-0.9201***	-0.7794	-0.1165	-1.517***	-0.9995***	-0.7550	-0.7970**	-1.282***
	(0.2837)	(0.6676)	(0.3675)	(0.3755)	(0.2636)	(0.6253)	(0.3235)	(0.4256)
CAR Acq. (z) [-5;-1]	0.4442*	0.8335	0.8310***	0.3629	0.2846	0.8374	-0.1669	0.9328**
	(0.2585)	(0.7293)	(0.2709)	(0.4718)	(0.3085)	(0.6663)	(0.4252)	(0.4457)
News Sentiment Acq. (z)	-0.9398***	-1.820**	-1.406***	-1.075**	-0.8929**	-1.551**	-1.282**	-0.8554
	(0.3116)	(0.7134)	(0.4612)	(0.4994)	(0.3764)	(0.7058)	(0.5024)	(0.5111)
Mean(LHS)	3.206	4.339	3.104	3.571	3.254	4.232	3.168	3.385
Coef. Diff. t-Stat (p-Value)	1.700	(0.089)	1.735	(0.083)	1.522	(0.128)	1.456	(0.145)
Observations	3,774	1,429	2,416	2,352	3,749	1,465	2,273	2,245
R^2	0.1475	0.3050	0.2148	0.2359	0.2123	0.2679	0.2317	0.2598
Deal Controls	✓	✓	✓	✓	✓	✓	✓	✓
Firm Controls	✓	✓	✓	✓	✓	✓	✓	✓
Social & News Media Controls	✓	✓	✓	✓	✓	✓	✓	✓
Year-by-Quarter FE	✓	✓	✓	✓	✓	✓	✓	✓
Acq. Industry (GIC2) FE	✓	✓	✓	✓	✓	✓	✓	✓

Table 10: 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 Economic Policy Uncertainty (EPU) and the EPU sub-component with respect to 'regulation', both obtained from Baker et al. (2016), and the CBOE's VIX in the month of the M&A deal announcement, 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.

	$\mathbb{1}$(Deal Withdrawn)					
Sample Split	EPU		EPU (Regulation)		VIX (S&P500)	
	Low (1)	High (2)	Low (3)	High (4)	Low (5)	High (6)
AbnSent (z) (StTw)	-0.5081	-1.076**	-0.2656	-1.268***	-0.5891*	-1.595***
	(0.2981)	(0.4203)	(0.3785)	(0.3827)	(0.2958)	(0.4882)
CAR Acq. (z) [-1;10]	-1.136***	-0.8376**	-0.9819***	-1.046***	-1.010***	-1.216***
	(0.3490)	(0.3626)	(0.3115)	(0.3697)	(0.3074)	(0.3740)
CAR Acq. (z) [-5;-1]	0.6760	0.5326	0.7534	0.5624	1.065***	-0.2015
	(0.4302)	(0.3630)	(0.4641)	(0.4190)	(0.3405)	(0.5241)
News Sentiment Acq. (z)	-1.398***	-1.039**	-1.862***	-0.6087	-1.315***	-1.099*
	(0.4720)	(0.4032)	(0.3900)	(0.4992)	(0.3794)	(0.5378)
N Tweets	-0.0006*	-0.0003	-0.0004	-0.0004	-0.0004	-0.0004
	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0005)
N News Articles	-0.0011	-0.0229**	-0.0120	-0.0119	-0.0097	-0.0143
	(0.0110)	(0.0102)	(0.0098)	(0.0141)	(0.0091)	(0.0148)
Mean(LHS)	3.205	3.362	3.599	2.949	3.282	3.281
Coef. Diff. t-Stat (p-Value)	1.049	(0.294)	1.826	(0.068)	1.647	(0.100)
Observations	2,309	2,201	2,306	2,204	3,108	1,402
R^2	0.2344	0.2308	0.2256	0.2409	0.2460	0.2068
Deal Controls	✓	✓	✓	✓	✓	✓
Firm 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:

$$f_m(x, y(x)) = \begin{cases} \frac{N(w,x)}{N(w)} & \text{if } w_m \in x \text{ and } x \text{ is classified as } y \\ 0 & \text{otherwise} \end{cases} \tag{4}$$

