#Fail: Social Media, Firm Distress, and Going-Concern Opinions

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ABSTRACT

Audit firms and regulators have both commented extensively on the potential for new sources of data to transform the audit process. Focusing on auditors' going-concern opinions, we use deep learning to measure the "bearishness" of posts on social media and find it strongly predicts the likelihood of firm failure. This association is incremental to other market-based signals, such as a firm's default likelihood or short interest. Cross-sectional tests suggest the association is strongest for non-accelerated filers, a subset of companies that fail more frequently and traditionally operate in more opaque information environments. Interestingly, bearishness appears largely orthogonal to an auditor's going-concern opinion, implying that social media provides information on future events that precipitate failure not fully considered by auditors. While we fail to observe a direct association between bearishness and going concern opinions, our evidence does suggest that going concern accuracy improves with bearishness. Finally, we consider potential channels for these results and find that bearishness foreshadows difficulties in raising capital, predicting the likelihood of future credit downgrades and equity issuances. Our evidence should be informative to regulators and audit firms, both of whom are currently evaluating the usefulness of "new" data to auditors.

Keywords: Stocktwits, Twitter, Social Media, Sentiment, Auditing, Going-Concern Opinions, Firm Failure

1 | INTRODUCTION

Social media platforms provide a continuous and immense volume of information to users. Recent studies suggest this information collectively carries valuable insights regarding the prospects of companies (Chen et al., 2014; Bartov et al., 2018; Farrell et al., 2022). Research in this area has predominantly explored how investors and firms utilize social media, and more recently, the interaction between social media and traditional news sources like professional analysts (Jame et al., 2022; Drake et al., 2023; Call et al., 2023). However, there is less research on the relevance of social media content to another critical player in the financial reporting process—auditors. This gap in the literature is made more pertinent in light of the Big 4 audit firms' recent and significant investments in new technologies to enhance audit efficiency and effectiveness. In fact, EY notes that audits could eventually be transformed by "a form of AI that can analyze unstructured data such as emails, *social media posts* and conference call audio files" (EY 2018, our emphasis), and recent changes to the audit evidence standard (AICPA 2019) aim to revamp what constitutes audit evidence given the proliferation of new technologies. Against this backdrop, our study focuses on one important assessment auditors provide in their audit opinion, an entity's ability to continue as a going concern (GC), and seeks to answer two key questions: First, is information on social media relevant to predicting the risk of firm failure? Second, to what extent do auditors' GC assessments reflect the information available on social media?

In addition to providing opinions on the quality of firms' systems of internal controls and attesting to the reliability of reported financial statements, auditors also evaluate whether a client is likely to continue as a going concern (hereafter, "GC" or the "GC opinion"). If the auditor concludes there is substantial doubt about a client's ability to do so, the audit opinion recognizes this concern. Given their broad access to management and intimate knowledge of potential issues with their clients, auditors are in a unique position to provide an opinion on a firm's ability to navigate financial hardship.

AS 2415, the audit standard outlining auditors' responsibilities for this GC assessment, identifies four areas that auditors should focus on in arriving at GC opinions: (1) negative trends, (2) other indications of financial difficulties (e.g., loan defaults, denial of credit, or the need to seek new financing sources), (3) internal matters (e.g., work stoppages), and (4) external matters (e.g., litigation) (PCAOB 2014). We believe the "crowds" on social media likely disseminate and share information relevant to several of these indicators that is incremental to traditional sources relied upon by auditors, such as client financial records or correspondence with customers, consistent with research suggesting the overall value relevance of social media opinions (e.g., Chen et al. 2014; Tang 2018; Bartov et al. 2018). Thus, our first tests center on the relevance of social media opinions for predicting firm failure and the likelihood of a GC opinion.[1]

Our next question examines whether social media opinions reflect information similar to that underlying auditors' GC assessments. Specifically, we investigate whether GC opinions mediate (subsume) any relation between social media sentiment and firm failure. We are skeptical that auditors' GC assessments include direct consideration of information on social media, at least during our sample period, but it is possible that the information on which social media users base their opinions shares some commonality with the evidence used by auditors. If this is the case, then bearishness should relate positively to GC opinions, and the auditor's GC opinion should attenuate or even subsume social media sentiment's association with the likelihood of future firm failure. On the other hand, social media users may base opinions on their own experiences, such as a

[1] Our tests include all information shared on social media, not just original opinions. Our view is that social media acts as an aggregator of value relevant news, and this news likely overlaps with other traditional sources.

willingness to purchase products from a firm in the future or to take new financial positions, making the information largely orthogonal to signals relied upon by auditors.

To test our predictions, we utilize data from two widely-used social media platforms: Twitter (now X) and Stocktwits.[2] Twitter is a popular, general purpose social media platform where users "tweet" opinions on various subjects, and extensive research has studied the relevance of Twitter to capital markets (e.g., Blankespoor et al. 2014; Bartov et al. 2018, Bartov et al. 2023). Stocktwits is very similar but focuses exclusively on investors' and potential investors' opinions on the attractiveness of a firm from an investing standpoint. Users can even indicate whether they are bearish or bullish at a given point in time. While there is less research on Stocktwits, recent evidence suggests the sentiment and discussions of Stocktwits users reasonably captures investor disagreement (Booker et al. 2023; Hirshleifer et al. 2025). Both Twitter and Stocktwits utilize a "cashtagging" system, and these tags allow systematic identification of messages about a given stock.[3]

We construct our sample using financially distressed firms with audit opinions dated between 2010 and 2018. We begin our sample in 2010 so that we have a critical mass of activity on both social media platforms, and we end in 2018 so we can explore firm failures in the subsequent years that occur prior to the Covid-19 pandemic. Consistent with prior research (Chen and Church 1992; Bruynseels et al. 2011; Bruynseels and Willekens 2012; Anantharaman et al. 2016), we define a financially distressed firm as one which has negative current year income, negative cash flows from operations, negative retained earnings, or negative working capital. We further restrict our sample to those firms with at least some social media coverage on either Twitter or Stocktwits

[2] Elon Musk purchased Twitter in 2022 and rebranded Twitter to X in 2023. Our data was collected prior to this purchase and rebranding, so we use the pre-purchase vernacular (e.g., Twitter, tweet, retweet, etc.).
[3] Twitter did not officially adopt cashtagging until 2012, though our data suggests they were used prior to this date. This is likely because Stocktwits and Twitter were integrated through early 2012.

in the 90 days preceding the audit opinion. While this limits our ability to speak to the potential usefulness of social media for firms that do not have coverage, it reduces impacts of selection biases (i.e., users do not post randomly) and allows us to measure bearishness across our full sample. Finally, we focus our main tests on *first-time* GC decisions, consistent with most GC research (e.g., Menon and Williams 2010; Myers et al. 2018). GC opinions often persist from year to year, and the initial GC decision is generally assumed to be the most difficult. In total, our sample comprises 15,184 firm year observations corresponding to 3,706 unique firms.

Our analyses require identification of firm failure and social media sentiment. To measure firm failure, we use bankruptcy and delisting data to identify likely firm failures or "near-failures" in the year subsequent each audit opinion, similar to Gutierrez et al. (2020).[4] To measure sentiment, we rely on a deep learning model to capture a domain-specific dimension of sentiment (e.g., Huang, Wang, and Yang 2023). Specifically, we rely on a Bidirectional Encoding Representations from Transformers (BERT) model that was fine-tuned to measure whether users are bearish or bullish about a given stock. We use this model to predict bearishness, or the level of negative opinions of social media, for all posts in our sample. This approach is ideal for our setting for several reasons. First, the preprocessing and tokenization process is designed to handle tweets, so hashtags and cashtags are properly identified and parsed. Second, the dimension of sentiment on which the model is trained is very similar to what we wish to measure. Third, BERT-based models account for context, improving accuracy and reliability. Fourth, we validate that the model works reasonably

[4] We collect bankruptcy data from multiple data sources, and we focus on delisting events arising from liquidation or exchange-driven departure (CRSP delisting codes 400-599). The latter type captures firms that violate a rule of the exchange, such as a minimum stock price. While perhaps not a true failure, this event does impair a firm's ability to raise capital and signifies considerable uncertainty about its ability to continue as a going concern. Additionally, section 802.01 of the New York Stock Exchange Listed Company Manual specifies a GC opinion as an event that "may lead to a company's delisting."

well with data on Twitter, which is similar in structure and format to Stocktwits, providing an objective measure for that platform as well.

We begin with our first research question and examine whether social media bearishness predicts firm failure. Consistent with other research suggesting social media is relevant for predicting future value-relevant news, we find a significantly positive association between average social media bearishness and the likelihood of firm failure, suggesting users' opinions convey information relevant to evaluating a firm's survival likelihood. This result is incremental to contemporaneous signals relevant for predicting firm failure, such as ex ante default likelihood and short interest. Further, coefficient estimates suggest that a one standard deviation increase in bearishness corresponds to a 6-basis point increase in the likelihood of failure, roughly 7 percent of the sample mean. We also evaluate Twitter and Stocktwits separately and find that bearishness on each platform predicts firm failure.

We next consider our second research question—do auditors' GC opinions incorporate information similar to that shared on social media? To answer, we regress GC opinions on social media bearishness and the same vector of controls as in the previous test as well as common auditor-based GC determinants. Unlike with predicting failure, we fail to find a significant association between bearishness and the likelihood a firm receives a GC opinion. When considering the two platforms separately, we find some weak evidence that bearishness on Stocktwits is predictive of GC opinions, though differences across platform are not significant. Perhaps not surprisingly, we find essentially no evidence that GC opinions mitigate the association between bearishness and the likelihood of failure. Combined, these two analyses suggest that social media provides a signal relevant to assessing the likelihood of firm failure, and this signal is largely orthogonal to that provided by an auditor's GC opinion.

Our primary tests suggest that GC opinions appear based on information that is largely unrelated to the information underlying social media users' bearishness. Despite this lack of direct association or mediation, it is possible that information on social media moderates the "quality" of GC opinions (e.g., Hopwood et al. 1994; Geiger and Rama 2006; Carson et al. 2013; Blay et al. 2016; Guierrez et al. 2020).[5] For instance, intense pessimism on social media may indicate low investor sentiment towards a stock, which is exacerbated by a GC opinion, making failure more likely. With this in mind, we conduct univariate analyses of Type I and Type II error rates. The literature defines a Type I error as an instance where an auditor issues a GC opinion, but the client continues as a going concern through the following year (i.e., the client does not fail). We sort our sample into terciles of bearishness and evaluate whether the Type I error rate varies across partitions. Our evidence suggests it does. Type I errors are significantly lower in the highest tercile of bearishness (81%) than lowest tercile (91%). Type II errors are defined as instances where a client fails in the year following an audit opinion but did not receive a GC opinion. Similar to Type I errors, the rate of Type II errors is significantly lower in the top tercile of bearishness (59%) than bottom (87%). Note that both of these results are robust to forming terciles from a measure of bearishness that is orthogonal to other relevant signals of distress. Overall, our evidence suggests that, while orthogonal to GC opinions, social media may enhance the informativeness of the GC opinion as an indicator of firm failure.

Next, we consider a potential mechanism by which social media users convey information relevant for assessing failure risk. Specifically, we examine the relation between bearishness and the

[5] AS 2415.04 specifically notes that "The fact that the entity may cease to exist as a going concern subsequent to receiving a report from the auditor that does not refer to substantial doubt… does not, in itself, indicate inadequate performance by the auditor" (PCAOB 2014). Similarly, suggesting an entity may cease to exist (a GC opinion) is not equivalent to stating the entity will fail. Nonetheless, research generally assumes that factors increasing "error rates" (Type I and Type II errors) degrade the quality of the GC opinion (DeFond and Zhang 2014).

likelihood of (1) a future credit rating downgrade and (2) a future equity issuance. Our evidence suggests that social media sentiment provides information predictive of both events: credit downgrades (equity issuances) are more (less) likely when bearishness is higher. These associations are not subsumed by controlling for GC opinions.[6] Interestingly, GC opinions exhibit associations *opposite* that of bearishness with these constructs, meaning firms with GCs are less likely to experience a credit downgrade and more likely to raise capital through future equity financing. One explanation for this pattern of evidence is that auditors consider plans to raise future capital to fund operations as a signal of financial distress.

