Bank Social Media Disclosure During a Banking Crisis

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Bank Social Media Disclosure During a Banking Crisis

Abstract

We investigate banks' social media disclosure during the 2023 U.S. banking crisis. We leverage large language models to identify depositor-relevant content from a comprehensive sample of bank tweets. Using a difference-in-differences design, we find that during the crisis, banks with higher pre-crisis uninsured deposit ratios issue more tweets conveying financial information about their fundamental performance. Cross-sectional analyses show that this effect is stronger in healthier banks, as measured by smaller mark-to-market losses. Moreover, we find that among banks with higher pre-crisis uninsured deposit ratios, those that issue these tweets during the crisis experience higher uninsured deposit growth in the subsequent year than those that remain silent. This deposit-stabilizing effect is concentrated among banks with smaller mark-to-market losses, when bank tweets receive greater engagement from Twitter users, and when bank tweets reference the most recent publicly available financial results before the crisis. Overall, our findings highlight banks' strategic disclosure on social media to mitigate panic contagion among uninsured depositors during a banking crisis in the digital era.

Keywords: social media disclosure, banking crisis, uninsured deposit, panic contagion
JEL Classification: D83, G01, G14, M41

1. Introduction

Banks play a central role in credit intermediation, yet they remain vulnerable to panic-based runs, in which mass deposit withdrawals can force even solvent institutions into distress (Diamond and Dybvig 1983). The 2023 U.S. regional banking crisis provides a striking example. The failure of Silicon Valley Bank (hereafter SVB) marked the second-largest failure of a bank insured by the Federal Deposit Insurance Corporation (FDIC) in U.S. history. More importantly, this episode exemplified a *digital* bank run, in which social media allowed depositors to rapidly spread concerns and digital banking enabled instant deposit withdrawals (Board of Governors of the Federal Reserve System 2023). These forces fundamentally reshaped the dynamics of panic contagion and accelerated the speed of bank runs.[1] Unprecedentedly, SVB received approximately $42 billion in deposit withdrawal requests within eight hours and collapsed within 36 hours (Board of Governors of the Federal Reserve System 2023; Kang et al. 2025). Recent evidence confirms the central role of social media in this banking crisis (Henninger 2023; Cookson et al. 2026). In the 48 hours preceding SVB's failure, discussions of bank run on Twitter surged significantly.[2] Moreover, panic-fuelled tweets quickly spread to other banks, generating contagion throughout the banking system.

Despite the importance of social media in digital bank runs, there is limited empirical evidence on whether and how banks disclose on social media to affect depositor actions. This paper addresses the gap in the literature by examining three questions in the context of the 2023 U.S. regional banking crisis. First, we provide descriptive evidence on what banks tweet to their depositors during the crisis. Second, we investigate how banks' reliance on uninsured deposits before the crisis influences their tweeting activities during the crisis. We focus on

[1] In contrast, information about bank runs during the 2008 financial crisis was disseminated largely through traditional media, and deposit withdrawals unfolded over days or weeks at physical branches. Specifically, the failure of Wachovia in 2008 involved about $10 billion in deposit outflows over eight days, while the failure of Washington Mutual involved about $19 billion over 16 days (Board of Governors of the Federal Reserve System 2023).

[2] Twitter was rebranded to X in July 2023, after the outbreak of the 2023 regional banking crisis.

depositors with uninsured deposits (i.e., uninsured depositors) because they face greater potential losses in the event of a run and are most responsive to information about bank fundamentals (Iyer and Puri 2012; Iyer et al. 2016; Chen et al. 2022; Cookson et al. 2026).[3] Third, we assess the effects of bank tweets on subsequent deposit flows.

Public information plays a critical role in aligning depositors' beliefs and coordinating their actions in bank runs (Diamond and Dybvig 1983; Morris and Shin 2002). Nevertheless, it is ex ante unclear whether banks issue tweets during a crisis to mitigate depositor panic and whether doing so relates to subsequent deposit flows. On the one hand, banks with strong fundamentals can immediately signal their soundness by issuing tweets that highlight financial performance. Amid panic-fuelled Twitter discussions, banks' tweets about their solvency may crowd out depositors' private information acquisition, reduce uncertainty, and help contain the spread of panic (He and Manela 2016). Such voluntary disclosures of financial condition are likely credible because they can be verified using publicly available bank financial data, such as Consolidated Reports of Condition and Income (Call Reports) that are mandated for all FDIC-insured banks and validated by banking regulators (Badertscher et al. 2018). Yet while Call Reports serve as a verification benchmark, their dense numerical schedules can be difficult for depositors to process, particularly during periods of heightened uncertainty.[4] Twitter, by contrast, allows banks to highlight their financial condition as an easily digestible signal that reaches the public instantly. As a result, bank tweets that convey financial information about their performance can help stabilize deposit flows.[5]

[3] Following prior research (e.g., Chen et al. 2022), we use the term "uninsured depositors" to refer to depositors whose deposit balances exceed the $250,000 deposit insurance limit set by the FDIC.
[4] Section 2.2 discusses the feasibility and challenges of inferring banks' mark-to-market losses from Call Reports; such losses were a central concern during the 2023 regional banking crisis.
[5] Bank tweets can directly affect depositors who are active on social media but may also reach others through several indirect channels. For example, a group of depositors who observe and react to bank tweets may trigger broader depositor responses through word-of-mouth and coordination behavior. Similarly, traditional media can relay the bank's message to depositors who are not on Twitter. For publicly traded banks, stock price movements triggered by trader reactions to bank tweets may further affect depositors' withdrawal decisions.

On the other hand, tweeting can backfire in a crisis. Information transmission on social media is interactive, and banks do not have control over user-initiated responses (Lee et al. 2015; Jung et al. 2018; Blankespoor et al. 2024). Tweets may attract greater online scrutiny and draw unwanted attention to the issuing banks, resulting in even more panic-driven discussions. Furthermore, bank-specific financial information can increase the sensitivity of uninsured deposit flows to bank fundamental performance (Chen et al. 2022), leading to a coordination problem among depositors (Morris and Shin 2002; Goldstein and Sapra 2014). Ultimately, whether banks with greater reliance on uninsured deposits post more tweets during the crisis, and how depositors respond to such tweets, are empirical questions.

We collect a comprehensive dataset on bank tweets for both the crisis and non-crisis periods. The crisis started on March 8, 2023, when SVB announced a concerning portfolio loss. SVB was acquired by First Citizens Bank on March 27, but the banking turmoil continued into April. Most notably, First Republic Bank experienced a nearly 50% decline in stock price on April 25 and was taken over by the FDIC on May 1, 2023, after which the banking crisis was considered to have subsided. Therefore, we define the approximately two-month period from March 8 to April 30, 2023, as the crisis period. We gather the universe of bank tweets posted during the crisis, twelve months prior to the crisis (i.e., the pre-crisis period), and twelve months after (i.e., the post-crisis period). Our final sample consists of 889 banks that tweeted at least once during the pre-crisis period.

To examine what banks convey to depositors on Twitter, we develop a framework to identify depositor-relevant tweets. Specifically, we use a large language model (OpenAI's GPT-4.1) to classify tweet content into five categories: (1) financial information about bank fundamental performance (e.g., earnings results, liquidity, or deposit metrics); (2) non-financial information about bank fundamental performance (e.g., "best bank" awards or service quality); (3) banking industry conditions (e.g., discussions of banking sector stability); (4) banks' routine operating activities (e.g., branch hours); and (5) a residual "other" category.

We first provide descriptive evidence that banks adjust their tweeting activities during the banking crisis. Tweets about bank financial performance primarily serve to disseminate information from publicly disclosed financial reports and therefore cluster in earnings-release months. However, we observe a sharp spike in March 2023, which is outside banks' quarterly reporting cycle but coincides with the onset of the crisis. During the crisis, banks posted 140 such tweets, often highlighting their capital positions, financial soundness, and differences from SVB's business model. We further find that these tweets rarely convey new information beyond what is already available through regulatory filings; rather, they largely reference already public financial information (e.g., tweets posted in March 2023 typically discuss year-end 2022 financial results).[6] Banks also increase their tweets on non-financial performance metrics, issuing 422 posts during the crisis, which primarily focus on service quality and awards. Tweets discussing banking industry conditions surge from near-zero baseline levels to 237 posts during the crisis, many emphasizing systemic stability. In contrast, the majority of bank tweets relate to routine operating activities, for which we do not observe significant changes during the crisis.

Next, we examine the relation between banks' reliance on uninsured deposits before the crisis and their tweeting activities during the crisis. We implement a difference-in-differences (DiD) design to estimate the effect of uninsured deposit ratios as of 2022-year-end on tweet issuance during the crisis period, using the pre-crisis period as the benchmark. We

[6] The only exception is Signature Bank of Georgia. On March 13, 2023, the bank published a press release and tweeted a link to this press at virtually the same time (10:39 a.m. EST), reporting key financial metrics, including its leverage ratio and liquidity ratio, as of February 28, 2023, well ahead of the bank's next scheduled quarterly filing. The tweet is available at https://x.com/signaturebankga/status/1635289445699297283 (accessed March 26, 2026). The press release originally linked in the tweet (https://www.signaturebankga.com/signature-bank-of-georgia-is-strong-and-well-capitalized/) has since expired; an archived version is available via EIN Presswire at https://www.einpresswire.com/article/621885312/signature-bank-of-georgia-is-strong-and-well-capitalized (accessed March 26, 2026).

include bank and time fixed effects to absorb time-invariant bank characteristics and common time-series shocks. We further control for a host of time-varying bank characteristics, including size, profitability, non-performing loans, loan growth, equity capital, loan portfolio composition, funding sources, and deposit rates. To mitigate concerns that tweeting may be part of banks' regular disclosure activities during earnings seasons, we further control for the interaction term between the pre-crisis uninsured deposit ratio and an indicator for earnings announcement periods.

In our baseline analysis, we find that during the crisis, banks with greater reliance on uninsured deposits issue more tweets conveying financial information about their fundamental performance, with an increase equivalent to 101% of the sample mean. These banks also issue more tweets about banking industry conditions, but do not increase tweets on other categories. Our evidence suggests that banks concerned about panic contagion among depositors actively manage their tweeting activities during the crisis.

In cross-sectional analyses, we test how bank health affects their disclosure behaviour. We posit that healthier banks have stronger incentives to use Twitter to signal their soundness and alleviate uninsured depositors' panic. Following Jiang et al. (2024), we measure bank health using mark-to-market losses on bank assets induced by interest rate hikes in 2022, which represented the primary bank fundamental concern during the crisis. We find that the positive relation between pre-crisis uninsured deposit ratios and tweet issuance is more pronounced among banks with smaller pre-crisis mark-to-market losses.

Next, we turn to the effects of tweet issuance on deposit flows. If tweeting mitigates depositor panic, we expect to observe more stabilized deposit flows. Using a difference-in-differences design, we compare changes in quarterly deposit growth between the one-year pre-crisis period and the one-year post-crisis period for tweeting and non-tweeting banks. We control for key bank fundamental characteristics and bank and quarter fixed effects. We find that, among banks that rely more heavily on uninsured deposits before the crisis, those that issue tweets during the crisis conveying financial information about their fundamental performance experience higher subsequent growth in uninsured deposits than comparable banks that do not issue such tweets. Economically, banks that issue these tweets experience a 2% increase in the uninsured deposit growth rate, equivalent to 24% of the sample standard deviation. We do not find a significant effect of these bank tweets on insured deposit growth, consistent with insured depositors' weak incentives to respond to bank financial information. This result continues to hold in an entropy-balancing-matched sample that mitigates the effect of observable fundamental differences between tweeting and non-tweeting banks. In contrast, we do not find that tweets on banking industry conditions stabilize deposit flows. Overall, these findings suggest that tweets conveying financial information about bank fundamental performance can direct uninsured depositors' attention toward bank financial condition, potentially mitigating depositor panic and reducing the run risk.

We conduct three cross-sectional analyses to shed light on how these tweets affect depositor actions. First, we show that the effect of these tweets on uninsured and total deposit growth is concentrated among banks with relatively small mark-to-market losses, indicating that social media disclosure can only temper online panic contagion for banks with strong fundamentals. The effect is also more pronounced when bank tweets receive more views from Twitter users, which reinforces our interpretation that bank tweeting affects depositors' actions. Last, the effect is stronger when bank tweets explicitly refer to the most recent financial results released prior to the crisis. This result supports the role of stale financial reports in mitigating depositor uncertainty amid sudden economic shocks (Hail et al. 2021).

We examine two additional consequences of bank tweets to further corroborate our inference. First, we study how stakeholders on social media respond to bank tweets. We use the sentiment of third-party user tweets about the tweeting bank to capture stakeholder responses. Focusing on three-day windows around banks' first financial performance tweets, we find that banks receive more positive user reactions after posting these tweets, consistent with these disclosures improving public perceptions. This evidence reinforces our main finding that tweets about financial performance help mitigate depositor panic and stabilize deposit flows. Second, we examine the stock market effects of bank tweets using a small sample of publicly listed banks. We observe positive market reactions following the initial issuance of financial performance tweets, especially for banks with higher pre-crisis uninsured deposit ratios. This finding suggests that equity investors may respond positively to bank tweets, although we caution against strong conclusions given the small sample size.

Our study contributes to several streams of literature. We extend the literature on the role of bank transparency in financial stability (see Acharya and Ryan 2016 for a review), with a particular focus on banks' social media disclosure during the 2023 regional banking crisis. We provide initial large-sample descriptive evidence that banks issue more tweets conveying financial and non-financial information about their fundamental performance, as well as more tweets discussing banking industry conditions. Our results further suggest that healthy banks with greater reliance on uninsured deposits post more tweets that convey financial information about their fundamentals, and that these tweets are associated with higher subsequent uninsured deposit growth. Our study highlights that banks' timely and easily accessible social media disclosures can mitigate depositor panic and stabilize deposit flows in a digital bank run.

Our findings also contribute to the literature on bank financial reporting and depositor behaviour. While recent research suggests that depositors respond to information in banks' financial reports (Lo 2015; Iyer et al. 2016; Beck et al. 2022; Chen et al. 2022; Chen et al. 2025), questions remain about whether and how these reports can mitigate depositor panic during a crisis (Beatty and Liao 2014; Acharya and Ryan 2016). These concerns arise because regulatory filings, while credible, often entail significant information processing costs

(Badertscher et al. 2018). Our results suggest that banks can use social media to highlight their most recent publicly available financial results and enhance the impact of regulatory financial disclosures. Our study complements recent evidence on the decision usefulness of past financial statement information in equity markets (Drake et al. 2016; Hail et al. 2021). By documenting social media as an information channel in a banking crisis, our study also extends prior research on social media (e.g., Blankespoor et al. 2014; Lee et al. 2015; Jung et al. 2018; Cao et al. 2021; Campbell et al. 2023; Crowley et al. 2024; Cao et al. 2025).

Two closely related studies on the 2023 U.S. regional banking crisis are worth mentioning. Chen et al. (2024) show that banks with greater coordination problems are more likely to provide press releases and website disclosures after the SVB's failure. Our study differs from Chen et al. (2024) by highlighting the role of two-way interactive social media. Moreover, while Chen et al. (2024) focus on the determinants of bank disclosure, we provide evidence on the effects of bank tweeting on deposit growth. Another study by Cookson et al. (2026) finds that banks' exposure to social media increases their run risks, highlighting that social media can catalyze a bank run. Our paper extends their study by showing that banks proactively use social media to signal their financial soundness and mitigate run risks.

We acknowledge that our study presents primarily descriptive evidence regarding banks' use of social media to mitigate depositor panic, which does not allow for definitive causal conclusions. The issuance of tweets is a voluntary choice made by banks. Although we control for an array of observable bank fundamental performance, admittedly, potential unobserved confounders could affect the inferences of our results. Nevertheless, the collective set of analyses in this study provides initial evidence on the role of bank social media disclosure in affecting depositor actions in the digital era.

2. Related Literature and Institutional Background

2.1. Prior literature on information and bank runs

The seminal work of Diamond and Dybvig (1983) provides the foundation for panic-based bank runs. Their model shows that banks' role in maturity transformation (i.e., financing illiquid long-term assets with demandable deposits) makes them inherently vulnerable to runs. Because early liquidation of illiquid assets is costly, a bank forced to sell assets to meet large withdrawals may realize substantial losses. Depositors therefore face a coordination problem: their decision to withdraw depends not only on beliefs about the bank's solvency but also on expectations of other depositors' actions. These strategic complementarities can generate coordination failure, whereby depositors withdraw simply because they expect others to do so, even when fundamentals are sound. Such expectations can shift the equilibrium from a no-run outcome to a run, making crises self-fulfilling and collectively inefficient despite individually rational behavior.

