Social Media as a Bank Run Catalyst

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July 7, 2023

Abstract

After the run on Silicon Valley Bank (SVB), U.S. regional banks entered a period of significant distress. We quantify social media's role in this distress using comprehensive Twitter data. During the SVB run period, banks in the top tercile of *pre-run* Twitter exposure lost 6.6 percentage points more stock market value, an effect unexplained by mark-to-market losses and uninsured deposits. Moreover, social media amplifies balance sheet risks and is associated with greater outflow of uninsured deposits during Q1 2023. During the run period, high Twitter message volume in the past four hours predicts hourly stock market losses, especially for banks with high balance sheet risk. At even higher frequency, negative sentiment tweets in the run period translate into immediate stock market losses. These high frequency effects are stronger for tweets with contagion keywords and tweets by tech startup users who are likely depositors in SVB.

Keywords: Bank Runs; Social Media; Social Finance; FinTech
JEL Codes: F30; F36; G38; Q50

1 Introduction

This paper investigates social media's role in the bank run on Silicon Valley Bank (SVB) and the distress of regional banks in the wake of SVB's failure on March 10, 2023. SVB's failure was preceded by a flurry of Twitter activity by apparent depositors who openly used words like "withdraw" in their tweets. The openness and speed of this coordination around a bank run is unprecedented, which led to immediate discussions about contagion to other banks. Indeed, given the potential for bank runs as an equilibrium (Diamond and Dybvig, 1983) and the role communication can play in models of such runs (Goldstein and Pauzner, 2005; Angeletos and Werning, 2006), observers were quick to suggest that social media fueled the run on SVB. Using comprehensive Twitter data, this paper shows that social media contributed to the run on SVB, *and* more importantly, social media amplified the severity of the episode for other banks.

To articulate why social media can amplify bank run risk, consider the model intuition in Jiang, Matvos, Piskorski, and Seru (2023b) who focus on the run risk originating from uninsured deposits and mark-to-market losses. They show formally that bank run risk depends on depositors' beliefs about the fraction of uninsured depositors s who request to withdraw their deposits, which is driven partly by expectations of bank health. Jiang et al. (2023b) simulate scenarios where all or half of uninsured deposits run (i.e., $s = 1$ and $s = 0.5$) to gain an understanding of system-wide bank run risk. Of course, s varies across banks (i.e., s_i). We argue that greater exposure to social media increases communication during the run, which amplifies bank run risk by increasing s_i.

Our results support this idea using data on tweets about U.S. banks and bank stock returns collected from FirstRate Data. Since high-frequency deposit outflow data are not readily available, we proxy for run severity using bank stock market declines during the run period. We estimate that banks in the top tercile of preexisting Twitter conversation have a 6.6 percentage points larger stock market loss from March 1 through March 14. This main effect is greater than the decline in bank stock prices for a standard deviation increase in uninsured deposits, and it is also robust to controlling for uninsured deposits. Consistent with Jiang et al. (2023b), we find that mark-to-market losses on their own do not explain bank exposure to run risk. Rather, the interaction between mark-to-market losses and the percentage of uninsured deposits – which we dub 'balance sheet risk' – matters for the decline in bank stock prices during the run.

More importantly, we find that pre-run Twitter exposure *interacts* significantly with mark-to-market losses and uninsured deposits to predict larger run period bank stock losses. Moreover, the main effects of uninsured deposits are insignificant and small when including the interaction with pre-run Twitter exposure. Further, the findings are nearly identical if we measure pre-run Twitter exposure using alternative pre-periods, dating back to October 2022. We also obtain similar findings after dropping large banks that experienced a "flight to safety" during the run period (Caglio, Dlugosz, and Rezende, 2023).

Next, we estimate an analogous cross-sectional specification, but with percentage of deposit outflows during Q1 2023 as the dependent variable. We find that high pre-run Twitter exposure predicts more deposit outflows of uninsured deposits, particularly if the bank relied on a high fraction of uninsured deposits and had larger mark-to-market losses on its balance sheet. Although the deposit data are at the quarterly frequency, the consistency of this evidence with our main tests helps to validate our approach to proxy for run severity using run period stock market losses.

We also analyze the content of the conversation surrounding the run. We find that most of the stock market declines associated with pre-run Twitter exposure are driven by banks with more intensive "run behavior" discussions during the run period (e.g., tweets that mention "withdraw"). For example, from March 8 through March 13, users posted 6,528 'run' tweets about SVB, which is roughly five times the number of the next most run discussed ticker (i.e., First Republic Bank, FRC, which also had a notable run discussion and failed on May 1, 2023). We see a similar pattern with tweets that mention banking contagion: SVB had 9,662 such tweets during the run period. However, the mechanism linking pre-run Twitter exposure to run-based tweets and bank run price declines is not limited to SVB. In a cross-sectional regression, we find that controlling for in-the-run discussion of "run behavior" and "contagion" significantly reduces the coefficient on pre-run Twitter exposure.

Going further, we exploit the detailed and high frequency nature of the Twitter data to provide evidence on the origins and extent of Twitter conversation during the run. We note that what matters for run risk is conversation *among depositors*. In the Twitter data, we track conversations about SVB's ticker "SIVB" separately from more general conversations about SVB (i.e., "SVB," "Silicon Valley Bank," etc.) to distinguish investor-contributed tweets from general conversation. As we show in Figure 1, which plots SVB-related tweets from March 8 through March 10, the conversation surrounding SVB began with tweets that reference the ticker SIVB. These investorcentric conversations were followed by a spike in general tweets about the bank later in the day. This pattern is consistent with depositors communicating on Twitter about withdrawing their deposits from the bank after investment-specific tweets alerted them to issues at the bank. The vast majority of pre-run tweets are never revisited during the run period. For those that are, their retweets spike after the run begins, reflecting social propagation of information. Though retweets are often informative, we also find unequivocal examples of the propagation of misinformation during the run. Overall, these findings show that Twitter facilitates both information sharing and the propagation of misinformation.

SVB's depositors were highly concentrated in the 'tech' start-up community. Due to the highly networked nature of this community, encouraged by venture capital firms, these depositors were not only concentrated in their deposits in SVB, but they also communicate often on Twitter. We classify startup community users using startup and founder words in user profiles (e.g., "entrepreneur" or "founder"). Consistent with the startup community playing a central role in the bank run, startup community tweets spike distinctly after the initial increase in tweet volume, and they are more likely to mention SVB than SIVB (see Figure 2). In the cross-section of banks, we then repeat the main analysis, based on pre-run exposure to the startup community, and the main findings strengthen. These findings point to the importance of highly concentrated and highly networked communication for bank run risk, beyond SVB.

Unlike the main tests that rely on pre-run Twitter exposure, one concern with these contextual analyses is that it is unclear whether the run period tweets occur before versus after the bank's stock market losses. To better understand this timing, we analyze *hourly* bank stock returns in a panel setting. First, we find a negative effect of 'balance sheet risk' — i.e., the interaction of MTM asset losses with % uninsured deposits — on bank returns, consistent with our cross-sectional tests. Crucially, this effect emerges only starting on March 09, 2023, 9am in the hourly sample.

Next, we estimate a triple-difference specification with an indicator for the run period (i.e., post-March 9, 9am), the number of tweets in the past four hours, and bank balance sheet risk. This test better distinguishes the timing of Twitter activity versus returns since it considers lagged tweet activity. We find a large, significant interaction effect of lagged number of tweets with balance sheet risk on bank returns in the run period, which supports our interpretation that Twitter conversation intensity amplified the negative effect of balance sheet risks during the SVB run. Comparing 'high' balance sheet risk banks to one another, banks in the top tercile of Twitter activity lost 15% more cumulative stock market value than banks with low Twitter activity (returns of −30% vs. −15%) between March 06 and March 14. The finding is similar after excluding SVB from the sample, which implies our findings reflect broader effects in the banking sector, beyond SVB. In robustness tests, we control for lagged bank stock returns to address concerns that tweets simply reflect past returns, and we exclude too-big-to-fail banks. The results remain unchanged.

As a final leg of our empirical analysis, we exploit the high frequency timing of tweets in tests that build on the approach in Bianchi, Cram, and Kung (2021) and Bianchi, Gómez-Cram, Kind, and Kung (2023). These tests help rule out confounding events from outside of a narrow window from 5 minutes before the tweet to 5 minutes afterwards. Using high frequency bank stock price information from FirstRate, we estimate a significant negative impact of neutral sentiment tweets on bank stock returns posted during the run period, while this effect is small and insignificant prior to the run. Additionally, tweets with more negative sentiment correspond with lower returns, especially during the run period. The impact of negative sentiment is roughly ten times stronger if the tweets are authored by someone in the 'tech' startup community or when the tweets contain words in the 'contagion' dictionary. These results are robust to excluding SVB and FRC or too-big-to fail banks from the sample. These findings reinforce our interpretation that social media helped fuel the bank run, and indeed, played this significant role by amplifying balance sheet risks beyond SVB.

Our main contribution is to provide evidence of rapid communication via social media as a bank run risk. Diamond and Dybvig (1983)'s insight is that coordination of run beliefs is foundational to bank run models. Building on this insight, scholars developed models of coordination via communication, which have enjoyed broad application in our understanding of bank runs and financial crises (Peck and Shell, 2003; Angeletos and Werning, 2006; Brunnermeier, 2009; Acemoglu, Ozdaglar, and Tahbaz-Salehi, 2015). Since the Global Financial Crisis and the rise of FinTech lenders, research has turned to investigate the risks posed by these new forms of banking (Jiang, Matvos, Piskorski, and Seru, 2020; Buchak, Matvos, Piskorski, and Seru, 2022, 2018; Fuster, Plosser, Schnabl, and Vickery, 2019), and the incentives of run-prone uninsured depositors in generating possible bank run equilibria (Egan, Hortaçsu, and Matvos, 2017; Drechsler, Savov, Schnabl, and Wang, 2023). Relative to this literature, which focuses on bank balance sheets and risk taking, our contribution is to highlight the role of social media as a communication technology that amplifies existing risks identified in the literature. The implication that social media matters for banking stability is potentially troubling because social platforms can spread inaccurate information, which could serve as a sunspot that leads to bank runs.[1]

Our research also relates to the banking literature that focuses specifically on financial contagion via social networks (Calomiris and Mason, 1997; Iyer and Puri, 2012). Like our work, this research focuses on communication as a contagion mechanism in bank runs. However, the literature's emphasis has been on how communication spreads through traditional social networks such as immigrant networks or word of mouth (e.g., Kelly and Gráda, 2000). Relative to offline social networks, social *media* has at least three features that make it more powerful as a coordination mechanism. First, social media's speed of communication is much more rapid than through personal connections. Second, information posted to Twitter is visible publicly, which transmits information well beyond close personal connections. Third, widely read tweets can be contributed by *anyone* on the platform, and thus, social media can reflect information from many sources. These aspects of social media naturally interact with one another to lead to more rapid and widespread coordination of ideas. If social media continues to be a forum for depositors to share information, this would prove to be particularly powerful mechanism that can amplify bank run risk.

There is a longstanding debate in the literature about whether runs are driven by communication about run intentions about otherwise healthy banks (Goldstein and Pauzner, 2005), or the release of information that leads to the unwinding of fundamentally insolvent banks (Calomiris and Mason, 1997). Social media can amplify bank run risks through either of these mechanisms. Relating to run intentions, social media serves as a natural and public 'sunspot' (Morris and Shin, 2000), which can coordinate depositor beliefs around the run equilibrium. Relating to the information channel, banks were troubled due to their limited hedging of interest rate risk (Jiang, Matvos, Piskorski, and Seru, 2023a), hold-to-maturity assets that had lost significant value (Granja, 2023), and exposure to commercial real estate lending (Jiang, Matvos, Piskorski, and Seru, 2023c). Rapid communication of these risks on social media could lead to faster and more effective discipline of insolvent banks, which is core to the functioning of banks (e.g., see Gorton and Pennacchi, 1990 Calomiris and Kahn, 1991, Diamond and Rajan, 2000, Pennacchi, 2006 and Granja, 2013).

[1] Other work has emphasized the role of trust in the financial system (Iyer and Puri, 2012; Traweek and Wardlaw, 2022). Indeed, trust is instrumental in encouraging participation in banking and financial markets more broadly (Gurun, Stoffman, and Yonker, 2018; Brown, Cookson, and Heimer, 2019; Stein and Yannelis, 2020; Dupont, 2022).

Our work also relates to a broader literature in economics on communication and contagion in networks (Chwe, 2000; Van Bommel, 2003; Golub and Jackson, 2010; Elliott, Golub, and Jackson, 2014; Falato, Hortacsu, Li, and Shin, 2021). With the advent of myriad technologies to communicate, there has been research into the real effects of this communication, particularly in politics (Parmelee and Bichard, 2011; Müller and Schwarz, 2021). In this respect, our contribution advances what is known about communication technologies such as radio (Strömberg, 2004) and television (Kearney and Levine, 2019), which have important effects as communication media. Notably, we closely relate to Ziebarth (2013), which studies the effect of radio on bank distress during the Great Depression. In contrast to radio, which provides sparse information and one-way communication, social media aggregates information from many sources, making it potentially a much stronger coordination device in the context of bank runs. As a communication technology, social media complements recent technological changes in banking, such as digital banking, which have been linked to destabilizing bank deposits (Koont, Santos, and Zingales, 2023).[2]

We also contribute to the social economics literature (Levy, 2021; Chetty et al., 2022a,b). In particular, we complement recent work that has emphasized social transmission of ideas and peer effects (Akçay and Hirshleifer, 2021; Hirshleifer, 2020; Kuchler and Stroebel, 2021; Cramer and Koont, 2021).[3] Bank runs are by their nature a social phenomenon, and social media is a natural place to study the formation and transmission of ideas. Much of this literature has focused on investment outcomes (Cookson, Engelberg, and Mullins, 2022; Han, Hirshleifer, and Walden, 2022; Pedersen, 2022), while only a few studies have looked into real outcomes (e.g., Hirshleifer and Plotkin, 2021; Cookson, Niessner, and Schiller, 2022). Although some research on social media has investigated political outcomes and ideologies (Müller and Schwarz, 2022), we are the first to provide direct evidence of a social transmission channel via social media for bank runs. As the financial sector is core to the macroeconomy, our finding that social media meaningfully amplifies bank run risk is a fundamental contribution.

[2] Our evidence on social media complements other research on the 2023 regional banking crisis, which revealed issues with commercial real estate lending (Jiang et al., 2023c), hold-to-maturity accounting (Granja, 2023), and interest rate hedging (Jiang et al., 2023a). Others emphasize flights to safety (Caglio et al., 2023), savings gluts (Vuillemey, 2023), the importance of interest rate hikes (Haddad, Hartman-Glaser, and Muir, 2023), and the distinction between banking on deposits versus uninsured deposits (Drechsler, Savov, and Schnabl, 2021; Drechsler et al., 2023).

[3] In a narrow sense, we relate to literature on financial social media (Chen, De, Hu, and Hwang, 2014; Giannini, Irvine, and Shu, 2019; Cookson and Niessner, 2020; Cookson, Lu, Mullins, and Niessner, 2022; Gil-Bazo and Imbet, 2022). This literature has focused on asset market effects (Renault, 2017; Cookson, Engelberg, and Mullins, 2020; Bianchi et al., 2021, 2023), whereas our focus is on the broader conversation that emerged about depositor issues.

2 Data and Measurement

2.1 Twitter Sample

Using academic access to Twitter's API, we collect all original tweets from 1 January 2020 until 13 March 2023 containing at least one cashtag ($ followed by the company's ticker) for all depository institutions with the three-digit SIC code 602, 603, or 609. The practice of using cashtags on Twitter began in 2012, and it is now commonplace to reference publicly traded companies using their cashtag. For our main sample, we focus on original tweets (i.e., no retweets) that are written in English. These sample filters yield a sample of 5,399,740 original tweets about banking firms from 2020 until March 2023. We complement our main sample with a separate sample of all cashtag-containing retweets from 1 January 2023 until 31 March 2023. Using the same filters as the main sample, this sample consists of 765,224 retweets. Tweet-level variables include the text of the tweet, a timestamp, an author identifier, and number of retweets.

In addition, we separately query author-level data for each of the 544,888 unique Twitter users who authored at least one tweet in our sample. Author-level variables provide information about the authors' accounts including number of followers, date of account creation, and a user-provided description (i.e, user biography).

For bank-day tests and cross-sectional tests, we aggregate the number of messages (of different types) to the appropriate level, but for the high-frequency analysis, we use the precise timestamp.

2.1.1 Processing and scoring of tweets

We score the sentiment of each tweet with Valence Aware Dictionary and sEntiment Reasoner (VADER), a sentiment classifier designed specifically for social media. Hutto and Gilbert (2014) propose VADER as a sentiment classifier for short messages that contain social text, like tweets, and show that it outperforms naive dictionary-based methods. Specifically, we use the VADER algorithm to compute a raw sentiment score based on the words contained in the tweet. The VADER algorithm is an aggregate of a negative component, a neutral component, and a positive component that load on negative, neutral and positive sentiment tokens, respectively. To compute sentiment, the VADER algorithm aggregates across these sub-components to form a sentiment score for each tweet, which is a number between -1 (very negative) and 1 (very positive).

For the high frequency tweet level tests, we employ the negative and positive components of the VADER scoring of the tweet as separate variables in the analysis. We do this to capture asymmetry in the impact of negative content versus positive content. In the context of sentiment analysis in accounting and finance, it is common to include positive and negative keywords separately (Loughran and McDonald, 2011, 2020).

2.1.2 Content dictionaries

We define four content dictionaries of terms used in tweets about banks during this period: "balance sheet", "cryptocurrency", "run behavior", and "contagion." We construct these dictionaries by adapting an iterative method in the spirit of Gentzkow and Shapiro (2011), which is similar to what was applied to a tweet sample by Cookson et al. (2020).

For each topic, we identify a small set of seed words. For example, the balance sheet dictionary includes 'hold-to-maturity' or 'HTM'; For run behavior, 'run' and 'get out'; For Contagion, 'systemic' or 'spillover'; For cryptocurrency, 'crypto.' The full set of seed words is italicized in the contextual dictionaries in Table 1. Using these seed words, we identify the subsample of tweets containing those words, which we use to compute the frequency distribution of words used. We identify the top 40 most *salient* words by topic in comparison to the overall distribution of words using the saliency measure from Goldsmith-Pinkham, Hirtle, and Lucca (2016). We then consolidate words into meaningful bigrams that emerged from the salience analysis (e.g., "liquidity" "management" $\rightarrow$ "liquidity management"), and eliminate terms that appear in multiple dictionaries at the same time (e.g., 'bank' appeared in all dictionaries). The resulting contextual dictionaries, summarized in the first four columns of Table 1, flag tweets that cover specific topics, which helps identify mechanisms.