Our final analyses examine whether social media appears more useful for predicting failure for certain types of firms. We first consider a company's filer status (e.g., large-accelerated filer, or LAF). Audit analytics reports that non-accelerated filers (NAFs) experience the greatest rate of GC opinions and, as such, also likely fail with greater frequency. In addition, these same firms likely operate in more opaque environments, which could allow information on social media, to the extent it is available, more useful. Our evidence suggests this is the case. Specifically, the association between bearishness and failure is significantly higher for NAFs. Second, failure risk tends to be greatest for younger firms early in their life cycles. We evaluate whether social media bearishness is more predictive of failure in younger firms and find some suggestive evidence this is the case.

Our paper makes several contributions to the audit and social media literatures. As mentioned, prior research focuses on firms' use of social media to disseminate information and communicate with investors (e.g., Blankespoor et al. 2014) or the relevance of information on crowdsourced platforms to investors (Campbell et al. 2019; Chen et al. 2014; Hales et al. 2018;

[6] We also consider whether social media bearishness predict other factors that may precede failure: actual debt issuances, significant litigation, and the loss of major customers. We fail to find evidence that bearishness predicts these outcomes.

Jame et al. 2016; Tang 2018; Bartov et al. 2018). More recently, research has begun to examine how online platforms affect the activities and usefulness of information produced by another prominent capital market intermediary, professional analysts (Jame et al. 2022, Drake et al. 2023), finding evidence of both complementary and substitutive relations, depending on the setting. More related to our study, Rozario et al. (2023) suggests that auditors' analytical procedures surrounding revenue could be improved by incorporating data from social media. Similar to this evidence, we find that social media users share information that is useful in evaluating the likelihood of firm failure, making it potentially relevant to auditors' GC decisions.

In addition, researchers, practitioners, and regulators have each commented on the potential usefulness of various types of external media for auditors. When speaking of the broader media, Miller and Skinner (2015, p. 232) note that "One promising approach is to consider the media's interaction with other players in financial markets, such as analysts, auditors, investors, etc." Focusing on social media and auditors, we answer this call. Similarly, Debreceny (2015, p. 3) comments that "exploration of social media trends would appear to provide powerful insights on corporations that auditors could leverage for the purposes of engagement planning and risk management." We provide insights into this potential. Finally, former PCAOB board member Steven Harris notes that "emerging technologies" including "text collected through social media" can help auditors "identify problematic areas or transactions, and benchmark a company's financial information against others based on industry, geography, size or other factors" (Harris 2016). We inform these opinions by documenting strong associations between an easily generated metric of aggregate investor opinions from social media and outcomes about which auditors are required to opine.

2 | RELATED RESEARCH AND HYPOTHESIS DEVELOPMENT

2.1 | Going-concern opinions

While the primary role of external auditors is to evaluate whether financial statements are prepared free of material misstatement, auditors are also tasked with evaluating whether there is substantial doubt about an entity's ability to continue as a going concern. This decision is important because financial statements are prepared under the assumption that firms will remain a going concern for the foreseeable future, and the auditor's assessment represents a relatively straightforward signal relevant for evaluating the likelihood of failure (Gutierrez et al. 2020).

Extant research examining this decision generally informs one of three streams (Carson et al. 2013). First, research investigates factors that influence firms' GC decisions, such as auditor compensation (DeFond et al. 2002), the client's own earnings forecasts (Feng and Li 2014), reliance on major customers (Dhaliwal et al. 2020), and even geographic factors (Anantharaman et al. 2016; Blay et al. 2016). Second, research investigates Type I and Type II "error" rates, which reflect the "quality" of the auditor's GC assessments (e.g., Hopwood et al. 1994; Geiger and Rama 2006; Blay et al. 2016; Guierrez et al. 2020). Finally, a third stream investigates investor (Menon and Williams 2010; Myers et al. 2018) and client (e.g., Carcello and Neal 2003; Kaplan and Williams 2013) responses to receiving a GC opinion. Our research focuses on the first and second streams of literature.

Audit evidence refers to information collected during an audit to inform the auditor's ultimate opinion, including a GC evaluation. Traditionally, auditors have relied on sample-based analytical procedures as well as knowledge of specific events, like difficulties in raising capital, when making this determination. However, rapid technological advances and the proliferation of data allow auditors to more completely evaluate traditional sources of audit evidence (e.g., full-population vs. sample-based testing) and potentially supplement this information with new sources of unstructured data, such as posts on social media (Yoon et al. 2015). Consistent with this potential, the AICPA cites “the use of emerging technologies by both preparers and auditors” and “the expanding use of external information sources” as factors motivating the revision to SAS 142 on audit evidence (AICPA 2019). We posit that the opinions of investors on social media could be germane to auditors’ GC evaluations.

2.2 | Social media in financial markets

Over the last decade, social media has become ubiquitous, and research suggests it plays an important role in financial markets. In essence, users of social media and crowdsourced platforms collectively serve as a new type of information intermediary by both providing original analyses and opinions and rapidly “re-broadcasting” news from other sources (e.g., retweeting, “liking”, etc.). One stream of research investigates the consequences of managers and employees’ social media use, suggesting benefits of using and potentially strategic use of Twitter to disseminate earnings news (Blankespoor et al. 2014; Jung et al. 2018). Similarly, research provides evidence that employee opinions on Glassdoor convey value relevant news to investors (Hales et al. 2018), particularly with respect to bad news (Huang et al. 2020), and provide information useful for predicting earnings quality and fraudulent misreporting (Ji et al. 2024).

Social media has also allowed individuals external to the firm to disseminate personal opinions on firms. While not without controversy, most research implies these opinions, at least on average, are informative. For instance, equity research appearing on Seeking Alpha is predictive of future earnings surprises and stock returns (Chen et al. 2014). Similarly, aggregate opinions on Twitter predict future sales and earnings (Tang 2018; Bartov et al. 2018), earnings estimates appearing on Estimize are incremental to traditional sell-side forecasts (Jame et al. 2016), and Stocktwits user disagreement surrounding earnings announcements predicts trading volume, consistent with a long line of theory (Giannini et al. 2019; Booker et al. 2023). Thus, social media appears to provide information relevant to evaluating a firm's prospects.

The aforementioned research evaluates the usefulness of information shared on social media by the degree to which it informs, or should inform, investors. Information on social media is also relevant to capital market intermediaries. Drake et al. (2023) provides evidence suggesting that news on social media lessens the relevance of forecasts produced by sell-side analysts and potentially alters properties of their forecasts. Similarly, Jame et al. (2022) suggest that crowdsourced earnings forecasts on Estimize discipline sell-side analysts. To our knowledge, only one published study, Rozario et al. (2023), considers the interplay between social media and auditors. Using a sample of 76 companies in consumer-facing industries, they find that models incorporating consumer *interest*, but not *sentiment*, improves analytical procedures around revenue. We extend this research by investigating whether social media could be useful for a key, more visible auditor assessment.

2.3 | Hypotheses

Each of the Big 4 has commented extensively on how the proliferation of information, data analytics, and other emerging technologies will transform the audit. For instance, KPMG publicizes "Clara", their "smart audit platform." KPMG argues auditors use Clara "to drive a risk-based, data-driven quality audit" (KPMG 2025). Similarly, EY's Helix platform allows its auditors to "take an analytics-driven approach to audit" (EY 2023). Deloitte's Omnia platform delivers more relevant insights, all while reducing the [audit] burden" on the client (Deloitte 2023), and PwC's Halo will "harness the power of data to help [audit] teams see what needs to be seen beyond the numbers on the page" (PwC 2023). In general, these technologies focus on the ability both to examine huge volumes of transactional data with advanced technologies, such as those based on machine learning, natural language processing, or artificial intelligence, to improve decision making.

Much of the materials promoting these tools do not delve into the underlying source data. There has been some mention of expanding audit evidence to better consider external data sources, such as social media (e.g., EY 2018), but to date little is known about whether auditors pay attention to this source of news for decision making.[7] Hale (2017) cites the United Airlines price drop following a video that went viral on social media as clear evidence that auditors should "keep an eye on social media channels" since events such as this could trigger accounting-related outcomes, like the need for impairment testing. Similarly, the PCAOB has commented that auditors and clients could consider consumer opinions on social media when evaluating company risk or the appropriateness of warranty reserves (PCAOB 2021). Signals available from social media posts are unlikely to ever be a first-order consideration for auditors, but these references suggest the potential for social media to play a supporting role in auditor decision making.

We expect that social media could be useful for predicting firm failure and, therefore, useful to an auditor for evaluating the likelihood a client continues as a going concern for three reasons. First, social media provides a timely indication of "what's happening" at any given point in time. AS 2415.06 instructs auditors to consider "conditions and events", such as indicators of "financial difficulty" and "external matters that have occurred" when evaluating the client's ability to continue as a going concern (PCAOB 2014). We expect these types of matters provide a basis for social media posts. To illustrate, on August 17, 2011, Stocktwits user @Street_Insider shared the following post, "Analyst Sees More Bankruptcies in Solar Sector; Says Energy Conversion ($ENER) Will Be Next http://streetinsider.com/rs/672638", tying recent news about struggles in the solar energy sector to energy conversion firms. Second, the opinions of investors participating on

[7] In 2014, KPMG Capital invested in Bottlenose, a "cloud-based trend intelligence solution analyzes real-time streaming data that enables enterprises to identify, anticipate and monitor the trends that drive their businesses" (KPMG Capital 2014). One source of such "streaming data" is social media, though publicized use cases appear more consulting than audit-focused (KPMG 2016).

social media sites likely reflect the willingness of equity investors to provide capital to firms facing financial difficulties. Along these lines, on January 2, 2014, Stocktwits user @MasterTheDream opined “$NADL Sorry; I’m not touching this until the SDRL bankruptcy dust has settled. It could take NADL with it and wipe out the shareholders.” The inability of a struggling firm to raise capital is a textbook indicator of financial distress. Third, the nature of social media often means perception is reality. That is, the opinions of certain influential social media participants can spread rapidly, causing stock price declines, poorer credit ratings, etc.[8] On January 14, 2014, Stocktwits user @Procent remarked “$NIHD Get out while you can. Just like their bonds with tripple [sic] C status = junk bonds – this company will hit the wall and bankruptcy.” Each of these opinions provides a clear signal about the posters’ beliefs about the cashtagged firm.[9]

Based on these arguments, our first hypothesis predicts that negative sentiment on social media (bearishness) relates positively to the likelihood of firm failure:

H1: Social media bearishness is positively associated with the likelihood of firm failure.

This prediction is not without tension. While extensive research links opinions of those on social media to firm performance, limited research specifically examines negative events that likely precipitate firm failure. Hales et al. (2018) find that employee opinions on the crowdsourced platform Glassdoor are predictive of future goodwill impairments and restructuring charges, events correlated with distress and potential failure, but these opinions reflect those of insiders. Additionally, our models control for traditional determinants of bankruptcy, so it’s possible that sentiment on social media is subsumed by these other signals.

[8] As an example, in February 2018 Kylie Jenner tweeted that she no longer uses SnapChat because of dissatisfaction with an interface redesign. SnapChat’s valuation sank by more than $1.3 billion (6 percent) following her tweet (Yurieff 2018).