Given this structure, information plays a central role in shaping bank runs. Morris and Shin (2002) show that as public information is commonly observed, it aligns beliefs and therefore exerts a disproportionate influence on agents' actions. When sufficiently precise, public signals improve coordination and reduce unnecessary runs. However, since agents tend to overweight public signals, an imprecise announcement may instead be destabilizing. Along similar lines, Dang et al. (2017) show that optimal bank design may require a degree of opacity, as keeping detailed loan information hidden prevents adverse coordination among investors. He and Manela (2016) reach a different conclusion by incorporating endogenous information acquisition into a bank-run setting. When depositors hear rumors about potential liquidity shortfalls, they acquire additional noisy private signals. Such information acquisition can subject even solvent but illiquid banks to runs and shorten the survival time of distressed banks. Importantly, they show that the public provision of solvency information can crowd out costly private information acquisition and thereby mitigate runs. This finding highlights that whether information stabilizes or destabilizes the banking system depends on which information is provided and how depositors would otherwise acquire information on their own.

Empirical research provides mixed evidence on the extent to which panic versus fundamentals drive bank runs and how information affects depositor behavior. Analyzing the 1933 banking crisis, Calomiris and Mason (2003) find that bank runs were largely driven by deteriorating fundamentals rather than pure depositor panic, suggesting that accurate information about bank performance plays a disciplining role. Anderson and Copeland (2023) find that state chartered banks whose balance sheet publication requirements were suspended during the 1933 crisis experienced smaller deposit outflows, consistent with the benefits of opacity during moments of acute stress. Consistently, Chen et al. (2022) indicate that transparency increases uninsured depositors' sensitivity to new information, and Chen et al. (2025) find that disclosures of loan fair values exacerbate bank fragility. In the context of the 2008 financial crisis, Bischof et al. (2021) show that banks were reluctant to recognize or disclose losses, delaying timely corrective action and impairing market discipline. Krupa et al. (2025) find that fundamentally strong banks use more positive tones on traditional disclosure platforms (8-K filings and conference calls) to distinguish themselves from weak banks. Two studies further examine the role of auditors in affecting depositors' perception about bank health. Lo (2015) suggests that banks with audited financial reports attract more uninsured funding during a liquidity shock. Beck et al. (2022) document that uninsured depositors withdraw funds from banks that share an audit firm with failed banks.

2.2. The 2023 U.S. regional banking crisis

The collapse of SVB represents the second-largest bank failure in U.S. history and is notable for the unprecedented speed at which events unfolded. On March 8, 2023, Silvergate Capital announced its intention to wind down operations. On the same day, SVB, whose deposits were 92.5% uninsured, disclosed a $1.8 billion loss from the sale of its bond portfolio. The following day, SVB failed to raise the planned $2.25 billion in new capital, causing its stock price to fall by 60%. By March 10, the bank was taken over by the FDIC, marking the most significant bank failure since the 2008 financial crisis.

SVB's sudden and unexpected failure triggered panic contagion in the banking system. In the days after SVB's failure, several banks, including First Republic, Signature Bank, and Western Alliance, experienced substantial deposit withdrawals. On March 14, Moody's downgraded its outlook on the U.S. banking system from "stable" to "negative". On March 27, First Citizens Bank acquired SVB, but uncertainty remained elevated in April. On April 25, First Republic's stock plunged nearly 50% after it revealed a 41% decline in first-quarter deposits. On May 1, the FDIC seized First Republic and sold it to J.P. Morgan, after which J.P. Morgan CEO Jamie Dimon commented that the banking crisis was over. Appendix A provides a detailed event timeline.

The combination of digital banking and the viral nature of social media significantly accelerated SVB's downfall. According to Koont (2023), the proportion of U.S. commercial banks offering mobile applications increased from nearly zero in 2011 to roughly 60% by 2019. This digital transformation made it easier for depositors to move funds instantaneously. Moreover, the rapid spread of panic narratives on social media exacerbated the run (Henninger 2023). Cookson et al. (2026) document a sharp surge in panic-driven Twitter discussions by presumed SVB depositors during the 48 hours preceding the bank's failure. They further find that banks with larger pre-crisis exposure to social media discussions and higher uninsured deposit shares experienced steeper stock price declines, consistent with panic contagion amplified by social media.

Aggressive monetary tightening in 2022 played a central role in precipitating the crisis (Granja et al. 2024; Jiang et al. 2024; Drechsler et al. 2025). The Federal Reserve increased the federal funds rate from 0% at the start of 2022 to 4.25%-4.50% by December. Rising interest rates undermine bank stability even for banks with ample liquidity. Long-duration assets such as Treasury bonds and mortgage-backed securities experienced substantial valuation losses as rates rose.[7] Although mark-to-market asset losses were a major concern for depositors during this episode, information about such losses in Call Reports cannot be easily processed. Loans are recorded at historical cost, and fair value information is not disclosed. For securities, while fair values are reported for both available-for-sale (AFS) and hold-to-maturity (HTM) portfolios, unrealized losses on HTM securities are not recognized on financial statements. Although unrealized losses on AFS securities are recognized, they bypass the income statement and are recorded in accumulated other comprehensive income (AOCI). Moreover, for most banks, regulatory capital excludes AOCI through the AOCI filter, meaning that declines in fair value do not reduce reported regulatory capital. Nonetheless, banks' fair value losses can be approximated using coarse data on asset maturity and repricing buckets. Jiang et al. (2024) leverage this information to estimate mark-to-market losses by applying changes in maturity-matched Treasury ETF prices to each bucket. Their estimates suggest that, on average, banks experienced mark-to-market declines equivalent to roughly 10% of total assets.

2.3. Prior research on social media

In recent years, it has become more common for stakeholders to rely on social media to make economic decisions. Such shifts have meaningfully altered the disclosure landscape for many companies, as firms increasingly use social media to communicate their messages. Regulators recognize that social media as a corporate communication channel carries both benefits and risks. Since 2008, the SEC has encouraged its use to improve transparency and efficiency, and in 2013 clarified that firms may disclose key information on social media if

[7] For example, the ten-year Treasury yield increased by 2.36% during 2022, reducing the value of a ten-year bond issued at par by roughly 18% (Flannery and Sorescu 2023).

investors know which platforms are used.[8] In 2020, due to the growing presence of online misinformation, the SEC implemented a marketing rule that prohibits investment advisors from making misleading statements on public platforms such as social media.[9]

Recent evidence highlights that social media can be a double-edged sword. On the one hand, social media enhances the corporate information environment by facilitating the dissemination of firms' announcements and collecting the crowdsourced insights of the user community. For example, Blankespoor et al. (2014) find that firms' Twitter use reduces information asymmetry and increases liquidity. Lee et al. (2015) show that social media mitigates the adverse effects of product recalls. Anticipating potential user interactions, firms strategically tailor their social media communication. This effect is evident in their practice of posting fewer tweets when releasing negative earnings news (Jung et al. 2018), issuing more tweets around extreme financial news (Crowley et al. 2024), and using fewer visuals in earnings announcements when performance is less stable (Nekrasov et al. 2022). Recent studies also explore how firms use Twitter to disseminate news about their peers to various stakeholders (e.g., Cao et al. 2021; Cao et al. 2025).

On the other hand, recent studies highlight the negative effects of social media. Due to its open and unregulated nature, firms often struggle to control the dissemination and interpretation of their social media posts. For instance, Campbell et al. (2023) find that earnings announcements with more extreme tones and less unique content are more likely to go viral on Twitter. This virality can distort market efficiency, as it is associated with decreased market liquidity and slower price discovery. Moreover, social media can function as a breeding ground for rumors, further deteriorating the corporate information environment. Jia et al. (2020) show that merger rumors on Twitter rarely materialize, yet the market often fails to immediately

[8] See https://www.sec.gov/newsroom/press-releases/2013-2013-51htm.
[9] See https://www.sec.gov/newsroom/press-releases/2020-334.

distinguish between valid and false information, resulting in inefficient price formation. Blankespoor et al. (2025) find persistent toxicity in the comments to Seeking Alpha articles, and such toxicity is associated with negative implications for firms of concern in the equity market. These findings underscore the risk that unverified content on social media can pose to financial markets, making it a double-edged sword for firms and users.

3. Data and Descriptive Results on Bank Tweets

3.1. Collecting the sample of bank tweets

We successfully collect Twitter accounts for 1,325 banks out of all banks listed on the Federal Financial Institutions Examination Council (FFIEC) that can be linked to banks' Call Reports.[10] We further exclude Twitter accounts that have never tweeted in the year before the crisis period, since these accounts may not still be in use. After requiring non-missing control variables constructed from the Call Reports, we have 889 banks in the final sample. In Appendix B, we describe the sample construction process and summarize key differences between banks included in and excluded from the sample. We note that larger and public banks are more likely to have active Twitter accounts in our sample, consistent with these banks having more resources to manage their social media presence. Next, we utilize Twitter's API and retrieve all bank tweets posted during the crisis period, as well as those posted in the one year preceding and the one year following the crisis. We include original tweets, retweets, and quotes, and remove tweets that are merely replies and that are not in English. The final tweet data consists of a total of 321,364 tweets by 889 unique banks.

[10] Our team of research assistants manually searches for the Twitter handles of 4,374 banks across their websites, Twitter, and Google. To minimize errors, two research assistants independently verify each bank's Twitter account by reviewing its description and content. As a comparison, Crowley et al. (2024) obtain 1,360 active Twitter accounts out of 2,199 public firms that were contained in the S&P 1500 between 2012 and 2018.

3.2. Identifying bank tweets relevant to depositors

To examine whether and how banks strategically use social media to affect depositor behavior during the banking crisis, it is essential to isolate the subset of disclosures most relevant to depositor decision-making. We therefore employ a large language model (OpenAI's GPT-4.1) to identify bank tweets that are likely relevant to depositors. Using a large language model offers several advantages over alternative approaches in our setting. First, manual classification is prohibitively costly given the large volume of tweets. Second, compared to dictionary-based methods, large language models incorporate semantic and contextual nuance, which is particularly important in the informal environment of social media. Third, although traditional machine learning models such as BERT can capture linguistic subtleties, they require substantial labeled training data (Fritsch et al. 2025). Constructing such a dataset is challenging in our setting because banks discuss a broad array of topics. Training samples drawn from random tweets would be dominated by the most common disclosure themes rather than the topics most salient to depositors during a banking crisis, which can bias model performance against detecting relatively rare yet economically meaningful bank disclosures. Large language models mitigate this challenge by leveraging extensive pre-training on diverse textual corpora, allowing them to perform domain-specific classification without the need for a human-coded training dataset. Nevertheless, we acknowledge the potential limitations of large language models and validate our classification with manual checks and word cloud outputs. In addition, we replicate our main regression results with a traditional researcher-labeled dictionary-based approach (Online Appendix A).

We develop an ex-ante framework to classify tweet content into categories that depositors are most likely to monitor. First, building on prior evidence that uninsured depositors respond to financial information about bank fundamental performance (Iyer et al. 2016), we include a category of tweets on "financial information about bank performance," such as earnings releases and highlights of financial results. Second, banks may also convey non-financial information on their fundamental performance, such as service quality or third-party ratings, to regain depositors' trust (category "non-financial information about bank performance"). Third, given the contagion risk in a banking crisis, industry-level signals can shape expectations about banking fragility (category "banking industry conditions"). Additionally, information on routine operating activities, such as branch openings, closures, and service disruptions, is relevant to depositors' savings and withdrawal decisions (category "bank routine operating activities"). Lastly, we include a residual category to capture other types of disclosures that fall outside the four primary depositor-relevant topics (category "others"). This framework enables us to systematically assess how banks adjust their social media disclosures in response to heightened depositor uncertainty during the banking crisis. Appendix C provides the prompt we use to instruct GPT-4.1 to implement our classification. In Appendix D, we provide several examples of each category of tweets. Out of 321,364 tweets posted by banks during our sample period, we identify 73,693 tweets relevant to depositors.[11]

In Figure 1, we present the word cloud for each category, separately for the crisis and non-crisis samples. In the "financial information about bank performance" category, the most frequently appearing words primarily relate to financial results and earnings announcements. During the crisis period, two additional prominent terms, "well capitalized" and "business model," emerge, suggesting that banks emphasize their strong capital positions and highlight their business models as distinct from those of the failed banks.

In terms of other categories, the "non-financial information about bank performance" category contains prominent words such as "Best Bank" and "Awards," highlighting banks' emphasis on service quality recognition. Tweets on "banking industry conditions" feature

[11] Although our classification framework allows a tweet to belong to multiple categories, such overlap is rare: only about 0.6% of tweets are assigned to more than one category, suggesting that banks typically communicate a single dominant topic per tweet.

prominent words such as “community bank” and “banking industry,” with terms related to “Silicon Valley Bank” becoming more prevalent during the crisis period. The “bank routine operating activities” category is dominated by terms such as “closed,” “Monday,” and “mobile banking,” indicating discussions of branch operations, service updates, and digital banking features. For “others,” the most common words include “Shred Day” and “Join US”, which relate to certain community engagement activities. Overall, the distinct clusters of words across categories support the validity of our LLM classification.

Table 1 presents the distribution of depositor-relevant tweets across the five categories during the non-crisis (Panel A) and crisis (Panel B) periods. During the non-crisis period, tweets about bank routine operating activities dominate, accounting for 87.1% of the 68,420 depositor-relevant tweets. During the crisis period, although such tweets still account for 77% of the 5,273 depositor-relevant tweets, tweets conveying financial or non-financial information about bank fundamental performance and discussing banking industry conditions increased from 5.6% to 15.1%, suggesting that banks pivoted their Twitter communication toward depositor reassurance following SVB’s failure.

This pattern is further illustrated in Figure 2, which shows the weekly frequency of bank tweets. Tweets containing financial information about bank performance exhibit a clear cyclical pattern, with regular spikes during earnings months (January, April, July, and October). This finding is consistent with prior evidence that firms use social media to disseminate financial results (Blankespoor et al. 2014; Jung et al. 2018). Notably, we also observe a pronounced spike in March 2023, outside the quarterly earnings cycle but coinciding with the onset of the regional banking crisis, suggesting that banks increased their financial-performance communication in response to heightened depositor concerns.

We also observe that banks regularly convey non-financial information about their fundamental performance, and that these tweets show no meaningful seasonality around earnings months. Yet during the crisis period, the weekly average volume of such tweets increased by 96%. This pattern suggests that banks may have sought to reinforce perceptions of customer service quality or reputational capital at a time when depositor trust was fragile. In addition, banks rarely comment on the stability or volatility of the banking industry during normal periods; however, such tweets rise sharply during the crisis, indicating that banks expanded their industry-wide commentary when systemic uncertainty became salient to depositors. Finally, we do not observe meaningful patterns for tweets about routine operating activities or those in the residual category in either the crisis or non-crisis periods.

3.3. The features of bank tweets relevant to depositors

We further examine whether financial performance tweets posted during the crisis disseminate new or stale financial information. This distinction is important because it helps determine whether these tweets provide incremental information to depositors or help depositors process already available disclosures. We manually read these tweets and any external links embedded within them. We find that banks rarely discuss non-public financial results but instead frequently reference already public financial results. See footnote 6 for the only instance in our sample of a tweet referencing financial results outside the quarterly reporting cycle. We further find that 20% of these tweets explicitly reference the most recent pre-crisis financial metrics (i.e., the 2022 annual results). While the 2022 annual results had already been released by late January and early February, they nonetheless represent the most credible and verifiable signals of bank financial condition available to depositors at the onset of the crisis. The remaining tweets either highlight financial soundness without citing specific metrics or reference first-quarter 2023 results once they became available in April 2023.

We explore several additional tweet-level characteristics in Table 1. We note that tweets on financial information about bank performance are more likely to include external Uniform Resource Locator (URL) links, compared with other categories. This finding is consistent with the role of social media to disseminate financial information (e.g., Blankespoor et al. 2014). Financial performance tweets posted during the crisis period are more positive and receive more than twice as many views as those posted during the non-crisis period, consistent with depositors becoming more attentive to bank financial signals during a bank run.[12] They receive the highest number of likes across categories.

In terms of other categories, tweets that convey non-financial information on bank fundamental performance have the most positive tone, consistent with the focus of these disclosures on bank awards and other positive certifications. In contrast, tweets on banking industry conditions have the lowest tone across categories, with an average between 0.293 and 0.327 (-1 means very negative and 1 means very positive), likely reflecting frequent references to bank failures and industry turmoil. These tweets also have the lowest percentage of original tweets, suggesting that banks are more likely to retweet or quote other tweets when they share comments about industry conditions. Most of bank tweets are original posts on routine operating activities, which suggests that banks use social media primarily as a direct communication channel to support routine customer service and operational needs. CEO statements are most commonly included in tweets on banking industry conditions, indicating that banks elevate message credibility when addressing financial stability.