In addition, we also construct a user-level dictionary by text mining the user description field for whether the user is part of the Twitter "startup community" which was a notably important subset of uninsured depositors in SVB. To do this, we employ a list of terms around the idea of "founder," "entrepreneur," and more generally, the VC-backed startup industry. This dictionary is reported in the final column of Table 1. Tweets flagged as "startup community" tweets are defined as those that are authored by a user with at least one of these terms in their user profile description.

2.2 Bank Balance Sheet Information

To measure balance sheet risk, we closely follow Jiang et al. (2023b) and obtain asset maturity and repricing data for all FDIC-insured banks from Call Reports provided on the Federal Financial Institutions Examination Council (FFIEC) website. These bank balance sheet data are available at the quarterly frequency. We first collect the value of residential mortgage backed securities (RMBS) and non-residential MBS, loans secured by family residential properties, and all other securities, loans, and leases across maturities and repricing breakdowns for Q1 of 2022. To impute changes in the value of loans and securities on the bank balance sheets since 2022:Q1, we use U.S. Treasury Bond ETFs from iShares and S&P Treasury Indices across different maturities m to match the maturity and repricing breakdowns of the bank assets. As shown in Appendix Figure A.1, Treasury Bond Indices and ETFs with the longest maturity were most strongly affected by recent interest rate increases and incurred the highest losses. Consequently, banks with a high share of long-duration assets incur the largest mark-to-market asset decline in our sample.

We estimate mark-to-market changes in the value of banks' assets between 2022:Q1 and 2023:Q1 as follows:

$$\begin{aligned}\Delta Assets\ MTM = &\sum_m \Big((RMBS_m + Mortgages_m) \times \Delta Treasury\ Price_m \times Multiplier\Big) \\ &+ \sum_m \Big(Treasuries,\ securities,\ loans_m \times \Delta Treasury\ Price_m\Big),\end{aligned} \tag{1}$$

where m indexes the maturity and repricing breakdowns (i.e., 0-3 months, 3-12 months, 1-3 years, 3-5 years, 5-10 years, and 15+ years). $\Delta Treasury\ Price_m$ is the market price change (in %) of Treasury Bonds corresponding to maturity m from 2022:Q1 to 2023:Q1. To account for repayment risk in RMBS and mortgages, we follow Jiang et al. (2023b) and construct the real-estate $Multiplier$ as the ratio of the change in the iShares MBS ETF over the change in the S&P Treasury Bond Index between 2022 and 2023 (Jiang et al. (2023b) provides more detail on the variable construction). We impute a bank's implied mark-to-market (MTM) asset value in 2023:Q1 as the 2022:Q1 value plus $\Delta Assets\ MTM$ from Equation (1), and define the variable "% Asset Decline MTM" as the % change in asset value from 2022:Q1 to 2023:Q1-MTM.

Appendix Figure A.2 shows the distribution of $\Delta Assets\ MTM$ across all FDIC-insured banks (Fig. A.2a) and across publicly listed bank holding companies (BHCs) (Fig. A.2b), which are aggregated at the bank holding company (BHC) level for BHCs with multiple FDIC-insured depository institutions. The range and mean of the distribution are comparable to the numbers documented in Jiang et al. (2023b) for both the full sample of banks and the publicly listed BHCs. Similar to Jiang et al. (2023b), we find that Silicon Valley Bank (SIVB) was not an outlier in terms of % Asset Decline MTM, with a mark-to-market loss in asset value of about 12%, which is close to the sample median. Appendix Figure A.3 displays the distribution of '% Asset Decline MTM' across bank size (i.e., asset value) percentiles. We find that medium to large size institutions (60th to 90th percentile) exhibit the highest 'balance sheet risk' due to asset value declines.

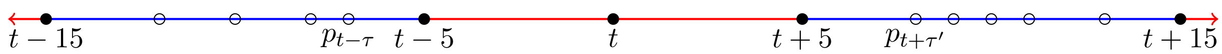
In addition, we obtain information on the total value of bank deposits below (data field RCONF049) and above (data field RCONF051) the FDIC insurance threshold of 250,000 USD from Call Report Schedule RC-O for Q4 of 2022. We calculate the % of uninsured deposits (i.e., RCONF051/(RCONF049+RCONF051)), which we then multiply by '% Asset Decline MTM' to construct our measure of 'balance sheet risk.' In robustness tests, we alternatively use the 'estimate of uninsured deposits' (data field RCON5597) to total deposits (data field RCONF236), and we find similar results.

2.3 Stock Price Data

The stock price data are from FirstRate Data, a provider of intraday stock trade data. From this data set, we obtain intraday stock price and volume data for bank stock tickers in intervals of one, five and thirty minutes. For each time interval, the data set includes the price of the first and last trade, the highest and lowest prices, and the trade volume. Prices are adjusted for both splits and dividends. We use bank stock price data to compute the cumulative change in stock prices from March 1st to March 14th as well as hourly stock returns.

We also use these data to look at price changes in a narrow time-window around the moment when a tweet is posted during trading hours. More specifically, following the methodology of Bianchi, Cram, and Kung (2021), we use the timestamp (in Eastern Time) of every tweet in our sample to determine two 10-minute windows: one from 15 to 5 minutes *before* the tweet and another one from 5 to 15 minutes *after* the tweet. Then, for each bank, we identify the price of the last trade in the [-15,-5] minute window and the price of the first trade in the [+5,+15] minute window and define log returns over the 5-minute window around each tweet as the difference in the logs of those prices. We exclude the observation from the sample if either the last price in the window before the tweet or the first price in the window after the tweet have zero associated volume in our data set.

The timeline of the analysis is depicted below:



where $p_{it} = \log(P_{it})$ is the logged stock price, $p_{i,t-\tau}$ is the last logged stock price observed in the [-15,-5] minute window, $p_{i,t+\tau'}$ is the first logged stock price observed in the [5,15] minute window, and $\Delta p_{it} = p_{i,t+\tau'} - p_{i,t-\tau}$ is the log return. The advantage of this high-frequency approach is that it is unlikely that other value-relevant information about the stock price becomes public during the short interval around the tweet. By estimating the log return using a starting price that was observed *before* the tweet was posted and an ending price after, we further ensure that any findings are unlikely to be driven reverse causality, i.e., the Twitter activity reacting to stock price changes.

2.4 Summary Statistics and Empirical Approach

In our main analysis, the main sample period spans from January 1, 2023 through March 14, 2023. We have comprehensive Twitter data through March 13, and we have high-frequency stock return data from FirstRate through the end of March 14. Figure 3 portrays the timeline of our sample period, and helps to illustrate our cross-sectional empirical strategy. We define the *pre-run period* to be January 1 through February 15, which ends before widespread Twitter discussion of potential bank runs in traditional banks. We validate this choice with contextual evidence on the content of tweets in the pre-run period, as well as retweeting frequency of tweets from this pre-period. We also consider robustness to alternative pre-periods for our main tests (see Table A.2, Panels b and c).

To understand the content of tweets in the pre-run period versus the run period, we compute the word frequency distribution for this 46-day pre-run period, and contrast it with the 5 day run-period (March 8 through March 13), which can be seen in the word clouds in Figure 4. The pre-run period word cloud contains no prominent mentions of bank run terms, such as depositors or withdrawing money, but the run-period is heavily populated with these terms, as well as references to Silicon Valley Bank. Reflected in the size of the words in the word cloud, the run period also has a much greater concentration around a few salient terms, whereas the pre-run period is not as concentrated.

Our first set of empirical tests exploits the wide variation in Twitter message volume during the pre-run period. In Panel (a) of Table 2, we present cross-bank distribution of total number of tweets in the pre-run period and run period, rescaled to be the number of tweets about a bank *per 30 days* so that the numbers are comparable to one another, despite the run period having only 5 days in it. The distribution of tweets in the pre-run period has a wide dispersion, leading to substantial variation in the extent to which Twitter users comment about different banks: For example, the 10th percentile bank has only 33 tweets per 30 days while the 90th percentile bank has 511 tweets per 30 days written about it during the pre-run period. This distribution is highly skewed, with a mean of 536 tweets per 30 days and a median of only 88.7 tweets per 30 days. To capture this wide variation while not giving undue influence to observations in the right tail, we divide the distribution into terciles. Panel (b) of Table 2 presents the mean and median number of tweets in the pre-run period and the run period. The top tercile's median number of tweets in the pre-run period is 344 compared with a median of 22.5 tweets in the bottom tercile.

The summary statistics in Panels (a) and (b) of Table 2 provide more information about the nature of the run's risks. Specifically, per 30 days, the run period has roughly 4 times the average number of tweets than the pre-period (mean of 2,278 versus 536). However, most of this increase is concentrated among the largest quantiles. The 66th percentile bank in the run period has a comparable tweet rate to the 66th percentile bank in the pre-run period (120 versus 136 per 30 days). However, the 90th percentile and above have much greater Twitter activity during the run period than during the pre-run period.

Next, we validate the contextual dictionaries by identifying the top 5 banks by the number of run period tweets in the "run behavior" dictionary. Panel (c) in Table 2 presents counts of run tweets, contagion tweets, pre-run tweets, and crypto tweets pre-run for these top 5 banks, as well as the 90th percentile of these counts. Consistent with causal empiricism, these tweets identify SIVB as the bank ticker with the most run-based conversation, with 6,528 "run" tweets. First Republic Bank (FRC), which also faced notable troubles during the run period (and subsequently failed on May 1, 2023), was next in this list with 1,249 run-based tweets. Moreover, all of these top-5 "run" mention banks have an abnormally high number of contagion tweets. In addition, all 5 banks are well above the 90th percentile for number of pre-run tweets (784), and they all have abnormally high cryptocurrency mentions (consistent with the visual evidence in Figure 4).

These summary statistics highlight that the banks that faced the greatest distress during the run period were also the ones that had the most Twitter attention in the pre-run period. Next, we present evidence on the dynamics of pre-run information sharing and the rapid spread of ideas in the run period using retweet data.

2.5 Dynamics of Information Sharing via Retweets

This section presents several statistics and examples on the timing and content of information sharing during the run period. For the subset of original tweets posted in 2023, the analysis presented in this section relies on comprehensive information on all of the retweets (RTs) through March 2023. By linking the content and timing of the RTs to the original tweets, this contextual evidence motivates aspects of our empirical approach and enriches the underlying information sharing mechanisms.

We begin with an analysis of how common it is for original tweets from the pre-run period to be retweeted during the run period. To do this, we flag each RT as a *run period retweet* if the retweet was posted after March 8th, 2023. Since this analysis starts with a data set of retweets, each original tweet in this sample was retweeted at least once. Using these retweeted tweets, we compute the fraction of original tweets that have at least one run period retweet, and plot this time series in Figure 5a. This figure shows that, even for tweets that are retweeted at least once, there is a very small likelihood ($< 5\%$) that original tweets authored during the pre-run period are *ever* retweeted during the run period. This small percentage throughout the pre-run period (January 1 − February 15) helps to validate our use of overall tweet counts as a proxy for pre-run exposure rather than such tweet volume reflecting information about the upcoming run period.

When we plot the average number of retweets instead (in Figure 5b), January 18th stands out as the only day in the pre-run period with a meaningful average number of run period retweets. To identify the tweets behind this pattern, we construct a list of the pre-run original tweets that had the most run period retweets. Out of 31,642 original tweets prior to the run, there were only 12 tweets with at least 30 run period retweets, which are listed in Appendix Table A.1. Ten of these 12 tweets were about SVB and were part of the same January 18th tweet thread, another tweet was about problems about Signature Bank ($SBNY) on January 10th, and another tweet was about an isolated incident at Bank of America. The remaining 31,630 original tweets in the pre-run period were not widely shared during the run.

The SIVB tweet thread on January 18th was authored by an account called 'Raging Capital Ventures,' which proved prescient of many of the issues that would face SVB in March. This thread highlighted issues with HTM assets, uninsured deposits, and pressure on management due to its exposure to the VC industry, among other issues. Figure 6a presents the text of the first tweet in this tweet thread (6b), together with a time series plot of when this tweet was retweeted. Consistent with this tweet having relatively little impact before the run period, there was a modest number of retweets after the original tweet was shared, but after this initial period of interest, the tweet was not retweeted until early March. Notably, the tweet appears to have been re-discovered during the run period when it went viral with over 1,000 retweets. A natural reason it was retweeted so much was because it offered a coherent explanation for why the run happened to SVB. This pattern is consistent with social media amplifying the sharing of run-relevant information.

2.5.1 An Example of Sharing Misinformation and Retweet Dynamics

Among the top 12 retweeted tweets, the other striking example is the Bank of America ($BAC) tweet. This tweet is an anomaly since BAC did not face a significant risk during the run period. Figure 7a shows a screenshot of the tweet itself, which was posted on January 18th, 2023. Far from being relevant to the SVB bank run, this tweet about BAC was about an isolated technology glitch at Bank of America in which Zelle mistakenly withdrew money from many Bank of America customer accounts. At the time, this created confusion among depositors, and people took to Twitter, Reddit, and TikTok to share their concerns. The tweet about BAC in our list contains a minute-long video in which a customer states that he is missing money and points the camera at other customers in a Bank of America branch lobby who are also missing money. All of this happened on January 18th, and the glitch was fully resolved by January 19th.

Despite this news being stale by March, completely resolved in January, and unrelated to any issues during the March run period, this tweet was retweeted 66 times after March 8th. Figure 7b presents a time series plot of the retweet dynamics from February 1 onward, which shows very few retweets in the weeks leading up to the run period, along with a sharp spike during the run. Unlike the SVB tweet thread, retweets of this Bank of America tweet reflect the propagation of misinformation since the tweet conveys an implicit message that Bank of America was experiencing problems in March. The tweet is clearly labeled as having been authored on January 18th, but the date stamp occurs at the bottom of the tweet, which is not salient for this type of tweet with an embedded video. Moreover, the tweet contained no mentions of when the problems occurred, nor did the video. Thus, it is reasonable for a reader to not realize that the original tweet was posted in January.

This example is clearly misinformation, which is difficult to label in the context of bank runs because misinformation can be self-fulfilling. For example, suppose that someone were to tweet that First Republic was facing unconfirmed troubles during this run period. Such a post could lead to a self fulfilling run.[4] Even if a tweet is truly misinformation, the fact that misinformation can create self-fulfilling sunspots in the context of bank runs makes it very difficult to label true misinformation *ex-post*.

3 Results

In this section, we present our main results that link social media exposure to bank run severity. We proxy for bank run severity using bank stock losses for publicly traded banks. We present four sets of results: (1) cross-sectional tests that relate the total bank stock losses in the run period (Mar 1 through Mar 14) and deposit outflows in 2023-Q1 to *pre-existing* Twitter exposure, (2) cross-sectional tests using deposit flow data from Q1 2023, which corroborate our main cross-sectional tests, (3) tests at the hourly frequency that link social media activity in a recent time window (e.g., previous 4 hours) to hourly returns, and (4) high frequency tests in the spirit of Bianchi et al. (2023) that examine the contemporaneous impact of social media activity and sentiment on bank stocks in 5-minute windows around the tweet.

3.1 Event Analysis around the Onset of the SVB Run

We validate the use of returns by estimating how returns for banks with high "balance sheet risk" versus banks with low "balance sheet risk" change around the onset of the run period. To understand the timing of the onset of the run period, consider Figure 1, which shows that the first substantial

[4] See for example this Reddit discussion of a short seller doing precisely this: `https://www.reddit.com/r/wallstreetbets/comments/11prc0y/mike_alfred_admitted_to_having_a_short_position/`

uptick of tweets about SVB (or SIVB) occurred in the morning of March 9. Thus, we take the onset of the bank-run period to be March 9. Aside from helping to identify the timing of the run on SVB, this figure also provides evidence on the social transmission of ideas: the run discussion originated in investment tweets (i.e., those that use the stock ticker SIVB), and then later, spilled over into discussions of the acronym (SVB), and later the name of the bank (Silicon Valley Bank).

To measure balance sheet risk, we follow Jiang et al. (2023b)'s procedure and construct the percentage loss due to mark-to-market assets from price changes in bond ETFs as detailed in Section 2. In addition, we compute the percentage of uninsured deposits relative to total deposits from the 2022:Q4 FDIC Call Reports. Appealing to arguments in Jiang et al. (2023b), the interaction between these two banking characteristics is our measure of "balance sheet risk." The intuition for this measure is simple: a higher % drop in assets due implies that the bank holds fewer to cover depositor claims. However, if deposits are fully insured depositors have little incentive to withdraw. Hence, the combination of high mark-to-market asset value decline with a low deposit insurance ratio leaves a bank potentially vulnerable to a run, as explained in Jiang et al. (2023b).

Table 3a provides evidence consistent with this intuition. We contrast the top tercile in "balance sheet risk", with the bottom two terciles, and separately compute the average hourly stock returns for March 1-8 (before the run on SVB) and March 9-14 (the run period). In line with the idea that high 'balance sheet risk' banks were more vulnerable after the onset of the SVB episode, the hourly returns on bank stocks in the top tercile of balance sheet risk are about 0.2 percentage points lower, with 95% confidence intervals that do not overlap.

We refine this unconditional test by estimating the following triple difference model using a bank-hour panel and hourly returns, which allows us to control for firm and time fixed effects:

$$
\begin{aligned}
r_{i,t} = {} & a + b_1 \times 1(\geq \text{Mar } 09)_t + b_2 \times \Delta\text{Assets MTM}_i + b_3 \times \%\ \text{Uninsured}_i \\
& + b_4 \times 1(\geq \text{Mar } 09)_t \times \Delta\text{Assets MTM}_i + b_5 \times 1(\geq \text{Mar } 09)_t \times \%\ \text{Uninsured}_i \\
& + b_6 \times \Delta\text{Assets MTM}_i \times \%\ \text{Uninsured}_{i,t-1} \\
& + b_7 \times 1(\geq \text{Mar } 09)_t \times \Delta\text{Assets MTM}_i \times \%\ \text{Uninsured}_i + \delta_i + \gamma_t + \epsilon_{i,t},
\end{aligned}
\tag{2}
$$

where $r_{i,t}$ is the hourly return for bank stock i during trading hour t (in %), ΔAssets MTM$_i$ is the implied percentage change (in %) of bank i's assets from 2022:Q1 to 2023:Q1 due to mark-to-market assets as defined in Equation (1), % Uninsured$_i$ is the percentage of deposits below the FDIC insurance threshold relative to total deposits, and $1(\geq \text{Mar } 09)_t$ is an indicator that equals 1 for all hours t after the onset of the SVB run at the beginning of March 9th (9am). The triple interaction model includes all lower order terms, as well as bank (δ_i) and day-by-hour (γ_t) fixed effects in some specifications. Standard errors are clustered at the bank level. The coefficient of interest is b_7, which reflects the degree to which banks with high balance sheet risk – captured by the interaction ΔAssets MTM$_i$ × % Uninsured$_i$ – experience greater stock market losses in the run period (i.e., when $1(\geq \text{Mar } 09)_t$ is equal to one) than before the run period. To facilitate interpretation in the regression tables, we standardize continuous RHS variables to have zero mean and standard deviation of one. This standardization does not change the statistical tests, but scales the tabulated magnitude to be for a one-standard deviation increase. We indicate that a variable is standardized in a regression table by adding '(z)' to the variable name.