[9] Note that we do not suggest the information underlying social media users’ opinions necessarily comes from private sources. In fact, it’s highly likely social media opinions reflect reactions to other public news (the press, firm disclosures, other social media posts). As noted earlier, we view social media as an aggregator of value relevant information.

Our second hypothesis explores whether audit opinions incorporate information similar to that underlying social media bearishness in arriving at their GC opinions. In other words, if GC opinions correctly incorporate publicly available information that is also reflected on social media, we expect firms that are the subject of relatively more negative social media posts will also be more likely to receive a GC opinion. Stated formally:

H2a: Social media bearishness is positively associated with the likelihood of receiving a GC opinion.

This hypothesis is also not without tension. Despite our prediction in H1, it is possible that social media opinions reflect noise which auditors ignore. Auditors could also base their GC opinion decision more on information collected through direct observation during the audit process than other information and circumstances prompting firm-specific social media attention.

In H1, we predict a positive association between social media bearishness and firm failure. Evidence consistent with H2a would suggest that opinions on social media are at least partially reflected in auditors' GC opinions, implying GC opinions may subsume bearishness in explaining failure. We formerly evaluate this with a statistical mediation test, which we articulate in H2b (Gow et al. 2016):

H2b: GC opinions mediate the association between social media bearishness and the likelihood of firm failure.

A test of mediation is the simplest form path analysis. Lennox and Payne-Mann (2023) scrutinize the use of path analyses in accounting research, noting that research frequently fails to recognize the assumptions of such tests. Namely, *causal* path analysis without exclusion restrictions (as in instrumental variables) requires exogeneity in both the direct and indirect paths. Absent these criteria, an exclusion restriction is necessary for causal identification. We fully recognize that social media bearishness likely correlates with many unobservable factors and those factors also correlate with both the risk of firm failure and auditors GC opinions, which would violate this assumption. However, we are not arguing that either GC opinions or social media bearishness *cause* failure. Rather, our purpose to descriptively evaluate whether the summary signal in social media bearishness is also captured (and subsumed) by an auditor's GC opinion. In other words, does one summary measure (GC opinions) reflect similar information in another summary measure (bearishness)?

3 | DATA AND RESEARCH DESIGN

3.1 | Social Media Data

To measure social media bearishness, we collect posts from Stocktwits and Twitter. We focus on these two platforms because of their widespread popularity and similarity in content. In fact, Stocktwits began as an application using Twitter to organize users' opinions of investments (Arrington 2010). In late 2009, Stocktwits launched an independent platform but remained heavily integrated with Twitter until 2013 (Stocktwits 2013). Stocktwits now boasts over 10 million users (Stocktwits 2025), and inspection of Stocktwits user profiles suggests most users are individual investors, albeit with some level of sophistication (e.g., frequent mentions of options, professional experience, etc.). Twitter, on the other hand, caters to a wide audience, and limited information is available on most users. Despite being general interest, investors frequently use Twitter to comment on stocks and disseminate financial news (Campbell et al. 2023). Users on both platforms associate their opinions with cashtags, or a firm ticker preceded by a dollar sign (e.g., $AAPL).[10] Note that cashtagging on Twitter was not officially adopted until 2012, but users used the ticker-tagging strategy before this date (likely due to Stocktwits' original integration with Twitter).

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[10] While Twitter is a general social media platform that hosts posts and opinions about virtually any subject, we suspect the use of cashtags increases the likelihood the content is investment-related. To evaluate whether this is the case, we had two RAs independently evaluate whether 100 randomly select tweets were investment related. After resolving differences, their review suggested 93 percent of tweets were investment related. They repeated this exercise with 100 randomly sampled posts on Stocktwits and found a similar percentage of investment related content.

The topics of posts on both platforms vary considerably. For example, users share trading strategies involving complex option positions, articles and links relevant to valuing stocks, or specific factors investors may want to consider when evaluating a buy/sell decision. Figure 1 provides examples of these types of posts. Panel A provides examples of Stocktwits posts. The first example, posted by @dennismccain, comments on a combination of short strategies he's using to build a position in a stock he is bullish about. The second example, by @Ro_Patel, cites recent news from a professional analyst on proprietary survey results. The third post, by @trade_nut, provides updated information on job cuts. The Twitter examples in Panel B also appear to provide some insight into each poster's general sentiment. The first example, by @StockReversals displays bullish sentiment, whereas the second example, by @MadeinMenlo, displays a bearish sentiment toward the respective companies' stocks. Note that both Twitter posts reflect the sharing of information that underlies the users' opinions. While not original analysis, we still view this content as relevant for assessing investors' bearishness of stocks as shared on social media.

3.2 | Sample

We begin our sample with 35,036 financially distressed observations at the intersection of Compustat, CRSP, and Audit Analytics between 2010 and 2018. Following prior research, we restrict our sample to financially distressed firms, or the subset of firms where auditors are most likely to face the decision to issue a GC opinion (e.g., Anantharaman et al. 2016). We use a broad measure of distress, which we define as firms that have negative net income, operating cash flows, working capital, or retained earnings (Chen and Church 1992; Bruynseels et al. 2011; Bruynseels and Willekens 2012; Anantharaman et al. 2016).

We then acquire social media posts about firms in this initial sample. We obtain data from Stocktwits using their Firestream API and data from Twitter from the v2 endpoint of its API.[11] For Stocktwits, we obtained the full universe of messages over our sample period. Twitter requires queries, so we searched for tweets containing cash tags related to any firm in our sample of audit opinions for distressed firms. In total, we obtain approximately 126 million posts, including 69 million Stocktwits posts and 57 million Twitter posts. We parse each data source, identifying the information in the actual social media post, the username, the posting date, and each ticker symbol referenced via cashtag in the post. Note that it is possible for the same user to cross-post on Twitter and Stocktwits, though the usernames (and other identifying information) may be different. While duplicate posts are unlikely to affect our inferences, we attempt to exclude by sorting posts by timestamp, cashtag, and message, and then dropping any duplicates.

A significant concern in research studying social media (or any type of "voluntary disclosure" setting) is that posts are non-random, both in timing and in subject. While this concern is difficult to fully address, we attempt to at least partially mitigate this issue in our setting by focusing on firm-year observations with at least some social media coverage.[12] Specifically, we restrict our sample to firms that are cashtagged in posts within the 90-day period prior to the audit report date in either Twitter or Stocktwits. This sample screen reduces our sample by 12,660 observations. This design choice increases the likelihood that social media users are actively monitoring and commenting on a given firm during the same period the auditor is evaluating the client's ability to continue as a going concern. However, we recognize that it also biases the sample

[11] We collected data from Twitter during a period which their premium API was available for free for academic use. This free access has since been discontinued, and the API we use is no longer available. The Stocktwits data was also free for academic use when we constructed our sample, but that is no longer the case.

[12] A downside of this choice is that we cannot benchmark against firms receiving no social media coverage at all, and firms receiving coverage tend to be larger than the average Compustat firm. Consistent with this, in untabulated analysis we find that the likelihood of failure is lower for firms receiving at least some social media coverage. Thus, we caveat that our inferences are limited to the types of firms we include in our sample.

towards larger firm, potentially from certain types of industries, that are visible enough to receive social media coverage.

To quantify these differences, we highlight a few descriptive differences and evaluate industry representation by comparing firms in our sample to those excluded because of a lack of social media coverage. Median assets (revenue) for our sample of firms is 276 (636) million, substantially larger than the median of 21 (56) million for excluded firms. We also observe a significantly higher median ROA for firms receiving social media coverage (-0.1 percent vs. – 11.8 percent). While the size and financial health of firms differs, Figure 2 suggests industry breakdown, for the most part, is comparable to the broader sample of distressed firms. Financial firms appear overrepresented, and, to a lesser degree, healthcare underrepresented, but other proportions are similar. In any case, we recognize that our sample is skewed towards larger firms.

Note that for our analyses, we focus on "first-time" GC decision and remove 2,513 observations where the firm received a GC opinion in both the current year and prior year. We eliminate 4,679 firm-year observations that do not contain sufficient information to construct the control variables in our analysis.[13] The final sample size is 15,184 firm year observations, representing 3,706 unique firms. Table 1 outlines sample construction and attrition.

3.3 | Research design

Our first hypothesis predicts that social media bearishness will relate positively to the likelihood a client fails in the upcoming year. To test this hypothesis, we estimate the following regression model:[14]

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[13] The greatest sample attrition comes from including our measure of financial distress, *PD12MONTH*, in the regression models. The final sample size is 16,228 when substituting the firm's Altman z-score in place of *PD12MONTH*. Inferences with this sample are largely similar. We use *PD12MONTH* since it is a stronger predictor of failure than the z-score.

[14] We use a linear-probability model (LPM), or OLS, to estimate model [1] since coefficients in LPMs can be directly compared across models, which simplifies mediation analyses (H2b). Wooldridge (2010) notes that the LPM often does "a very good job" of estimating average partial effects. However, results are similar when using a logit model.

$$FAILURE_{it} = \beta_0 + \beta_1 BEARISH_{it} + \Sigma\gamma Controls + \Sigma\psi Industry\text{-}Year + \varepsilon_{it} \quad [1]$$

where *FAILURE* is an indicator variable equal to one if the firm declares bankruptcy or delists for financial reasons within one year of the audit opinion date, consistent with the FASB's prescribed horizon for management that went into effect during our sample period.[15] *BEARISH* is our (inverse) measure of social media sentiment. Our first hypothesis predicts that β_1 is positive, indicating a positive relation between investor bearishness and the likelihood of client failure.

To measure bearishness, we rely on a finetuned deep-learning model designed to capture investors' opinions about a stock's prospects, which was developed using data from Stocktwits. Stocktwits allows users to signal whether they are bearish or bullish about a given stock. Under the assumption that bearish (bullish) users likely include language that conveys pessimism (optimism) in their posts, researchers from the National University of Singapore (NUS) fine-tuned the base RoBERTa model to classify labeled tweets as either bullish (coded 1) or bearish (coded 0).[16] The developers report out-of-sample classification accuracy of 93 percent.

While the model documentation suggests accurate classification for social media users on Stocktwits that indicated their opinion, it is not clear whether this accuracy translates to (1) unlabeled Stocktwits messages and (2) Twitter posts. To further validate the model for these two groups, we randomly sample 100 tweets from Twitter and from unlabeled posts on Stocktwits (200 total). Two research assistants independently assessed each post as either bullish or bearish

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Additionally, we refer to marginal effects at the sample means of these untabulated tests when discussing economic significance since LPM does not constrain predicted values to a unit interval.

[15] AS 2415.02 prescribes a shorter consideration window than the one-year horizon we use, denoted as "a reasonable period of time, not to exceed one year beyond the date of the financial statements being audited" (PCAOB 2014). If we use the PCAOB's shorter window to define *FAILURE*, our results are qualitatively similar.

[16] RoBERTa is a "retrained" version of Google's BERT model developed by Facebook. RoBERTa includes some minor modifications to the original BERT design to improve performance in a variety of settings. We rely on a fine-tuned RoBERTa-based model to predict users' "bearish" or "bullish" designations. See https://huggingface.co/zhayunduo/roberta-base-stocktwits-finetuned. Recent research has trained other deep learning models to measure properties such as financial sentiment or the presence of ESG-related language (Huang, Wang, and Yang 2023)

(Bochkay et al. 2023). Raters agreed approximately 85 percent of the time. More importantly, the raters' assessments agreed with the model's classification for approximately 85 percent of posts, which we view as additional validation of the efficacy of the model in our setting.

Our variable of interest, *BEARISH,* is the average bearishness in posts in the 90 days prior to the audit opinion; in other words, we invert model predictions such that 1 is negative sentiment. Control variables included in model [1] generally follow prior research and reflect variables that are predetermined with respect to and likely contribute to both to the likelihood of firm failure and social media bearishness (Whited et al. 2022). We use three sets of control variables, which we introduce sequentially.