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:

$$\frac{1}{|\mathcal{X}|} \sum_{x \in \mathcal{X}} f_m(x, y(x)) = \frac{1}{|\mathcal{X}|} \sum_{x \in \mathcal{X}} \sum_{y \in \mathcal{Y}} p(y|x) f_m(x, y) \tag{5}$$

$$p(y|x) \geq 0 \text{ for all } x, y \tag{6}$$

$$\sum_{y} p(y|x) = 1 \text{ for all } x. \tag{7}$$

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.:

$$p^*(y|x) = \underset{p(y|x) \in \mathcal{P}}{\operatorname{argmax}} H(p(y|x)) = \underset{p(y|x) \in \mathcal{P}}{\operatorname{argmax}} \sum_{x \in \mathcal{X}} p(y|x) log\left(\frac{1}{p(y|x)}\right) \tag{8}$$

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

$$p^*(y|x) = \frac{exp\left(\sum_m \lambda_m f_m(x, y)\right)}{\sum_{y \in \mathcal{Y}} exp\left(\sum_m \lambda_m f_m(x, y)\right)} \tag{9}$$

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:

$$score(x, y) \equiv p(y) \times \prod_{m=1}^{M} p(w_m|y). \tag{10}$$

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

$$p(y|x) \equiv \frac{score(x, y)}{\sum_{y' \in \mathcal{Y}} score(x, y)}. \tag{11}$$

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.

As a verification exercise, Table A.1 in the Internet Appendix 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.2c and A.2d) for both algorithms, indicating that sentiment classification algorithms perform similarly well during merger announcement periods as during the overall sample period.

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.2c and A.2d 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)

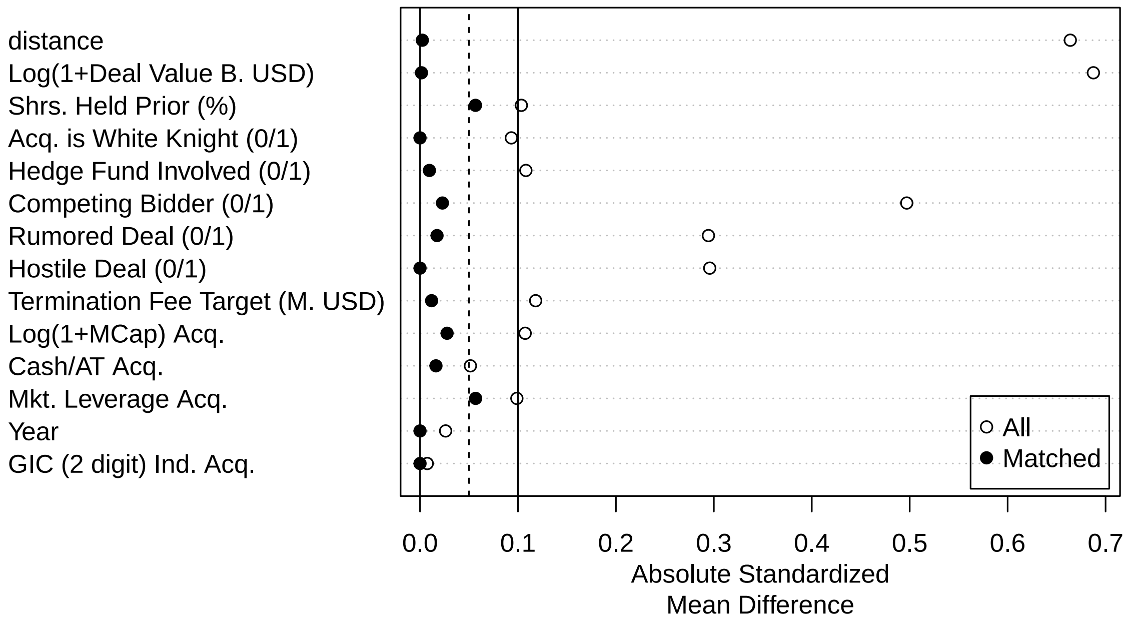
S1	S2	S3	S4	S5	S6	S7	S8	S9	S10	S11	S12	S13	S14	S15	S16	S17	S18	S19	S20
1																			
0.88	1																		
0.87	0.87	1																	
0.87	0.87	0.87	1																
0.88	0.88	0.87	0.87	1															
0.88	0.88	0.87	0.87	0.88	1														
0.85	0.85	0.86	0.86	0.84	0.84	1												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