4. Pre-Crisis Uninsured Deposit Ratios and Bank Tweets During the Crisis

We first examine whether banks with larger proportions of uninsured deposits issue more tweets during the crisis period, and more importantly, what types of messages they choose to communicate. Financial information on bank fundamental performance is highly important during a banking crisis, as depositors closely monitor signals about bank solvency and liquidity conditions. By signaling their financial soundness on Twitter, banks can quickly direct

[12] Only five financial performance tweets posted during the crisis have negative sentiment. Therefore, we do not conduct further analyses based on the tone of these tweets.

depositors' attention to their fundamental health. The ease of access, concise format, and immediacy of Twitter communications make tweets a low-cost mechanism for banks to reassure depositors using credible, externally verifiable financial information. As a result, we expect that during the banking crisis, banks with higher uninsured deposits post more tweets conveying financial information about fundamental performance.

It is less clear if banks disclose tweets of other topics to reduce depositor panic. Commenting on the stability of the banking industry may help mitigate contagion concerns. However, such tweets may be less effective as they do not convey information about a specific bank. Similarly, although non-financial information about bank fundamental performance can signal long-term bank brand value, it is less relevant to assessing near-term bank solvency in a crisis setting. When liquidation risk is real, depositors may prioritize credible, verifiable financial indicators of bank health. As a result, non-financial disclosures may not serve as an effective tool for mitigating immediate depositor panic. For routine operating activities and other categories of communication, we do not expect banks to strategically use these tweets to reduce panic among depositors as they do not directly address concerns about financial stability.

4.1. Research design

We aggregate tweets into a panel with 13 observations per bank, each corresponding to a two-month window: one during the crisis period, six in the pre-crisis period, and six in the post-crisis period.[13] For each window, we count tweets in each topic category and use these counts as the dependent variables. We implement a difference-in-differences (DiD) design that compares tweeting activities for banks with varying levels of ex-ante uninsured deposit ratios (1st difference) and between the crisis and pre-crisis periods (2nd difference). Specifically, we estimate the following model:

[13] The crisis period spans March 8 to April 30 and is approximately two months in length.

$$BankTweet_{i,t} = \beta_0 + \beta_1 HighPreUDR_i \times Crisis_t + \beta_2 HighPreUDR_i \times PostCrisis_t$$

$$+ \beta_3 HighPreUDR_i \times EA_t + \beta_4 ROE_{i,q-1} + \beta_5 Size_{i,q-1} + \beta_6 NPL_{i,q-1} + \beta_7 LoanGrowth_{i,q-1}$$

$$+ \beta_8 CapitalRatio_{i,q-1} + \beta_9 CILoans_{i,q-1} + \beta_{10} RealEstateLoans_{i,q-1}$$

$$+\beta_{11} UnusedCommitments_{i,q-1} + \beta_{12} WholeSaleFunding_{i,q-1} + \beta_{13} DepositRate_{i,q-1}$$

$$+ \beta_{14} StdWriteoff_{i,q-1} + \mu_i + \gamma_t + \varepsilon_{i,t}, \quad (1)$$

where i indexes bank, t indexes two-month intervals, and q indicates the quarter corresponding to the first day of each two-month interval. $BankTweet_{i,t}$ represents the number of tweets in each category for bank i in period t, corresponding to five variables: $TweetFinN_{i,t}$ (financial information about bank performance), $TweetNonFinN_{i,t}$ (non-financial information about bank performance), $TweetIndN_{i,t}$ (banking industry conditions), $TweetOperationN_{i,t}$ (routine operating activities), and $TweetOtherN_{i,t}$ (other depositor-relevant tweets). $HighPreUDR_i$ indicates if a bank's uninsured deposit ratio at the end of 2022 falls within the highest quartile of the sample. Uninsured deposit ratio is calculated as the amount of uninsured deposits (i.e., deposits above the FDIC insurance threshold of $250,000) divided by the amount of total deposits (Chen et al. 2022). *Crisis* equals one for the period from March 8, 2023 to April 30, 2023, and zero otherwise. Our variable of interest is the interaction term: $HighPreUDR_i \times Crisis_t$. To allow for potential post-crisis learning effect, we include an interaction term between $HighPreUDR_i \times PostCrisis_t$. Therefore, the coefficient on $HighPreUDR_i \times Crisis_t$ captures changes in bank tweets from the pre-crisis period to the crisis period by banks with high versus low levels of pre-crisis uninsured deposit ratios.

We control for key time-varying bank fundamental characteristics in the most recent quarter preceding a given two-month interval. Specifically, we control for return on equity (*ROE*), total assets (*Size*), non-performing loans (*NPL*), loan growth (*LoanGrowth*), capital ratio (*CapitalRatio*), the share of commercial and industrial loans (*CILoans*), the share of loans secured by real estate (*RealEstateLoans*), unused commitments (*UnusedCommitments*), wholesale funds (*WholesaleFunding*), deposit rate (*DepositRate*), and the standard deviation of write-off (*StdWriteoff*). Furthermore, because our crisis period includes one earnings-release month (i.e., April 2023), we add a control term $HighPreUDR_i \times EA_t$ to account for potential differences in tweeting behavior between earnings and non-earnings periods that may systematically vary between banks with high versus low uninsured deposit ratios. Lastly, we include bank (μ_i) and two-month interval fixed (γ_t) effects to control for banks' fixed idiosyncratic disclosure policies and time-series shocks, which absorb the standalone $HighPreUDR_i$ and time indicators. We cluster standard errors at the bank level to account for potential correlations in banks' tweeting activities over time.

4.2. Descriptive statistics and regression results

Table 2 reports the descriptive statistics for the sample. Panel A presents the summary statistics of the main variables. On average, banks post 0.07 tweets on financial information about performance over the full sample period, with the mean rising to 0.133 during the crisis period. Banks, on average, post 0.259 tweets to convey non-financial information about performance, with this number increasing to 0.442 during the crisis period. Tweets related to the banking industry conditions average 0.032 overall and 0.142 during the crisis. Most tweets concern routine operating activities, with an average of 5.416 tweets per period across the full sample and 4.549 tweets during the crisis. Tweets categorized as "other" but still relevant to depositors average 0.477 overall and 0.569 during the crisis. Banks have an uninsured-deposit ratio of 0.458 at year-end 2022, and 25% observations correspond to banks with high uninsured-deposit ratios. The average mark-to-market loss (divided by total assets) in 2022 is -0.115. Panel B provides the Pearson correlations among the main variables. We find that uninsured deposit ratio has a positive and significant correlation with tweets on financial or non-financial information about bank performance, as well as tweets on banking industry conditions, but has a negative and significant correlation with tweets on operation and other tweets. We also note that larger banks issue more tweets of all categories.

Table 3 presents the regression results of Equation (1) for our determinants analysis, with columns 1 to 6 corresponding to the five tweet categories as dependent variables. In column 1 where the dependent variable is *TweetFinN* and the control *HighPreUDR* × *EA* is excluded, we find that the coefficient on *HighPreUDR* × *Crisis* is 0.086 (*t*-statistic: 2.863). The coefficient on *HighPreUDR* × *Crisis* remains positive and significant (coefficient: 0.071, *t*-statistic: 2.449) after we include *HighPreUDR* × *EA* in column 2, which suggests that our finding is not driven by the confounding earnings announcement month. The coefficient in column 2 indicates that, during the crisis period, banks with high uninsured-deposit ratios increase their tweets about financial results by 0.071 more than banks with low uninsured-deposit ratios. This increase is economically significant, as it represents 101% of the sample mean of 0.070. Turning to the post-crisis period, we do not observe an increase in banks' tweets about their financial performance relative to the pre-crisis period (the coefficient on *HighPreUDR* × *PostCrisis* is 0.018 and is statistically insignificant and smaller than the coefficient on *HighPreUDR* × *Crisis*), consistent with the notion that uncertainty surrounding bank health was largely resolved after the crisis.

In terms of other categories, we do not find significant evidence that banks with higher uninsured deposit ratios increase their tweets that convey non-financial information on fundamental performance (column 3). However, we find that banks with higher ex-ante uninsured-deposit ratios post a significantly higher number of tweets on banking industry conditions (column 4). Moreover, banks continue their discussions of the condition of the banking industry in the post-crisis period. This finding suggests sustained interest in communicating industry-related information even after the acute phase of the crisis had passed. In columns 5 and 6, we do not find that during the crisis, these banks increase their tweets on routine operating activities or other depositor-relevant tweets. These findings suggest that, during periods of heightened depositor concern about bank runs, banks selectively provide more financial information about their fundamental performance and the overall health of the banking industry. For subsequent analyses, we focus on tweets on these two categories.

4.3. Cross-sectional tests on bank mark-to-market loss

We further predict that the effect of uninsured deposit ratios on bank tweets is stronger among financially healthier banks. This prediction is built on the unravelling results of voluntary disclosure: when uninsured depositors face uncertainty, banks with better financial performance have stronger incentives to reveal favorable information to distinguish themselves from weaker peers, reassure depositors, and mitigate potential panic. In contrast, banks with poorer fundamentals face higher costs of disclosure because releasing unfavorable information may intensify depositor concerns and accelerate withdrawals.

In the context of the 2023 banking crisis, mark-to-market losses became a central focus of depositor scrutiny and emerged as a salient indicator of bank health. These unrealized losses, primarily on long-term securities portfolios, highlighted concerns about balance-sheet weakness and interest-rate risk exposure. Therefore, we examine whether banks with higher uninsured-deposit ratios increase their tweeting activity only when they also exhibit relatively smaller mark-to-market losses. We follow Jiang et al. (2024) in calculating bank-level mark-to-market losses from 2022Q1 to 2022Q4.[14] Table 4 reports results consistent with this expectation. Specifically, we re-estimate Equation (1) by replacing *HighPreUDR* × *Crisis* with two interaction terms that separate banks based on their mark-to-market losses: *HighPreUDR* × *Crisis, Healthy* and *HighPreUDR* × *Crisis, UnHealthy*. *Healthy* equals one if a bank's

[14] First, we measure banks' assets as of 2022Q1, including loan portfolios held to maturity—not marked-to-market—and securities linked to real estate (e.g., mortgage-backed securities, commercial mortgage-backed securities, U.S. Treasuries, and other asset-backed securities). These assets comprise over two-thirds of bank assets (72% of $24 trillion). Second, we use price changes in U.S. Treasury Bond ETFs from iShares and S&P Treasury Indices with various maturities from 2022Q1 to 2022Q4 as proxies for the price changes of these assets.

absolute mark-to-market loss is smaller than the sample median, and zero otherwise. *UnHealthy* equals one minus *Healthy*.

In Table 4 column 1 (the dependent variable is *TweetFinN*), we find that the coefficient on *HighPreUDR × Crisis, Healthy* is 0.098 (*t*-statistic: 2.547) and the coefficient on *HighPreUDR × Crisis, UnHealthy* is 0.007 (*t*-statistic: 0.161). The results are similar in column 2 where the dependent variable is *TweetIndN*. Specifically, the coefficient on *HighPreUDR × Crisis, Healthy* is 0.089 (*t*-statistic: 2.366) and the coefficient on *HighPreUDR × Crisis, UnHealthy* is -0.024 (*t*-statistic: -0.674). Taken together, these results indicate that banks with high uninsured deposit ratios increase their crisis period tweeting only when they have relatively smaller mark-to-market losses. This finding highlights the importance of underlying financial strength in affecting banks' communication strategies during the crisis and is consistent with the prediction from disclosure theory that healthier banks have stronger incentives to signal their soundness to reassure depositors during a banking crisis.

5. Bank Tweets Posted During the Crisis and Subsequent Deposit Growth

5.1. Research design

We test whether bank tweets during the 2023 U.S. regional banking crisis are associated with changes in subsequent deposit flows by comparing deposit growth at tweeting banks with that of comparable non-tweeting banks from the pre-crisis to post-crisis periods. We focus on tweets about bank financial performance because these tweets directly signal financial soundness and are most relevant for depositors to evaluate bank health. We estimate the following difference-in-differences specification:

$$\begin{aligned} \textit{Uninsured Deposit Growth}_{i,q} = {} & \beta_0 + \beta_1\, \textit{TweetFin}_i \times \textit{Post}_q + \beta_2\, \textit{ROE}_{i,q-1} + \beta_3\, \textit{Size}_{i,q-1} \\ & + \beta_4\, \textit{NPL}_{i,q-1} + \beta_5\, \textit{LoanGrowth}_{i,q-1} + \beta_6\, \textit{CapitalRatio}_{i,q-1} + \beta_7\, \textit{CILoans}_{i,q-1} \\ & + \beta_8\, \textit{RealEstateLoans}_{i,q-1} + \beta_9\, \textit{UnusedCommitments}_{i,q-1} + \beta_{10}\, \textit{WholeSaleFunding}_{i,q-1} \\ & + \beta_{11}\, \textit{DepositRate}_{i,q-1} + \beta_{12}\, \textit{StdWriteoff}_{i,q-1} + \mu_i + \gamma_q + \varepsilon_{i,q}, \end{aligned} \tag{2}$$

where *Uninsured Deposit Growth*$_{i,q}$ is the quarterly deposit growth rate for bank *i* in quarter *q*, measured as the percentage change in ending uninsured deposit balances between *q-1* and *q*, scaled by the ending balance in *q-1*. *TweetFin*$_i$ indicates whether bank *i* issued tweets during the crisis period related to its own financial performance. Our determinant analyses suggest that banks increase both financial performance tweets and banking industry tweets. Therefore, to further isolate the effect of financial performance tweets, we construct *TweetOnlyFin* that indicates if a bank tweets about its own financial performance but does not tweet about the banking industry conditions, and *TweetOnlyInd* that indicates if a bank tweets about the banking industry conditions but does not tweet about its own financial performance. The benchmark non-tweeting group consists of banks that did not post tweets about their own financial performance or the banking industry conditions during the crisis period.

We index quarters in event time around the 2023 March–April crisis. *Post*$_t$ equals zero for the four pre-crisis quarters from 2022Q1 to 2022Q4 and equals one for the four post-crisis quarters from 2023Q3 to 2024Q2. We exclude the crisis quarters 2023Q1 and 2023Q2 to ensure that we study changes in deposit flows *after* bank tweets issued during the crisis period.[15] We include bank and quarter fixed effects and cluster standard errors by bank. To examine whether depositors respond differently to tweets from banks with a larger base of uninsured deposits, we partition the sample into two groups: banks in the top quartile of the pre-crisis uninsured deposit ratio ("*HighPreUDR=1*") and all other banks ("*HighPreUDR=0*").

Table 5 reports descriptive statistics for the bank-quarter panel used in the consequence analysis. Panels A and B present the summary statistics for banks with high and low ex-ante uninsured deposit ratios, respectively. Banks with higher uninsured deposits are more likely than banks with lower uninsured deposits to issue tweets that highlight their own financial

[15] Results are similar if we include the crisis quarters (2023Q1 and 2023Q2) as the post-crisis period.

condition, consistent with our determinant analyses. These banks also tend to be larger and have higher mark-to-market losses.

5.2. Depositor responses to bank tweets

We test whether bank tweets about their financial performance during the crisis period are associated with changes in subsequent deposit growth. Table 6 presents our regression results of Equation (2). In all panels, columns 1, 3, and 5 examine the subsample of banks with high uninsured deposit ratios, whereas columns 2, 4, and 6 examine the remaining banks. As shown in Panel A, we find that in the subsample of banks with a high pre-crisis uninsured deposit ratio, banks with tweets on financial performance have relatively higher uninsured deposit growth rates after the crisis than comparable banks without such tweets. In terms of economic magnitude, issuing financial performance tweet is associated with about 2 percentage points higher uninsured deposit growth in the post-crisis periods relative to non-tweeting peers. This effect corresponds to 24% of a standard deviation of uninsured deposit growth (0.020 / 0.084). We further find no significant difference in insured deposit growth between tweeting and non-tweeting banks, whereas total deposit growth is 1 percentage point higher for tweeting banks relative to non-tweeting banks. In addition, among banks with low reliance on uninsured deposits, we find no differential responses in uninsured, insured, or total deposits between tweeting and non-tweeting banks. These patterns indicate that bank tweets on financial performance matter primarily for banks that ex ante rely more on uninsured funding, and that depositors' responses in the post-crisis periods operate mainly through uninsured deposits.