We begin with a set of fundamental firm and auditor characteristics. Most importantly, we include a measurement of financial distress (*PD12MONTH*) provided by the Credit Risk Initiative (CRI) at the National University of Singapore (Gutierrez et al. 2020). This measure is based on Duan et al. (2012) and reflects a conditional forward probability of survival on a specific date as a function of (a) survival until that point in time and (b) a range of macro and firm-specific factors (e.g., economy-wide distance to default, level and trend in cash, relative size); see CRI (2022) for more details. In addition, we include common controls from the literature, like firm size (*SIZE*) and age (*AGE*), whether the firm had a current year net loss (*LOSS*), the ratio of debt to assets (*LEVERAGE*), the trend in the firm's leverage (*CH_LEVERAGE*), cash flows from operations (*OPCF*), the firm's need for external financing (*FINANCE*), and the firm's current level of investments (*INVEST*). Each of these firm characteristics captures a factor that research suggests signals potential failure, which likely shapes the opinions of those on social media. Additionally, we control for *BIG4*, which partially reflects the attention firms receive on social media as well as auditor quality, and the level of social media activity (*NUM_TWEETS*) about the firm during the 90-day period prior to the audit report date.

Our second set of controls includes market-level factors commonly associated with financial distress, which also likely affect the nature of social media posts (*RET*, *BETA*, *VOLATILITY*). We also control for the proportion of investors holding a short interest in the firm's outstanding stock during the 90-day period prior to the audit report date (*SHORT_INTEREST*).

Third, we introduce other significant signals of distress that may also drive social media bearishness and provide information on the likelihood of firm failure. Specifically, we control for analyst downgrades (*NET_DOWNGRADES*), credit rating downgrades (*CREDIT_DOWNGRADE*), business press sentiment (*PRESS_SENTIMENT*), and the number of analysts following the firm (*ANALYST_FOLLOWING*). Note that credit rating downgrades further limits our sample since we only have access to ratings information through 2016.[17] Finally, all specifications include crossed industry-year fixed effects to control for unobservable factors that contribute to intertemporal variation in industry-specific conditions, which contribute to the likelihood of failure and social media bearishness, and we cluster standard errors by firm to correct for serial correlation in residuals (Petersen 2009).

To test H2a, we estimate the following model:

$$FIRST\_GCO_{it} = \beta_0 + \beta_1 BEARISH_{it} + \Sigma\gamma Controls + \Sigma\psi Industry\text{-}Year + \varepsilon_{it} \qquad [2]$$

where *FIRST_GCO* is an indicator variable if the firm received a GC opinion in the current year and did not receive one in the prior year, and zero otherwise. We use the same sets of controls as in equation [1], supplemented with three variables research commonly associates with GC opinions:

[17] Our rating data comes from Compustat's Ratings file, which ceased updates in February 2017. Note that untabulated analyses suggest that *PD12MONTH* subsumes *CREDIT_DOWNGRADE* in explaining failure, suggesting we likely control for the impact of credit downgrades even absent the *CREDIT_DOWNGRADE* control.

the length of the audit-firm relationship (*TENURE*), the time between the firm's fiscal year-end and the audit opinion date (*REPORT_LAG*), and the ratio of non-audit fees to total fees (*FEE_RATIO*). To examine H2b, we estimate a model similar to equation [1], while controlling for *FIRST_GCO*. We then examine whether the *BEARISH* coefficient (β_1) is significantly different in this regression than in our formal test of H1.

3.4 | Descriptive statistics and correlations

Table 2 presents descriptive statistics for variables included in our models; all continuous variables are winsorized at the first and 99th percentiles. We find that 2.1 percent of our sample of financial-distressed firms receive a first-time GC opinion, a rate that is somewhat lower than that in other research (e.g., Anantharaman et al. 2016; Gutierrez et al. 2020). We highlight three potential reasons for this. First, we consider a broader definition of distress, supplementing negative cash flows and/or earnings with negative retained earnings or negative working capital. Second, our sample period begins after the financial crisis, which led to significantly higher rates of GC opinions. Third, our tests require coverage on ST or Twitter, and, as noted earlier, social media participants devote more attention to larger, more stable companies that are less likely to receive GC opinions (Carson et al. 2013). If we do not require social media coverage and define our sample of financially distressed firms based on only negative net income or negative operating cash flows (as in Anantharaman et al. 2016), our first-time GC opinion rate is approximately 7 percent, similar to prior research. For firm failure, we find that 0.8 percent of firm-years in our sample correspond to either a declared bankruptcy or delisting from their respective stock exchanges.[18]

[18] This rate is approximately half of that in Gutierrez et al. (2020), who report that 1.8% of their observations experience a "default event", defined similar to us. The reason for this difference is our sample period begins after the financial crisis whereas Gutierrez et al. (2020)'s sample period includes both the financial crisis and the dot-com bubble burst. Expanding our sample of default events to include these years produces very similar rates of failure.

Table 3 presents Pearson correlations for variables included in our models. The correlation between *BEARISH* and *FAILURE* is positive, as expected but we report a negative correlation between *BEARISH* and *FIRST_GCO*, inconsistent with H2a. Interestingly, *BEARISH* exhibits correlations with many firm characteristics that are opposite those of *PD12MONTH*, our main measure of default risk (e.g., *LOSS, OPCF, BETA*). This potentially indicates that *BEARISH* is a unique signal among others relevant for assessing distress risk. Finally, untabulated variance inflation factors did not exceed 2.99 with a mean value of 1.42, suggesting that multicollinearity is unlikely a significant concern.

4 | PRIMARY RESULTS

4.1 | The association between social media bearishness and firm failure (H1)

Table 4 presents the results for our test of H1, which predicts that social media users express more bearish sentiment for firms that will fail in the near future compared to firms that will not. Panel A uses *BEARISH* from both platforms. Column (1) presents the results of estimating model [1], controlling for firm-related factors in the estimation model. Column (2) adds market-related controls, and column (3) adds other external signals indicating firm financial distress. The results in Panel A strongly support H1. Specifically, we find strong, positive coefficients on *BEARISH* ranging from 0.016 to 0.020 (p <0.01 for all three columns). LPMs can misstate marginal effects at extreme values of regressors, so we estimate our models using a logit regression in untabulated tests and compute the marginal effect of social media bearishness at the sample mean of other regressors. We find that a one standard-deviation increase in *BEARISH* corresponds to between a 4 and 6 basis point increase in the likelihood of firm failure, which is significant compared to the sample mean of 0.8 percent.[19]

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[19] We find similar support for H1 using the two alternative windows for measuring *BEARISH* (1 year prior to the opinion date, or between the fiscal year end and audit opinion date).

As for control variables, we find that *PD12MONTH* strongly predicts the risk of failure. We also find that firms with high leverage and large changes in leverage (*LEVERAGE* and *CH_LEVERAGE*) are more likely to fail, as are older firms (*AGE*). High beta firms (*BETA*) are less likely to fail, while high volatility firms are more likely to fail. Remaining coefficients are either insignificant or inconsistent across columns.

In Panels B and C, we repeat our tests using *BEARISH* derived only from Stocktwits (Panel B) or Twitter (Panel C). In Panel B, we continue to find a positive, though marginally significant associations between *BEARISH* and *FAILURE* when using only Stocktwits posts ($p < 0.10$) except in Column (1; *t-stat* = 1.67). Panel C reports significant coefficients ($p < 0.05$) in all three specifications. While Panels B and C provide some support that each social media source is relevant for predicting *FAILURE*, we note that the association is the strongest, both economically and statistically, in Panel A when using both social media sources together to measure *BEARISH*.

4.2 | Social media bearishness and going-concern opinions (H2a and H2b)

H2a predicts that social media bearishness predicts GC opinions. To test this hypothesis, we estimate equation [2]. We report results in Panel A of Table 5. The first column excludes *BEARISH* and provides evidence general consistent with prior research. For instance, the probability of default strongly predicts *FIRST_GCO*. *SIZE, OPCF* and *INVEST* relate negatively whereas *LEVERAGE* and *REPORT_LAG* relate positively to the likelihood of a firm receiving a first-time GC opinion. Columns 2 through 4 include *BEARISH* and introduce controls as done in Table 4. Across all columns, we fail to find any evidence that *BEARISH* relates to auditors first-time GCO decisions. All three coefficients are positive, but fall well short of conventional statistical significance levels (*t*-statistics < 1).[20] Thus, we fail to find support for H2a.

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[20] In untabulated analyses, we repeat these tests by platform. We find some marginal evidence that Stocktwits bearishness predicts *FIRST_GCO* ($t = 1.8$ in column 2, $t<1.6$ in columns 1 and 3). Twitter bearishness does not relate to

Given the lack of evidence for H2a, it seems unlikely we would observe evidence that *FIRST_GCO* mediates the association between *BEARISH* and *FAILURE*. Statistical mediation requires four results. First, there must be a significant association between our measures of social media bearishness and *FIRST_GCO*. Second, the mediator (*FIRST_GCO*) must significantly predict the outcome of interest (*FAILURE*). Third, the relation between *BEARISH* and *FAILURE* should be significant, and, fourth, this final relation should attenuate once conditioning on *FIRST_GCO* (i.e., including both *FIRST_GCO* and *BEARISH* in equation [1]). Panel A of Table 5 reports results relevant to this first link, which fails. Nonetheless, we conduct remaining tests for mediation.

Panel B of Table 5 reports estimations of equation [1], adding the three audit-related controls from equation [2]: *TENURE, REPORT_LAG,* and *FEE_RATIO.* Column 1 reports evidence similar to Table 4, confirming these new controls do not influence the association between *BEARISH* and *FAILURE.* Column 2 confirms that *FIRST_GCO* strongly predicts the likelihood of failure, consistent with prior literature (e.g., Gutierrez et al. 2020). Column 3 includes both *BEARISH* and *FIRST_GCO* in the failure model, suggesting essentially no mediation. The coefficient on *BEARISH* does decline slightly (0.017 in column 1 vs. 0.016 in column 3), but these estimates are not statistically different from one another (untabulated).

In sum, our primary tests provide evidence that social media bearishness provides information relevant for evaluating the likelihood of firm failure. However, we fail to observe any evidence that auditors impound information similar to that conveyed by social media in their GC opinions.

FIRST_GCO. However, these estimates are statistically indistinguishable. Given results in Table 4 suggesting the combined bearishness measure is the strongest predictor of *FAILURE*, remaining tests focus on the combined measure.

5 | ADDITIONAL ANALYSES

In this section, we report the results of several additional analyses aimed at further exploring the relevance of social media bearishness in auditors' GC opinions. We then conclude with several robustness tests.

5.1 | Social media bearishness & GC reporting accuracy

While we fail to find evidence consistent with H2a and H2b, it is possible that the "quality" of GC opinions varies with social media bearishness. Note that PCAOB is clear that neither a lack of failure following a GC opinion nor a lack of GC opinion preceding a failure necessarily constitutes an invalid GC opinion, as auditors are not expected to "predict the future." Nonetheless, the literature frequently investigates variation in these two types of "errors", denoted Type I and Type II errors, respectively, to provide insight on when auditor's GC opinions more closely align with observed outcomes (Carson et al. 2013). There are at least two reasons why *BEARISH* may correlate with GC reporting accuracy, or Type I and Type II errors. On the one hand, the fact that we fail to observe an association between *BEARISH* and *FIRST_GCO* may imply a reduction in GC opinion quality since our evidence suggests *BEARISH* is a relevant signal of firm failure. On the other hand, higher levels of social media bearishness may correspond to greater salience of negative events that the auditor does consider, improving certain aspects of GC reporting accuracy. Given the lack of clear prediction, we view these tests as exploratory.