Table 3b presents the results, which robustly show that $b_7 < 0$. In column 1, we estimate a triple interaction of -0.0412, which implies that a bank with high balance sheet risk (one SD above the mean for both 'ΔAssets MTM (z)' and '%Uninsured (z)') is expected to lose an additional 4.12 basis points of return per hour more during the run period than before it. The two-way interactions of '$1(\geq$ Mar 09)' with 'ΔAssets MTM (z)' and '%Uninsured (z)' provide a natural benchmark for the economic magnitude of this estimate. Both coefficients on '$1(\geq$ Mar 09)' × 'ΔAssets MTM (z)' and '$1(\geq$ Mar 09)' × '%Uninsured (z)' are strongly negatively related to average returns (between 6.2 and 10.7 basis points per hour, respectively). Aside from these estimates being highly significant, they are also stable upon the inclusion of bank and day-by-hour fixed effects, even though these fixed effects explain substantial variation (R^2 goes from 0.0098 to 0.2576 upon their inclusion).

To provide evidence that this difference in returns, indeed, emerges precisely at the onset of the social media discussion about SVB, we plot the cumulative returns from March 06 through March 14 for banks with *ex-ante* high versus low balance sheet risk (i.e., 'ΔAssets MTM (z)' × '%Uninsured (z)') in Figure 8. In the pre-run period up until the end of March 09, there are virtually no differences in the returns for high versus low "balance sheet risk" banks. However, following the onset of the run, banks with both a high MTM asset value decline *and* low deposit insurance ratios experience sharper declines in returns. Not only are these results consistent with the message in Jiang et al. (2023b) that bank run risk is tied to uninsured deposits, but this evidence shows that our identification of the timing of the onset of the run via Twitter activity is valid and that our use of returns to understand the extent of bank run risk is reasonable.

3.2 The Role of Preexisting Exposure to Twitter Activity

Building on the finding that return movements of bank stocks during the run period reflect exposure to bank run risks, we next conduct a series of tests that examine how *pre-run* Twitter exposure interacts with mark-to-market bank losses and the percentage of uninsured deposits.

To do this, we measure pre-run Twitter exposure by counting the number of tweets that mention a bank's cashtag between January 1, 2023 and February 15, 2023. Consistent with this choice of pre-period, Figure 4 presents word clouds that emphasize the most frequently used words in this pre-run period versus the run-period. The run period's conversation is concentrated in discussion about the implications of the SVB run, whereas the pre-run period has a wider range of topics. Our goal is to construct a measure of pre-run exposure to Twitter in the absence of bank run discussions, and thus, attribute any estimated effects to the bank's *exposure to social media conversation* rather than any information contained in social media about how run prone is one bank versus another.

We estimate a cross-sectional specification that interacts balance sheet characteristics that make bank i more or less run prone with preexisting exposure to Twitter:

$$Stock\_Loss_i = \beta_1 Loss_i \times Uninsured_i \times SocialExp_i + lower\ order\ terms + \epsilon_i \tag{3}$$

where $Stock\_Loss_i$ is the percentage of bank i's stock market value that was lost from March 1st until March 14th. We include tercile of tweet activity indicators in our main tests, instead of the continuous variable $SocialExp_i$, because the distribution of tweets is right skewed. The main coefficients of interest are those on the top tercile tweet-activity indicator (on its own and interacted with $Loss_i \times Uninsured_i$). The coefficients on the lower order terms in the specification are also of interest. For example, being largely reliant on uninsured deposits can be risky irrespective of mark-to-market losses. Thus, we are interested in the main effect on $Uninsured$, but also its interactions with $Loss$ and $SocialExp$. These coefficients provide a natural benchmark for magnitudes as well. In fact, the relative importance of these terms in comparison to one another speaks to how important exposure to social media is versus well-studied balance sheet characteristics (e.g., Egan et al., 2017; Jiang et al., 2020, 2023b).

Table 4 presents the main results. Column 1 of Panel 4a presents a specification without the interaction with pre-run Twitter exposure. Broadly, this specification confirms the emphasis of Jiang et al. (2023b) on the role of uninsured deposits. Interpreting the main effect, a standard deviation increase in the percentage of uninsured deposits is associated with a 4.1 percentage point decline in the bank's stock during the SVB bank run. The relation of mark-to-market bank losses to bank stock losses is not statistically significant, nor is the interaction with uninsured deposits. However, the magnitudes of these estimated coefficients are economically meaningful and in the direction hypothesized: A standard deviation increase in marked-to-market losses is associated with 0.8 percentage points more stock market losses during the run, and for a bank with a high fraction of uninsured deposits (one standard deviation above the mean), this magnitude more than doubles due to the interaction coefficient estimate of 0.943.

In column 2 of Panel 4a, we present evidence on the link between high (or medium) pre-run Twitter exposure and the percentage bank stock loss during the SVB run. This social media channel predicts bank stock market losses during the run and the estimated magnitude is similar to the coefficient on percent uninsured deposits. A bank with top tercile pre-run Twitter exposure has, on average, 6.66 percentage points greater stock market loss during the run period than a bank in the bottom tercile of pre-run Twitter exposure. By contrast to top tercile pre-run Twitter exposure, we see no significant difference between banks in the middle tercile of pre-run Twitter exposure and banks in the bottom tercile.

Communication via social media ought to affect bank run severity through amplifying existing risks. To test this, in columns 3 through 5, we estimate specifications that interact pre-run Twitter exposure and bank run characteristics. Consistent with social media communication amplifying these bank balance sheet risks, the inclusion of these interaction terms leads the main effects on % Loss and % Uninsured to become smaller and insignificant. Moreover, we estimate a significant positive interaction between *top tercile pre-run Twitter exposure* and % Uninsured. These results emphasize the importance of communication via social media: % Uninsured deposits matters for bank run severity, but it relates to bank run severity only insofar as it coincides with significant pre-run Twitter exposure, which facilitates coordination among uninsured depositors. Moreover, we estimate a positive and highly significant triple interaction, which implies that a bank with high "balance sheet risk" (one sd above the mean for both MTM bank losses and uninsured deposits) can expect 3.014 percentage points lower return during the run period. These findings highlight the importance of social media communication as an *ex ante* risk factor that leads to greater bank run severity via heightened communication.

We perform several robustness exercises. One concern is that the largest banks — which were known to experience deposit *inflows* (see Caglio et al., 2023) – are also the bellwethers of the banking industry, and thus, their stock prices are more responsive to banking industry distress, but not for run reasons. To alleviate this concern, we re-estimate the main specification after dropping financial institutions with greater than $ 500 billion in deposits. The results on this subsample are virtually identical to our main specification, as shown in Appendix Table A.2a.

Another natural concern is that the pre-run period from January 1 through February 15 is a period when tweet volume reflected banks with poor fundamentals, and thus, likely to perform poorly during the run period — i.e., the pre-run Twitter exposure variable might not reflect pure social media exposure, but also information about bank fundamentals. The validation exercises in Section 2.5 help to alleviate this concern, as does the nature of the terminology used in the Jan 1 through Feb 15 pre period (Figure 4) since the conversation does not appear to be about bank fundamentals. However, to further alleviate this concern, we re-estimate the main specification with two alternative pre-exposure periods: November 15 − December 31, and October 1 − November 15. The results, reported in the Appendix Tables A.2b and A.2c, are very similar to the estimates with our main pre-period.

3.2.1 Tweets by Startup Community Users

An important feature of the SVB bank run is that SVB's depositors were highly concentrated among startups and founders whose companies were VC-backed. In addition to the usual risks of being exposed to a single industry's deposits, this particular startup community is also highly connected through social media, making SVB's social media communication risks unusually high.

We examine the role of the startup community in the run by flagging users as startup community members based on keywords in their user description field (e.g., "startup," or "founder"). We then follow the discussion of startup community users over time and evaluate how cross-sectional exposure to this highly connected group of users influences the observed bank run severity.

Using pre-run exposure to Twitter activity by startup community users, we re-estimate equation (3). Panel 4b reports the estimated coefficients using pre-run startup community tweet activity. We estimate a slightly weaker triple interaction coefficient than using overall tweets. However, the two-way interaction between top tercile startup tweets and % Uninsured remains highly significant, and the main effect terms on % Uninsured, % MTM Loss, and their interaction are all small and non-significant in the fully interacted model. Thus, even using a subset of the Twitter activity in the pre-run period, we conclude that Twitter exposure plays an important role in amplifying balance sheet risk.

3.2.2 Tweets about Running and Contagion During the Run

Next, we investigate how pre-run Twitter exposure could lead to heightened attention and discussion of bank run topics during the run period. For this analysis, we estimate a cross-sectional test with the bank stock market loss as the dependent variable, but enriching the specification in equation (3) by controlling at the bank level for Twitter activity *during* the run period on run-specific topics. Specifically, we use the "run behavior" and "contagion" content dictionaries to identify run-relevant tweets during the run period. We also investigate the role of 'tech' startup community tweets during the run period.

Panel 4c presents the results from estimating these specifications. Column 1 presents the regression without any controls for run-period tweet volumes. Repeating our main specification, top tercile pre-run Twitter predicts a 6.66 percentage point loss during the bank run. However, upon controlling individually for Contagion Tweets, Run Tweets, or Startup Tweets during the run period, individually (columns 2 through 4) or all together (column 5), the coefficient on pre-run Twitter exposure diminishes in both economic and statistical significance. This finding suggests that pre-run Twitter exposure affects bank run severity because it leads to more run and contagion tweets, as well as more Twitter activity by members of the startup community on Twitter. These tweets served to coordinate and communicate among depositors during the run.

3.3 Pre-Run Twitter Exposure and Deposit Flows

Next, we investigate how social media is connected to deposit outflows during Q1 of 2023 using the change in uninsured deposits and total deposits reported in the FDIC Call Reports from Q4:2022 to Q1:2023. To do so, we estimate the following cross-sectional specification:

$$Deposit\_Outflow_i = \beta_1(Loss_i \times Uninsured_i \times SocialExp_i) + lower\ order\ terms + \epsilon_i \qquad (4)$$

where $Deposit\_Outflow_i$ is the percentage loss of deposits for either uninsured deposits or total deposits — i.e., $Deposit\_Outflow_i = 100 \times \frac{Deposits_{Q4:2022} - Deposits_{Q1:2023}}{Deposits_{Q4:2022}}$. The variables $Loss_i$ and $Uninsured_i$ are computed using the data available as of Q4 2022. As in the main specification in equation (3), we include terciles of pre-run Twitter exposure in our main tests, instead of the continuous variable $SocialExp_i$. The main coefficient of interest is β_1 with respect to the top tercile indicator, which captures how much greater the percentage decline in deposit outflows among banks with high balance sheet risks (i.e., one standard deviation above the mean of mark-to-market losses and uninsured deposits) is for banks with high (i.e., tercile 3) compared to low (tercile 1) social media exposure. Because the dependent variable is $Outflow$, a positive coefficient reflects a more severe run.

Table 5 presents the results from estimating equation (4). Consistent with the tests using run period returns, we find that the percentage of *uninsured* deposits is strongly related to deposit outflows. A standard deviation increase in % Uninsured in Q4:2022 is associated with 4.38 percent lower uninsured deposits (col 1) and 2.28 percent lower total deposits (col 3).

In the triple interaction specification, we estimate that the top tercile of pre-run Twitter exposure is associated with significantly more deposit outflows, particularly reflected through the interaction terms. For banks with high balance sheet risk (a standard deviation above the mean of % Loss and % Uninsured), top tercile pre-run Twitter exposure is associated with a 3.37 percentage point increase in uninsured deposit outflows. This is in addition to large positive coefficients on the double interactions (3.79 ppt for T3 × % Uninsured, 4.72 ppt for T3 × % Loss). Moreover, the main effects on the balance sheet risk terms become small and statistically insignificant in this interactive specification. This finding reveals that deposit outflows are not sensitive to these banking characteristics if the bank's Twitter exposure is low.

Consistent with the idea that uninsured deposits are especially run-prone (Egan et al., 2017), we estimate smaller or null effects when we employ *total* deposit outflows as the dependent variable. Overall, this evidence from quarterly deposits is complementary to the bank stock return evidence in our main tests. Because this data is at the quarterly frequency, it is not possible for us to determine when exactly the deposit outflows occurred during Q1 2023. Thus, this evidence should be taken as suggestive that *run period* deposit outflows were sensitive to pre-run Twitter exposure. Complementary with these tests, recent work by Caglio et al. (2023) indicates that most of the unusual deposit activity happened in the week of the SVB collapse using confidential regulatory weekly data on deposits from the Federal Reserve. These results corroborate our main interpretations that the run period stock market prices are informative of the run itself.

We present related robustness tests in Appendix Table A.4. Specifically, in Panel A.4a we multiply 'Assets Loss MTM (%)' with '% Uninsured' to measure 'Balance Sheet Risk'. The regressions also include the stock value loss during the run period, '% Run Loss', as an additional control. We find similar results as in Table 5. Similarly, in Panels A.4b and A.4c we exclude too-big-to-fail banks and consider triple-interactions with 'Assets Loss MTM (%)' and '% Uninsured', respectively. The results remain similar.

One limitation of these cross-sectional tests of run period activity is that the tweets during the run period might not precede the return reactions. To provide finer-grained insight into the timing of run period tweets, we next turn to examine the impact of tweet activity in a bank-hourly panel.

3.4 Hourly Bank Stock Returns and Twitter Activity

In this section, we employ the following hourly return specification that augments the specification in equation (2) to examine the role of Twitter activity:

$$
\begin{aligned}
r_{i,t} = a &+ b_1 \times 1(\geq \text{Mar } 09)_t + b_2 \times \text{Balance Sheet Risk}_i + b_3 \times \text{N Tweets}_{i,t-1} \\
&+ b_4 \times 1(\geq \text{Mar } 09)_t \times \text{Balance Sheet Risk}_i + b_5 \times 1(\geq \text{Mar } 09)_t \times \text{N Tweets}_{i,t-1} \\
&+ b_6 \times \text{Balance Sheet Risk}_i \times \text{N Tweets}_{i,t-1} \\
&+ b_7 \times 1(\geq \text{Mar } 09)_t \times \text{Balance Sheet Risk}_i \times \text{N Tweets}_{i,t-1} + \delta_i + \gamma_t + \epsilon_{i,t},
\end{aligned} \tag{5}
$$

where $r_{i,t}$ is the hour t return for bank i measured in percentage points, the indicator '$1(\geq \text{Mar } 09)_t$' captures hours after the onset of the run on March 09th (9am). 'Balance Sheet Risk$_i$' is the product of mark-to-market bank losses and percentage uninsured deposits of bank i, 'N Tweets$_{i,t-1}$' is the number of tweets about bank i over the past 4 *hours*. This specification contrasts hourly returns for banks with high balance sheet risk during the run period for banks with high versus low recent Twitter activity. By observing this high frequency (4 hour) lag of Twitter conversation intensity ('N Tweets$_{i,t-1}$') about bank i, we alleviate concerns that stock returns may drive twitter activity rather than the reverse. The main sample of bank-hour observations is drawn from March 6th until March 14th (March 11 and 12 were weekend days, i.e., non-trading days).

Table 6a presents the results from estimating this specification. The number of Tweets in the past four hours exhibits a significant triple interaction with 'Balance Sheet Risk' and 'Run Period', particularly after controlling for firm fixed effects and day-by-hour fixed effects. That is, we can attribute significantly lower hourly returns of stocks with high balance sheet risk to a higher *recent* Twitter conversation intensity about the bank. Our estimates are consistent with a social contagion interpretation, suggesting that bank returns are following Twitter conversation for banks with high balance sheet risk during the run period.

We perform several robustness exercises on this result. First, in Panel 6b, we report the results when dropping Silicon Valley Bank (SIVB) from the sample. The triple interaction remains highly significant, while being slightly smaller in magnitude. Second, we consider a shorter time window around the onset of the bank run period: one day before (March 8) through the first full day (March 9). This sample of days leaves us with roughly one third of the sample size, but we find larger coefficient estimates for b_7 across all specifications, indicating that much of our result is driven by the period around the onset of the SVB run, and not the regulatory response, which was communicated in the evening on March 12. Next, we address concerns that past stock returns drive our findings, we include lagged bank stock returns (accumulated over the past 4 hours, similar to N $Tweets$) as a control variable in equation (5). The results are very similar (see Appendix Table A.3a). In Appendix Table A.3b we also exclude too-big-to-fail banks, and find similar results.

To examine the dynamics of the return reaction during the event period and rule out pre-trends, we plot the cumulative returns of banks with high and low Twitter activity in Figure 9. The sample underlying this figure includes only firms with 'high' balance sheet risk (i.e., above the median), to isolate the effect of Twitter activity in the pre- and post run period. Consistent with the run period driving the interaction between balance sheet risk and Twitter activity, cumulative returns diverge meaningfully for the first time when the run begins (March 9th). We see a very similar pattern if we drop SIVB from this analysis (see Figure 9b). These results show that social media played a role, not only in the bank run on SVB, but the banking distress that emerged after SVB failed.

3.5 High frequency tests of Market Impacts of Tweets

In this section, we analyze price changes in the stocks of banks over very short time intervals around tweets that make reference to banks. More specifically, we study changes in log prices of bank stocks in 10-minute windows around the time of the bank-related tweets in our sample constructed as detailed in Section 2.3. This high frequency analysis allows for clean identification of the impact of *contemporaneous* conversations on social media on stock prices. The key identifying assumption is that no other events take place in such narrow time windows that could confound the observed effects. Our analysis follows Bianchi et al. (2021) who use a similar approach to study the effect of legislators' tweets on the stock prices of targeted firms. A similar methodology has also been used by Bianchi et al. (2023) to study the impact of Presidential tweets on Fed funds futures.

We define the log return of bank i's stock over the 10-minute window around a tweet taking place at time t and containing the bank's cashtag as $\Delta p_{it} = p_{i,t+\tau'} - p_{i,t-\tau}$, where $p_{i,t-\tau}$ and $p_{i,t+\tau'}$ denote the log price of the last trade in the $[t-15', t-5']$-window and the log price of the first trade in the $[t+5', t+15']$-window, respectively. An advantage of this design is that we observe the starting price before the tweet is posted and the ending price after the tweet is posted when constructing returns. This alleviates concerns that stock prices drive Twitter activity, rather than the reverse. In our main high-frequency specification, we then regress log returns of bank i on the tone of the tweet:

$$\Delta p_{i,t} = a + b \times \text{VADER Pos}_{i,t} + c \times \text{VADER Neg}_{i,t} + \gamma_i + \epsilon_{i,t}, \tag{6}$$

where $\Delta p_{i,t}$ is winsorized at the 1% level and expressed in basis points, VADER $\text{Pos}_{i,t}$ and VADER $\text{Neg}_{i,t}$ are the positive and negative components of the sentiment score assigned by VADER to the tweet, and γ_i denotes bank fixed effects. To ease comparability, both negative and positive components have been standardized to have a mean of zero and a standard deviation of one in the full sample. In all regressions, we cluster standard errors at the bank-day level.