To further isolate the effect of financial-performance tweets, we redefine the treatment group to be banks that tweet exclusively about their own financial performance (*TweetOnlyFin*) in Table 6 Panel B. We use banks that only tweet about banking industry conditions (*TweetOnlyInd*) as the treatment group in Table 6 Panel C. We find that among banks with high uninsured-deposit ratios, those that tweet exclusively about their own financial performance experience greater uninsured and total deposit growth than control banks. In contrast, across both the high- and low-uninsured-deposit subsamples, banks that tweet exclusively about banking industry conditions do not experience higher post-crisis uninsured deposit growth.[16]

Taken together, our findings in Table 6 suggest that only tweets about banks' own financial performance are effective in reassuring uninsured depositors, and these effects are concentrated among banks with high ex ante uninsured funding. Bank-specific financial performance tweets provide useful information, such as a bank's liquidity, that depositors can cross-check against call reports and annual reports. By contrast, tweets about the banking industry conditions represent information regarding the banking industry as a whole, which is less effective at alleviating depositor concerns about bank-specific solvency.

5.3. Cross-sectional tests on bank mark-to-market loss

We examine whether banks' ex-ante financial health moderates the deposit reactions to bank tweets on their financial performance. We expect that such tweets have stronger effects among healthier banks, for which public reassurances on Twitter can help stabilize depositor sentiment during a crisis. In contrast, when a bank's underlying financial condition is weak, social media disclosure may do little to restore confidence. Empirically, we partition the *TweetOnlyFin*×*Post* in Equation (2) into two dummies: *TweetOnlyFin*×*Post*, *Healthy* that equals *TweetOnlyFin*×*Post* multiplied by the indicator that the bank's mark-to-market loss (in absolute magnitude) is lower than the sample median (i.e., healthy banks) and

[16] Online Appendix B reports univariate changes in uninsured deposit growth from the pre- to post-crisis periods, comparing tweeting and non-tweeting banks. Panel A compares banks that only tweet about their financial performance with non-tweeting banks. We find that for banks with low ex-ante uninsured deposit ratios (*HighPreUDR* = 0), the pre- to post-crisis changes in uninsured deposit growth are similar for tweeting and non-tweeting banks, yielding a univariate difference-in-differences of 0.003 (*t*-statistic: 0.207). In contrast, among banks with high ex-ante uninsured deposit ratios (*HighPreUDR* = 1), non-tweeting banks experience a small decline of -0.003, whereas tweeting banks exhibit an increase of 0.013, implying a univariate difference-in-differences of 0.016 (*t*-statistic: 1.347). Panel B compares banks that only tweet about banking industry conditions with non-tweeting banks. We find that for banks with low ex-ante uninsured deposit ratios (*HighPreUDR* = 0), the univariate difference-in-differences in uninsured deposit growth is 0.005 (*t*-statistic: 0.587). In contrast, among banks with high ex-ante uninsured deposit ratios (*HighPreUDR* = 1), the univariate difference-in-differences in uninsured deposit growth is -0.014 (*t*-statistic: -0.759).

TweetOnlyFin×Post, *Unhealthy* that equals *TweetOnlyFin×Post* multiplied by the indicator that the bank's mark-to-market loss is higher than the sample median (i.e., unhealthy banks).

Table 7 Panel A reports the results. We find that the positive association between financial performance tweets and deposit growth is concentrated (muted) in healthy (unhealthy) banks. Specifically, the coefficient on *TweetOnlyFin×Post, Healthy* is positive and significant for the uninsured deposits (4.2%) and total deposits (3.4%). Economically, the association between tweets and deposit growth is more than one and a half times as strong for healthy banks as for the average bank in the subsample with high uninsured deposits in Table 6 Panel B. Overall, these results suggest that healthier banks are better able to use tweets on their financial performance to stabilize uninsured deposits during a banking crisis, relative to less healthy banks.

5.4. Cross-sectional tests on bank tweet characteristics

Furthermore, we test whether the association between financial performance tweets and deposit growth is moderated by tweet characteristics. First, we test whether the association is stronger when such tweets attract greater attention from Twitter users. We proxy for user attention using the number of views on bank tweets by Twitter users.[17] Second, we test whether the association varies with whether financial performance tweets reference the most recent financial results available prior to the onset of the banking crisis in March 2023. We construct an indicator for whether the bank references its 2022 financial results, either by discussing them directly or by providing a link to its 2022 annual report or regulatory filings. Referencing 2022 results (the most recent, already public results) is potentially important because it anchors banks' social media communication in verifiable financial disclosures. This anchoring can be especially relevant during a banking crisis, when depositors' demand for credible information spikes, but they face severe time constraints for verifying banks' claims.

[17] We measure Twitter user views as of May 2023, when we scraped the Twitter data.

Empirically, similar to the research design in Section 5.3, we implement these cross-sectional tests by decomposing the *TweetOnlyFin×Post* term into two interaction terms along each dimension. Specifically, in Table 7 Panel B, we split *TweetOnlyFin×Post* into *TweetOnlyFin×Post, HighViews*, and *TweetOnlyFin×Post, LowViews*, where *HighViews* (*LowViews*) equals one if the average number of views of a bank's financial performance tweets is above (below) the sample median. Similarly, in Table 7 Panel C, we decompose *TweetOnlyFin×Post* into *TweetOnlyFin×Post, Fin2022,* and *TweetOnlyFin×Post, NoFin2022*, where *Fin2022* (*NoFin2022*) equals one if the bank does (does not) reference its 2022 financial results in its financial performance tweets.

We find in Table 7 Panel B that the positive association between financial performance tweets and deposit growth is stronger among banks with high Twitter user views. *TweetOnlyFin×Post, HighViews* is positive and significant for uninsured deposits (4.0%) and total deposits (2.5%), while the corresponding estimates for *TweetOnlyFin×Post, LowViews* are smaller and insignificant. Table 7 Panel C shows a similar pattern when conditioning on whether financial tweets mention 2022 results: the association is concentrated in tweets that reference 2022 financial results (4.4% for uninsured deposits and 3.7% for total deposits), whereas tweets without such references have a small and insignificant estimate. Overall, these results suggest that, for banks with high ex-ante uninsured funding, the association between financial performance tweets and deposit growth is more pronounced when those tweets reach a larger audience or reference credible information from the bank's most recent financial results.

6. Supplemental Analyses

6.1. Depositor responses to financial performance tweets in a matched sample

We implement an entropy-balancing procedure to mitigate the concerns that our results on banks' financial performance tweets may reflect underlying differences in bank fundamentals. Specifically, we reweight non-tweeting banks so that their weighted pre-crisis key fundamental characteristics, including ROE, size, loan growth, non-performing loans, capital ratio, and mark-to-market losses as of 2022Q4, closely match those of tweeting banks. We perform this balancing procedure separately within subsamples of banks with high and low uninsured deposit ratios.

Table 8 presents our findings using the entropy-balanced sample. We find consistent evidence that tweeting banks in the top-quartile uninsured deposit group exhibit significantly higher post-crisis deposit growth (uninsured and total deposits) relative to entropy-balanced control banks, whereas the effect remains insignificant among banks with lower uninsured deposits. This pattern lends support to our interpretation that banks with high uninsured deposits can use tweets highlighting their financial strength to bolster depositor confidence and help stabilize their funding base during periods of stress.

6.2. Twitter users' reactions to bank tweets on financial performance

We examine user reactions to bank financial performance tweets by analyzing third-party user tweets that tag (i.e., "@") a specific bank and reference the crisis. To identify crisis-related user tweets, we expand the dictionary in Cookson et al. (2026) as shown in the keyword list in Online Appendix C. We use the tone of these tweets to capture user sentiment, where positive sentiment reflects a more favorable user perception of banks. We expect that bank tweets on financial performance signal strength and improve user perception, which is important for stabilizing deposit flows.

We examine changes in the tone of Twitter users' tweets in the days before and after banks' first tweets about their own financial performance, focusing on banks with high ex ante uninsured funding.[18] Since banks release their tweets at different times, we perform a *stacked* difference-in-differences regression to alleviate concerns about biases in staggered models

[18] We focus on banks' first tweets because the earliest message may be more powerful in influencing social media discussions. Since we aim to identify the tweet-level effect of financial performance tweets, we do not restrict the sample to banks that post only financial performance tweets.

(Cengiz et al. 2019; Callaway and Sant'Anna 2021; Baker et al. 2022). Our sample consists of 27 stacks (i.e., the number of days that at least one bank issues financial performance tweets), each including banks that post financial performance tweets for the first time and banks that never post any financial or industry tweets. In each stack, a bank has two observations: one for the three days before the stack day and another for the three days (including the stack day) after the bank's tweet. For each observation, we aggregate user tweets within the three-day window at the bank level.[19]

We estimate the effect of bank financial performance tweets on Twitter users' crisis-related discussions with the following model:

$$UserTone_{s,i,t} = \beta_1\, TweetFin_{s,i} \times PostFirst_{s,t} + \alpha_{s,i} + \gamma_{s,t} + \varepsilon_{i,t}, \qquad (3)$$

where s, i, t indicate stack day s, bank i, and time window t. *UserTone* is measured with three variables: (1) *Positive* equals one if there is at least one user tweet with a positive tone over the three-day window and zero otherwise; (2) *PositiveN* equals the number of user tweets with a positive tone over the three-day window; (3) *PositiveRatio* equals the number of user tweets with a positive tone divided by the total number of user tweets over the three-day window. *PostFirst* is an indicator that equals one for the three-day window after stack day s and zero for the three-day window before stack day s. β_1 captures the change in the tone of user tweets when a bank posts its first tweet on the financial performance compared with non-tweeting banks. We include stack-bank and stack-period fixed effects to absorb time-invariant bank characteristics and time trends. We cluster standard errors at the bank level.

Table 9 presents the results. We find that banks' financial performance tweets are followed by more positive user tone across all specifications, whether measured as the presence of any positive user tweet (column 1), the count of positive user tweets (column 2), or the share

[19] Our results remain robust when we do not aggregate user tweets to three-day windows and instead conduct the analysis using bank-day panel data (untabulated).

of positive tweets among all user discussions (column 3). This pattern is consistent with the interpretation that bank financial performance tweets enhance Twitter users' perception about posting banks.[20]

6.3. Stock market reactions to bank financial performance tweets

Lastly, we examine how equity market investors respond to banks' financial performance tweets during the crisis. We use the New York Fed's linking table between banks' RSSD IDs and CRSP PERMNOs to identify banks with available stock price data. For each bank, we define the event date as the day of its first financial performance tweet and compute cumulative abnormal returns (CARs) over short event windows using the banking-industry-adjusted benchmark. To construct the industry benchmark, we exclude tweeting banks when calculating daily value-weighted returns for the banking industry. We report in Table 10 cumulative abnormal returns over the pre-tweet window [−2, 0] and the post-tweet window [+1, +2], along with associated *t*-statistics, and further partition the sample by banks' ex-ante reliance on uninsured funding. We focus on [+1, +2] as the cleaner post-event window because 63% of financial performance tweets are posted after the morning trading session concludes.

We find in Table 10 that banks' first tweets about their own financial performance are preceded by significantly negative abnormal returns in the [−2, 0] window. In the post-tweet window [+1, +2], average abnormal returns of the full sample are positive and significant at the 10% level (column 1). When we partition the sample by banks' ex-ante reliance on uninsured deposit funding, post-tweet abnormal returns are larger for banks with higher uninsured funding (column 2) than for banks with lower uninsured funding (column 3). This finding suggests that banks' tweets on their financial performance during the banking crisis may help alleviate equity investors' uncertainty about run risk, especially for banks that are

[20] In untabulated analyses, we do not find a significant change in user tone following banks' tweets about the banking industry conditions. One possible interpretation is that, during periods of heightened uncertainty, depositors place relatively more weight on bank-specific fundamentals that speak directly to run risk, while reassurances on banking industry conditions may be perceived as more generic and less informative.

more vulnerable to uninsured depositor withdrawals.[21] At the same time, given the small sample size and limited statistical significance, we view this result as suggestive and do not interpret it as implying that equity investors substantially revise firm valuations in response to banks' Twitter communications.

7. Conclusion

This study highlights banks' use of social media disclosure during the 2023 U.S. banking crisis. We document that banks post more tweets conveying both financial and non-financial information about their fundamental performance, as well as tweets commenting on banking industry conditions. These tweets highlight banks' financial soundness, service quality, and banking industry stability. Using a difference-in-differences design, we further find that during the crisis, banks with higher pre-crisis uninsured deposit ratios post more tweets on their financial performance. Moreover, such tweets are associated with higher uninsured deposit growth after the crisis. These relations are stronger among healthier banks, as measured by smaller mark-to-market losses. Bank financial performance tweets also have a larger effect on subsequent deposit growth when these tweets attract a larger audience and reference the most recent publicly available financial results before the crisis. These results suggest that healthy banks' use of Twitter to direct depositors' attention to their financial performance mitigate depositor panic and stabilizes deposit flows. In conclusion, our evidence from the 2023 banking crisis underscores the importance of social media for banks in managing the rapidly evolving online information environment and affecting depositors' behavior in the digital era.

[21] In untabulated analyses, we find no significant abnormal stock return reactions around banks' first tweets about banking industry conditions.

Declaration of Generative AI and AI-assisted Technologies in the Manuscript Preparation Process

The authors used ChatGPT and OpenAI's API in the following capacities.
First, the authors used ChatGPT-5.2 for copy editing purposes to improve clarity, grammar, and readability of the manuscript. All substantive arguments, interpretations, and conclusions were developed by the authors. The authors have reviewed and edited the content after AI usage and take full responsibility of the content of the article.
Second, the authors used OpenAI's GPT-4.1 to classify bank tweets. See Section 3.2 for details and Appendix C for the prompt. The authors reviewed and validated the outputs generated by the model. In Online Appendix A, the authors replicate the main findings of the study using a traditional dictionary-based approach to classify bank tweets.

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Appendix A: Timeline of the 2023 U.S. Banking Crisis

Date	Event
2023/03/08	Silvergate Capital announced bankruptcy. SVB reported a bond portfolio selling loss of $1.8 billion and the need to raise $2 billion in capital. Moody's downgraded SVB's outlook from stable to negative.
2023/03/09	SVB CEO Greg Becker urged investors and depositors to stay calm during a conference call.
2023/03/10	SVB failed after a bank run. The banking crisis continued, with First Republic, Signature Bank, and Western Alliance suffering significant deposit outflows and stock declines. U.S. Treasury Secretary Janet Yellen reassured investors that the banking system was resilient.
2023/03/12	Regulators seized Signature Bank and announced that "depositors will have access to all of their money starting Monday, March 13th." Regulators announced further measures to prevent further financial instability, including systemic risk exception that allows the government to pay back uninsured depositors and Fed emergency lending program.
2023/03/13	President Biden said that the U.S. banking system was safe and emphasized that taxpayers would not pay for any bailouts.
2023/03/14	Moody's downgraded its outlook on the U.S. banking system to "negative" from "stable."
2023/03/16	First Republic Bank received $30 billion in deposits from 11 big banks, including JPMorgan Chase, Wells Fargo, and Morgan Stanley. Janet L. Yellen testified to reassure the public that America's banks remain "sound." Yellen tells a U.S. Senate hearing that uninsured deposits would only be guaranteed in banks deemed a contagion threat, raising fears about smaller banks.
2023/03/17	Many banks continued to experience stock price declines. First Republic's stock plummeted again.
2023/03/21	U.S. Treasury Secretary Janet Yellen told bankers that she was prepared to intervene to protect depositors in smaller U.S. banks.
2023/03/27	First Citizens Bank said it would acquire the deposits and loans of failed Silicon Valley Bank.
2023/03/30	President Biden called for strengthened regulatory oversight of mid-sized banks.
2023/04/04	Jamie Dimon says the banking crisis is not over.
2023/04/25	First Republic's stock plunged nearly 50% after the bank disclosed a 41% drop in first-quarter deposits.
2023/04/28	The Fed released a report acknowledging that it failed to "take forceful enough actions" ahead of SVB's collapse. The FDIC issued a separate report criticizing Signature Bank for poor risk-management practices.
2023/05/01	First Republic Bank was seized by the FDIC and immediately sold to J.P. Morgan. Jamie Dimon commented that the banking crisis was over.

Summarized based on a New York Times article. See https://www.nytimes.com/2023/05/01/business/banking-crisis-failure-timeline.html.

Appendix B: Bank Tweet Sample Construction

This appendix presents the construction of our bank tweet sample in Panel A and summarizes key differences in characteristics between banks with and without Twitter accounts in Panel B.