To evaluate whether social media bearishness correlates with GC reporting accuracy, we form terciles of observations based on *BEARISH*. Then, within each tercile, we compute the mean error rates. Type I errors are defined as instances where a firm receives a first-time GC opinion but does not experience a default event in the year subsequent the opinion. Type II errors are defined as instances where firms receive "clean" GC opinions but subsequently experience default events. Note that Type I (II) errors are only defined for firms receiving GC opinions (experiencing default events), which greatly reduces the sample size for these tests. Due to these reduced sample sizes, we conduct univariate analyses, consistent with other research (e.g., Blay et al. 2016).

We present these results in Table 6; Panel A presents results for Type I errors, and Panel B results for Type II. Beginning with Panel A, our evidence suggests that Type I errors are significantly lower in the highest tercile (80.8%) of *BEARISH* than the lowest (91.4%), and this difference is statistically significant ($p = 0.03$; two-tailed). The right-most column presents an alternative set of sorts based on a version of *BEARISH* orthogonalized to controls in the paper (*BEARISH_R*), increasing the likelihood that we are sorting on *BEARISH* instead of some other correlated factor. To construct *BEARISH_R*, we regress *BEARISH* on controls used in Table 4, column 2, and obtain the residual (we use column 2 to avoid data loss). We then form tercile sorts using this residual. As shown, results are largely similar using this orthogonalized measure. Interestingly, the middle tercile exhibits the highest Type I error rate (98.1%, 95.1%) in both columns. One ex-post explanation for this pattern is that the middle tercile captures relatively neutral sentiment, which corresponds to the most uncertain type of information environment.

Panel B reports results for Type II errors. Consistent with Panel A, we again find that Type II errors are lowest in the highest tercile of *BEARISH*, or where social media opinions are most negative. The difference between the lowest (87.2%) and highest (59.0%) terciles is also statistically significant ($p < 0.01$, two-tailed). This result persists for *BEARISH_R* as well. Overall, evidence in Table 6 implies that GC opinions are of higher quality when social media users are more negative.

5.2 | Why is social media relevant?

Our evidence supporting H1 suggests that social media bearishness contains information relevant to GC decisions but short of explaining what that information is. In this section, we attempt to provide some insight into what kind of news or events social media users foreshadow, though we recognize there could be many reasons for this association. AS2415.06 identifies numerous factors that auditors should consider when evaluating an entity's ability to continue as a going concern. We focus on two issues related to firms' ability to finance operations: credit rating downgrades (*FUT_CREDIT_DOWNGRADE*) and the likelihood of equity capital issuance (*FUT_EQUITY*).

Credit downgrades may make raising capital from debt markets cost prohibitive. We rely on the S&P long-term issuer ratings available in Compustat's S&P Ratings data, which ends in early 2017, so our sample for this test only extends into early 2016. We define *FUT_CREDIT_DOWNGRADE* equal to 1 if the firm's long-term S&P rating declines by at least one "notch" in the year following the audit opinion date, and 0 otherwise. We use *FUT_CREDIT_DOWNGRADE* as the dependent variable in model [1] and report results in Panel A of Table 7. Note that we control for contemporaneous downgrades (*CREDIT_DOWNGRADE*) to capture any rating trends (or correction), which ensures any results we observe are distinct from the correlation between social media bearishness and credit rating movement (i.e., bearish sentiment could be prompted by a recent credit downgrade). Consistent with predictions, we observe positive coefficients on *BEARISH* in columns 1 and 2 ($p < 0.10$), and these estimates are unaffected by conditioning on *FIRST_GCO*. In fact, *FIRST_GCO* relates *negatively* to the likelihood of a credit downgrade.

Like debt, new equity financing can be an important source of funds for distressed firms. We define an equity issuance (*FUT_EQUITY*) as an indicator equaling 1 if a firm sells stock in year t+1, and 0 otherwise. We use this measure as the dependent variable in model [1] and report results in Panel B of Table 7 and control for current year equity issuance (*EQUITY*). Consistent with results in Panel A, we again observe that social media provides a signal relevant to this future outcome. Specifically, column 1 reports a significantly negative coefficient on *BEARISH,* implying firms with high levels of bearishness are less likely to raise future capital. Column 2 introduces *FIRST_GCO*. Similar to the prior test, *FIRST_GCO* relates *positively* to the likelihood a firm raises significant capital. More importantly, the coefficient on *BEARISH* is unaffected.

In addition to these two outcomes, we consider two alternative proxies related to debt-related financing in untabulated tests—significant downgrades (moving from investment grade to junk) and actual debt issuance. Dropping below an investment grade rating, defined as instances where the credit rating drops below BBB, can severely impact the ability of a firm to issue debt. We explore this as an alternative outcome and fail to find a significant association between *BEARISH* and these significant downgrades. Note that the incidence of these downgrades is extremely rare (0.3% in our sample), limiting the power of this test. We also consider actual debt issuance, similar to our definition of *FUT_EQUITY*. We fail to find evidence that social media bearishness predicts the likelihood of debt issuance. One explanation for this finding is that the firms needing to raise new sources of debt financing are the same ones who find it more costly to do so after a downgrade.

Overall, the evidence in Table 7 provides evidence that social media bearishness provides information about a financially distressed firm's ability to obtain certain types of future financing. Conditioning on *FIRST_GCO* does little to impact these associations, again suggesting that information on social media is largely orthogonal to the signal provided by an auditors GC opinion.

5.4 | Cross-sectional Tests

While we rely on a sample of distressed firms, or firms exhibiting some characteristic increasing the likelihood of failure, we recognize that not all firms face the same ex ante failure risk. In this section we focus on two criteria that likely correspond to elevated failure risk.

First, we identify the filing status of each firm. Audit Analytics (2024) reports that going concern opinion rates increase dramatically when moving from accelerated to non-accelerated filer status. In addition, research suggests that information on social media tends to be more relevant for firms operating in relatively poorer information environments (e.g., Blankespoor et al. 2014; Gomez et al. 2024), which are likely the same firms that face greater ex ante likelihood of failure. On the other hand, non-accelerated filers may be less visible on social media, weakening the power of the signal. We partition our sample into large accelerated filers (LAF), accelerated filers (AF), and non-accelerated filers (NAF). Consistent with Audit Analytics (2024) statistics for GC opinions, we observe monotonically decreasing failure rates moving from LAF to AF to NAF (1.8%, 0.6%, 0.1%, untabulated). We assess whether the predictive ability of *BEARISH* varies by status by partitioning our sample into LAFs, AFs, and NAFs, and report results from estimating equation [1] in Panel A of Table 8. We only observe a significantly positive coefficient in column 3, or in the NAF group. Tests of *BEARISH* coefficients between columns 1 and 3 (LAF vs. NAF) and between 2 and 3 (AF vs. LAF) are significant ($p<0.05$; untabulated). In sum, it appears that social media bearishness is most predictive of failure for NAFs, the group of companies who typically face greatest risk of failure.

Next, we consider firm age since research typically observes negative associations between firm failure and firm age (e.g., Blay et al. 2016). As with the arguments for NAFs, younger firms likely receive less attention from traditional sources (e.g., press, analysts), making information on social media potentially more useful. We measure firm age using the first date a firm appears in Compustat and partition the sample at the median (16 years, untabulated). We again estimate equation [1] in subsamples and report results in Panel B of Table 8. We find that the coefficient on *BEARISH* is larger in magnitude in the below-median sample (column 2). However, the difference in coefficients across partitions is not significant. Overall, we view these analyses as providing some suggestive evidence that social media bearishness may be more useful for predicting failure for firms typically facing greater ex ante failure likelihood.

5.5 | Robustness checks and Untabulated Additional Analyses

We conclude with several robustness tests to assess the sensitivity of our results to some of our design choices. While researchers traditionally focus on first-time GC decisions, we recognize that audit firms are likely interested in all GC evaluations. Thus, we repeat our tests (untabulated) using all GC opinions. Our inferences are unchanged. Our sample includes financially distressed firms, which we broadly define as firms that have negative net income, operating cash flows, retained earnings, or working capital. Research examining GC opinions (e.g., Anantharaman et al. (2016)) sometimes uses a narrower definition to define financially distressed firms, limiting their samples to firms with negative net income or negative operating cash flows. We examine our hypotheses using this narrower definition of financial distressed firms, which reduces our sample to 9,006 observations and find results consistent with those reported in Tables 4 and 5. We further restrict our sample to financially distressed firms with both negative net income and negative operating cash flows, as in Blay et al. (2016) and continue to find similar inferences with 3,847 observations. We also consider whether firms in highly regulated industries are influencing our results, as incentives for both auditors and investors likely vary for these firms. We exclude from our sample firms in the utility and financial service industries. We again find results consistent with our original analyses after excluding these firms.

Our sample period spans from 2010 to 2018, and the focus on "big data" and social media by the audit firms largely occurs in the latter half of our sample period, and the quality of information on social media also likely changed over time. To evaluate potential time period effects, we partition our sample into three time periods, 2010-2012, 2013-2015, and 2016-2018. We find support for H1 in the first and last time period, though results become in significant in the middle. Further analysis suggests this attenuated significance is fully driven by 2013 and 2014.

Finally, we explore whether our results vary for auditor type. The Big 4 are more vocal about commitments to investment in technology, though non-Big 4 clients are smaller and thus more likely to fail. We partition our sample into Big 4 and non-Big 4 subsamples and estimate equations [1] and [2] (untabulated). The coefficients on *BEARISH* are significant in both subsamples ($p<0.10$ or better) when predicting failure. The magnitude on *BEARISH* when predicting failure is larger in magnitude for non-Big 4 firms (0.028 vs. 0.012), but the difference is not significant. The coefficients on *BEARISH* in both subsamples are not significant ($p>0.10$) when predicting GC issuance, similar to the results in Table 5, Panel A.

6 | CONCLUSIONS

In this study, we provide evidence that the opinions shared and disseminated on social media likely provide value relevant information for firms in financial distress. Specifically, the bearishness of posts on the social media platforms Stocktwits and Twitter relate positively to the likelihood of a future default event. Our evidence also suggests that auditors' GC opinions appear to be a largely orthogonal to social media bearishness, though Type I and Type II errors decline with bearishness. We also provide evidence suggesting social media users provide information predictive of difficulties with obtaining financing, a future event that often precipitates failure, and that the predictive ability of bearishness is stronger for non-accelerated filers.

Our study contributes to the growing social media literature by providing initial evidence that the platforms we examine could serve as a relevant source of information for auditors, at least in terms of evaluating a distressed client's ability to continue as a going concern. Relatedly, our evidence speaks to the appropriateness of incorporating external sources of audit evidence derived from new sources of data, a possibility discussed by both regulators and audit firms. Finally, we provide evidence on how specific social media platforms, Stocktwits and Twitter, can be useful for evaluating firms in financial distress. To date, research examining this specific type of information is generally limited to the opinions of insiders posting on Glassdoor.

We conclude by recognizing three important caveats. First, our evidence is consistent with the inferences we draw, but not conclusive evidence. For instance, it could be some unobservable feature that explains both social media bearishness and the outcomes we examine. Even if this is the case, though, we still view our evidence as informative since social media provides a central repository of information that correlates with this unobservable signal. Second, we recognize that our evidence generalizes only to firms with social media coverage. We view social media as an outlet for investors to express their opinions about firms. Such opinions exist for firms not receiving coverage on social media, but we cannot comment on whether this sentiment, if observable, would exhibit patterns similar to those we document in the paper, nor whether our results extend to firms receiving social media coverage for the first time. Finally, our findings speak only to average effects in our sample period, which includes the "non-crisis period" falling between the great recession and covid and predates relevant events like advancements in AI. Unfortunately changes in data availability for both platforms we examine limit our ability to explore more recent time periods. While we cannot verify this, we suspect that the volume and quality of signals aggregated on social media has only increased over time, suggesting our evidence likely provides a lower bound of its potential.