Table 7 reports the results from estimating equation (6). As shown in column 1, we estimate a strong negative and immediate price response to the negative component of the VADER sentiment score (VADER $\text{Neg}_{i,t}$). The estimate indicates a 1.60 basis point lower return for a one-standard deviation increase in the negative sentiment component of the tweet's VADER score. Importantly, we do not find a similar effect for positive tweet sentiment, the coefficient estimate is economically small and indistinguishable from zero despite the very large sample size ($N = 1,521,078$) and relatively small standard error ($SE = 0.16$).

Next, we investigate the role of the startup community as a driver of this effect. To this end, we augment the specification in Equation (6) by interacting both VADER $\text{Pos}_{i,t}$ and VADER $\text{Neg}_{i,t}$ with the dummy variable '*Startup Flag*', which takes the value of one if the tweet author is in our 'Startup community' dictionary. Consistent with the idea that tweets of startup community members, as likely depositors, were important for the bank run severity, we estimate a significantly negative interaction effect of -2.13 for VADER $\text{Neg}_{i,t} \times 1$(Startup Community). The magnitude of this estimate implies that the negative high frequency effect of negative tweet sentiment on bank stock returns more than doubles when the tweet came from a member of the startup community.

In the remaining tests in Table 7, we restrict the sample period to after the SVB run began on March 09. By comparing estimates obtained from the full sample (Columns 1 and 2) to estimates from the run period sample, we can infer how the run period interacts with tweet sentiment, Twitter user identity (i.e., startup community), and tweet content. We find a stronger effect of negative tweets on returns and a much stronger effect of tweets by members of the startup community in the post-run period: the coefficient estimate for VADER $\text{Neg}_{i,t} \times 1$(Startup Community) jumps to -21.82 (significant at the 1% level). In line with this finding, we also find a stronger effect of negative tweet sentiment on returns when the Tweet is part of our 'contagion' dictionary (see Section 2.1.2). Last, similar to Table 6, we find much more pronounced unconditional negative returns in the post-run period, i.e., the constant term in columns (3) through (6) is negative, large in magnitude, and highly significant. The negative constant term shows that even neutral tweets have immediate negative impact during the run period.

Interestingly, when we consider interactions for whether the tweet contained terms in the "run behavior" dictionary or tweets about banks with high balance sheet risk, we do not observe a significant interaction between tweet sentiment and these characteristics. In light of our findings in the hourly tests, there are at least two possibilities for these non-results. First, run behavior and banks with high balance sheet risk could be characteristics for which the price reaction is not immediate because it takes time for the market to impound this information into prices. Since the time horizon extends only up to 15 minutes in these tests, this may not allow enough time for the effect to emerge. A second possibility is that these characteristics and their impact on price could be relatively independent of the *sentiment* expressed in such tweets. For example, once a Twitter user utters the word "run," it may not be as relevant to the price reaction that the tweet used moderately negative tone or extremely negative tone. In this case, the volume of "run behavior" tweets is likely to be much more informative. We do not distinguish these possibilities, as the required tests to do so are beyond the scope of this analysis.

Table 8 presents tests analogous to Table 7, excluding Silicon Valley Bank (SIVB) and First Republic Bank (FRC) from the sample. With this restriction, the post-run sample size declines from 43,597 to 19,673. While the coefficient estimates are smaller in magnitude compared to Table 7, the main takeaways remain unchanged. We continue to find that the negative tweet sentiment component has a significant negative effect on 10-min bank stock returns, and this effect is much stronger when the tweet was posted by a member of the startup community. Finally, the estimated effects and their significance remain, and are even slightly larger, if we exclude too-big-to-fail national banks from the sample, as presented in the Appendix.

Overall, the tests in this section support our interpretation that Twitter conversation played an important role in amplifying bank distress during the run period. In addition to the tests in previous sections, the use of VADER negative sentiment reinforces the view that the content of the social media conversation had much to do with the banking distress that surrounded the collapse of SVB. Moreover, the relation of bank stock returns strengthens in its connection to both this negative sentiment and the role of tweets by startup community members. These findings reinforce evidence for our core mechanism that bank distress following SVB was amplified by Twitter conversations.

4 Conclusion

This paper presents comprehensive evidence that exposure to social media conversation about bank stocks amplifies classical bank run risks. Our empirical tests show that banks with a large *preexisting* Twitter exposure performed much worse during the March 2023 SVB bank run, particularly if they have large mark-to-market losses and a large percentage of uninsured deposits. At the hourly frequency, we show that negative returns emerge after periods of intense Twitter conversation, but this effect only emerges after the run on SVB begins. This timing is also consistent with the timing of notable pre-run tweets beginning to go viral on Twitter. When we perform a high-frequency analysis as in Bianchi et al. (2023), the immediate price reactions reinforce many of these core lessons. The severity of bank runs increases markedly when banks are in a Twitter conversation.

The effect that we uncover — though a modern phenomenon linked to rapid communication over social media — is one that is classically rooted in bank run models, going back to Diamond and Dybvig (1983). These models have always posited that communication and coordination pose a risk to banks, especially when many of the deposits in the bank are uninsured. Increasingly, in today's society, social media provides a means for individuals to coordinate and communicate beyond what older technologies allow. The amplification of bank run risk via Twitter conversations is a unique opportunity to observe communication and coordination that shapes a critically important economic outcome — distress in banks. Given the increasingly pervasive nature of social communication on and off Twitter, we do not expect this risk to go away, but rather, it is likely to influence other outcomes, as well.

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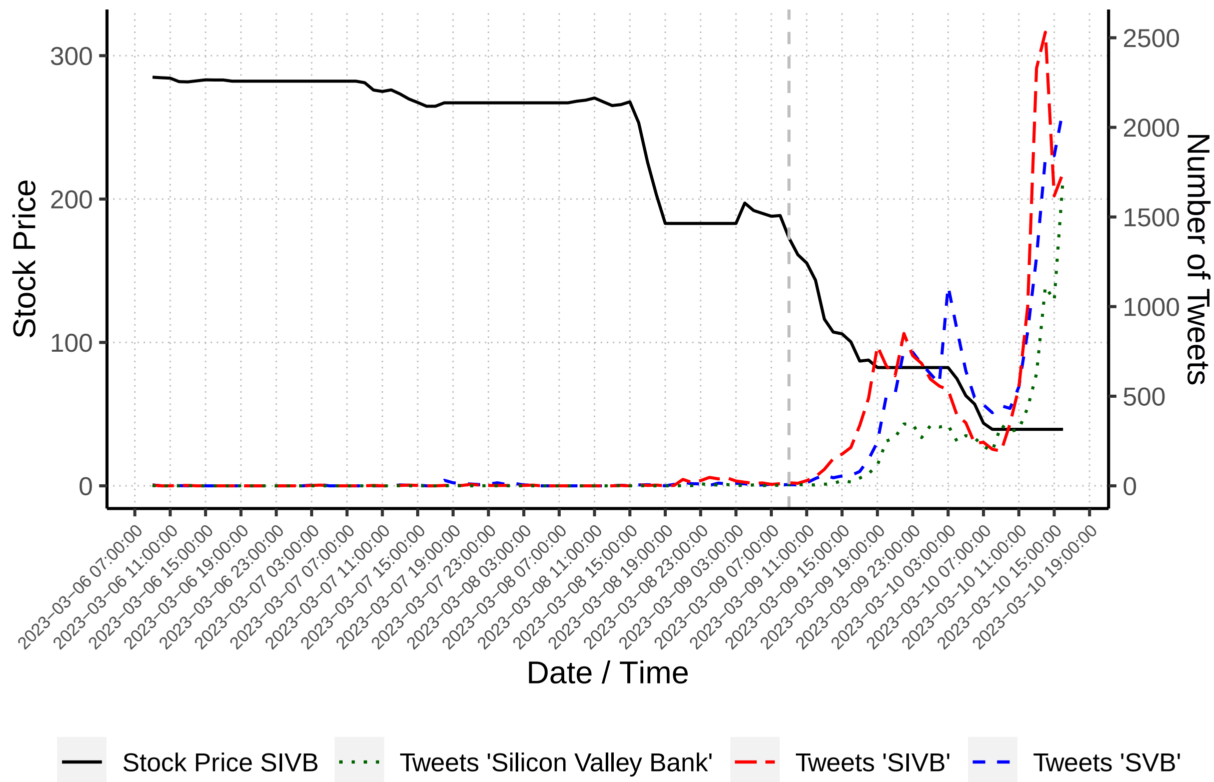
Figure 1: Silicon Valley Bank Stock Price and Twitter Mentions

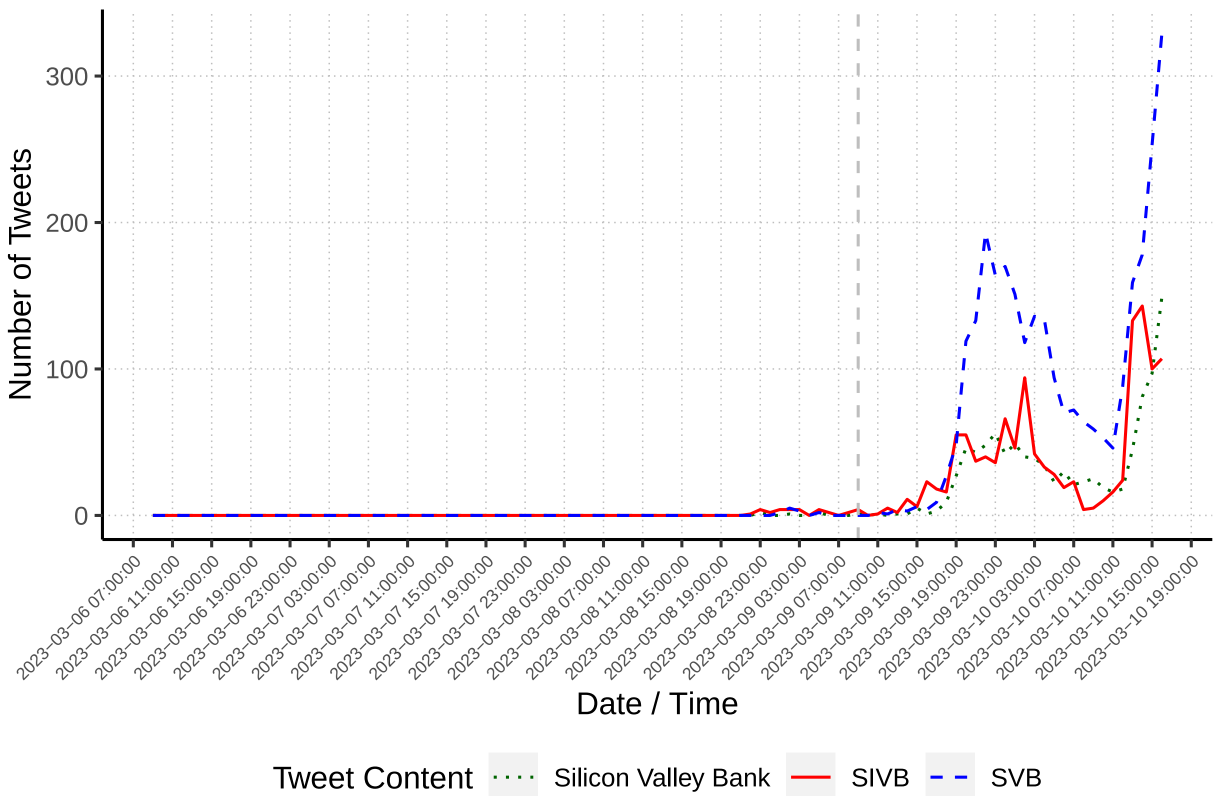
Investor tweets (ticker = SIVB) lead general discussion tweets (SVB and Silicon Valley Bank) within the run period.



Notes: This figure shows the stock price of Silicon Valley Bank (SIVB) (black solid line), as well as the number of tweets mentioning “SIVB” (blue dashed line), “SVB” (red long-dashed line), and “Silicon Valley Bank” (green dotted line), over the period from March 06, 2023 at 9am (market open) to March 10, 2023 at 4pm (market close). The stock price is indicated on the left y-axis and the number of Tweets is indicated on the right y-axis. The grey vertical dashed line indicates March 09, 2023 at 9am.

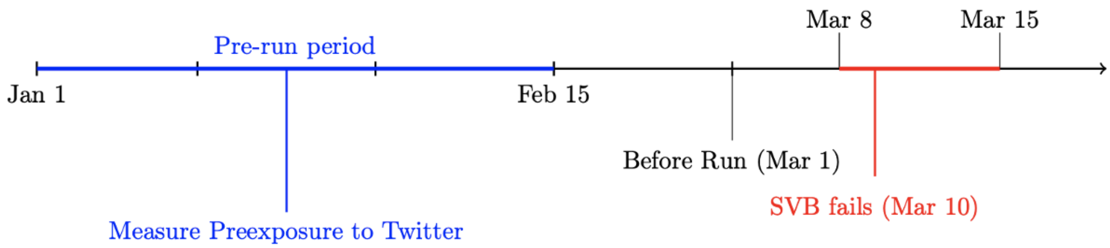
Figure 2: Startup Community Tweets about Silicon Valley Bank

Twitter Startup Community users post mostly general discussion tweets, which start distinctly after the initial wave of tweets.



Notes: This figure shows the number of tweets mentioning "SIVB" (blue solid line), "SVB" (red dashed line), and "Silicon Valley Bank" (green dotted line), over the period from March 06, 2023 at 9am (market open) to March 10, 2023 at 4pm (market close). The sample includes only tweets sent by users who are part of the startup community as defined by corresponding dictionary of terms in the Twitter user biography. The grey vertical dashed line indicates March 09, 2023 at 9am.

Figure 3: Timeline of SVB Run and Illustration of Empirical Strategy

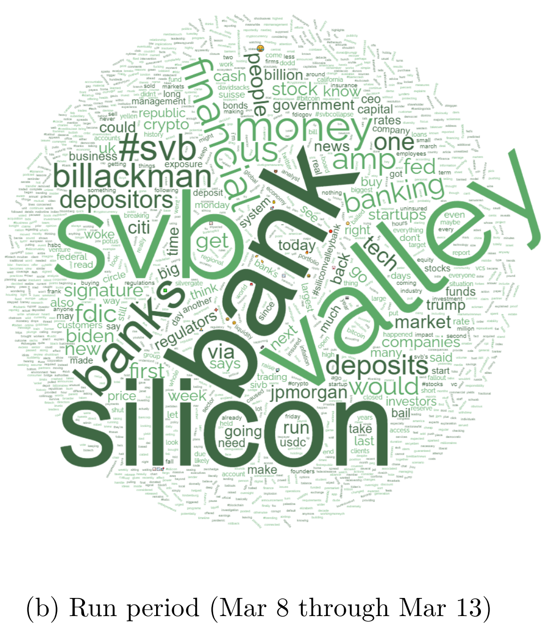


Notes: This figure presents a timeline that spans our main sample period from January 1 through March 15. It also illustrates definitions we use throughout the paper for pre-run period (January 1 − February 15) and run period (March 8 − March 15). Our main cross-sectional empirical strategy measures pre-exposure to Twitter by the number of original tweets authored about the bank's in the pre-run period and relates this pre-exposure to bank stock declines from March 1 (before the run) to the end of the run period. Figures 4 and 5 validate that tweet volume in the pre-period contains scant forward looking information in either its content or retweet patterns. Table A.2, Panels b and c, show robustness to alternative pre-periods.

Figure 4: Content of Tweets about Bank Stocks – pre-run period and run period

Tweets in the pre-run period are unrelated to bank run risks while tweets in the post-run period are.

(a) Pre-run period (Jan 1 through Feb 15)

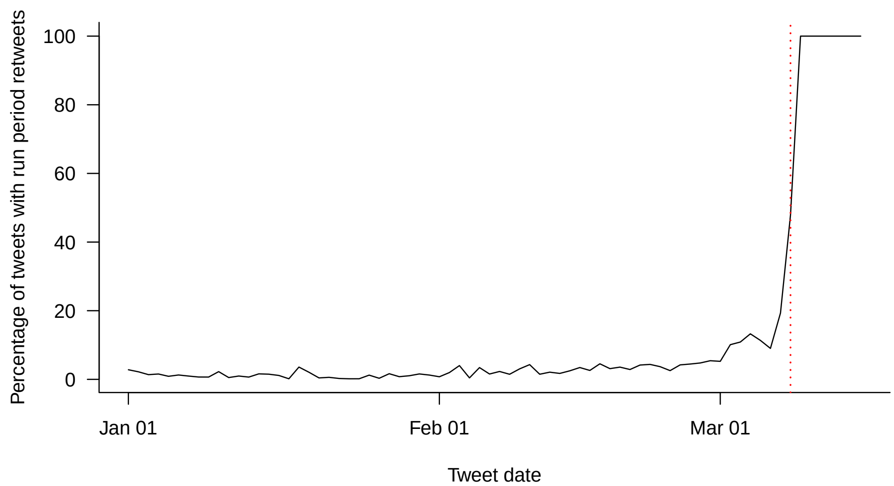


(b) Run period (Mar 8 through Mar 13)

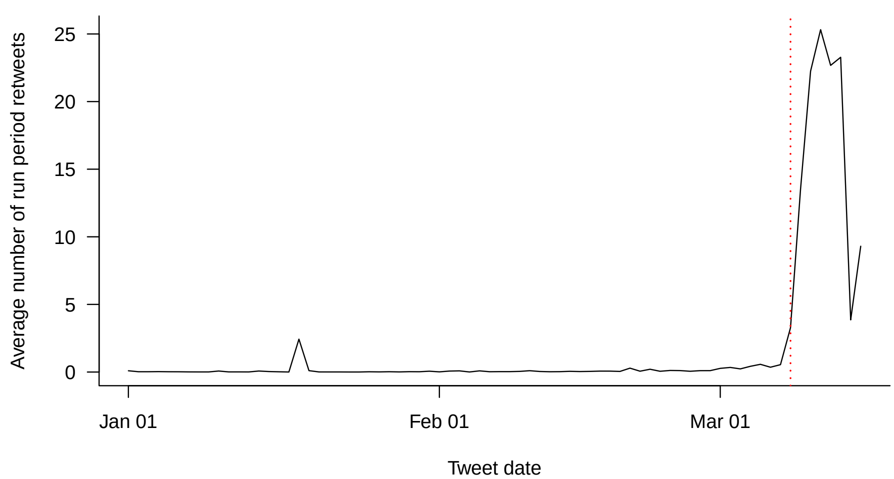
Notes: This figure presents word clouds, depicting the most commonly used words in the pre-run period from January 1 through February 15 (Panel a) and the run period from March 8 through March 13 (Panel b). The size of the words in the word cloud reflects their relative frequency in comparison to other words.