Panel A: Sample selection of bank tweets

Steps:	Number of banks	Number of total tweets
1. Banks with official Twitter accounts out of the universe of 4,374 banks from FFIEC.	1,325	-
2. Keep banks with active Twitter accounts (i.e., accounts that posted at least one tweet in the pre-crisis period) and have non-missing bank-level controls. Non-English tweets and replies are excluded.	889	321,364
Banks with tweets relevant to depositors.	853	73,693

Panel B: Differences between banks with and without Twitter accounts

	Banks without active Twitter account N=3,464	Banks with active Twitter account N=889	*p*-value of the difference
PreUDR	0.410	0.458	0.000***
PreMTML	-0.114	-0.115	0.345
ROE	0.174	0.147	0.673
Size	12.583	14.080	0.000***
NPL	0.006	0.005	0.014**
Loan Growth	0.055	0.084	0.000***
CapitalRatio	0.095	0.091	0.035**
CILoans	0.021	0.063	0.000***
RealEstateLoans	0.725	0.749	0.001***
UnusedCommitments	0.023	0.046	0.000***
WholesaleFunding	0.147	0.137	0.012**
DepositRate	0.012	0.014	0.000***
StdWriteoff	0.003	0.003	0.455
Public	0.057	0.196	0.000***

Appendix C: GPT-4.1 Prompt to Classify Bank Tweets Relevant to Depositors

Here is a tweet posted by a bank on Twitter/X:
"{Tweet}"

Please evaluate whether the tweet discusses any of the following information that we consider of interest to DEPOSITORS (including individual and business depositors):

Category_1. Bank Fundamentals & Financial Performance:
1.1 Announcing or disseminating the bank's quarterly/annual financial reports or financial results
1.2 Discussing revenues, earnings, capital, liquidity, or other financial metrics

Category_2. Other NON-FINANCIAL Information about the Bank's Fundamental Performance:
2.1 Describing the bank's own strengths relevant to depositors WITHOUT referring to financial metrics
2.2 Evaluations or commentaries by third parties on the bank's fundamental performance relevant to depositors

Category_3. Community Banks and Banking Industry:
3.1 Commenting on the stability or fragility of the banking industry
3.2 Commenting on the stability or fragility of community banks

Category_4. Bank Operations Targeting DEPOSITORS:
4.1 Promoting online/mobile banking, debit cards, certificates of deposit, ATMs, savings/checking accounts, deposit rates, or other savings products to depositors
4.2 Notifying changes in branch hours due to holidays, festivals, bad weather, or other events
4.3 Announcing new branch openings or closures
4.4 Offering tips on account security and scam prevention to depositors
4.5 Providing guidance on savings, retirement funds, or emergency funds, or discussing other initiatives to improve financial literacy
4.6 Mentioning that the bank is an FDIC member and that the bank's deposits are FDIC-insured WITHOUT referring to the percentage of insured deposits

Category_5. Other Information Relevant to DEPOSITORS:
5.1 Any information not covered in Categories 1–4 but still relevant to depositors

Please strictly follow the rules below:
1) DO NOT assign a tweet to Category_2 if it mainly discusses the bank's ESG performance, general customer relationship and experiences, or cybersecurity and IT system.
2) DO NOT assign a tweet to Category_3 if it only discusses macro or market updates WITHOUT specifically referring to the banking industry or community banks.
3) DO NOT assign a tweet to Category_5 unless it does not cover any information in Category_1-4.
4) DO NOT assign a tweet to any category if it mentions loans, mortgages, credit cards, lending, lender, or other borrower-related information.
5) DO NOT assign a tweet to any category if it mentions employee performance, achievements, teamwork, recruitment, or other employee-related information.
6) A tweet may fall into one or more categories above, or none at all.

Please return the output in strict JSON format with the following fields:
Category_1: (1 if the tweet matches Category_1 "Bank Fundamentals & Financial Performance" | 0 otherwise)
PointList_1: (if Category_1 = 1, return a list of specific subpoint(s) under Category 1 (e.g. "1.1", "1.2") that are discussed in the tweet. Otherwise, return an empty list)

Category_2: (1 if the tweet matches Category_2 “Other NON-FINANCIAL Information about the Bank’s Fundamental Performance” | 0 otherwise)
PointList_2: (if Category_2 = 1, return a list of specific subpoint(s) under Category 2 (e.g. “2.1”, “2.2”) that are discussed in the tweet. Otherwise, return an empty list)
Category_3: (1 if the tweet matches Category_3 “Community Banks and Banking Industry” | 0 otherwise)
PointList_3: (if Category_3 = 1, return a list of specific subpoint(s) under Category 3 (e.g. “3.1”, “3.2”) that are discussed in the tweet. Otherwise, return an empty list)
Category_4: (1 if the tweet matches Category_4 “Bank Operations Targeting DEPOSITORS” | 0 otherwise)
PointList_4: (if Category_4 = 1, return a list of specific subpoint(s) under Category 4 (e.g. “4.1”, “4.2”, ...) that are discussed in the tweet. Otherwise, return an empty list)
Category_5: (1 if the tweet matches Category_5 “Other Information Relevant to Depositors” | 0 otherwise)
PointList_5: (if Category_5 = 1, return a list of specific subpoint(s) under Category 5 (e.g. “5.1”) that are discussed in the tweet. Otherwise, return an empty list)

Appendix D: Examples of Bank Tweets

Tweeting Bank	Tweet Time	Tweet Content	Tweet Category
1st Source Bank	2022-07-22T14:17:23	1st Source Corporation Reports Second Quarter Results, a Record Quarter Adjusted for PPP Income Due to Government Response to COVID-19; Cash Dividend Increasedhttps://t.co/nDGUAXr9ty https://t.co/nmQ4ESQsC3	Financial information about bank performance
Ion Bank	2023-03-13T17:04:39	With the recent news coming from the financial industry, we want you to know that Ion Bank is a well-capitalized and strong institution. Safety and security are our first priority. Our Annual Report is available to view at https://t.co/da8uifIySC. #bank #communitybank	Financial information about bank performance
Amalgamated Bank	2024-01-25T17:20:29	🌎 Our Q4 Earnings Report is ready to view!Priscilla Sims Brown, President and CEO: "In today's highly constrained liquidity environment, we are punching well above our weight, giving us many options to deliver above peer returns:Read now: https://t.co/QeXhuFP9GL https://t.co/EQl6znoAVb	Financial information about bank performance
Washington Trust Bank	2022-11-03T20:54:12	A lot has happened since 1902. Today, on Washington Trust Bank's 120th anniversary, we're honored to reflect on this milestone and all that we've accomplished over the years. Click below for a special message from our CEO and Chairman, Pete Stanton.https://t.co/RxIcGby4N6	Non-financial information about bank performance
Capitol Bank	2023-03-13T20:19:27	Looking for peace of mind from your bank? We're proud to be a 5⭐Rated SUPERIOR Bank & a TOP 200 Healthiest US Bank (https://t.co/1g9QT6uiwJ). If your bank has been going through a lot of changes, maybe it's time to change your bank. Check us out! #BankLocally #5Star https://t.co/Or62IbwgLK	Non-financial information about bank performance
Independence Bank (1776 Bank)	2023-05-10T16:17:47	Thank YOU for voting us Platinum for Best Bank in the 2023 Best of @OboroLiving! We pride ourselves on giving back in all of our communities and thank you to the place we call home for continuing to support us. #HereForGood 📸Owensboro Living https://t.co/Naht1J16fE https://t.co/e3oShPf6C3	Non-financial information about bank performance
Associated Bank	2022-12-05T17:16:08	Hope you're ready for Wednesday's webinar on How Community Banks Can Take Back Main Street From the Fintechs with Cornerstone Advisors' John Meyer, @AmountFintech's Johnathan Katz and @AssociatedBank's Ashley Lucas. Register	Banking industry conditions

		now! https://t.co/LrVojunh7e #fintech #communitybanks https://t.co/aJtnPSOmkM	
Bna Bank	2023-03-13T13:36:45	In light of the news around Silicon Valley Bank and consequent customer concerns, community banks across this country are reminding consumers that they are in the best position to support customers and small businesses. #BankLocally is as important as ever. (a thread)	Banking industry conditions
Canandaigua National Bank And Trust Company	2023-03-14T15:24:41	CNB's President and CEO Frank H. Hamlin III sat down with @news10nbc Deanna Dewberry (@whec_DDewberry) at our Alexander Park location to discuss the current news relating to recent bank failures in the financial industry. Watch for his interview on Channel 10. https://t.co/IU1qEwn9pe	Banking industry conditions
Independence Bank (1776 Bank)	2022-06-29T23:00:09	All locations will be closed in observance of the federal holiday, Independence Day on Monday 7/4. Visit one of our ITM or ATM locations, or bank from wherever you find yourself with the convenience of Digital Banking and Telephone Banking. https://t.co/jzobVVw1iS https://t.co/srXOBCDgtH	Bank routine operating activities
William Penn Bank	2023-03-17T15:49:28	Make your money work for you with this 4.00% APY* Business Money Market Special! Don't sleep on this great deal! Fill out our form and get started today: https://t.co/kKrIwvx2pT https://t.co/zDsQwYLiim	Bank routine operating activities
Citizens National Bank (yourcnb)	2024-03-08T00:29:37	.@YourCNB's Meridian President Neil Henry enjoyed visiting with MS Power Company employees this week & shared tips of how to stay on alert against fraud. CNB wants to do everything we can to help you safeguard your accounts & personal information. #PowerofLocal #StaySecure https://t.co/MqNLOZCoI1	Bank routine operating activities
AmeriServ Bank	2023-11-17T17:00:05	Join us tonight, from 5:30pm to 7:30pm for the 4th annual Christmas Stroll and Light Up Night, hosted by Discover Downtown Johnstown Partnership. Don't forget to stop in at the downtown branch lobby to vote on your favorite decorated tree and to see the vintage displays! 🎄🎅🤶 https://t.co/oCOLcpCJar	Others
GBC Bank	2023-04-06T15:11:07	2023 GBC Bank Community Shred Days: Free on-site shredding of paper documents. Be prepared to transfer shred documents from your vehicle to the shred truck attendant. https://t.co/YCcw0UKHS3 https://t.co/vyMpGPQ639	Others

Oak View National Bank	2022-06-07T13:29:13	Stop by our Culpeper, Marshall or Warrenton branch tomorrow for Customer Appreciation Day to celebrate 13 years! 🥳🤩 Food, fun and prizes from 11-2 tomorrow, including a raffle to win a Yeti cooler filled with bank goodies! #OVNB #communitybanking https://t.co/jYFuB0o0iT	Others

Appendix E: Variable Definitions

Variable	Definition
	Determinant analyses
TweetFinN	The number of tweets conveying financial information about bank fundamental performance in each two-month period.
TweetNonFinN	The number of tweets conveying non-financial information about bank fundamental performance in each two-month period.
TweetIndN	The number of tweets related to the banking industry conditions in each two-month period.
TweetOperationN	The number of tweets related to a bank's routine operating activities in each two-month period.
TweetOtherN	The number of other tweets relevant to depositors in each two-month period.
Crisis	An indicator that equals one if a period falls within the regional banking crisis (i.e., from March 8 to April 30, 2023), and zero otherwise.
PostCrisis	An indicator that equals one if a period falls after the regional banking crisis (i.e., from May 1, 2023 to April 30, 2024), and zero otherwise.
PreUDR	The ratio of uninsured deposits to total deposits as of December 31, 2022. Uninsured deposits are deposits above the FDIC insurance threshold of $250,000, calculated as the difference between total deposits (RCFD 2200) and insured deposits (RCONF 049 + RCONF 045).
HighPreUDR	An indicator that equals one if a bank's uninsured deposit ratio is in the top quartile, and zero otherwise.
PreMTML	The bank-level mark-to-market losses from 2022Q1 to 2022Q4 calculated following Jiang et al. (2024). Bank assets include banks' loan portfolios held to maturity, which have not been marked-to-market, and securities linked to real estate (such as mortgage-based securities (MBS)), commercial mortgage-backed securities (CMBS), U.S. Treasuries, and other asset-based securities (ABS). Changes in prices are proxied with price changes in U.S. Treasury Bond ETFs from iShares and S&P Treasury Indices.
Healthy	An indicator that equals one if a bank's pre-crisis mark-to-market loss (in absolute magnitude) is below the sample median, and zero otherwise.
UnHealthy	An indicator that equals one if a bank's pre-crisis mark-to-market loss (in absolute magnitude) is above the sample median, and zero otherwise.
ROE	Annualized net income (RIAD 4300, adjust year-to-date reporting to within quarter) divided by equity capital (RCFD 3210).
Size	The natural logarithm of total assets (RCFD 2170).
NPL	Non-performing loans (RCFD 1403 + RCFD 1407) divided by total loans (RCFD 2122).
Loan Growth	Annualized growth rate in total loans as a percentage of lagged assets.
CapitalRatio	Equity capital divided by total assets.
CILoans	Commercial and industrial loans (RCFD 1763 + RCFD 1764) divided by total loans.
RealEstateLoans	Loans secured by real estate (RCFD 1410) divided by total loans.
UnusedCommitments	Unused commitments (RCFD 3814 + RCFD F164 + RCFD F165 + RCFD 3817 + RCFD J457 + RCFD J458 + RCFD J459 + RCFD 6550 + RCFD 3411) divided by the sum of loans and unused commitments.
WholesaleFunding	Wholesale funds (RCFN 2200 + RCFD 3200 + RCON B993 + RCFD B995 + RCFD 3190 + RCON J473 + RCON J474) divided by total assets.
DepositRate	Annualized deposit interest expenses (RIAD HK03 + RIAD 4508 + RIAD 0093 + RIAD HK04, adjust year-to-date reporting to within quarter) divided by deposit balance (RCON HK16 + RCON 3485 + RCON B563 + RCON HK17).

StdWriteoff	Standard deviation of write-off (RIAD 4635) to lagged equity ratio over the past 12 quarters.
EA	An indicator that equals one if a two-month observation includes an earnings release month (i.e., January, April, July, and October), and zero otherwise.
	Consequence analyses
Total Deposit Growth	The growth rate of total deposits (RCFN2200 or RCON 2200) over a quarter.
Insured Deposit Growth	The growth rate of insured deposits (RCONF049+ RCONF045) over a quarter.
Uninsured Deposit Growth	The growth rate of uninsured deposits over a quarter.
TweetFin	An indicator that equals one if a bank posts any tweets related to its own financial performance during the crisis period.
TweetOnlyFin	An indicator that equals one if a bank tweets about its own financial performance but does not tweet about the banking industry conditions during the crisis period.
TweetOnlyInd	An indicator that equals one if a bank tweets about the banking industry conditions but does not tweet about its own financial performance during the crisis period.
Post	An indicator that equals one for quarters after the crisis, and zero otherwise.
HighViews	An indicator that equals one if the number of views of a bank's financial performance tweets is above the sample median, and zero otherwise.
LowViews	An indicator that equals one if the number of views of a bank's financial performance tweets is below the sample median, and zero otherwise.
Fin2022	An indicator that equals one if a bank refers to its 2022 financial results in its financial performance tweets, and zero otherwise.
NoFin2022	An indicator that equals one if a bank does not refer to its 2022 financial results in its financial performance tweets, and zero otherwise.
Positive	An indicator that equals one if there is at least one user tweet with a positive tone over the three-day window and zero otherwise.
PositiveN	The number of user tweets with a positive tone over the three-day window.
PositiveRatio	The number of user tweets with a positive tone divided by the total number of user tweets over the three-day window. It equals zero for banks without any user tweets over the three-day window.
PostFirst	An indicator that equals one for the three-day window after stack day *s* (including the stack day) and zero for the three-day window before stack day *s*.

Figure 1: Word Cloud of Bank Tweets

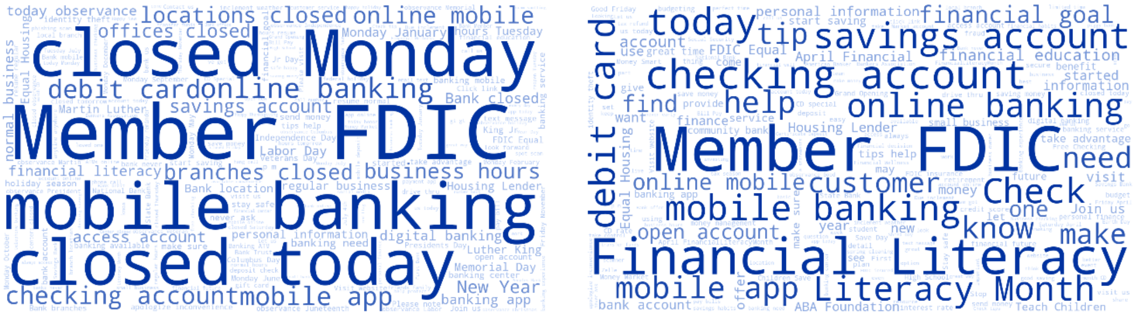
This figure compares word clouds of bank tweets by category between the non-crisis period (i.e., pre- and post-crisis periods) versus the crisis period. For each category, the word cloud on the left corresponds to the non-crisis period, and the word cloud on the right corresponds to the crisis period. A larger font indicates a higher frequency appearing in the sample of each category.