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Appendix
Variable Definitions

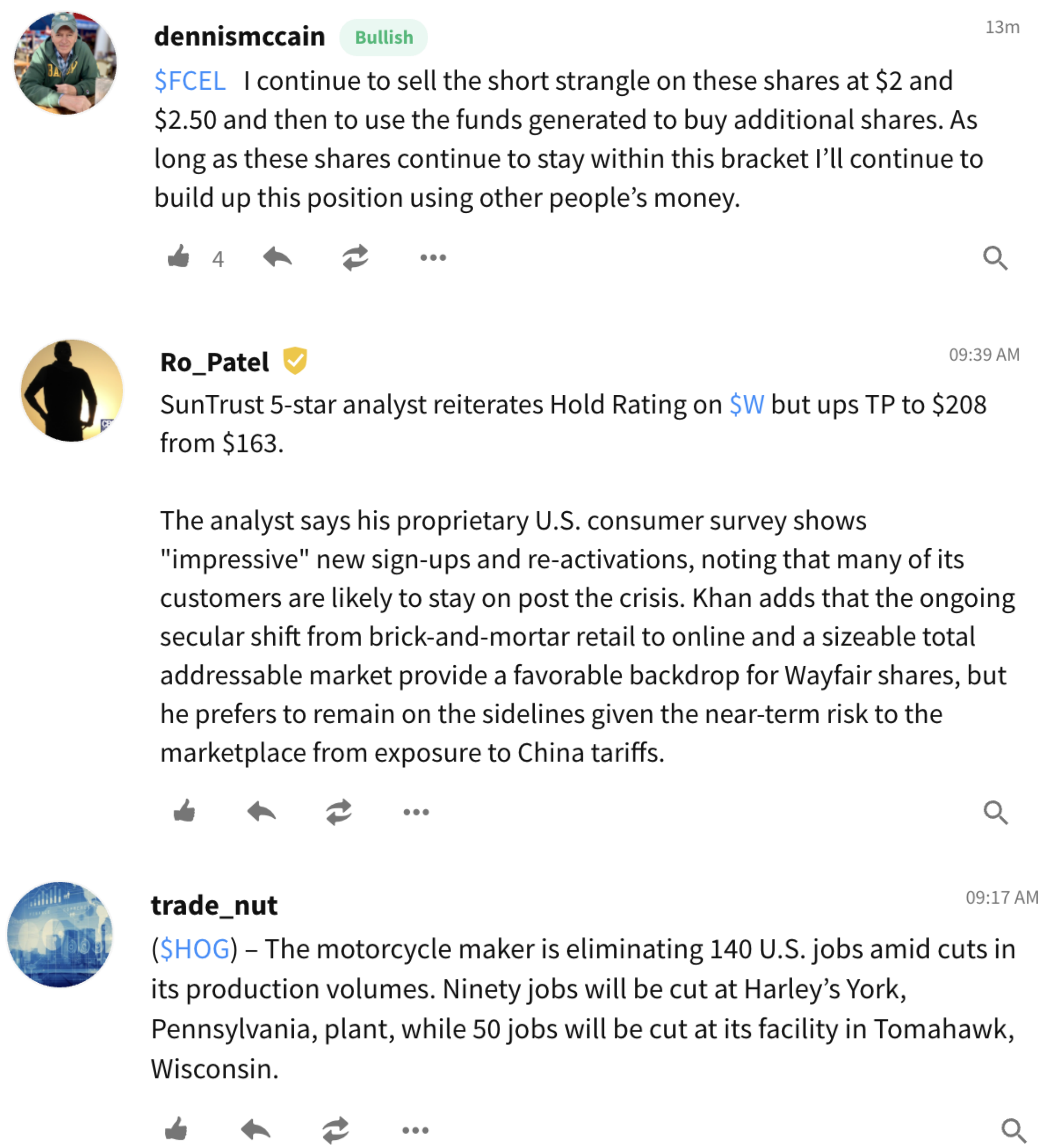
Unless otherwise noted, all referenced variable inputs are measured in fiscal year *t*.

Variable	Definition
AGE	The natural log of the firm's age in years. We use the first date a firm appears in Compustat to estimate age.
ANALYST_FOLLOWING	The natural log of the total number of unique forecasts appearing in the consensus immediately prior to the annual earnings announcement
BETA	The firm's beta estimated using the CRSP value-weighted index (CRSP VWRETD) in a market model, estimated using monthly returns (CRSP RET) over the current fiscal year
BIG4	An indicator variable set equal to one if the auditor is one of the Big 4 accounting firms (Audit Analytics AUDITOR_FKEYS less than five), and zero otherwise
BEARISH	The average level of bearishness of social media posts appearing on Stocktwits and Twitter in the 90 days preceding the audit opinion. Bearishness is obtained from predictions generated by a fine-tuned large language model available at https://huggingface.co/zhayunduo/roberta-base-stocktwits-finetuned.
CH_LEVERAGE	The change in the leverage ratio from year t-1 to t. Leverage is computed as LT/AT (all Compustat mnemonics).
CREDIT_DOWNGRADE	An indicator variable equal to one if there was a decrease in the firm's S&P long-term issuer credit rating (SPLTICRM in Compustat Ratings file) during the 90-day period prior to the audit report date, and zero otherwise. Includes years 2010-2016.
FAILURE	An indicator variable equal to one if the firm either filed for bankruptcy or was delisted (CRSP delisting codes 400-599) from its stock exchange within one year of the audit opinion date, and zero otherwise. We obtain data on bankruptcies from Audit Analytics Bankruptcy Notification File.
FEE_RATIO	The ratio of non-audit fees to total fees paid to the firm's auditor (Audit Analytics NON_AUDIT_FEES/TOTAL_FEES).
FIRST_GCO	An indicator variable equal to one if the firm received a going-concern opinion in the current year and did not receive a going-concern opinion in the previous year, and zero otherwise. We obtain audit opinion data from the Audit Analytics Audit Opinions file (GOING_CONCERN).
FINANCE	The firm's need for external financing, measured as an indicator variable equal to one if the firm obtained either debt or equity financing in year t+1, and zero otherwise (Compustat DLTIS and SSTK).
FUT_CREDIT_DOWNGRADE	An indicator variable equal to one if there a decrease in the firm's S&P long-term issuer credit rating during the 365-day period after the audit report date, and zero otherwise (SPLTICRM in Compustat Ratings file). Includes years 2010-2016.
FUT_EQUITY	An indicator variable equal to one if the firm obtained equity financing in year t+1, and zero otherwise (Compustat SSTK).
INVEST	Total investments, including short-term and long-term investments and cash and cash equivalents, scaled by total assets (Compustat [CHE+IVAEQ+IVAO]/AT).
LEVERAGE	The ratio of total liabilities to total assets (Compustat LT/AT)
LOSS	An indicator variable set equal to one if net income is negative, and zero otherwise (Compustat IB).
NET_DOWNGRADES	Total analyst downgrade recommendations less total analyst upgrade recommendations, scaled by analyst following, during the 90-day period prior to the audit report date (IBES IRECCD).
NUM_TWEETS	The natural log of the number of ST and Twitter posts where a firm is tagged during the 90-day period prior to the audit report date.
OPCF	Cash flows from operations scaled by total assets (Compustat OANCF/AT)
PD12MONTH	The likelihood a firm will be unable to meet its financial obligations in the next 12 months (pd12month in the CRI data). We use the pd12month estimate available

	closest but prior to the opinion date. This data is available from the Credit Research Initiative (CRI) at the National University of Singapore.
PRESS_SENTIMENT	The average event sentiment score (ESS) from business press articles published in the 90 days prior to the audit opinion date appearing in the Dow-Jones edition of Ravenpack. We restrict articles to those with relevance scores of 100, ensuring the focal company is the subject of the article. *PRESS_SENTIMENT* is set to 0 for firms with no press coverage.
REPORT_LAG	The natural log of one plus the number of days from the firm's fiscal year end and the audit opinion date (Audit Analytics SIG_DATE_OF_OP).
RET	The buy-and-hold 12-month return during the current year, computed using monthly CRSP returns (RET)
SHORT_INTEREST	The percentage of a firm's outstanding shares of stock sold short and remain outstanding during the 90-day period prior to the audit report date (CRSP SHROUT and Compustat SHORTINT).
SIZE	The natural log of total assets (Compustat AT)
TENURE	The natural log of one plus the number of years the firm has been audited by its current auditor (Audit Analytics AUDITOR_FKEY).
VOLATILITY	The standard deviation of residuals from the market model over the current year. We obtain residuals from models used to estimate *BETA*.

FIGURE 1

Panel A: Examples of Stocktwits Posts



Panel B: Examples of Twitter Posts

TheMarketAnalysts.com📈
@StockReversals

$DATA 3rd time in its uptrend life its done the same thing.. .always a buy.

4:26 PM · Jul 30, 2015

Made in Menlo
@MadeinMenlo

The Regulators
@SEC_News 🤑
Looking Reckless
Irresponsible + Pathetic.
#BILLIONS Lost by 📉
Consumers after Rosy
$SNAP #IPO #SEC Oversaw.

Bill Gurley and 4 others

9:51 PM · May 10, 2017

FIGURE 2

Industry Composition for Financially-Distressed Firms with and without Social Media Coverage

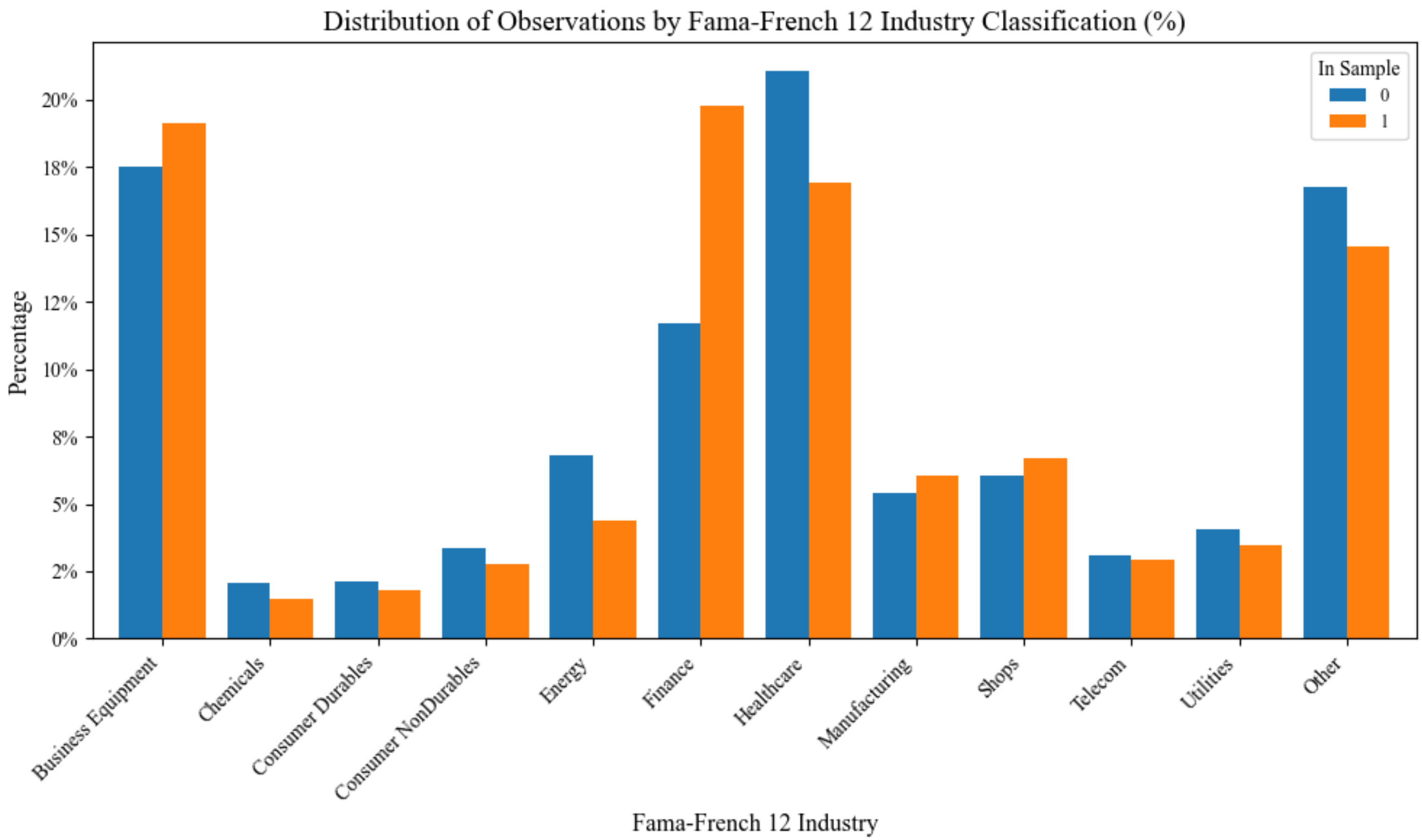


TABLE 1
Sample Selection

Sample Selection	**N**
Financially distressed observations with available data from Compustat, CRSP, and Audit Analytics between 2010 and 2018	35,036
Less: observations where the firm was not cashtagged in at least one social media post during the 90-day period prior to the audit opinion date	(12,660)
Less: observations where the auditor issued a going-concern opinion in both the current year and prior year	(2,513)
Less: observations missing control variable data	(4,679)
Sample	**15,184**