Figure 5: Likelihood of Original Tweets from the Pre-Run Period to be Retweeted During the Run (Original Tweets with at least one RT)

(a) Percentage of Run Period Retweets by Original Tweet Date



(b) Average Number of Run Period Retweets by Original Tweet Date

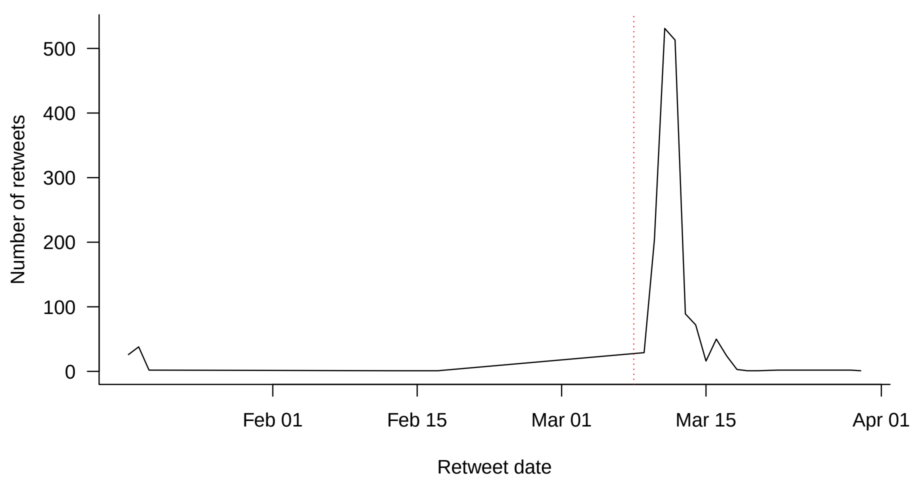


Notes: This Figure presents the likelihood (5a) and average number (5b) of run period retweets of original tweets posted from January 1 through the regional banking crisis run period. The vertical red dotted line is placed on March 8, 2023.

Figure 6: Information Dynamics of the Raging Capital Ventures Tweet Thread about SVB

(a) Raging Capital Ventures Tweet on Jan 18, 2023

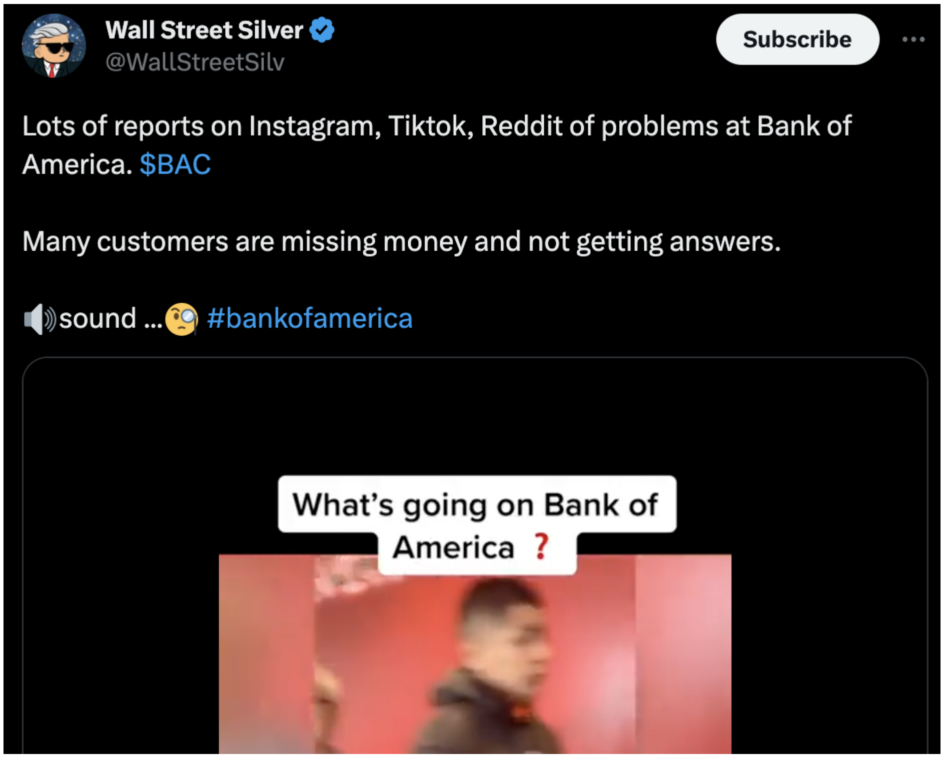
(b) Dynamics of Retweets of Raging Capital Ventures Tweet



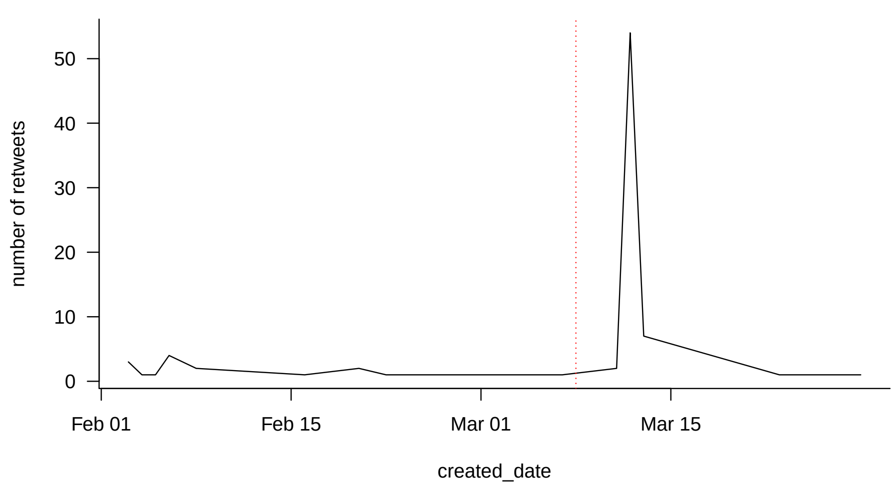
Notes: This Figure presents a screenshot of the most retweeted tweet from the pre-run period by Raging Capital Ventures (5a) and a time series plot of the count of retweets of this tweet by the retweet date (5b). The vertical red dotted line is placed on March 8, 2023.

Figure 7: Sharing Misinformation: Tweet about Bank of America and its Retweet Dynamics

(a) WallStreetSilv Tweet about Bank of America on Jan 18, 2023



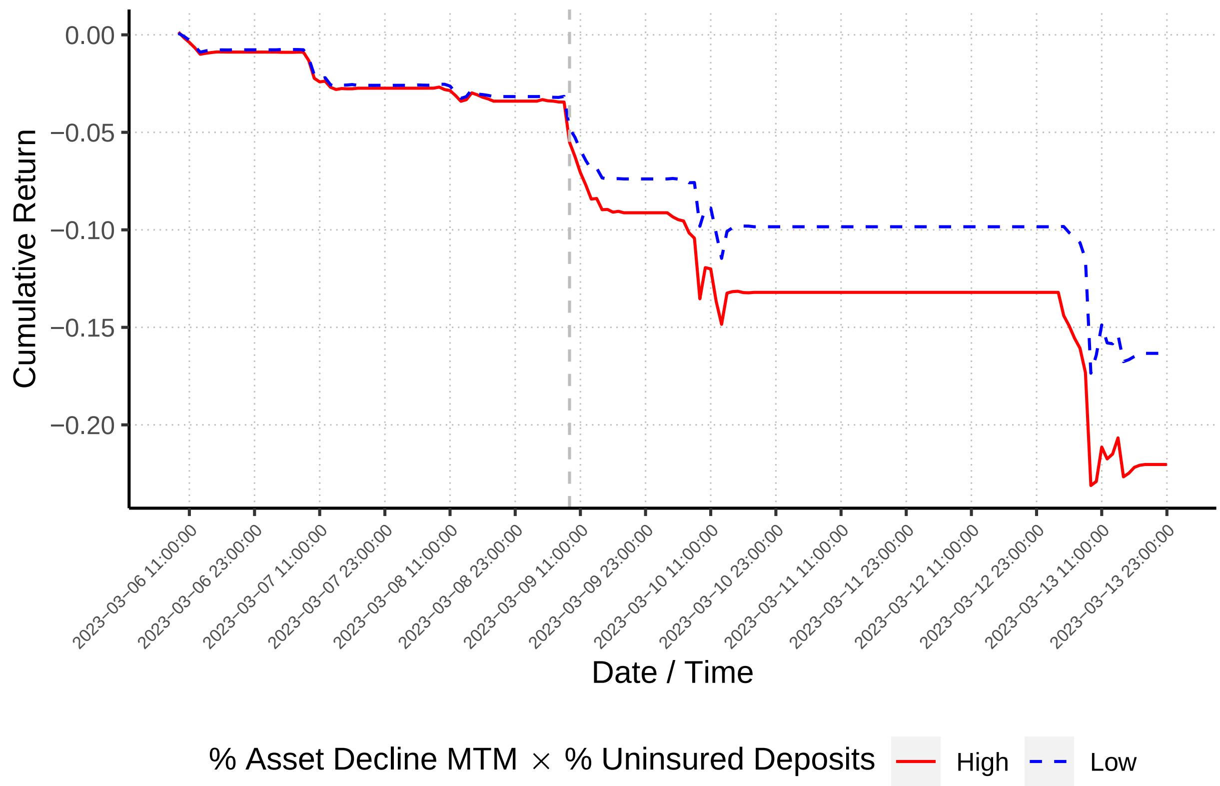
(b) Dynamics of Retweets of Bank of America Tweet



Notes: This Figure presents a screenshot of the tweet about the Bank of America incident from January 18th (5a) and a time series plot of the count of retweets of this tweet by the retweet date from February 1 onward (5b). The vertical red dotted line is placed on March 8, 2023.

Figure 8: Balance Sheet Risk and Cumulative Returns

Banks with more uninsured deposits and mark-to-market losses experience greater stock losses in the run period.

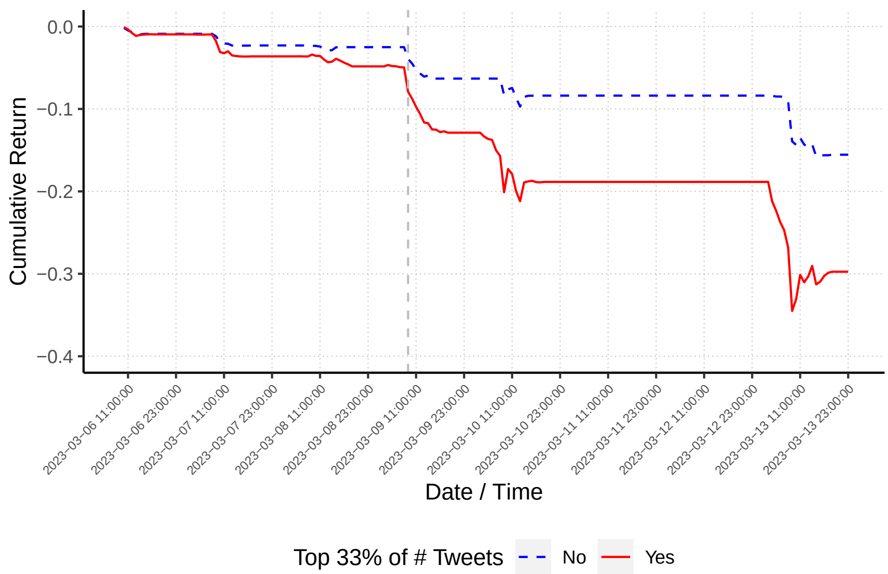


Notes: This figure shows the cumulative returns of a group of US publicly listed bank holding companies (BHCs) from March 06 until March 14, 2023. The sample is split by "Balance Sheet Risk" defined as the % Asset Decline due to mark-to-market × the % of uninsured deposits. 'High' represents the top tercile (red solid line), 'Low' represents the bottom two terciles (blue dashed line). The grey vertical dashed line indicates March 09, 2023 at 9am.

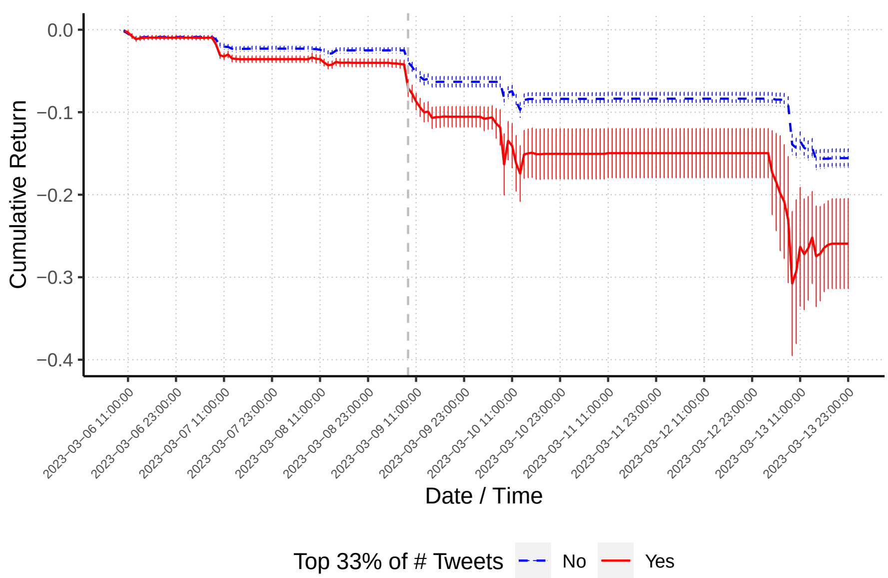
Figure 9: Social Media and the Bank Run – Only "High" Balance Sheet Risk Banks

Comparing only banks at risk, more Twitter conversation corresponds to greater stock losses after the onset of the run.

(a) Including SIVB



(b) Excluding SIVB



Notes: This figure shows the cumulative returns of a group of US publicly listed bank holding companies (BHCs) from March 06 until March 14, 2023. The sample includes only BHCs with bank balance sheet risks (i.e., % Asset Decline MTM × % Uninsured Deposits) in the top 50%. We then split the sample by the number of Tweets about the BHC in the sample period. 'Yes' represents the top tercile (red solid line), 'No' represents the bottom two terciles (blue dashed line). The grey vertical dashed line indicates March 09, 2023 at 9am. Figure 9b includes 95% confidence intervals around the mean cumulative return.

Table 1: Contextual Dictionaries for Classifying Types of Tweets

This table presents the keyword dictionaries for the major content dictionaries that we employ to classify tweets in to "Run," "Contagion,", "Balance Sheet,", "Cryptocurrency," and "Startup Community" authors. For each of our content dictionaries we provide the seed words used, in the iterative creation process, in italics.

Balance Sheet	*Run Behavior*	*Contagion*	*Crypto*	*Startup Community*
duration	*run*	*systemic*	*crypto*	VC
cover & cash	*withdraw*	*spillover*	USDC	entrepreneur
mortgage backed securities	deposit money	fed	Circle	start up
mismatch	access accounts	regulator	Bitcoin	startup
long maturity	pull & out	#contagion	stablecoin	founder
maturity mismatch	*get & out*	backstop	tech	_venture
marked to market		whole system	FTX	venture capital
mark to market		spreading	peg	
portfolio management		sparks	BlockFi	
liquidity		broader effects	Ripple	
insured deposits		financial system	depeg	
MBS		meltdown	#crypto	
hold to maturity		*contagion*	#blockchain	
HTM			BTC	
portfolio of loans			*silverlake*	
liquidity management				
uninsured deposits				
balance sheet				

Table 2: Summary Statistics on Tweet Activity

This table presents summary statistics on the number of tweets at the bank level. Panel (a) presents the number of tweets about a bank's cashtag per 30 days for the pre-run period (Jan 1 through Feb 15, 46 days) and the run period (Mar 8 through Mar 13, 5 days). Panel (b) presents the average and median number of tweets in and out of the run period by tercile. Panel (c) presents the counts of tweets by bank for "Run" behavior during the run period, "Contagion" tweets during the run period, the total number of tweets in the pre-run period ("Tweets Pre-Run"), and tweets that co-mention cryptocurrency discussion in the pre-run period ("Crypto Pre-Run"). For this table, the pre-run period is Jan 1 through Feb 15, 2023. The run period is defined as Mar 8 through Mar 13. As a comparison to these specific examples, we also report the 90th percentile of tweet counts across all banks in our sample.