Panel A: Top words for tweets conveying financial information on bank fundamental performance

Panel B: Top words for tweets conveying *non*-financial information on bank fundamental performance

Panel C: Top words for tweets about the banking industry conditions

Panel D: Top words for tweets about bank routine operating activities

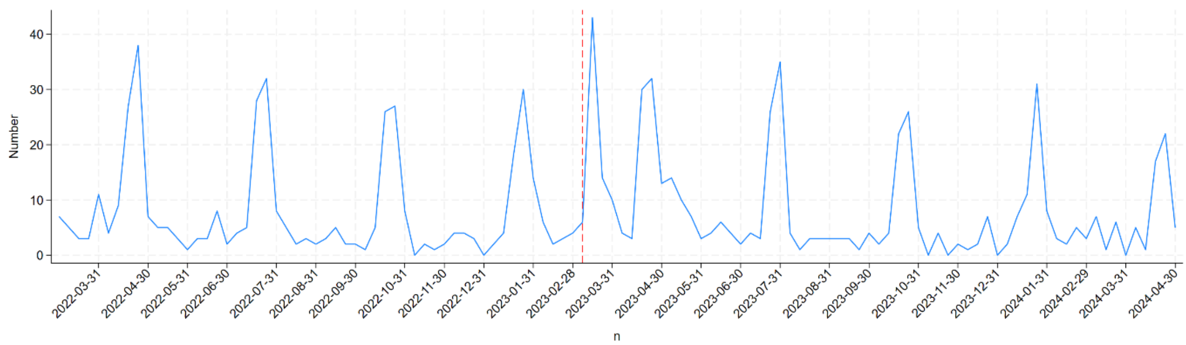


Panel E: Top words for other tweets relevant to depositors

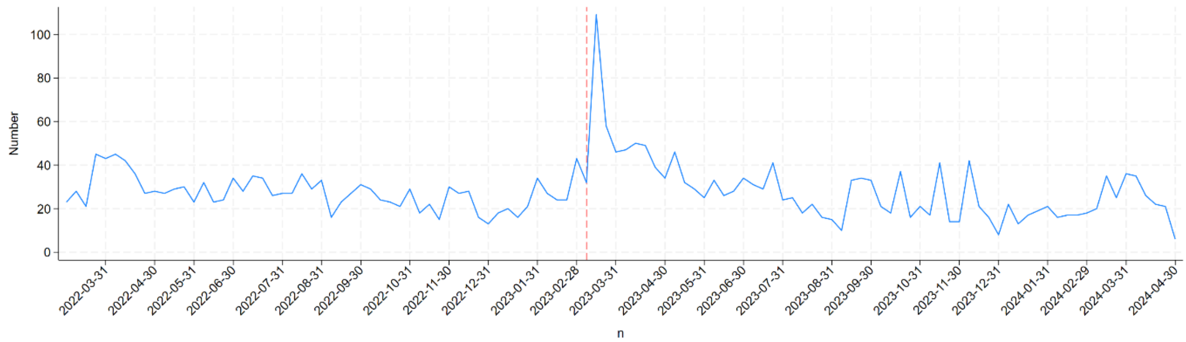
Figure 2: The Weekly Frequency of Bank Tweets

This figure plots the weekly distribution of bank tweets in the sample period. Panel A shows tweets conveying financial information about bank fundamental performance. Panel B shows tweets conveying non-financial information about bank fundamental performance. Panel C shows tweets about the banking industry conditions. Panel D shows tweets about bank routine operating activities. Panel E shows tweets about other topics that may be relevant to depositors. The red dashed line marks the onset of the banking crisis.

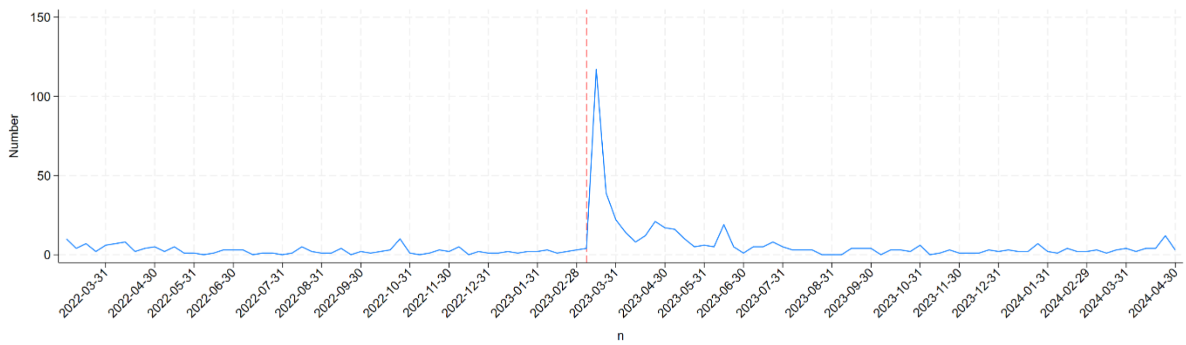
Panel A: Tweets conveying financial information on bank fundamental performance



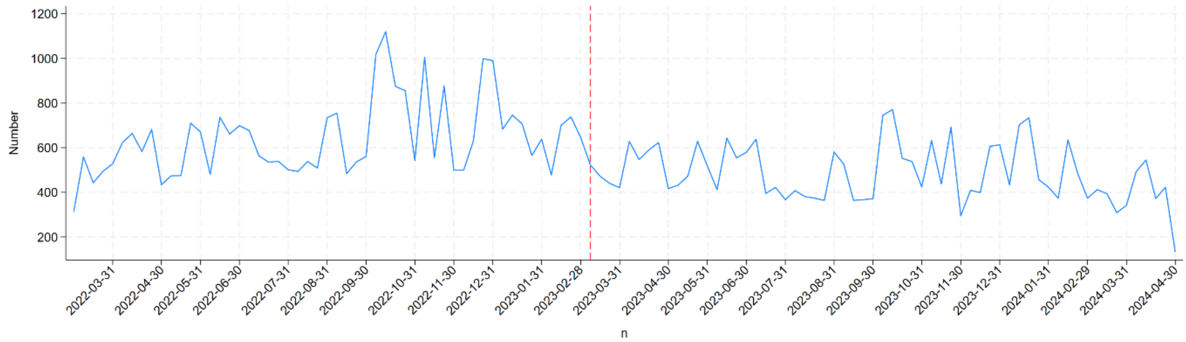
Panel B: Tweets conveying *non*-financial information on bank fundamental performance



Panel C: Tweets about the banking industry conditions



Panel D: Tweets about bank routine operating activities



Panel E: Other tweets relevant to depositors

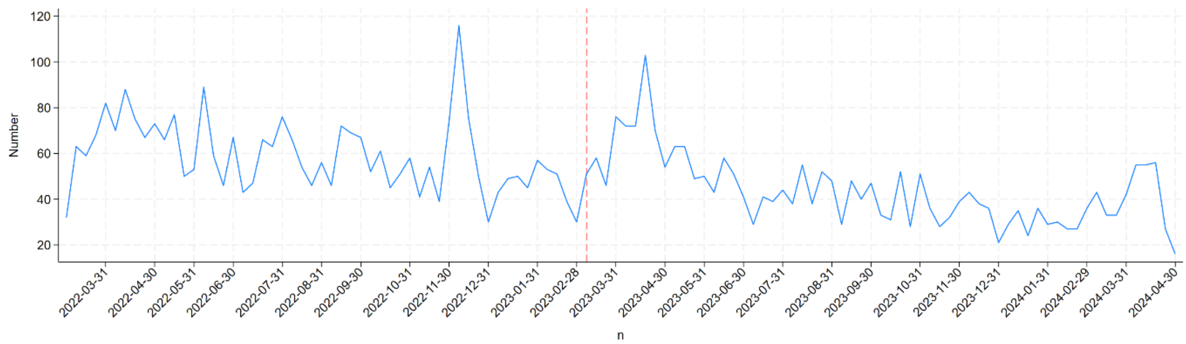


Table 1: Descriptive Statistics for Bank Tweets

Panel A (B) shows the content features at the tweet level for all tweets posted during the non-crisis (crisis) period.

Panel A: Tweet-level content features for all tweets posted during the non-crisis period

Tweet Categories	N	URL Link	CEO Statements	Tone	Original	ViewN	LikeN
Financial Information on Bank Fundamental Performance	780	0.778	0.168	0.409	0.887	467.499	3.010
Non-Financial Information on Bank Fundamental Performance	2,752	0.497	0.067	0.657	0.907	2,546.279	2.586
Banking Industry Conditions	355	0.499	0.307	0.293	0.651	187.470	1.442
Bank Routine Operating Activities	59,576	0.525	0.000	0.370	0.976	7,676.406	1.513
Others	5,255	0.467	0.000	0.537	0.961	1,388.044	1.346
All Tweets Relevant to Depositors	68,420	0.522	0.006	0.394	0.970	6,897.570	1.557

Panel B: Tweet-level content features for all tweets posted during the crisis period

Tweet Categories	N	URL Link	CEO Statements	Tone	Original	ViewN	LikeN
Financial Information on Bank Fundamental Performance	140	0.650	0.157	0.522	0.843	1,034.493	3.871
Non-Financial Information on Bank Fundamental Performance	422	0.514	0.102	0.654	0.891	346.356	2.019
Banking Industry Conditions	237	0.502	0.232	0.327	0.641	278.857	2.418
Bank Routine Operating Activities	4,064	0.586	0.004	0.414	0.970	13,292.300	1.159
Others	532	0.421	0.006	0.508	0.953	162.385	0.921
All Tweets Relevant to Depositors	5,273	0.563	0.021	0.440	0.951	10,324.300	1.309

Table 2: Descriptive Statistics for the Determinant Analysis

Panel A reports summary statistics for the main variables in the sample used in the determinants analysis. Panel B presents Pearson correlations among the main variables. Correlations in bold are statistically significant at the 5% level or lower.

Panel A: Summary statistics

Variables	obs	mean	sd	max	min	p25	p50	p75
TweetFinN	11,495	0.070	0.308	2.000	0.000	0.000	0.000	0.000
TweetNonFinN	11,495	0.259	0.668	4.000	0.000	0.000	0.000	0.000
TweetIndN	11,495	0.032	0.177	1.000	0.000	0.000	0.000	0.000
TweetOperationN	11,495	5.416	6.590	31.000	0.000	0.000	3.000	8.000
TweetOtherN	11,495	0.477	0.996	5.000	0.000	0.000	0.000	1.000
TweetFinN (Crisis)	889	0.133	0.420	2.000	0.000	0.000	0.000	0.000
TweetNonFinN (Crisis)	889	0.442	0.877	4.000	0.000	0.000	0.000	1.000
TweetIndN (Crisis)	889	0.142	0.349	1.000	0.000	0.000	0.000	0.000
TweetOperationN (Crisis)	889	4.549	5.833	31.000	0.000	0.000	3.000	7.000
TweetOtherN (Crisis)	889	0.569	1.066	5.000	0.000	0.000	0.000	1.000
HighPreUDR	11,495	0.250	0.433	1.000	0.000	0.000	0.000	0.000
PreUDR	11,495	0.458	0.139	0.877	0.140	0.363	0.449	0.540
PreMTML	11,495	-0.115	0.033	-0.027	-0.180	-0.140	-0.111	-0.098
Healthy	11,495	0.499	0.500	1.000	0.000	0.000	0.000	1.000
ROE	11,495	0.120	0.086	0.483	-0.145	0.076	0.113	0.156
Size	11,495	14.084	1.620	19.624	11.525	12.957	13.758	14.828
NPL	11,495	0.005	0.006	0.036	0.000	0.001	0.003	0.006
LoanGrowth	11,495	0.075	0.088	0.461	-0.098	0.023	0.059	0.107
CapitalRatio	11,495	0.093	0.027	0.188	0.033	0.076	0.090	0.106
CILoans	11,495	0.062	0.097	0.411	0.000	0.000	0.000	0.111
RealEstateLoans	11,495	0.748	0.176	0.994	0.045	0.675	0.785	0.867
UnusedCommitments	11,495	0.046	0.060	0.376	0.000	0.011	0.031	0.058
WholesaleFunding	11,495	0.147	0.090	0.448	0.009	0.079	0.131	0.197
DepositRate	11,495	0.015	0.011	0.045	0.001	0.005	0.014	0.023
StdWriteoff	11,495	0.003	0.004	0.026	0.000	0.001	0.001	0.003
EA	11,495	0.692	0.462	1.000	0.000	0.000	1.000	1.000

Panel B: Pearson correlations

	TweetFinN	*TweetNonFinN*	*TweetIndN*	*TweetOperationN*	*TweetOtherN*	*HighPreUDR*	*PreUDR*	*PreMTML*	*LowPreMTML*	*ROE*
TweetNonFinN	**0.211*****									
TweetIndN	**0.242*****	**0.214*****								
TweetOperationN	**0.069*****	**0.206*****	**0.052*****							
TweetOtherN	**0.065*****	**0.208*****	**0.073*****	**0.431*****						
HighPreUDR	**0.123*****	**0.071*****	**0.064*****	**-0.045*****	**-0.051*****					
PreUDR	**0.181*****	**0.130*****	**0.096*****	**-0.031*****	**-0.027*****	**0.756*****				
PreMTML	**0.070*****	**0.057*****	**0.044*****	-0.017	-0.012	**0.192*****	**0.182*****			
LowPreMTML	**0.119*****	**0.072*****	**0.050*****	**0.029*****	0.015	**0.202*****	**0.221*****	**0.793*****		
ROE	**0.019****	0.006	-0.013	-0.009	-0.011	**0.049*****	0.018	**0.107*****	**0.051*****	
Size	**0.254*****	**0.136*****	**0.067*****	**0.111*****	**0.052*****	**0.243*****	**0.352*****	**0.146*****	**0.338*****	-0.003
NPL	0.003	-0.004	0.005	-0.007	0.005	-0.012	**-0.065*****	**0.155*****	**0.113*****	-0.013
LoanGrowth	-0.006	**0.028*****	**-0.019****	0.010	0.003	**0.020****	**0.033*****	**0.113*****	**0.064*****	**0.034*****
CapitalRatio	**0.046*****	0.010	0.021**	**-0.019****	**-0.038*****	**0.078*****	**0.054*****	**0.308*****	**0.258*****	**-0.211*****
CILoans	**0.203*****	**0.094*****	**0.061*****	**0.072*****	**0.029*****	**0.247*****	**0.310*****	**0.158*****	**0.275*****	**0.047*****
RealEstateLoans	**-0.139*****	**-0.054*****	**-0.063*****	**0.024****	-0.004	**-0.095*****	**-0.058*****	**-0.263*****	**-0.274*****	**-0.169*****
UnusedCommitments	**0.177*****	**0.083*****	**0.061*****	**0.041*****	**0.046*****	**0.039*****	**0.146*****	**-0.031*****	**0.104*****	**-0.083*****
WholesaleFunding	**-0.037*****	**-0.043*****	-0.009	**-0.043*****	**-0.063*****	**-0.062*****	**-0.073*****	**0.049*****	-0.003	**-0.122*****
DepositRate	**0.062*****	-0.005	**0.043*****	**-0.093*****	**-0.096*****	**0.137*****	**0.152*****	**0.180*****	**0.134*****	**-0.086*****
StdWriteoff	-0.010	0.004	-0.001	0.010	0.008	**-0.052*****	**-0.116*****	**0.114*****	**0.071*****	**0.069*****

	Size	*NPL*	*LoanGrowth*	*CapitalRatio*	*CILoans*	*RealEstateLoans*	*UnusedCommitments*	*WholesaleFunding*	*DepositRate*
NPL	**0.084*****								
LoanGrowth	-0.011	**-0.053*****							
CapitalRatio	**0.131*****	**0.157*****	**0.092*****						
CILoans	**0.617*****	**0.056*****	-0.008	**0.052*****					
RealEstateLoans	**-0.314*****	**-0.255*****	**-0.019****	**-0.048*****	**-0.343*****				
UnusedCommitments	**0.525*****	-0.012	**-0.080*****	**-0.028*****	**0.303*****	**-0.168*****			
WholesaleFunding	**-0.110*****	**0.080*****	**-0.020****	**0.035*****	**-0.145*****	**-0.027*****	**-0.092*****		
DepositRate	**0.136*****	**0.081*****	**-0.026*****	**0.099*****	**0.065*****	**-0.137*****	**-0.025*****	**0.473*****	
StdWriteoff	0.004	**0.293*****	**0.026*****	**-0.025*****	**0.058*****	**-0.349*****	**-0.100*****	**0.055*****	**0.100*****