Table 1 presents sample selection procedures and reasons for attrition.

TABLE 2
Descriptive Statistics

VARIABLES	N	Mean	St. Dev.	Q1	Median	Q3
FAILURE	15,184	0.008	0.087	0.000	0.000	0.000
BEARISH	15,184	0.231	0.180	0.102	0.204	0.320
FIRST_GCO	15,184	0.021	0.142	0.000	0.000	0.000
PD12MONTH	15,184	0.008	0.019	0.000	0.001	0.005
SIZE	15,184	6.524	2.138	4.917	6.457	8.032
AGE	15,184	2.791	0.717	2.197	2.833	3.258
LOSS	15,184	0.519	0.500	0.000	1.000	1.000
LEVERAGE	15,184	0.564	0.332	0.342	0.552	0.745
CH_LEVERAGE	15,184	0.014	0.205	-0.027	0.006	0.052
OPCF	15,184	-0.020	0.276	-0.030	0.042	0.090
FINANCE	15,184	0.911	0.285	1.000	1.000	1.000
INVEST	15,184	0.350	0.326	0.074	0.220	0.599
BIG4	15,184	0.716	0.451	0.000	1.000	1.000
NUM_TWEETS	15,184	5.106	1.523	4.277	5.242	6.111
TENURE	15,184	2.048	0.638	1.609	2.079	2.565
REPORT_LAG	15,184	4.180	0.232	4.043	4.143	4.317
FEE_RATIO	15,184	0.138	0.138	0.022	0.099	0.217
RET	15,184	0.405	0.208	0.283	0.380	0.477
BETA	15,184	1.067	0.597	0.656	1.030	1.441
VOLATILITY	15,184	0.028	0.017	0.016	0.025	0.036
SHORT_INTEREST	15,184	0.046	0.054	0.010	0.027	0.062
NET_DOWNGRADES	15,184	-0.038	0.235	0.000	0.000	0.000
CREDIT_DOWNGRADE	11,564	0.011	0.105	0.000	0.000	0.000
PRESS_SENTIMENT	15,184	0.017	0.115	0.000	0.000	0.031
ANALYST_FOLLOWING	15,184	1.184	0.970	0.000	1.099	1.946
FUT_CREDIT_DOWNGRADE	9,626	0.039	0.193	0.000	0.000	0.000
FUT_EQUITY	15,184	0.754	0.431	1.000	1.000	1.000

Table 2 presents descriptive statistics. See the Appendix for variable definitions.

TABLE 3
Pearson Correlations

	VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
(1)	*FAILURE*													
(2)	*BEARISH*	0.02												
(3)	*FIRST_GCO*	0.15	-0.02											
(4)	*PD12MONTH*	0.19	0.07	0.21										
(5)	*SIZE*	-0.07	0.24	-0.17	*-0.01*									
(6)	*AGE*	*-0.01*	0.03	-0.06	-0.09	0.26								
(7)	*LOSS*	0.06	-0.05	0.13	0.13	-0.39	-0.17							
(8)	*LEVERAGE*	0.05	0.08	0.07	0.19	0.30	0.11	-0.12						
(9)	*CH_LEVERAGE*	0.06	0.02	0.12	0.11	-0.03	-0.03	0.12	0.27					
(10)	*OPCF*	-0.04	0.05	-0.28	-0.05	0.38	0.17	-0.32	-0.04	-0.20				
(11)	*FINANCE*	-0.05	0.04	*-0.01*	-0.06	0.13	-0.05	-0.07	0.04	*0.01*	-0.02			
(12)	*INVEST*	-0.02	-0.03	*0.02*	-0.12	-0.20	-0.24	0.11	-0.25	-0.03	-0.31	*0.00*		
(13)	*BIG4*	-0.06	0.16	-0.07	-0.02	0.46	*0.01*	-0.12	0.10	*0.01*	0.11	0.14	0.03	
(14)	*NUM_TWEETS*	-0.04	0.26	*0.00*	*0.00*	0.29	0.05	*0.00*	0.06	0.02	-0.06	0.16	0.04	0.26
(15)	*TENURE*	-0.04	0.09	-0.05	-0.06	0.31	0.42	-0.13	0.11	*-0.01*	0.11	0.06	-0.05	0.40
(16)	*REPORT_LAG*	0.08	-0.19	0.15	0.13	-0.52	-0.16	0.25	-0.10	0.03	-0.17	-0.17	-0.02	-0.34
(17)	*FEE_RATIO*	-0.02	*0.01*	-0.04	-0.02	0.16	0.04	-0.11	0.05	*-0.01*	0.05	0.05	0.02	0.11
(18)	*RET*	-0.04	-0.03	-0.12	-0.18	0.02	0.03	-0.16	*0.00*	-0.13	0.11	0.08	0.05	0.03
(19)	*BETA*	-0.03	0.10	-0.03	0.07	0.13	-0.07	0.12	*0.02*	*0.01*	-0.04	0.12	*0.01*	0.25
(20)	*VOLATILITY*	0.12	-0.09	0.22	0.26	-0.57	-0.22	0.43	-0.10	*0.01*	-0.35	-0.11	0.05	-0.29
(21)	*SHORT_INTEREST*	*0.01*	0.17	*0.00*	0.10	0.08	-0.04	0.13	0.05	0.05	-0.09	0.10	0.07	0.17
(22)	*NET_DOWNGRADES*	*0.01*	0.09	0.02	0.05	0.07	0.06	-0.03	0.05	0.02	0.05	-0.03	-0.05	0.02
(23)	*CREDIT_DOWNGRADE*	0.04	0.04	*0.01*	0.15	0.10	0.04	0.05	0.08	0.04	0.03	*0.00*	-0.06	0.05
(24)	*PRESS_SENTIMENT*	-0.03	-0.09	-0.05	-0.06	0.11	0.03	-0.22	0.05	-0.03	0.08	0.02	-0.03	*0.00*
(25)	*ANALYST_FOLLOWING*	-0.07	0.24	-0.11	-0.07	0.57	0.04	-0.19	0.11	*0.00*	0.18	0.19	-0.05	0.41
(26)	*FUT_CREDIT_DOWNGRADE*	0.04	0.09	*-0.01*	0.13	0.19	0.08	0.04	0.11	0.03	0.06	*0.02*	-0.12	0.09
(27)	*FUT_EQUITY*	-0.03	*-0.01*	0.02	-0.10	-0.08	-0.09	*0.01*	-0.08	*0.01*	-0.10	0.55	0.11	0.07

TABLE 3
Pearson Correlations (continued)

	VARIABLES	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)	(22)	(23)	(24)	(25)	(26)
(14)	*NUM_TWEETS*													
(15)	*TENURE*	0.18												
(16)	*REPORT_LAG*	-0.29	-0.26											
(17)	*FEE_RATIO*	0.02	0.08	-0.08										
(18)	*RET*	0.08	0.02	-0.07	*0.01*									
(19)	*BETA*	0.29	0.09	-0.18	-0.04	0.08								
(20)	*VOLATILITY*	-0.03	-0.23	0.41	-0.11	*-0.02*	0.09							
(21)	*SHORT_INTEREST*	0.33	0.07	-0.19	-0.03	*-0.01*	0.39	0.09						
(22)	*NET_DOWNGRADES*	*0.00*	0.05	*-0.02*	*0.01*	-0.07	*-0.01*	-0.06	*0.02*					
(23)	*CREDIT_DOWNGRADE*	0.05	0.03	-0.03	*0.00*	-0.06	0.06	*0.01*	0.09	0.03				
(24)	*PRESS_SENTIMENT*	-0.02	*0.01*	-0.07	0.05	0.08	-0.03	-0.12	-0.05	-0.16	-0.03			
(25)	*ANALYST_FOLLOWING*	0.41	0.23	-0.45	0.11	0.07	0.25	-0.35	0.27	*0.01*	0.06	0.07		
(26)	*FUT_CREDIT_DOWNGRADE*	0.09	0.07	-0.09	*0.00*	-0.08	0.10	-0.04	0.11	0.04	0.17	-0.03	0.11	
(27)	*FUT_EQUITY*	0.11	*0.01*	-0.08	0.02	0.11	0.10	*0.00*	0.11	-0.05	-0.05	*0.00*	0.13	-0.05

Notes: Variable definitions are provided in the Appendix. All correlations are significant at 5% levels except those in italics.

TABLE 4
The Association between Social Media Bearishness and Firm Failure (H1)

Panel A: All Social Media Posts

DV = *FAILURE* **VARIABLES**	**(1)**	**(2)**	**(3)**
BEARISH	**0.016*****	**0.017*****	**0.020*****
	(0.006)	**(0.006)**	**(0.008)**
PD12MONTH	0.809***	0.745***	0.943***
	(0.125)	(0.125)	(0.157)
SIZE	-0.003***	-0.001	-0.000
	(0.001)	(0.001)	(0.001)
AGE	0.003**	0.003**	0.003*
	(0.001)	(0.001)	(0.001)
LOSS	0.003**	0.002	0.002
	(0.002)	(0.002)	(0.002)
LEVERAGE	0.009**	0.008**	0.008*
	(0.004)	(0.004)	(0.004)
CH_LEVERAGE	0.013*	0.015**	0.015*
	(0.007)	(0.007)	(0.009)
OPCF	0.000	0.002	0.004
	(0.005)	(0.005)	(0.006)
FINANCE	-0.008*	-0.006	-0.008
	(0.004)	(0.004)	(0.005)
INVEST	0.004	0.006**	0.008**
	(0.003)	(0.003)	(0.003)
BIG4	-0.006***	-0.003	-0.004
	(0.002)	(0.002)	(0.002)
NUM_TWEETS	-0.000	-0.001	-0.002
	(0.001)	(0.001)	(0.001)
RET		0.002	0.003
		(0.005)	(0.006)
BETA		-0.006***	-0.007***
		(0.002)	(0.002)
VOLATILITY		0.387***	0.397***
		(0.105)	(0.132)
SHORT_INTEREST		0.013	0.023
		(0.019)	(0.022)
NET_DOWNGRADES			-0.001
			(0.003)
CREDIT_DOWNGRADE			0.013
			(0.016)
PRESS_SENTIMENT			-0.001
			(0.006)
ANALYST_FOLLOWING			-0.002
			(0.001)
Industry-Year FE	Included	Included	Included
Observations	15,184	15,184	11,564
Adjusted R^2	0.049	0.053	0.069

Panel B: Stocktwits Posts Only

DV = *FAILURE* VARIABLES	(1)	(2)	(3)
BEARISH	**0.010**	**0.010***	**0.013***
	(0.006)	**(0.006)**	**(0.007)**
Observations	14,376	14,376	10,898
Controls	Panel A Column 1	Panel A Column 2	Panel A Column 3
Adjusted R^2	0.047	0.051	0.067

Panel C: Twitter Posts Only

DV = *FAILURE* VARIABLES	(1)	(2)	(3)
BEARISH	**0.014****	**0.014****	**0.015****
	(0.005)	**(0.005)**	**(0.007)**
Observations	14,125	14,125	10,568
Controls	Panel A Column 1	Panel A Column 2	Panel A Column 3
Adjusted R^2	0.042	0.044	0.057

Table 4 presents the estimation results for model [1]. Panel A reports results for all social media platforms. Panel B (C) reports results using only Stocktwits (Twitter). For brevity, we suppress control coefficient estimates in Panels B and C. Variable definitions are provided in the Appendix. Reported standard errors (in parentheses) are clustered by firm. *, **, and *** indicate two-tailed statistical significance at the 10%, 5%, and 1% levels, respectively.