(a) Distribution of tweets per 30 days across banks − Run and Pre-Run Periods

	Mean	Std	Min	10%	33%	50%	66%	90%	Max
Pre-run period total tweets	536.74	2207.19	1.96	33.26	60.65	88.70	136.30	511.30	23478.91
Run period	2278.98	23178.72	6.00	12.00	42.00	66.00	120.00	732.00	415746.00

(b) Average and Median Number of Tweets by Tercile, Run and Pre-Run Periods

	Bottom Tercile		Middle Tercile		Top Tercile	
	Mean	Median	Mean	Median	Mean	Median
Pre-run period total tweets	22.24	22.5	94.58	89	2,061.47	344
Run period	9.35	8	40.72	39	4,622.62	165

(c) Top Five Banks by "Run Behavior" Dictionary

	Run	Contagion	Tweets Pre-Run	Crypto Pre-Run
SIVB	6,528	9,662	1,163	20
FRC	1,249	1,368	1,257	343
SI	343	342	20,774	356
SBNY	260	106	2,403	106
JPM	206	245	30,063	275
90th Percentile	3	2	784	3

Table 3: Hourly Bank Stock Losses and Bank Balance Sheet Risk

This table presents sample splits and ordinary least squares (OLS) estimates for the effect of mark-to-market losses and percentage of uninsured deposits on bank stock losses at the hourly frequency during the run period. Panel 3a shows the average hourly returns for bank holding companies in our sample, split by "Balance Sheet Risk" (i.e., mark-to-market losses × percentage of uninsured deposits), for the period from March 01st to 08th and for March 9th to 14th, as well as the mean and confidence interval of the difference. The dependent variable in Panel 3b is the hourly return (in %) for a bank stock in our sample. '% Uninsured (z)' is the percentage of deposits at the bank that exceed the FDIC threshold of $250,000, drawn from 2022:Q4's FDIC Call Reports. '% Loss MTM (z)' is the percentage of mark-to-market bank asset losses between 2022:Q1 to 2023:Q1, following the construction of Jiang et al. (2023b). All variables labeled with '(z)' are scaled to have mean of zero and standard deviation of one. The indicator variable '1(≥ Mar 9)' equals one after the onset of the SIVB bank run on March 9th, at 9am, and zero otherwise. Firm- and Day-by-Hour fixed effects are included as indicated. Robust standard errors that are clustered at the bank level are reported in parentheses. *, ** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

(a) Sample Split by Balance Sheet Risk and Run Occurrence

	Mean Hourly Stock Returns (in %)			
% Loss MTM × % Uninsured	[Mar 01–08]	[Mar 09–14]	Mean Diff.	90% CI Diff.
Bottom 67%	-0.0929	-0.5344	0.4414	[0.3576; 0.5253]
Top 33%	-0.0959	-0.7100	0.6141	[0.5302; 0.698]

(b) Regression with Hourly Stock Returns

	Hourly Stock Return (%)		
	(1)	(2)	(3)
1(≥ Mar 09)	-0.4287***	-0.4339***	
	(0.0217)	(0.0253)	
% Loss MTM (z)	0.0054		
	(0.0099)		
% Uninsured (z)	-0.0391**		
	(0.0162)		
1(≥ Mar 09) × % Loss MTM (z)	-0.0616**	-0.0631**	-0.0725***
	(0.0240)	(0.0259)	(0.0271)
1(≥ Mar 09) × % Uninsured (z)	-0.1073**	-0.1401*	-0.1324*
	(0.0503)	(0.0798)	(0.0743)
% Loss MTM (z) × % Uninsured (z)	0.0044		
	(0.0065)		
1(≥ Mar 09) × % Loss MTM (z) × % Uninsured (z)	-0.0412**	-0.0352**	-0.0401**
	(0.0169)	(0.0178)	(0.0195)
Constant	-0.1404***		
	(0.0079)		
Observations	13,026	13,026	13,026
R^2	0.0098	0.0211	0.2576
Within R^2		0.0091	0.0010
Firm FE		✓	✓
Day-by-Hour FE			✓

Table 4: Bank Stock Losses and Social Media Exposure

This table presents OLS estimates for the effect of social media exposure, mark-to-market losses, and percentage of uninsured deposits on bank stock losses during the run period. The dependent variable in all panels is the percentage of bank stock value that is lost by March 14. In Panel 4a, social media exposure is measured as the number of tweets in the pre-run period from January 1 through February 15 that contain the bank's cashtag. All specifications employ terciles of this social media exposure variable to mitigate the influence of outlier observations. '% Uninsured' is the percentage of deposits at the bank that exceed the FDIC threshold of $250,000 from 2022-Q4's FDIC Call Reports. '% Loss MTM' is the percentage of mark-to-market bank asset losses as in Jiang et al. (2023b). Panel 4b is similar to Panel 4a but employs terciles of the fraction of startup community tweets about a cashtag during the run period, instead of aggregate tweet activity. This specification tests whether exposure to VC-backed startup depositors on Twitter matters for bank run risk. In Panel 4c, total 'Run' and 'Contagion' tweets during the run count the number of tweets with at least one word in the 'Run' and 'Contagion' dictionaries between March 8 and March 13, and then divided into three groups: zero (the omitted group), below-median and above-median. Startup community tweets are counted over the same period, but based on the number of tweets about the bank stock posted by users with at least one startup community term in their Twitter user description. Robust standard errors are reported in parentheses. *, ** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

(a) Baseline Result

	% of Stock Value Lost During Run				
	(1)	(2)	(3)	(4)	(5)
% Uninsured (z)	4.117***		1.223		1.288
	(1.025)		(0.895)		(0.893)
% Loss MTM (z)	0.804			−0.069	−0.487
	(0.873)			(0.362)	(0.733)
% Uninsured (z) × % Loss MTM (z)	0.943				−0.980
	(0.735)				(0.782)
1(Social Exp. Tercile = 2) (T2)		0.579	0.074	0.575	0.276
		(0.798)	(0.870)	(0.834)	(0.861)
T2 × % Uninsured (z)			1.527		1.588
			(1.143)		(1.150)
T2 × % Loss (z)				0.461	1.425
				(0.689)	(0.966)
T2 × % Uninsured (z) × % Loss MTM (z)					0.990
					(1.005)
1(Social Exp. Tercile = 3) (T3)		6.660***	5.209***	6.464***	6.302***
		(1.490)	(1.306)	(1.542)	(1.497)
T3 × % Uninsured (z)			3.278*		4.157**
			(1.831)		(2.016)
T3 × % Loss MTM (z)				−0.866	2.170
				(1.201)	(1.990)
T3 × % Uninsured (z) × % Loss MTM (z)					3.014**
					(1.277)
Constant	16.368***	13.453***	13.893***	13.477***	13.735***
	(0.618)	(0.538)	(0.686)	(0.587)	(0.665)
Observations	280	280	280	280	280
R^2	0.158	0.093	0.219	0.097	0.258

... continued

(b) Startup Community Tweets during the Run

	% of Stock Value Lost During Run				
	(1)	(2)	(3)	(4)	(5)
% Uninsured (z)	4.117***		0.691		0.654
	(1.025)		(0.555)		(0.615)
% Loss MTM (z)	0.804			−0.051	0.753
	(0.873)			(0.303)	(0.518)
% Uninsured (z) × % Loss MTM (z)	0.943				0.666
	(0.735)				(0.411)
1(Startup Tweets Tercile = 2) (T2)		0.801	0.602	0.689	0.556
		(0.747)	(0.745)	(0.744)	(0.773)
T2 × % Uninsured (z)			1.853**		2.026**
			(0.869)		(1.012)
T2 × % Loss MTM (z)				−1.047**	−0.993
				(0.528)	(0.795)
T2 × % Uninsured (z) × % Loss MTM (z)					−0.060
					(0.779)
1(Startup Tweets Tercile = 3) (T3)		8.200***	6.322***	8.112***	6.706***
		(1.561)	(1.269)	(1.569)	(1.341)
T3 × % Uninsured (z)			3.633**		4.544**
			(1.668)		(1.831)
T3 × % Loss MTM (z)				−0.949	−0.989
				(1.391)	(1.422)
T3 × % Uninsured (z) × % Loss MTM (z)					2.083
					(1.412)
Constant	16.368***	13.116***	13.346***	13.124***	13.464***
	(0.618)	(0.470)	(0.526)	(0.479)	(0.526)
Observations	280	280	280	280	280
R^2	0.158	0.139	0.244	0.145	0.280

... continued

(c) Controlling for Tweet Activity During Run Period

	% of Stock Value Lost During Run				
	(1)	(2)	(3)	(4)	(5)
1(Social Exp. Tercile = 2) (T2)	0.579	0.562	0.456	−0.298	0.133
	(0.798)	(1.280)	(1.271)	(1.459)	(1.275)
1(Social Exp. Tercile = 3) (T2)	6.660***	2.589*	1.950	2.533	0.210
	(1.490)	(1.368)	(1.396)	(1.741)	(1.543)
1("Contagion" Tweets in Run < Median)		10.814***			5.050
		(2.914)			(3.117)
1("Contagion" Tweets in Run ≥ Median)		17.712***			9.301***
		(1.983)			(2.651)
1("Run" Tweets in Run < Median)			3.282		1.128
			(2.212)		(2.288)
1("Run" Tweets in Run ≥ Median)			19.177***		11.282***
			(1.992)		(2.762)
1(Startup Tweets Tercile = 2) (T2)				0.589	0.507
				(1.407)	(1.229)
1(Startup Tweets Tercile = 3) (T3)				6.536***	2.705*
				(1.624)	(1.514)
Constant	13.453***	13.204***	13.453***	12.927***	13.034***
	(0.538)	(0.992)	(0.983)	(1.180)	(1.030)
Observations	280	280	280	280	280
R^2	0.093	0.310	0.322	0.151	0.363

Table 5: Social Media Exposure and Deposit Flows

This table presents OLS estimates for the effect of social media exposure, mark-to-market losses, and percentage of uninsured deposits on bank deposit flows. The dependent variable, 'Deposit outflows (%)' is measured as the percentage change in bank deposits from the end of Q4-2022 to the end of Q1-2023, as reported on the banks' call reports, multiplied by -1 so that a higher number indicates larger outflows. Columns (1) and (2) use the uninsured deposits (above the FDIC threshold of $250K), columns (3) and (4) use all deposits. Social media exposure ('Social Exp.') is measured as the number of tweets in the pre-run period from January 1 through February 15 that contain the bank's cashtag. All specifications employ terciles of this social media exposure variable to mitigate the influence of outlier observations. % Uninsured is the percentage of deposits at the bank that exceed the FDIC threshold of $250,000, drawn from 2022:Q4's FDIC Call Reports. % Loss is the percentage of mark-to-market bank asset losses, construction following Jiang et al. (2023b). Robust standard errors are reported in parentheses. *, ** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

	Deposit Outflows (%)			
	Uninsured		Total	
	(1)	(2)	(3)	(4)
% Uninsured (z)	4.381***	1.109	2.282***	-0.662
	(1.315)	(1.529)	(0.787)	(1.268)
% Loss MTM (z)	1.216	-1.826	0.529	-0.632
	(1.014)	(1.111)	(0.750)	(0.921)
% Uninsured (z) × % Loss MTM (z)	-0.118	-2.725*	0.245	-0.847
	(0.821)	(1.540)	(0.747)	(1.192)
1(Social Exp. Tercile = 2) (T2)		-3.056*		-1.828
		(1.807)		(1.193)
T2 × % Uninsured (z)		5.085		3.031*
		(3.236)		(1.573)
T2 × % Loss MTM (z)		1.812		0.960
		(2.020)		(1.319)
T2 × % Uninsured (z) × % Loss MTM (z)		1.110		1.374
		(2.328)		(1.509)
1(Social Exp. Tercile = 3) (T3)		1.181		0.882
		(2.405)		(1.780)
T3 × % Uninsured (z)		3.789		4.165**
		(2.372)		(2.051)
T3 × % Loss MTM (z)		4.721**		1.751
		(2.019)		(1.731)
T3 × % Uninsured (z) × % Loss MTM (z)		3.370*		1.625
		(1.867)		(1.708)
Constant	5.512***	6.160***	-0.929	-0.720
	(0.965)	(1.074)	(0.689)	(0.821)
Observations	258	258	233	233
R^2	0.067	0.104	0.039	0.072

Table 6: Social Media and the Bank Run – Hourly Frequency

This table presents OLS estimates for the effect of social media activity on the relationship between hourly stock returns and balance sheet risk around the onset of the SVB bank run on March 09, 2023. The dependent variable in all Panels is the hourly return (in %) for a bank stock in our sample. Similar to Table 3, "Balance Sheet Risk (z)" is defined as % Asset Loss MTM' (i.e., the % of mark-to-market bank asset losses as in Jiang et al., 2023b) × '% Uninsured' (i.e., the % of deposits below the FDIC insurance threshold). The indicator variable '1(≥ Mar 9)' equals one after the onset of the SIVB bank run on March 9th, at 9am, and zero otherwise. Firm- and Day-by-Hour fixed effects are included as indicated. '# Tweets (4h) (z) (t-1)' is the number of Tweets posted about the bank in the 4 hours prior to the current period t, i.e., in hours $t-5$ through $t-1$. The sample is organized at the firm-by-day-by-hour level. All variables labeled with '(z)' are standardized to have mean zero and standard deviation of one. Panel 6a presents the baseline estimations using observations between March 06th and March 14th. Panel 6b uses a similar sample period but excludes Silicon Valley Bank (SIVB). Panel 6c uses a sample from March 07 (9am) to March 09 (4pm). Firm- and Day-by-Hour fixed effects are included as indicated. Robust standard errors that are clustered at the bank level are reported in parentheses. *, ** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

$$
\begin{aligned}
r_{i,t} = a &+ b_1 \times 1(\geq \text{Mar } 09)_t + b_2 \times \text{Balance Sheet Risk}_i + b_3 \times \text{N Tweets}_{i,t-1} \\
&+ b_4 \times 1(\geq \text{Mar } 09)_t \times \text{Balance Sheet Risk}_i + b_5 \times 1(\geq \text{Mar } 09)_t \times \text{N Tweets}_{i,t-1} \\
&+ b_6 \times \text{Balance Sheet Risk}_i \times \text{N Tweets}_{i,t-1} \\
&+ b_7 \times 1(\geq \text{Mar } 09)_t \times \text{Balance Sheet Risk}_i \times \text{N Tweets}_{i,t-1} + \delta_i + \gamma_t + \epsilon_{i,t}
\end{aligned}
$$

(a) Balance Sheet Risk and Tweet Volume over the prior 4 hours

	Hourly Stock Return (%)		
	(1)	(2)	(3)
1(≥ Mar 09)	-0.4462***	-0.4712***	
	(0.0226)	(0.0281)	
Balance Sheet Risk (z)	-0.0002		
	(0.0131)		
# Tweets (4h) (z) (t-1)	-0.0435	0.1233	-0.3499
	(0.1189)	(0.2322)	(0.2643)
1(≥ Mar 09) × Balance Sheet Risk (z)	-0.0960***	-0.1374***	-0.1321***
	(0.0321)	(0.0378)	(0.0346)
1(≥ Mar 09) × # Tweets (4h) (z) (t-1)	-0.3022	-0.4407	-0.1424
	(0.3453)	(0.3139)	(0.3604)
Balance Sheet Risk (z) × # Tweets (4h) (z) (t-1)	0.2839	1.175***	1.103***
	(0.1951)	(0.3947)	(0.3650)
1(≥ Mar 09) × Balance Sheet Risk (z) × # Tweets (4h) (z) (t-1)	-0.1908	-1.058***	-0.9453***
	(0.2093)	(0.3443)	(0.3264)
Constant	-0.1437***		
	(0.0087)		
Observations	12,915	12,915	12,915
R^2	0.0138	0.0263	0.2630
Within R^2		0.0135	0.0085
Firm FE		✓	✓
Day-by-Hour FE			✓
SE Cluster	Firm	Firm	Firm

... continued

(b) Excluding Silicon Valley Bank (SIVB)

	Hourly Stock Return (%)		
	(1)	(2)	(3)
1(≥ Mar 09)	-0.4354***	-0.4513***	
	(0.0182)	(0.0227)	
Balance Sheet Risk (z)	0.0042		
	(0.0122)		
# Tweets (4h) (z) (t-1)	-0.1064	0.2045	-0.4067**
	(0.1154)	(0.2234)	(0.1664)
1(≥ Mar 09) × Balance Sheet Risk (z)	-0.0867***	-0.1027***	-0.0991***
	(0.0316)	(0.0341)	(0.0303)
1(≥ Mar 09) × # Tweets (4h) (z) (t-1)	0.1904**	-0.1001	0.2701**
	(0.0862)	(0.2105)	(0.1319)
Balance Sheet Risk (z) × # Tweets (4h) (z) (t-1)	0.2100	0.7163**	0.6261**
	(0.2074)	(0.2982)	(0.2842)
1(≥ Mar 09) × Balance Sheet Risk (z) × # Tweets (4h) (z) (t-1)	-0.2063	-0.6944**	-0.5487**
	(0.1997)	(0.2887)	(0.2713)
Constant	-0.1404***		
	(0.0080)		
Observations	12,865	12,865	12,865
R^2	0.0098	0.0162	0.2563
Within R^2		0.0106	0.0028
Firm FE		✓	✓
Day-by-Hour FE			✓
SE Cluster	Firm	Firm	Firm

(c) Shorter Time Window: March 08, 9am – March 09, 4pm

	Hourly Stock Return (%)		
	(1)	(2)	(3)
1(≥ Mar 09)	-0.5873***	-0.6261***	
	(0.0287)	(0.0460)	
Balance Sheet Risk (z)	-0.0073		
	(0.0280)		
# Tweets (4h) (z) (t-1)	-0.1953	0.5753	0.5607
	(0.1717)	(0.4701)	(0.5914)
1(≥ Mar 09) × Balance Sheet Risk (z)	-0.0834***	-0.1306***	-0.1293***
	(0.0319)	(0.0495)	(0.0472)
1(≥ Mar 09) × # Tweets (4h) (z) (t-1)	-0.7844***	-0.9962**	-1.133**
	(0.1919)	(0.4897)	(0.5570)
Balance Sheet Risk (z) × # Tweets (4h) (z) (t-1)	0.5214*	1.702***	1.645***
	(0.2722)	(0.5486)	(0.4804)
1(≥ Mar 09) × Balance Sheet Risk (z) × # Tweets (4h) (z) (t-1)	-0.9332***	-1.492***	-1.480***
	(0.2717)	(0.5342)	(0.4344)
Constant	-0.0734***		
	(0.0223)		
Observations	4,109	4,109	4,109
R^2	0.0766	0.1415	0.2728
Within R^2		0.0754	0.0245
Firm FE		✓	✓
Day-by-Hour FE			✓
SE Cluster	Firm	Firm	Firm

Table 7: High Frequency Return Responses to Tweets

This table presents OLS estimates for the impact of the sentiment and content on the tweets in our sample on banks' stock price changes. In all regressions, the dependent variable $\Delta p_{i,t}$ is the log change in Bank i's price between the last trade of the $[-15, -5]$ minute window and the first trade of the $[+5, +15]$ minute window around the tweet happening at time t. $\Delta p_{i,t}$ is winsorized at the 1% level and expressed in basis points. VADER Pos (z) and VADER Neg (z) are the positive and negative components of the VADER sentiment respectively standardized using the sample used in each regression. 'Startup Flag' indicates that a given tweet was posted by a member of the startup community, as constructed in Section 2.1.2. 'Contagion Tweet' and 'Run Tweet' indicate if the tweet contains at least one token in the contagion and run behavior dictionaries respectively. 'High Balance Sheet Risk' indicates if the bank belongs to the top 50 banks with highest bank balance sheet risk (MTM losses × uninsured deposits). We exclude observations for which the traded volume associated with the last price in the window before the tweet or the first price in the window after the tweet is zero. In all regressions, we include fund fixed effects. Standard errors are reported in parenthesis and doubled clustered at the bank-day level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% significance level, respectively.

$$\Delta p_{i,t} = a + b \times \text{VADER Pos (z)}_{it} + c \times \text{VADER Neg (z)}_{it} + \gamma_i + \epsilon_{i,t}$$

	(1) $\Delta p_{i,t}$	(2) $\Delta p_{i,t}$	(3) $\Delta p_{i,t}$	(4) $\Delta p_{i,t}$	(5) $\Delta p_{i,t}$	(6) $\Delta p_{i,t}$
VADER Pos(z)	-0.06	-0.02	-1.59	-1.46	-1.54	-0.79
	(0.16)	(0.16)	(1.43)	(1.44)	(1.57)	(0.92)
VADER Neg(z)	-1.60***	-1.56***	-2.72	-2.62	-3.21	-4.61***
	(0.27)	(0.28)	(2.20)	(2.38)	(1.97)	(1.41)
Startup Flag		3.49***	4.92			
		(1.29)	(10.86)			
VADER Pos(z) × Startup Flag		-1.49*	9.85			
		(0.82)	(8.89)			
VADER Neg(z) × Startup Flag		-2.13**	-21.82***			
		(0.93)	(7.29)			
Contagion Tweet				41.71		
				(36.77)		
VADER Pos(z) × Contagion Tweet				21.68		
				(23.73)		
VADER Neg(z) × Contagion Tweet				-28.18**		
				(14.32)		
Run Tweet					-2.68	
					(8.12)	
VADER Pos(z) × Run Tweet					5.32	
					(7.63)	
VADER Neg(z) × Run Tweet					-0.52	
					(9.69)	
VADER Pos(z) × High Balance Sheet Risk						-0.79
						(2.41)
VADER Neg(z) × High Balance Sheet Risk						1.93
						(3.23)
Constant	-0.78	-0.85	-26.17***	-26.06***	-25.90***	-26.19***
	(0.78)	(0.76)	(4.79)	(4.88)	(4.83)	(4.63)
Observations	1521078	1521078	43597	43597	43597	43597
R^2 (%)	1.01	1.02	2.47	2.47	2.46	2.45
Bank FE	✓	✓	✓	✓	✓	✓
Sample	All	All	≥ Mar09	≥ Mar09	≥ Mar09	≥ Mar09