Table 3: Pre-Crisis Uninsured Deposit Ratios and Bank Tweets During the Crisis

This table examines whether banks with higher uninsured deposit ratios at the year-end 2022 are more likely to tweet during the crisis period. It presents the OLS estimation results of Equation (1). *TweetFinN* is the number of tweets conveying financial information about bank fundamental performance in each two-month period. *TweetNonFinN* is the number of tweets conveying non-financial information about bank fundamental performance in each two-month period. *TweetIndN* is the number of tweets related to the banking industry conditions in each two-month period. *TweetOperationN* is the number of tweets related to a bank's routine operating activities in each two-month period. *TweetOtherN* is the number of tweets relevant to depositors in each two-month period. *HighPreUDR* is an indicator that equals one if a bank's uninsured deposit ratio is in the top quartile, and zero otherwise. *Crisis* is an indicator that equals one if a period falls within the regional banking crisis (i.e., from March 8 to April 30, 2023), and zero otherwise. *PostCrisis* is an indicator that equals one if a period falls after the regional banking crisis (i.e., from May 1, 2023, to April 30, 2024), and zero otherwise. In columns 2-6, we control for *HighPreUDR* multiplied by *EA,* which is an indicator that equals one if a period includes an earnings release month (i.e., January, April, July, and October), and zero otherwise. Bank and time fixed effects are included. We cluster standard errors at the bank level. *t*-statistics are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Dependent Variable =	*Tweet FinN*	*Tweet FinN*	*Tweet NonFinN*	*Tweet IndN*	*Tweet OperationN*	*Tweet OtherN*
	(1)	(2)	(3)	(4)	(5)	(6)
HighPreUDR × Crisis [1]	0.086***	0.071**	0.056	0.048*	-0.103	0.042
	(2.863)	(2.449)	(0.818)	(1.709)	(-0.313)	(0.591)
HighPreUDR × PostCrisis [2]	0.018	0.018	0.016	0.026***	0.283	0.097**
	(1.107)	(1.116)	(0.435)	(2.934)	(0.876)	(2.085)
HighPreUDR × EA		0.046*	-0.011	-0.006	0.235	0.047
		(1.938)	(-0.426)	(-0.805)	(1.602)	(1.294)
ROE	0.091*	0.090*	-0.030	-0.014	-0.438	-0.282*
	(1.681)	(1.656)	(-0.260)	(-0.570)	(-0.532)	(-1.665)
Size	-0.008	-0.008	-0.272	-0.029	0.879	-0.242
	(-0.195)	(-0.208)	(-1.635)	(-1.030)	(0.965)	(-1.611)
NPL	0.052	0.037	-0.181	0.013	-2.008	5.949**
	(0.060)	(0.043)	(-0.097)	(0.020)	(-0.120)	(2.088)
LoanGrowth	0.003	0.003	0.194**	-0.030	0.802	0.087
	(0.084)	(0.092)	(1.987)	(-1.353)	(1.038)	(0.767)
CapitalRatio	-0.247	-0.246	-1.078	-0.247	5.225	-1.976*
	(-0.771)	(-0.768)	(-1.155)	(-1.082)	(0.776)	(-1.904)
CILoans	-0.252	-0.253	-0.256	-0.114	1.267	0.436
	(-1.114)	(-1.116)	(-0.353)	(-0.607)	(0.327)	(0.644)
RealEstateLoans	0.111	0.108	-0.241	0.025	4.461*	0.440
	(1.011)	(0.982)	(-0.553)	(0.286)	(1.714)	(1.092)
UnusedCommitments	-0.897	-0.909*	0.293	0.515**	11.417	2.426**
	(-1.637)	(-1.667)	(0.173)	(2.275)	(1.485)	(2.281)
WholesaleFunding	-0.019	-0.015	0.234	-0.015	2.341	-0.530*

	(-0.215)	(-0.170)	(0.920)	(-0.252)	(1.024)	(-1.677)
DepositRate	0.949	0.940	1.803	1.306**	-11.496	2.837
	(1.246)	(1.235)	(0.652)	(1.995)	(-0.625)	(0.981)
StdWriteoff	-0.517	-0.548	2.433	0.148	30.953	1.978
	(-0.563)	(-0.592)	(0.883)	(0.224)	(0.953)	(0.496)
p-value: [1] = [2]	0.026	0.068	0.543	0.382	0.264	0.439
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Two-month Interval FE	Yes	Yes	Yes	Yes	Yes	Yes
Cluster	Bank	Bank	Bank	Bank	Bank	Bank
N	11,495	11,495	11,495	11,495	11,495	11,495
Adjusted R^2	0.433	0.434	0.285	0.176	0.644	0.343

Table 4: Cross-Sectional Analysis on Mark-to-Market Loss in the Determinant Analysis

This table presents the results of cross-sectional tests on banks' mark-to-market losses for the association between uninsured deposit ratios at the year-end 2022 and bank tweets related to financial performance and industry condition. *TweetFinN* is the number of tweets conveying financial information about bank fundamental performance in each two-month period. *TweetIndN* is the number of tweets related to the banking industry conditions in each two-month period. *HighPreUDR* is an indicator that equals one if a bank's uninsured deposit ratio is in the top quartile, and zero otherwise. *Crisis* is an indicator that equals one if a period falls within the regional banking crisis (i.e., from March 8 to April 30, 2023), and zero otherwise. *PostCrisis* is an indicator that equals one if a period falls after the regional banking crisis (i.e., from May 1, 2023, to April 30, 2024), and zero otherwise. *Healthy* is an indicator that equals one if a bank's mark-to-market loss for the year 2022 (absolute magnitude) is below the sample median, and zero otherwise. *UnHealthy* equals one minus *Healthy*. We cluster standard errors at the bank level. *t*-statistics are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Dependent Variable =	*Tweet FinN* (1)	*Tweet IndN* (2)
HighPreUDR × Crisis, Healthy [1]	0.098**	0.089**
	(2.547)	(2.366)
HighPreUDR × Crisis, UnHealthy [2]	0.007	-0.024
	(0.161)	(-0.674)
Crisis × Healthy	0.011	-0.016
	(0.506)	(-0.658)
HighPreUDR × PostCrisis	0.018	0.025***
	(1.118)	(2.925)
HighPreUDR × EA	0.046*	-0.006
	(1.937)	(-0.807)
p-value: [1] = [2]	0.107	0.025
Controls	Yes	Yes
Bank FE	Yes	Yes
Two-month Interval FE	Yes	Yes
Cluster	Bank	Bank
N	11,495	11,495
Adjusted R^2	0.434	0.177

Table 5: Descriptive Statistics for the Consequence Analysis

This table reports descriptive statistics for the bank–quarter panel used in the consequence analysis. Panels A and B present summary statistics for banks with high and low ex-ante uninsured deposit ratios, respectively.

Panel A: Bank-quarter level summary statistics (*HighPreUDR* = 1)

Variables	obs	mean	sd	max	min	p25	p50	p75
UninsuredDepositGrowth	1,763	0.014	0.084	0.403	-0.236	-0.031	0.004	0.045
InsuredDepositGrowth	1,763	0.017	0.073	0.323	-0.131	-0.016	0.004	0.031
TotalDepositGrowth	1,763	0.013	0.052	0.213	-0.091	-0.017	0.007	0.035
TweetFin	1,619	0.206	0.405	1.000	0.000	0.000	0.000	0.000
TweetOnlyFin	1,437	0.106	0.308	1.000	0.000	0.000	0.000	0.000
TweetOnlyInd	1,429	0.101	0.301	1.000	0.000	0.000	0.000	0.000
ROE	1,763	0.122	0.080	0.469	-0.131	0.077	0.115	0.156
Size	1,763	14.769	1.783	19.629	11.542	13.503	14.522	15.798
NPL	1,763	0.005	0.007	0.038	0.000	0.001	0.003	0.007
LoanGrowth	1,763	0.074	0.095	0.465	-0.103	0.017	0.056	0.110
CapitalRatio	1,763	0.097	0.029	0.188	0.033	0.079	0.093	0.110
CILoans	1,763	0.103	0.119	0.413	0.000	0.000	0.068	0.174
RealEstateLoans	1,763	0.719	0.176	0.994	0.045	0.630	0.748	0.850
UnusedCommitments	1,763	0.050	0.080	0.377	0.000	0.008	0.024	0.051
WholesaleFunding	1,763	0.140	0.092	0.452	0.009	0.071	0.121	0.185
DepositRate	1,763	0.018	0.014	0.046	0.001	0.004	0.015	0.029
StdWriteoff	1,763	0.002	0.004	0.029	0.000	0.001	0.001	0.003
Healthy	1,763	0.378	0.485	1.000	0.000	0.000	0.000	1.000
UnHealthy	1,763	0.622	0.485	1.000	0.000	0.000	1.000	1.000
HighViews	1,437	0.056	0.229	1.000	0.000	0.000	0.000	0.000
LowViews	1,437	0.050	0.218	1.000	0.000	0.000	0.000	0.000
Fin2022	1,437	0.033	0.180	1.000	0.000	0.000	0.000	0.000
NoFin2022	1,437	0.072	0.259	1.000	0.000	0.000	0.000	0.000

Panel B: Bank-quarter level summary statistics (*HighPreUDR* = 0)

Variables	obs	mean	sd	max	min	p25	p50	p75
UninsuredDepositGrowth	5,296	0.013	0.093	0.403	-0.236	-0.037	0.007	0.053
InsuredDepositGrowth	5,296	0.015	0.056	0.323	-0.131	-0.012	0.006	0.027
TotalDepositGrowth	5,296	0.012	0.043	0.213	-0.091	-0.012	0.007	0.029
TweetFin	4,810	0.081	0.274	1.000	0.000	0.000	0.000	0.000
TweetOnlyFin	4,618	0.043	0.204	1.000	0.000	0.000	0.000	0.000
TweetOnlyInd	4,904	0.099	0.299	1.000	0.000	0.000	0.000	0.000
ROE	5,296	0.112	0.082	0.469	-0.131	0.069	0.105	0.144
Size	5,296	13.861	1.493	19.629	11.542	12.834	13.557	14.511
NPL	5,296	0.005	0.007	0.038	0.000	0.001	0.003	0.007
LoanGrowth	5,296	0.069	0.087	0.465	-0.103	0.018	0.053	0.102
CapitalRatio	5,296	0.093	0.026	0.188	0.033	0.076	0.090	0.106
CILoans	5,296	0.048	0.085	0.413	0.000	0.000	0.000	0.081
RealEstateLoans	5,296	0.758	0.174	0.994	0.045	0.689	0.795	0.872
UnusedCommitments	5,296	0.044	0.052	0.377	0.000	0.012	0.033	0.059
WholesaleFunding	5,296	0.154	0.092	0.452	0.009	0.084	0.137	0.205
DepositRate	5,296	0.015	0.012	0.046	0.001	0.004	0.012	0.024
StdWriteoff	5,296	0.003	0.005	0.029	0.000	0.001	0.001	0.003
Healthy	5,296	0.498	0.500	1.000	0.000	0.000	0.000	1.000
UnHealthy	5,296	0.502	0.500	1.000	0.000	0.000	1.000	1.000
HighViews	4,618	0.016	0.124	1.000	0.000	0.000	0.000	0.000
LowViews	4,618	0.028	0.164	1.000	0.000	0.000	0.000	0.000
Fin2022	4,618	0.007	0.083	1.000	0.000	0.000	0.000	0.000
NoFin2022	4,618	0.036	0.187	1.000	0.000	0.000	0.000	0.000

Table 6: Depositor Responses to Bank Tweets on Financial Performance and Banking Industry Conditions

This table presents results on the association between bank tweets and deposit growth, separately for banks with high versus low ex-ante uninsured deposits. The dependent variables are the quarterly growth rates in uninsured deposits (columns 1–2), insured deposits (columns 3–4), and total deposits (columns 5–6). Panels A and B focus on tweets about banks' own financial performance. *TweetFin* equals one if a bank posts any tweets related to its own financial performance during the March 8–April 30, 2023 crisis window, while *TweetOnlyFin* equals one if a bank tweets about its own financial performance but does not tweet about the banking industry conditions during the crisis period. Panel C focuses on tweets about the banking industry conditions, where *TweetOnlyInd* equals one if a bank tweets about the banking industry conditions but does not tweet about its own financial performance during the same crisis window. The control group consists of banks that do not post tweets about their own financial performance or the banking industry conditions during the crisis period. *Post* equals one for the post-crisis periods. Columns 1, 3, and 5 restrict the sample to banks in the top quartile of the uninsured deposit ratio, whereas columns 2, 4, and 6 include all other banks. We include bank and quarter fixed effects to absorb time-invariant bank characteristics and time trends. Standard errors are clustered at the bank level. *t*-statistics are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Banks with financial performance tweets (*TweetFin*) and deposit flows

Dependent Variable =	*Uninsured Deposit Growth*		*Insured Deposit Growth*		*Total Deposit Growth*	
	(1)	(2)	(3)	(4)	(5)	(6)
TweetFin × Post	0.020**	0.012	-0.005	-0.011	0.010*	-0.003
	(2.270)	(1.330)	(-0.583)	(-1.504)	(1.702)	(-0.698)
ROE	-0.007	-0.006	0.070	0.033*	0.030	0.008
	(-0.167)	(-0.187)	(1.481)	(1.897)	(1.035)	(0.609)
Size	-0.050*	-0.076**	-0.030	-0.054**	-0.017	-0.049***
	(-1.897)	(-2.158)	(-0.956)	(-2.274)	(-0.815)	(-3.461)
NPL	-1.317	-0.618	-0.175	0.054	-0.899*	-0.161
	(-1.593)	(-1.229)	(-0.298)	(0.199)	(-1.812)	(-0.786)
LoanGrowth	0.242***	0.202***	0.183***	0.223***	0.189***	0.189***
	(6.188)	(7.243)	(4.684)	(13.046)	(8.145)	(15.350)
CapitalRatio	0.828***	0.928***	0.614**	0.606***	0.913***	0.757***
	(2.919)	(4.445)	(1.978)	(4.385)	(4.288)	(7.270)
CILoans	-0.042	-0.116	-0.096	0.026	-0.080	-0.010
	(-0.460)	(-1.373)	(-1.161)	(0.275)	(-1.272)	(-0.169)
RealEstateLoans	-0.039	0.074	-0.234**	-0.068	-0.096	-0.024
	(-0.351)	(0.968)	(-2.448)	(-1.507)	(-1.535)	(-0.658)
UnusedCommitments	-0.323**	0.258	0.113	-0.080	-0.097	0.006
	(-2.137)	(1.311)	(0.899)	(-0.543)	(-1.096)	(0.073)
WholesaleFunding	0.308***	0.397***	0.175**	0.171***	0.239***	0.265***
	(4.126)	(7.697)	(2.466)	(4.832)	(6.235)	(12.135)
DepositRate	2.122***	1.860***	1.711***	1.645***	1.711***	1.739***
	(3.986)	(3.602)	(2.646)	(5.217)	(4.713)	(7.920)
StdWriteoff	-1.129	-0.087	1.023	-0.292	-0.886	-0.033

	(1)	(2)	(3)	(4)	(5)	(6)
	(-0.760)	(-0.155)	(0.741)	(-0.923)	(-1.396)	(-0.138)
Sample (*HighPreUDR*)	Yes	No	Yes	No	Yes	No
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
N	1,619	4,810	1,619	4,810	1,619	4,810
Adjusted R^2	0.115	0.060	0.097	0.175	0.206	0.257

Panel B: Banks with only financial performance tweets (*TweetOnlyFin*) and deposit flows

Dependent Variable =	*Uninsured Deposit Growth*		*Insured Deposit Growth*		*Total Deposit Growth*	
	(1)	(2)	(3)	(4)	(5)	(6)
TweetOnlyFin × Post	0.025**	0.014	0.001	0.001	0.017**	0.003
	(2.360)	(1.222)	(0.082)	(0.150)	(2.149)	(0.588)
Sample (*HighPreUDR*)	Yes	No	Yes	No	Yes	No
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
N	1,437	4,618	1,437	4,618	1,437	4,618
Adjusted R^2	0.127	0.060	0.122	0.175	0.226	0.260

Panel C: Banks with only industry condition tweets (*TweetOnlyInd*) and deposit flows

Dependent Variable =	*Uninsured Deposit Growth*		*Insured Deposit Growth*		*Total Deposit Growth*	
	(1)	(2)	(3)	(4)	(5)	(6)
TweetOnlyInd × Post	0.002	0.006	0.012	-0.001	0.008	0.000
	(0.162)	(1.112)	(0.912)	(-0.258)	(1.063)	(0.163)
Sample (*HighPreUDR*)	Yes	No	Yes	No	Yes	No
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
N	1,429	4,904	1,429	4,904	1,429	4,904
Adjusted R^2	0.135	0.054	0.102	0.171	0.225	0.250