TABLE 5
Social Media Bearishness & Going-Concern Opinions
Panel A: Test of H2a

DV = *FIRST_GCO* **VARIABLES**	**(1)**	**(2)**	**(3)**	**(4)**
BEARISH		**0.003**	**0.006**	**0.004**
		(0.006)	**(0.006)**	**(0.007)**
PD12MONTH	1.305***	1.304***	1.145***	1.336***
	(0.148)	(0.148)	(0.147)	(0.178)
SIZE	-0.006***	-0.006***	-0.003***	-0.003***
	(0.001)	(0.001)	(0.001)	(0.001)
AGE	0.002	0.002	0.002	0.003
	(0.002)	(0.002)	(0.002)	(0.002)
LOSS	-0.002	-0.002	-0.006***	-0.005*
	(0.002)	(0.002)	(0.002)	(0.002)
LEVERAGE	0.019***	0.019***	0.020***	0.021***
	(0.007)	(0.007)	(0.007)	(0.008)
CH_LEVERAGE	0.030*	0.030*	0.030*	0.018
	(0.016)	(0.016)	(0.016)	(0.018)
OPCF	-0.115***	-0.115***	-0.107***	-0.098***
	(0.018)	(0.018)	(0.018)	(0.020)
FINANCE	0.007	0.007	0.012***	0.013**
	(0.005)	(0.005)	(0.005)	(0.005)
INVEST	-0.019***	-0.019***	-0.013***	-0.012**
	(0.005)	(0.005)	(0.005)	(0.005)
BIG4	0.002	0.002	0.006*	0.006
	(0.004)	(0.004)	(0.004)	(0.004)
NUM_TWEETS	0.002	0.002	0.003**	0.001
	(0.001)	(0.001)	(0.001)	(0.001)
TENURE	0.002	0.002	0.002	0.003
	(0.002)	(0.002)	(0.002)	(0.003)
REPORT_LAG	0.038***	0.038***	0.024***	0.029***
	(0.008)	(0.008)	(0.008)	(0.009)
FEE_RATIO	-0.006	-0.006	-0.013	-0.012
	(0.008)	(0.008)	(0.008)	(0.009)
RET			-0.047***	-0.044***
			(0.007)	(0.008)
BETA			-0.015***	-0.016***
			(0.003)	(0.003)
VOLATILITY			0.768***	0.870***
			(0.164)	(0.193)
SHORT_INTEREST			-0.059**	-0.023
			(0.026)	(0.030)
NET_DOWNGRADES				0.012**
				(0.005)
CREDIT_DOWNGRADE				-0.024*
				(0.013)
PRESS_SENTIMENT				0.004
				(0.011)
ANALYST_FOLLOWING				0.002
				(0.002)
Industry-Year FE	Included	Included	Included	Included
Observations	15,184	15,184	15,184	11,564
Adjusted R^2	0.128	0.128	0.138	0.144

Panel B: Test of H2b

DV = *FAILURE* **VARIABLES**	**(1)**	**(2)**	**(3)**
BEARISH	**0.017*****		**0.016*****
	(0.006)		**(0.006)**
FIRST_GCO		**0.065*****	**0.065*****
		(0.017)	**(0.017)**
PD12MONTH	0.741***	0.673***	0.666***
	(0.125)	(0.122)	(0.122)
SIZE	-0.001	-0.000	-0.001
	(0.001)	(0.001)	(0.001)
AGE	0.003**	0.003**	0.003**
	(0.001)	(0.001)	(0.001)
LOSS	0.001	0.002	0.002
	(0.002)	(0.002)	(0.002)
LEVERAGE	0.008**	0.007**	0.007**
	(0.004)	(0.003)	(0.003)
CH_LEVERAGE	0.015**	0.013**	0.013**
	(0.007)	(0.007)	(0.007)
OPCF	0.002	0.009*	0.009*
	(0.005)	(0.005)	(0.005)
FINANCE	-0.006	-0.007*	-0.007*
	(0.004)	(0.004)	(0.004)
INVEST	0.006**	0.007**	0.007**
	(0.003)	(0.003)	(0.003)
BIG4	-0.003	-0.003	-0.003
	(0.002)	(0.002)	(0.002)
NUM_TWEETS	-0.001	-0.001	-0.001
	(0.001)	(0.001)	(0.001)
TENURE	-0.000	-0.000	-0.000
	(0.001)	(0.001)	(0.001)
REPORT_LAG	0.004	0.002	0.002
	(0.003)	(0.003)	(0.003)
FEE_RATIO	-0.003	-0.002	-0.002
	(0.005)	(0.005)	(0.005)
RET	0.002	0.005	0.005
	(0.005)	(0.005)	(0.005)
BETA	-0.006***	-0.005***	-0.005***
	(0.002)	(0.002)	(0.002)
VOLATILITY	0.378***	0.325***	0.328***
	(0.107)	(0.103)	(0.103)
SHORT_INTEREST	0.014	0.022	0.018
	(0.019)	(0.018)	(0.019)
Industry-Year FE	Included	Included	Included
Observations	15,184	15,184	15,184
Adjusted R^2	0.0525	0.0612	0.0621

Table 5 presents the estimation results for model [2] (Panel A) and then a test of H2b, where we add *FIRST_GCO* to equation [1] (Panel B). Variable definitions are provided in the Appendix. Reported standard errors (in parentheses) are clustered by firm. *, **, and *** indicate two-tailed statistical significance at the 10%, 5%, and 1% levels, respectively.

TABLE 6
Type I and Type II Error Rates

Panel A: Type I Error Rates by Social Media Bearishness Tercile

Tercile	*BEARISH*	*BEARISH_R*
1	91.43%	91.43%
2	98.08%	95.19%
3	80.77%	83.65%
High - Low	-10.66%	-7.77%
t-statistic	-2.245	-1.707
p-value	0.026	0.089

Panel B: Type II Error Rates by Social Media Bearishness Tercile

Tercile	*BEARISH*	*BEARISH_R*
1	87.18%	79.49%
2	74.36%	82.05%
3	58.97%	58.97%
High - Low	-28.21%	-20.51%
t-statistic	-2.923	-1.987
p-value	0.005	0.051

Table 6 presents type I and type II GC error rates by tercile of *BEARISH,* and *BEARISH_R.* We define *BEARISH_R* for use in this test by regressing *BEARISH* on the control variables used in Table 4, column 2. *BEARISH_R* is the residual of this regression model. Panel A table presents Type I (percentage of *FIRST_GCO=1* observations where *FAILURE=0*) rates by tercile, and Panel B presents Type II (percentage of *FAILURE=1* observations where *FIRST_GCO = 0*) by tercile. The top row of each panel denotes the variable for which terciles were formed. Further, terciles for Panel A (B) were formed within the subset of firms where *FIRST_GCO=1* (*FAILURE=1*).

TABLE 7
The Association Between Bearishness and Intermediaries

Panel A: Credit Downgrades in Year t+1

DV = *FUT_CREDIT_DOWNGRADE* **VARIABLES**	(1)	(2)
BEARISH	**0.021***	**0.022***
	(0.012)	**(0.012)**
FIRST_GCO		-0.024**
		(0.010)
CREDIT_DOWNGRADE	0.196***	0.196***
	(0.042)	(0.042)
PD12MONTH	0.656***	0.687***
	(0.183)	(0.185)
Controls	Table 4 Column 2	Table 4 Column 2
Industry-Year FE	Included	Included
Observations	9,626	9,626
Adjusted R^2	0.101	0.101

Panel B: Equity Financing in Year t+1

DV = *FUT_EQUITY* **VARIABLES**	(1)	(2)
BEARISH	-0.048**	-0.048**
	(0.021)	(0.021)
FIRST_GCO		0.097***
		(0.029)
EQUITY	0.488***	0.488***
	(0.013)	(0.013)
PD12MONTH	-0.528**	-0.660***
	(0.250)	(0.254)
Controls	Table 4 Column 2	Table 4 Column 2
Industry-Year FE	Included	Included
Observations	11,564	11,564
Adjusted R^2	0.327	0.328

Table 7 presents the estimation results for model [1], replacing the dependent variable with *FUT_CREDIT_DOWNGRADE* (Panel A) or *FUT_EQUITY* (Panel B). Column 1 (2) excludes (includes) *FIRST_GCO* in the regression model to examine whether the *BEARISH* coefficient value changes when controlling for whether the firm received a going-concern opinion. Variable definitions are provided in the Appendix. Reported standard errors (in parentheses) are clustered by firm. *, **, and *** indicate two-tailed statistical significance at the 10%, 5%, and 1% levels, respectively.

TABLE 8
Cross sectional tests

Panel A: Association Between Social Media Sentiment and Firm Failure by Filing Status

DV = *FAILURE*	(1)	(2)	(3)
VARIABLES	**Large Accelerated Filers**	**Non-large Accelerated Filers**	**Non-accelerated Filers**
BEARISH	**0.001**	**0.005**	**0.042****
	(0.004)	**(0.007)**	**(0.017)**
PD12MONTH	0.327**	0.443**	1.443***
	(0.134)	(0.184)	(0.279)
Observations	6,920	3,615	4,649
Controls	Table 4 Column 2	Table 4 Column 2	Table 4 Column 2
Year & Industry FE	Included	Included	Included
Adjusted R^2	0.0430	0.0187	0.0766

Panel B: Association Between Social Media Sentiment and Firm Failure by Company Age

DV = *FAILURE*	(1)	(2)
VARIABLES	**Above Median**	**Below Median**
BEARISH	**0.013***	**0.020****
	(0.008)	**(0.009)**
PD12MONTH	0.695***	0.772***
	(0.203)	(0.160)
Observations	7,480	7,704
Controls	Table 4 Column 2	Table 4 Column 2
Year & Industry FE	Included	Included
Adjusted R^2	0.0450	0.0621

Table 8 presents the estimation results for model [1] within two sets of cross-sections. Panel A reports results after partitioning into Large Accelerated Filers (column 1), Accelerated Filers (column 2), and Non-accelerated Filers (column 3). Filing status is obtained from Audit Analytics. Panel B reports results for firms above (column 1) and below (column 2) the median age of observations. Variable definitions are provided in the Appendix. Reported standard errors (in parentheses) are clustered by firm. *, **, and *** indicate two-tailed statistical significance at the 10%, 5%, and 1% levels, respectively.