Table 8: High Frequency Bank Responses to Tweets – excluding SIVB and FRC

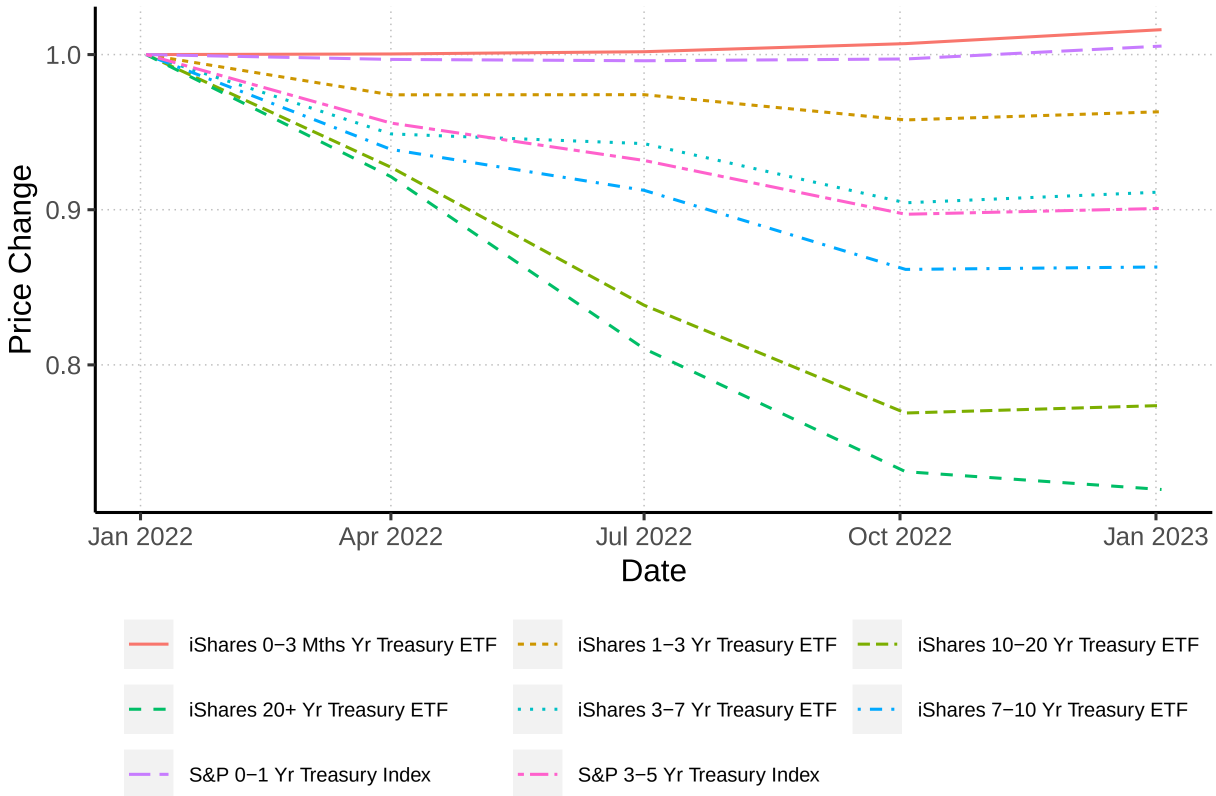
This table presents OLS estimates for the impact of the sentiment and content on the tweets in our sample on banks' stock price changes excluding Silicon Valley Bank (SIVB) and First Republic Bank (FRC) from the sample. In all regressions, the dependent variable $\Delta p_{i,t}$ is the log change in Bank i's price between the last trade of the $[-15,-5]$ minute window and the first trade of the $[+5,+15]$ minute window around the tweet happening at time t. $\Delta p_{i,t}$ is winsorized at the 1% level and expressed in basis points. VADER Pos (z) and VADER Neg (z) are the positive and negative components of the VADER sentiment respectively standardized using the sample used in each regression. 'Startup Flag' indicates that a given tweet was posted by a member of the startup community, as constructed in Section 2.1.2. 'Contagion Tweet' and 'Run Tweet' indicate if the tweet contains at least one token in the contagion and run behavior dictionaries respectively. 'High Balance Sheet Risk' indicates if the bank belongs to the top 50 banks with highest bank balance sheet risk (MTM losses × uninsured deposits). We exclude observations for which the traded volume associated with the last price in the window before the tweet or the first price in the window after the tweet is zero. In all regressions, we include fund fixed effects. Standard errors are reported in parenthesis and doubled clustered at the bank-day level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% significance level, respectively.

$$\Delta p_{i,t} = a + b \times \text{VADER Pos (z)}_{it} + c \times \text{VADER Neg (z)}_{it} + \gamma_i + \epsilon_{i,t}$$

	(1) $\Delta p_{i,t}$	(2) $\Delta p_{i,t}$	(3) $\Delta p_{i,t}$	(4) $\Delta p_{i,t}$	(5) $\Delta p_{i,t}$	(6) $\Delta p_{i,t}$
VADER Pos(z)	-0.00	0.04	-0.98	-0.52	-0.78	-0.72
	(0.16)	(0.16)	(0.94)	(0.91)	(1.27)	(0.85)
VADER Neg(z)	-1.38***	-1.34***	-3.63***	-4.03***	-4.26***	-3.95***
	(0.26)	(0.27)	(1.08)	(1.23)	(1.14)	(1.21)
Startup Flag		3.21**	0.06			
		(1.25)	(11.72)			
VADER Pos(z) × Startup Flag		-1.79**	18.60			
		(0.74)	(13.62)			
VADER Neg(z) × Startup Flag		-1.82**	-17.72***			
		(0.82)	(5.94)			
Contagion Tweet				-6.47		
				(34.30)		
VADER Pos(z) × Contagion Tweet				-10.09		
				(21.78)		
VADER Neg(z) × Contagion Tweet				-2.11		
				(16.77)		
Run Tweet					8.98	
					(6.13)	
VADER Pos(z) × Run Tweet					5.82	
					(20.67)	
VADER Neg(z) × Run Tweet					-0.86	
					(9.00)	
VADER Pos(z) × High Balance Sheet Risk						2.51
						(6.27)
VADER Neg(z) × High Balance Sheet Risk						-3.13
						(3.16)
Constant	-0.09	-0.15	-6.45	-6.53	-6.99	-6.57
	(0.77)	(0.76)	(4.64)	(4.52)	(4.61)	(4.52)
Observations	1484132	1484132	19673	19673	19673	19673
R^2 (%)	.49	.5	.91	.87	.88	.87
Bank FE	✓	✓	✓	✓	✓	✓
Sample	All	All	≥ Mar09	≥ Mar09	≥ Mar09	≥ Mar09

Appendix

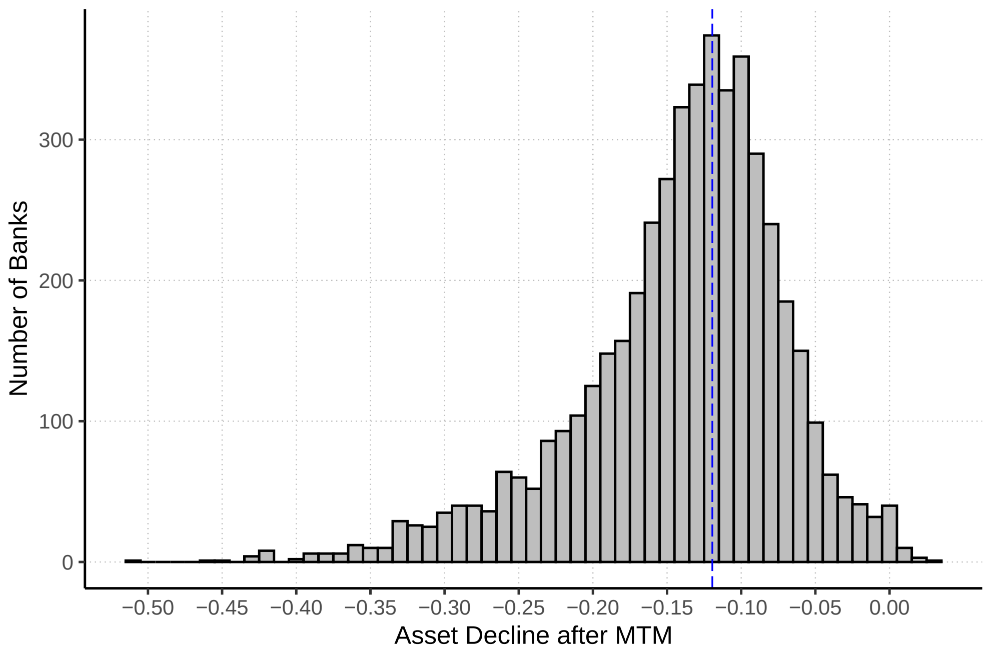
Figure A.1: Prices of Treasury ETFs across maturities



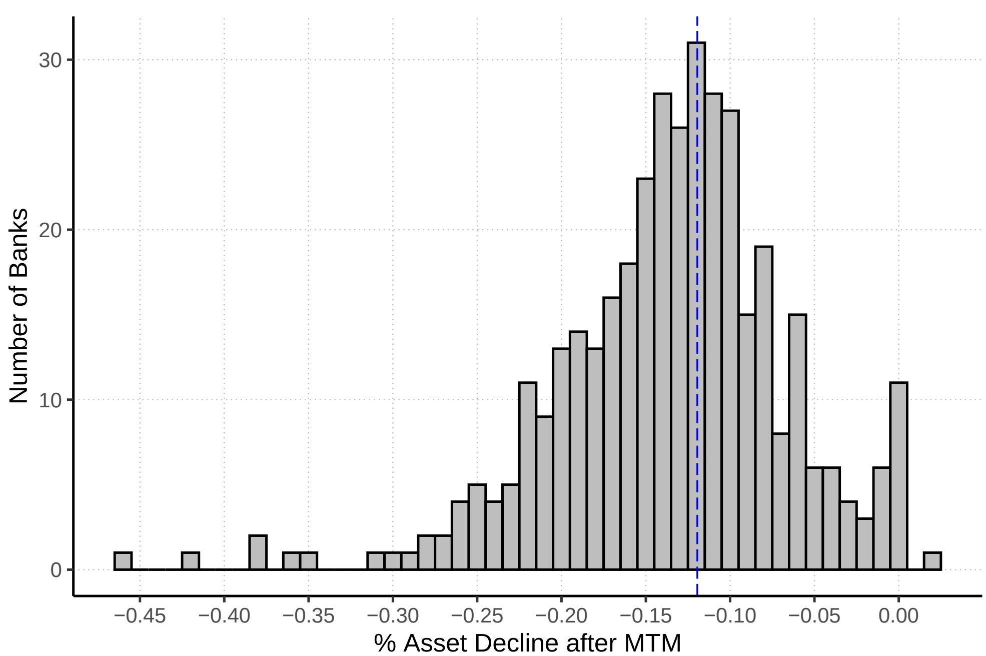
Notes: This figure shows changes in the prices of iShares Treasury Bond ETFs and S&P Treasury Indices across various maturities at the quarterly frequency, for the period from 2022:Q1 to 2023:Q1. ETF Prices and Treasury Indices are scaled by starting values in 2022:Q1.

Figure A.2: Distribution of mark-to-market asset declines across banks

(a) All banks

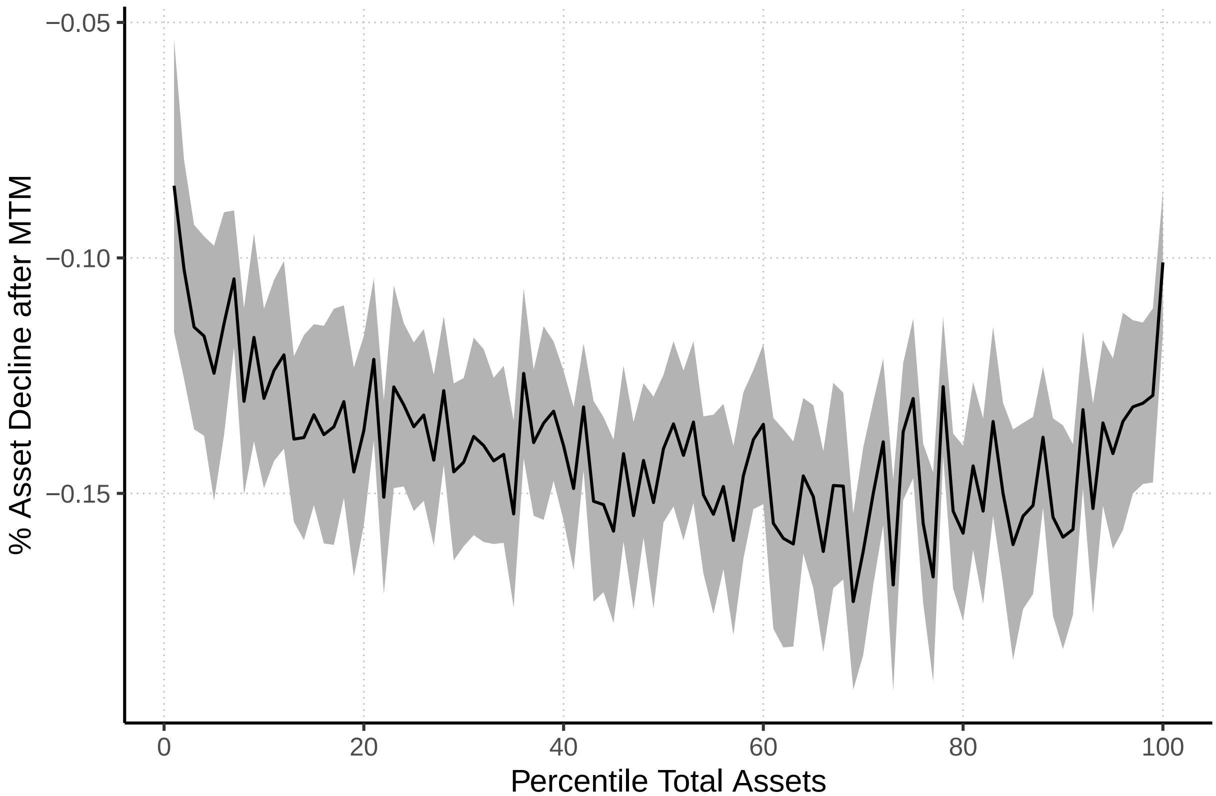


(b) Publicly listed bank holding companies (BHCs)



Notes: This figure shows the distribution of mark-to-market implied asset value changes between Q1 of 2022 and Q1 of 2023, constructed following Jiang et al. (2023b). The blue, dashed, vertical line indicates Silicon Valley Bank (SVB). Figure A.2a includes all FDIC-insured banks with call reports available from the FFIEC. Figure A.2b includes all public bank holding companies with available stock return data after aggregating at the bank holding company level.

Figure A.3: Mark-to-market asset declines and bank asset size



Notes: This figure shows the distribution of average mark-to-market implied bank asset changes between 2022:Q1 and 2023:Q1 (constructed following Jiang et al., 2023b) across percentiles of bank size measured as total assets in 2022:Q1. The smallest banks are in the percentile on the very left of the figure, the largest banks are in the percentile on the very right of the figure. The grey-shaded are indicates two standard deviations around the mean.

Table A.1: Which Original Tweets from the Pre-Run Period were reshared during the run period?

This table presents the characteristics and content of the original tweets that accumulated the most run period retweets. The table reports the ticker, date of original tweet, number of retweets in the run period, number of total retweets, the number of replies, the number of likes, and the number of quote tweets.