Table 7: Cross-Sectional Analysis in the Consequence Analysis

This table presents results on whether the association between bank financial performance tweets and deposit growth varies with ex-ante bank health (Panel A) or tweet characteristics (Panels B and C). The dependent variables are the quarterly growth rates in uninsured deposits (column 1) and total deposits (column 2). We restrict the sample to banks in the top quartile of the uninsured deposit ratio. *TweetOnlyFin* equals one if a bank tweets about its own financial performance but does not tweet about the banking industry conditions during the March 8 to April 30, 2023 crisis window. The control group consists of banks that do not post tweets about their own financial performance or the banking industry conditions during the crisis period. *Post* equals one for the post-crisis periods. In Panel A, *TweetOnlyFin×Post, Healthy (Unhealthy)* equals *TweetOnlyFin×Post* multiplied by an indicator that the bank's pre-crisis mark-to-market loss (in absolute magnitude) is below (above) the sample median. In Panel B, *TweetOnlyFin×Post, HighViews (LowViews)* equals *TweetOnlyFin×Post* multiplied by an indicator that the number of Twitter user views of the bank's financial performance tweets is above (below) the sample median. In Panel C, *TweetOnlyFin×Post, Fin2022 (NoFin2022)* equals *TweetOnlyFin×Post* multiplied by an indicator that the bank does (does not) reference its 2022 financial results in its financial performance tweets. We include bank and quarter fixed effects to absorb time-invariant bank characteristics and time trends. Standard errors are clustered at the bank level. *t*-statistics are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Cross-sectional analysis by mark-to-market loss

Dependent Variable =	*Uninsured Deposit Growth*	*Total Deposit Growth*
	(1)	(2)
TweetOnlyFin × Post, Healthy [1]	0.042*	0.034**
	(1.936)	(2.061)
TweetOnlyFin × Post, UnHealthy [2]	0.016	0.008
	(1.369)	(1.044)
Post, Healthy	-0.016*	-0.005
	(-1.781)	(-0.880)
Sample (*HighPreUDR*)	Yes	Yes
p-value:[1] = [2]	0.300	0.169
Controls	Yes	Yes
Bank FE	Yes	Yes
Quarter FE	Yes	Yes
N	1,437	1,437
Adjusted R^2	0.128	0.226

Panel B: Cross-sectional analysis by tweet views

Dependent Variable =	*Uninsured Deposit Growth*	*Total Deposit Growth*
	(1)	(2)
TweetOnlyFin × Post, HighViews [1]	0.040***	0.025**
	(2.920)	(2.203)
TweetOnlyFin × Post, LowViews [2]	0.005	0.006
	(0.415)	(0.685)
Sample (*HighPreUDR*)	Yes	Yes
p-value:[1] = [2]	0.058	0.161
Controls	Yes	Yes
Bank FE	Yes	Yes
Quarter FE	Yes	Yes

N	1,437	1,437
Adjusted R^2	0.128	0.226

Panel C: Cross-sectional analysis by reference to 2022 financial results

Dependent Variable =	*Uninsured Deposit Growth*	*Total Deposit Growth*
	(1)	(2)
TweetOnlyFin × Post, Fin2022 [1]	0.044**	0.037**
	(2.365)	(2.418)
TweetOnlyFin × Post, NoFin2022 [2]	0.016	0.007
	(1.356)	(0.940)
Sample (*HighPreUDR*)	Yes	Yes
p-value:[1] = [2]	0.207	0.082
Controls	Yes	Yes
Bank FE	Yes	Yes
Quarter FE	Yes	Yes
N	1,437	1,437
Adjusted R^2	0.127	0.228

Table 8: Depositor Responses to Bank Financial Performance Tweets Using Entropy-Balanced Control Sample

This table presents results on the association between banks' financial performance tweets and deposit growth using the entropy-balanced control sample. The dependent variables are the quarterly growth rates in uninsured deposits (columns 1–2), insured deposits (columns 3–4), and total deposits (columns 5–6). *TweetOnlyFin* equals one if a bank tweets about its own financial performance but does not tweet about the banking industry conditions during the March 8 to April 30, 2023 crisis window. The control group consists of banks that do not post tweets about their own financial performance or the banking industry conditions during the crisis period. *Post* equals one for the post-crisis periods. Columns 1, 3, and 5 restrict the sample to banks in the top quartile of the uninsured deposit ratio, whereas columns 2, 4, and 6 include all other banks. We include bank and quarter fixed effects to absorb time-invariant bank characteristics and time trends. Standard errors are clustered at the bank level. *t*-statistics are in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Dependent Variable =	*Uninsured Deposit Growth*		*Insured Deposit Growth*		*Total Deposit Growth*	
	(1)	(2)	(3)	(4)	(5)	(6)
TweetOnlyFin × Post	0.023**	0.009	0.005	0.007	0.017**	0.003
	(2.039)	(0.728)	(0.445)	(1.362)	(2.190)	(0.753)
Sample (*HighPreUDR*)	Yes	No	Yes	No	Yes	No
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
N	1,437	4,618	1,437	4,618	1,437	4,618
Adjusted R^2	0.241	0.164	0.148	0.173	0.328	0.309

Table 9: Twitter User Reactions to Bank Financial Performance Tweets

This table presents Twitter users' reactions to tweets about banks' own financial performance. We estimate a stacked difference-in-differences specification following Baker et al. (2022). The sample consists of 27 stacks corresponding to the number of days on which at least one bank issues its first tweet about its financial performance. Each stack includes banks that post the relevant tweet for the first time and banks that never post any tweets related to either financial performance or the banking industry conditions during the crisis. In each stack, a bank has two observations: one for the three days before the stack day and one for the three days after (including the stack day). Twitter user tweets are aggregated at the bank level within each three-day window. User discussions are measured using three variables: (1) *Positive*, an indicator equal to one if there is at least one user tweet with a positive tone over the three-day window, and zero otherwise; (2) *PositiveN*, the number of user tweets with a positive tone over the three-day window; and (3) *PositiveRatio*, the number of user tweets with a positive tone divided by the total number of user tweets over the three-day window. *TweetFin* equals one if a bank posts any tweets related to its own financial performance during March 11 to April 28, 2023. *PostFirst* is an indicator that equals one for the three-day window after stack day *s* and zero for the three-day window before stack day *s*. All columns restrict the sample to banks in the top quartile of the uninsured deposit ratio. All specifications include stack-bank and stack-period fixed effects. Standard errors are clustered at the bank level. t-statistics are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Dependent Variable =	*Positive*	*PositiveN*	*PositiveRatio*
	(1)	(2)	(3)
TweetFin × PostFirst	0.125**	0.331**	0.127**
	(2.147)	(2.391)	(2.438)
Sample (*HighPreUDR*)	Yes	Yes	Yes
Stack-Bank FE	Yes	Yes	Yes
Stack-Period FE	Yes	Yes	Yes
N	9,738	9,738	9,738
Adjusted R^2	0.443	0.427	0.342

Table 10: Stock Market Reactions to Bank Financial Performance Tweets

This table presents stock market reactions to banks' financial performance tweets. We obtain daily stock returns from CRSP and link banks' RSSD IDs to CRSP permnos using the New York Fed's linking table. For each bank, we define the event date as the day of its first financial performance tweet and compute abnormal returns around the event using banking industry-adjusted benchmarks. We exclude the tweeting banks to calculate the daily return of the banking industry. We report the abnormal returns in the pre-event window [-2, 0] and post-event window [+1, +2], along with the associated *t*-statistics. We further partition the sample by banks' ex-ante reliance on uninsured funding. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

	CARs		
	(1)	(2)	(3)
[-2, 0]	-0.045**	-0.128*	-0.019*
	(-2.430)	(-1.906)	(-1.924)
[+1, +2]	0.018*	0.052*	0.007
	(1.728)	(2.077)	(0.679)
Sample	Full Sample	High PreUDR	Low PreUDR
N	46	11	35

Online Appendix A: Replication of Main Results Using a Dictionary-Based Approach to Identify Depositor-Relevant Tweets

A1: Dictionary to identify tweets conveying financial information about bank fundamental performance and banking industry conditions

Financial Information about Bank Fundamental Performance	#annualreport, #earnings, #earnings_release_conference, #earningscall, #earningsreport, #earningssantander, #financialresults, #sttannualreport, 1q2023, 1st_quarter, 2021_annual, 2021_annual_report, 2022_annual_report, 2022_earnings, 2023_annual_report, 2023_earnings, 2023_financial_results, 2023_results, 23_earnings, 2nd_quarter, 2q2023, 3rd_quarter, 4th_quarter, announce_first, announced_first_quarter, announced_second, asset_quality, balance_sheet, bank_reports, billion_assets, capitalization, capitalized_well, conference_call, credit_quality, december_31_2022, declares_quarterly, deposit_balances, deposit_base, deposit_growth, earnings_call, earnings_growth, earnings_per_share, earnings_quarter, earnings_read_full, earnings_release, earnings_release_conference, earnings_report, earnings_results, et_conference_call, financial_performance, financial_position, financial_report, financial_results, financial_results_call, financial_strength, first_quarter, first_quarter_2022, first_quarter_2023, first_quarter_2024, first_quarter_earnings, first_quarter_results, fourth_quarter, fourth_quarter_2022, fourth_quarter_2023, full_year_2022, insured_deposits, insured_deposits, million_assets, million_earnings_per, net_income, net_interest_income, net_interest_margin, per_diluted_share, per_share, profit, profitability, q1_2022, q1_2023, q1_2024, q1_earnings, q2_2022, q2_2023, q3_2022, q3_2023, q3_earnings, q4_2022, q4_2023, quarter_2022, quarter_2022_financial, quarter_2023_financial, quarter_earnings, quarter_financial, quarter_financial_results, quarter_year, read_full_report, reported_financial_results, reports_first_quarter, reports_net_income, reports_second_quarter, revenues, safety_soundness, second_quarter, second_quarter_2022, second_quarter_2023, shareholders_meeting, strong_performance, third_quarter, third_quarter_2022, third_quarter_2023, total_assets, total_deposits, uninsured_deposits, uninsured_deposits, well_capitalized, well_capitalized_well
Banking Industry Conditions	#communitybankdifference, #firstrepublicbank, #svb, @signaturebnkchi, @silvergatebank, bank_failures, bank_recently, banking_system, best_banking_industry, big_banks, big_news, challenging_times, closures, community_banking_industry, current_banking, discuss_recent, discusses_recent, industry_events, industry_news, industry_trends, large_banks, light_recent, recent_bank, recent_bank_failures, recent_banking, recent_events, recent_industry, recent_news, silvergate, silicon_valley_bank, signature_bank, solid_community_bank, svb, turmoil, turbulent, turbulence, uncertain_times

A2: Replication of Table 3 and Table 6 using a dictionary-based approach

Panel A (B) reports replicated results of Table 3 (Table 6) using a dictionary-based approach to identify bank tweets.

Panel A: Determinant analysis on pre-crisis uninsured deposit ratios and bank tweets

Dependent Variable =	*Tweet FinN*	*Tweet IndN*
	(1)	(2)
HighPreUDR × Crisis [1]	0.069*	0.043
	(1.960)	(1.536)
HighPreUDR × PostCrisis [2]	0.015	0.015
	(0.785)	(1.598)
HighPreUDR × EA	0.041*	-0.015
	(1.761)	(-1.377)
p-value: [1] = [2]	0.094	0.302
Controls	Yes	Yes
Bank FE	Yes	Yes
Two-month Interval FE	Yes	Yes
Cluster	Bank	Bank
N	11,495	11,495
Adjusted R^2	0.363	0.123

Panel B1: Depositor responses to bank tweets on financial performance

Dependent Variable =	*Uninsured Deposit Growth*		*Insured Deposit Growth*		*Total Deposit Growth*	
	(1)	(2)	(3)	(4)	(5)	(6)
TweetOnlyFin × Post	0.019**	-0.003	-0.006	-0.002	0.007	-0.002
	(2.259)	(-0.421)	(-0.699)	(-0.486)	(1.460)	(-0.518)
Sample (*HighPreUDR*)	Yes	No	Yes	No	Yes	No
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
N	1,630	5,244	1,630	5,244	1,630	5,244
Adjusted R^2	0.114	0.059	0.094	0.177	0.218	0.253

Panel B2: Depositor responses to bank tweets on the banking industry conditions

Dependent Variable =	*Uninsured Deposit Growth*		*Insured Deposit Growth*		*Total Deposit Growth*	
	(1)	(2)	(3)	(4)	(5)	(6)
TweetOnlyInd × Post	0.008	0.006	0.010	-0.005	0.007	-0.003
	(0.560)	(0.872)	(0.809)	(-1.070)	(1.018)	(-0.819)
Sample (*HighPreUDR*)	Yes	No	Yes	No	Yes	No
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
N	1,531	5,316	1,531	5,316	1,531	5,316
Adjusted R^2	0.136	0.051	0.107	0.157	0.229	0.227

Online Appendix B: Univariate Changes in Uninsured Deposit Growth

Panel A (B) reports univariate changes in uninsured deposit growth rates from the pre- to post-crisis periods, comparing banks that only tweet about their financial performance (about the banking industry conditions) with those that do not. *t*-statistics are reported in parentheses.

Panel A: Univariate changes in uninsured deposit growth (*TweetOnlyFin*)

	HighPreUDR = 0			*HighPreUDR* = 1		
	(a) Pre	(b) Post	(c) (b)- (a)	(a) Pre	(b) Post	(c) (b)- (a)
(i) *TweetOnlyFin* = 0	0.016	0.009	-0.007**	0.017	0.014	-0.003
			(-2.357)			(-0.642)
(ii) *TweetOnlyFin* = 1	0.014	0.010	-0.004	0.000	0.013	0.013
			(-0.302)			(1.184)
Difference (ii) – (i)	-0.002	0.001	**0.003**	-0.017	-0.001	**0.016**
	(-0.198)	(0.085)	(0.207)	(-1.618)	(-0.160)	(1.347)

Panel B: Univariate changes in uninsured deposit growth (*TweetOnlyInd*)

	HighPreUDR = 0			*HighPreUDR* = 1		
	(a) Pre	(b) Post	(c) (b)- (a)	(a) Pre	(b) Post	(c) (b)- (a)
(i) *TweetOnlyInd* = 0	0.016	0.009	-0.007**	0.017	0.014	-0.003
			(-2.357)			(-0.642)
(ii) *TweetOnlyInd* = 1	0.014	0.012	-0.002	0.031	0.013	-0.017
			(-0.265)			(-0.936)
Difference (ii) – (i)	-0.002	0.003	**0.005**	0.013	-0.001	**-0.014**
	(-0.326)	(0.423)	(0.587)	(1.155)	(-0.110)	(-0.759)

Online Appendix C: Dictionary to Identify Relevant User Tweets

Balance Sheet	#fdic, #liquidity, #liquiditycoverageratio, #liquiditycrisis, @fdic_oig, @fdicgov, balance sheet, balance sheets, capital ratio, capital ratios, fdic insurance, fdic insured, held to maturity, hold to maturity, insured deposit, insured deposits, liquidity, liquidity concern, liquidity concerns, liquidity coverage, liquidity crisis, liquidity fear, liquidity fears, liquidity issue, liquidity issues, liquidity position, liquidity positions, liquidity problem, liquidity problems, liquidity risk, liquidity risks, mark to market, mbs, mismatch of duration, mortgage backed securities, stress test, stress tested, stress testing, stress tests, tier 1, uninsured deposit, uninsured deposits, well capitalized, well positioned
Run Behavior	#bankrun, #bankrun2023, #bankruns, #bankruns2023, #runonbanks, #runonthebank, bank run, bank runs, deposit run, deposit runs, panic, run on banks
Industry and Systemic Risk	#bailout, #bailoutamericans, #bailouts, #bankbailout, #bankcollapse, #bankcrash, #bankfailure, #bankfailures, #bankingcrisis, #bankruptcy, #bigbanks, #contagion, #economiccrash, #economiccrisis, #financialcrisis, #largebanks, #marketvolatility, #nobailouts, #recession, #turmoil, #volatility, #wallstreetbailout, back stop, bailout, bailouts, bank closure, bank closures, bank failure, bank failures, banking crisis, big banks, bankruptcy, contagion, financial crisis, large banks, meltdown, recession, systemic risk, systemic risks, systemically important, too big to fail, turmoil, volatility
2023 Banking Crisis	#signature, #signature_bank, #signaturebank, #signaturebankcollapse, #silicon_valley_bank, #siliconvalleybank, #silvergate, #silvergatebank, #svb, #svbcollapse, #sivb, $sivb, @signaturebank, @silvergatebank, @svb_financial, recent event, recent events, signature bank, silicon valley bank, silvergate bank, svb