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 Withdrawn)		
	(1)	(2)	(3)
AbnSent (z) (StTw)	-0.2803***		
	(0.0838)		
AbnSent (z) (MaxE)		-0.2492***	
		(0.0914)	
AbnSent (z) (Bayes)			-0.1921*
			(0.0996)
CAR Acq. (z) [-1;10]	-0.2496***	-0.2574***	-0.2604***
	(0.0679)	(0.0635)	(0.0644)
CAR Acq. (z) [-5;-1]	0.1063	0.1124	0.1124
	(0.0866)	(0.0846)	(0.0847)
News Sentiment Acq. (z)	-0.2990***	-0.3110***	-0.3080***
	(0.0767)	(0.0733)	(0.0733)
N Tweets	-0.0003	-0.0003	-0.0003
	(0.0002)	(0.0002)	(0.0002)
N News Articles	-0.0008	-0.0007	-0.0007
	(0.0012)	(0.0012)	(0.0012)
Mean(LHS)	0.0350	0.0349	0.0349
Observations	4,971	5,046	5,046
Deal Controls	✓	✓	✓
Firm Controls	✓	✓	✓
Year-by-Quarter FE	✓	✓	✓
Acq. Industry (GIC2) FE	✓	✓	✓

Figure A.1: PSM Matching Balance



Notes: This figure summarizes the covariate balance of the propensity score matching (PSM) procedure detailed in Section X, 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.1. 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)
AbnSent (z) (StTw)	-3.887***		
	(1.194)		
AbnSent (z) (MaxE)		-3.280**	
		(1.227)	
AbnSent (z) (Bayes)			-3.765***
			(1.340)
CAR Acq. (z) [-1;10]	-2.440**	-2.830**	-2.775**
	(1.192)	(1.132)	(1.132)
CAR Acq. (z) [-5;-1]	-0.4075	-0.2302	-0.2817
	(1.785)	(1.722)	(1.721)
News Sentiment Acq. (z)	-4.596***	-4.667***	-4.676***
	(1.429)	(1.409)	(1.426)
N Tweets	-0.0003	-0.0013	-0.0013
	(0.0010)	(0.0008)	(0.0009)
N News Articles	-0.0527**	-0.0438*	-0.0440*
	(0.0255)	(0.0229)	(0.0233)
Mean(LHS)	14.39	14.25	14.25
Observations	716	730	730
R^2	0.1419	0.1349	0.1366
Deal Controls	✓	✓	✓
Firm Controls	✓	✓	✓
Year-by-Quarter FE	✓	✓	✓
Acq. Industry (GIC2) FE	✓	✓	✓

Table A.5: 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)
AbnSent (z) (StTw)	-1.985**	-0.4985**	-1.946**	-0.4915**
	(0.7931)	(0.2025)	(0.7274)	(0.2067)
Mean(LHS)	3.801	3.150	3.801	3.150
Coef. Diff. t-Stat (p-Value)	-1.707	(0.088)	-1.847	(0.065)
Observations	947	3,556	947	3,556
R^2	0.4598	0.0472	0.5700	0.1171
Deal Controls	✓	✓	✓	✓
Firm Controls	✓	✓	✓	✓
Social & News Media Controls			✓	✓
Stock Return Controls	✓	✓	✓	✓
Year-by-Quarter FE	✓	✓	✓	✓
Acq. Industry (GIC2) FE	✓	✓	✓	✓

Table A.6: 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 YYY. 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 YYY. Naive Bayes sentiment scores are distributed between -1 and 1. *Data source:* StockTwits.
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') × 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 following Gao et al. (2017) as the number of positive minus negative newspaper articles, scaled by the total number of newspaper articles about the M&A deal. As in Gao et al. (2017), we classify each news article as positive if the corresponding Event Sentiment Score (ESS) provided by Ravenpack News Analytics (Dow Jones Edition) is in the upper tercile of all news articles in the sample, and categorize each news article as negative if the ESS is in the lower tercile. 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.
EPU (Regulation)	The Economic Policy Uncertainty index obtained from Baker et al. (2016) and the sub-component of the EPU index related to 'regulation'. *Data source:* Nick Bloom's website.
VIX (S&P500)	The option-implied volatility index of the S&P500 provided by the CBOE. *Data source:* CBOE website.
N SIC4	The number of 4-digit SIC industry segments the target (acquiring) firm is actively operating in. *Data source:* SDC Platinum.
Same SIC4	Indicator variable that takes the value of one if the target and acquiring firms operate in the same SIC 4-digit industry. *Data source:* SDC Platinum.
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.
Distance HQ	The geographic distance between the acquiring and target firm headquarters (HQ) in kilometers. *Data source:* SDC Platinum and Bing Maps API.