Ticker	Date	Retweets_run_period	Retweet_count	Reply_count	Like_count	Quote_count
SIVB	1/18/23	1026	1055	175	6008	927
Silicon Valley Bank $SIVB reports earnings tomorrow Investors have rightfully been fixated on $SIVB's large exposure to the stressed venture world, with the stock down a lot. However, dig just a little deeper, and you will find a much bigger set of problems at $SIVB... 1/10						
SIVB	1/18/23	103	104	15	875	83
$SIVB's big problems are with its HTM portfolio. The bank basically increased its security portfolio by 700% at a generational TOP in the bond market, buying $88 b of mostly 10+ year mortgages with an average yield of just 1.63% at Sept 30th. Oops! 4/10 https://t.co/B50DeQpFQj						
SIVB	1/18/23	79	80	8	756	51
$SIVB's HTM securities had mark-to-market losses as of Q3 of $15.9 b...compared to just $11.5 b of tangible common equity!! Luckily, regulators do not force $SIVB to mark HTM securities to market. But the bank would be functionally underwater if it were liquidated today. 5/10 https://t.co/WoM5789o4X						
SIVB	1/18/23	75	78	86	1163	22
$SIVB's mgmt has tried to blame its challenges on its venture-related exposure. However, it is hard to hide from the fact that mgmt bought the TOP of the bond market. Tomorrow's earnings and this year should be interesting. Caveat Emptor! (Disclosure: I am short) 10/10						
BAC	1/18/23	66	8896	2278	24909	1656
Lots of reports on Instagram, Tiktok, Reddit of problems at Bank of America. $BAC Many customers are missing money and not getting answers. Sound on #bankofamerica https://t.co/t1hQPdG2xU						
SIVB	1/18/23	64	64	12	693	48
The risk for $SIVB is that deposit outflows accelerate at such a pace that it is forced to either raise equity capital and/or sell down its HTM securities portfolio, thus realizing substantial losses. You can bet that $SIVB is praying for a Fed pivot! 8/10						
SIVB	1/18/23	53	54	7	593	12
$SIVB rode the VC boom like a champ Deposits grew from $61b at Q4 '19 to $189 b at Q4 '21. Interest rates were so low, these deposits were like free money (˜25 bps avg. cost). 2/10						
SIVB	1/18/23	41	41	6	555	8
$SIVB used these inflows to: - Increase loans 100% to $66 b - Go hog wild with its 'held-to-maturity' (HTM) securities portfolio, ramping its mostly Agency mortgage holdings from $13.5 b at Q4 '19 to $99 b at Q4 '21. 3/10 https://t.co/59Nn36t9S1"						
SIVB	1/18/23	34	35	2	482	7
On top of this, due to the Fed's interest rate hikes, $SIVB is seeing accelerating deposit outflows (-6.5% ytd), a mix shift away from non-interest accounts, and skyrocketing interest costs (money markets now yield 4%). Also, $SIVB's venture clients are burning cash! 6/10						
SBNY	1/10/23	32	162	24	513	31
NEW: SIGNS OF TROUBLE AT SIGNATURE BANK. Banking crypto comes with risks. New revelations suggest legal and regulatory problems loom for $SBNY. Summary https://t.co/jxj22WJ4z9						
SIVB	1/18/23	32	34	4	422	4
$SIVB's clients also face a risk. With the bank's stretched balance sheet, will it tighten and/or pull back on credit lines? Worse, could customers become uncomfortable with $SIVB as a counter-party, due to unrealized balance sheet losses? 9/10						
SIVB	1/18/23	31	34	2	460	3
Basically, as its funding costs reset higher, $SIVB is facing a massive negative carry cost on its HTM, largely fixed-yield securities portfolio (which is not running off quickly, due to the nature of mortgage convexity). 7/10						

Table A.2: Bank Stock Losses and Social Media Exposure – Robustness

This table presents ordinary least squares estimates for the effect of social media exposure, mark-to-market losses, and percentage of uninsured deposits on bank stock losses during the run period, analogous to Table 4. In Panel A.2a, we drop the largest banks from the sample – i.e., too-big-to-fail – national banks (Tickers "JPM", "C", "BAC", "WFC", "USB", "PNC", and "TFC"). The dependent variable is the percentage of bank stock value that is lost by March 14. All specifications employ terciles of this social media exposure variable to mitigate the influence of outlier observations. '% Uninsured' is the percentage of deposits at the bank that exceed the FDIC threshold of $250,000, drawn from 2022:Q4's FDIC Call Reports. '% Loss MTM' is the percentage of mark-to-market bank asset losses, construction following Jiang et al. (2023b). Panels A.2b and A.2c use alternative pre-run periods to calculate social media exposure. Specifically, in Panel A.2b, social media exposure is measured as the number of tweets in the pre-run period from November 15 to December 31 that contain the bank's cashtag. Panel A.2c does the same for a pre-run period of October 1 to November 15. All other variables are defined as in Table 4. Robust standard errors and reported in parentheses. *, ** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

(a) Dropping Banks with more than $ 500 Billion in Deposits

	% of Stock Value Lost During Run				
	(1)	(2)	(3)	(4)	(5)
% Uninsured(z)	4.140***		1.234		1.292
	(1.043)		(0.903)		(0.899)
% Loss MTM (z)	0.768			−0.070	−0.483
	(0.879)			(0.365)	(0.733)
% Uninsured(z) × % Loss MTM (z)	0.926				−0.996
	(0.752)				(0.796)
1(Social Exp. Tercile = 2) (T2)		0.579	0.062	0.579	0.276
		(0.799)	(0.866)	(0.833)	(0.857)
T2 × % Uninsured(z)			1.541		1.611
			(1.154)		(1.160)
T2 × % Loss (z)				0.464	1.428
				(0.695)	(0.968)
T2 × % Uninsured(z) × % Loss MTM (z)					1.007
					(1.023)
1(Social Exp. Tercile = 3) (T3)		6.670***	5.224***	6.459***	6.323***
		(1.561)	(1.359)	(1.608)	(1.557)
T3 × % Uninsured(z)			3.335*		4.210**
			(1.855)		(2.046)
T3 × % Loss (z)				−0.977	2.056
				(1.210)	(1.999)
T3 × % Uninsured(z) × % Loss MTM (z)					3.031**
					(1.308)
Constant	16.277***	13.453***	13.883***	13.476***	13.721***
	(0.628)	(0.538)	(0.682)	(0.586)	(0.660)
Observations	274	274	274	274	274
R^2	0.158	0.091	0.220	0.096	0.258

... continued

(b) Social Media Exposure from Nov 15 to Dec 31, 2022

	% of Stock Value Lost During Run				
	(1)	(2)	(3)	(4)	(5)
% Uninsured (z)	4.117***		1.253**		1.271*
	(1.025)		(0.635)		(0.702)
% Loss MTM (z)	0.804			−0.397	−0.576
	(0.873)			(0.383)	(0.548)
% Uninsured (z) × % Loss MTM (z)	0.943				−0.583
	(0.735)				(0.597)
1(Social Exp. Tercile = 2) (T2)		0.364	−0.133	0.344	0.099
		(0.846)	(0.829)	(0.877)	(0.888)
T2 × % Uninsured (z)			2.439**		3.040***
			(0.978)		(1.077)
T2 × % Loss MTM (z)				1.343	3.187**
				(1.194)	(1.368)
T2 × % Uninsured (z) × % Loss MTM (z)					0.685
					(1.338)
1(Social Exp. Tercile = 3) (T3)		6.253***	4.570***	6.007***	5.253***
		(1.552)	(1.280)	(1.580)	(1.421)
T3 × % Uninsured (z)			2.891*		3.599*
			(1.680)		(1.876)
T3 × % Loss MTM (z)				−0.571	1.583
				(1.172)	(1.690)
T3 × % Uninsured (z) × % Loss MTM (z)					2.404**
					(1.163)
Constant	16.368***	13.860***	14.277***	13.954***	14.255***
	(0.618)	(0.476)	(0.549)	(0.507)	(0.549)
Observations	280	280	280	280	280
R^2	0.158	0.083	0.203	0.089	0.241

... continued

(c) Social Media Exposure from Oct 1 to Nov 15, 2022

	% of Stock Value Lost During Run				
	(1)	(2)	(3)	(4)	(5)
% Uninsured (z)	4.117***		0.806		0.855
	(1.025)		(0.551)		(0.658)
% Loss MTM (z)	0.804			−0.280	−0.432
	(0.873)			(0.383)	(0.569)
% Uninsured (z) × % Loss MTM (z)	0.943				−0.489
	(0.735)				(0.629)
1(Social Exp. Tercile = 2) (T2)		2.036**	1.841**	1.935**	1.987**
		(0.793)	(0.811)	(0.829)	(0.828)
T2 × % Uninsured (z)			1.588		1.490
			(1.036)		(1.131)
T2 × % Loss MTM (z)				−0.152	1.019
				(0.668)	(0.960)
T2 × % Uninsured (z) × % Loss MTM (z)					1.128
					(0.812)
1(Social Exp. Tercile = 3) (T3)		7.339***	5.046***	7.406***	5.525***
		(1.585)	(1.294)	(1.740)	(1.439)
T3 × % Uninsured (z)			3.933**		6.490***
			(1.826)		(2.304)
T3 × % Loss MTM (z)				0.835	1.317
				(1.751)	(1.835)
T3 × % Uninsured (z) × % Loss (z)					4.614**
					(1.860)
Constant	16.368***	12.961***	13.266***	13.049***	13.229***
	(0.618)	(0.499)	(0.556)	(0.554)	(0.573)
Observations	280	280	280	280	280
R^2	0.158	0.097	0.208	0.098	0.274

Table A.3: Hourly Frequency Results – Robustness

This table presents robustness tests for the effect of social media activity on the relationship between hourly stock returns and balance sheet risk around the onset of the SVB bank run on March 09, 2023, analogous to Table 6. The dependent variable in all Panels is the hourly return (in %) for a bank stock in our sample. All explanatory variables are similar as in Table 6. Panel A.3a additionally includes the variable "Ret (Cum-4h) (z) (t-1)", which measures the bank's cumulative return over the last four hours (analogous to social media activity over the last four hours), lagged by one period. Panel A.3b estimates the same model as Table 6, but excluding the very largest – i.e., too-big-to-fail – national banks (i.e., Tickers "JPM", "C", "BAC", "WFC", "USB", "PNC", and "TFC"). All variables labeled with '(z)' are standardized to have mean zero and standard deviation of one. Firm- and Day-by-Hour fixed effects are included as indicated. Robust standard errors that are clustered at the bank level are reported in parentheses. *, ** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

(a) Including lagged returns and interactions

	Hourly Stock Return (%)		
	(1)	(2)	(3)
1(≥ Mar 09)	-0.5605***	-0.6130***	
	(0.0325)	(0.0359)	
Balance Sheet Risk (z)	-0.0023		
	(0.0123)		
# Tweets (4h) (z) (t-1)	-0.0209	-0.0420	-0.3604**
	(0.0890)	(0.1834)	(0.1585)
Ret (Cum.-4h) (z) (t-1)	0.0198	-0.1789***	-0.1632***
	(0.0820)	(0.0494)	(0.0599)
1(≥ Mar 09) × Balance Sheet Risk (z)	-0.0670	-0.1110*	-0.1260**
	(0.0496)	(0.0612)	(0.0599)
1(≥ Mar 09) × # Tweets (4h) (z) (t-1)	-0.1515	-0.1377	0.0287
	(0.2695)	(0.1943)	(0.1866)
Balance Sheet Risk (z) × # Tweets (4h) (z) (t-1)	0.1862	0.7129**	0.7039**
	(0.1556)	(0.3181)	(0.3198)
1(≥ Mar 09) × Ret (Cum.-4h) (z) (t-1)	-0.3293***	-0.1910***	-0.0852
	(0.0590)	(0.0576)	(0.0640)
Balance Sheet Risk (z) × Ret (Cum.-4h) (z) (t-1)	0.0096	-0.1148*	-0.0931
	(0.0896)	(0.0665)	(0.0711)
1(≥ Mar 09) × Balance Sheet Risk (z) × # Tweets (4h) (z) (t-1)	-0.1377	-0.6359**	-0.5874**
	(0.1512)	(0.2765)	(0.2839)
1(≥ Mar 09) × Balance Sheet Risk (z) × Ret (Cum.-4h) (z) (t-1)	0.0957	0.2204***	0.1483*
	(0.0888)	(0.0736)	(0.0796)
Constant	-0.1433***		
	(0.0084)		
Observations	12,915	12,915	12,915
R^2	0.0264	0.0456	0.2691
Within R^2		0.0330	0.0167
Firm FE		✓	✓
Day-by-Hour FE			✓
SE Cluster	Firm	Firm	Firm

... continued

(b) Excluding too-big-to-fail banks

	Hourly Stock Return (%)		
	(1)	(2)	(3)
1(≥ Mar 09)	-0.4476***	-0.5084***	
	(0.0300)	(0.0290)	
Balance Sheet Risk (z)	-0.0015		
	(0.0102)		
# Tweets (4h) (z) (t-1)	-0.2774*	0.4610**	-0.6631*
	(0.1489)	(0.1885)	(0.3538)
1(≥ Mar 09) × Balance Sheet Risk (z)	-0.0967***	-0.1657***	-0.1432***
	(0.0341)	(0.0372)	(0.0301)
1(≥ Mar 09) × # Tweets (4h) (z) (t-1)	0.0111	-0.7037***	0.2738
	(0.3876)	(0.2313)	(0.2822)
Balance Sheet Risk (z) × # Tweets (4h) (z) (t-1)	0.2001	1.373***	1.002***
	(0.1432)	(0.2901)	(0.1806)
1(≥ Mar 09) × Balance Sheet Risk (z) × # Tweets (4h) (z) (t-1)	-0.1192	-1.271***	-0.8672***
	(0.1376)	(0.2526)	(0.1504)
Constant	-0.1578***		
	(0.0086)		
Observations	12,474	12,474	12,474
R^2	0.0132	0.0266	0.2660
Within R^2		0.0138	0.0082
Firm FE		✓	✓
Day-by-Hour FE			✓
SE Cluster	Firm	Firm	Firm

Table A.4: Social Media Exposure and Deposit Flows – Robustness

This table presents robustness tests for the effect of social media exposure on the relationship between balance sheet risk and deposit flow, analogous to Table 5. Similar to Table 5, 'Deposit outflows (%)' are measured as the percentage change in bank deposits from the end of Q4-2022 to the end of Q1-2023, as reported on the banks' call reports, multiplied by −1 so that a higher number indicates larger outflows. Similar to Table 3, "Balance Sheet Risk (z)" in Panel A.4a is defined as % Loss MTM' (i.e., the percentage of mark-to-market bank asset losses as in Jiang et al., 2023b) × '% Uninsured' (i.e., the percentage of deposits below the FDIC insurance threshold). '% Run Loss (z)' is the bank's stock value decline (in %) during the SVB run period. All other variables are defined similarly as in Table 5. Variables denoted with '(z)' are standardized to have zero mean and standard deviation of 1. Panel A.4b excludes too-big-to-fail banks (over B$500 in deposits). Panel A.4c is similar to Table 5 but additionally includes '% Run Loss (z)' and the corresponding interactions. Robust standard errors are reported in parentheses. *, ** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

(a) Uninsured deposit outflows and run-period stock losses

	Uninsured Deposit Outflows (%)				
	(1)	(2)	(3)	(4)	(5)
Balance Sheet Risk (z)	2.099*	1.308		-0.7366	-0.5581
	(1.093)	(0.8688)		(1.060)	(0.9697)
% Run Loss (z)		4.961***	0.6513	4.908***	0.7281
		(1.190)	(1.992)	(1.149)	(1.985)
Social Exp. Tercile = 2			-2.381	-3.547*	-2.736
			(1.608)	(1.802)	(1.694)
Social Exp. Tercile = 3			-1.719	-2.111	-1.510
			(1.870)	(1.829)	(1.821)
% Run Loss (z) × 1(Social Exp. Tercile = 2)			5.114		4.399
			(3.184)		(2.986)
% Run Loss (z) × 1(Social Exp. Tercile = 3)			4.974**		4.560*
			(2.339)		(2.389)
Balance Sheet Risk (z) × 1(Social Exp. Tercile = 2)				2.408	2.191
				(2.097)	(1.953)
Balance Sheet Risk (z) × 1(Social Exp. Tercile = 3)				2.756*	2.471
				(1.574)	(1.531)
Constant	5.318***	5.061***	6.375***	7.255***	6.471***
	(0.9091)	(0.8681)	(0.9294)	(1.009)	(0.9726)
Observations	263	257	257	257	257
R^2	0.0193	0.1223	0.1295	0.1347	0.1401
Adjusted R^2	0.0155	0.1154	0.1122	0.1139	0.1124

... continued

(b) Excluding too-big-to-fail banks

	Uninsured Deposit Outflows (%)				
	(1)	(2)	(3)	(4)	(5)
Balance Sheet Risk (z)	2.108*	1.309		-0.7388	-0.5581
	(1.095)	(0.8689)		(1.062)	(0.9700)
% Run Loss (z)		5.059***	0.6513	4.959***	0.7281
		(1.189)	(1.992)	(1.140)	(1.985)
Social Exp. Tercile = 2			-2.381	-3.550*	-2.736
			(1.609)	(1.803)	(1.695)
Social Exp. Tercile = 3			-1.444	-1.814	-1.209
			(1.947)	(1.896)	(1.891)
% Run Loss (z) × 1(Social Exp. Tercile = 2)			5.114		4.399
			(3.185)		(2.987)
% Run Loss (z) × 1(Social Exp. Tercile = 3)			5.057**		4.634*
			(2.329)		(2.380)
Balance Sheet Risk (z) × 1(Social Exp. Tercile = 2)				2.402	2.191
				(2.097)	(1.954)
Balance Sheet Risk (z) × 1(Social Exp. Tercile = 3)				2.828*	2.537*
				(1.569)	(1.524)
Constant	5.362***	5.163***	6.375***	7.264***	6.471***
	(0.9258)	(0.8857)	(0.9296)	(1.010)	(0.9729)
Observations	258	252	252	252	252
R^2	0.0194	0.1249	0.1321	0.1375	0.1432
Adjusted R^2	0.0156	0.1179	0.1145	0.1164	0.1149

... continued

(c) With triple interactions

	Uninsured Deposit Outflows (%)				
	(1)	(2)	(3)	(4)	(5)
Constant	5.443***	4.941***	6.160***	6.997***	6.325***
	(0.9469)	(0.8712)	(1.074)	(1.183)	(1.121)
% Uninsured (z)	4.351***	2.683**	1.109	0.2926	1.010
	(1.313)	(1.239)	(1.528)	(1.768)	(1.624)
% Loss MTM (z)	1.215	0.9317	-1.826	-1.795	-1.885*
	(1.012)	(0.8472)	(1.110)	(1.240)	(1.126)
% Uninsured (z) × % Loss MTM (z)	-0.1319	-0.7819	-2.725*	-2.380	-2.770*
	(0.8200)	(0.6293)	(1.539)	(1.714)	(1.545)
% Run Loss (z)		4.576***		4.579***	0.1236
		(1.290)		(1.288)	(2.060)
1(Social Exp. Tercile = 2)			-3.056*	-3.380*	-2.878
			(1.806)	(1.894)	(1.825)
1(Social Exp. Tercile = 3)			0.8922	-2.189	-1.951
			(2.303)	(2.024)	(2.000)
% Uninsured (z) × 1(Social Exp. Tercile = 2)			5.085	4.436	4.243
			(3.234)	(3.356)	(3.225)
% Uninsured (z) × 1(Social Exp. Tercile = 3)			3.716	2.403	1.274
			(2.377)	(2.270)	(2.238)
% Loss MTM (z) × 1(Social Exp. Tercile = 2)			1.812	1.575	1.756
			(2.019)	(2.083)	(2.017)
% Loss MTM (z) × 1(Social Exp. Tercile = 3)			4.676**	4.167**	4.165**
			(2.014)	(1.730)	(1.615)
% Uninsured (z) × % Loss MTM (z) × 1(Social Exp. Tercile = 2)			1.110	0.7117	1.121
			(2.327)	(2.449)	(2.338)
% Uninsured (z) × % Loss MTM (z) × 1(Social Exp. Tercile = 3)			3.312*	1.636	1.767
			(1.865)	(1.855)	(1.678)
% Run Loss (z) × 1(Social Exp. Tercile = 2)					2.816
					(2.762)
% Run Loss (z) × 1(Social Exp. Tercile = 3)					5.343**
					(2.490)
Observations	263	257	263	257	257
R^2	0.0659	0.1436	0.1024	0.1712	0.1801
Adjusted R^2	0.0550	0.1300	0.0631	0.1304	0.1327

Table A.5: High Frequency Bank Responses to Tweets. Robustness to Dropping Banks with more than $ 500 Billion in Deposits

This table presents OLS estimates for the impact of the sentiment and content on the tweets in our sample on banks' stock price changes excluding too big to fail banks from the sample (Tickers JPM, C, BAC, WFC, USB, PNC, and TFC). In all regressions, the dependent variable $\Delta p_{i,t}$ is the log change in Bank i's price between the last trade of the $[-15, -5]$ minute window and the first trade of the $[+5, +15]$ minute window around the tweet happening at time t. $\Delta p_{i,t}$ is winsorized at the 1% level and expressed in basis points. VADER Pos (z) and VADER Neg (z) are the positive and negative components of the VADER sentiment respectively standardized using the sample used in each regression. Startup Flag' indicates that a given tweet was posted by a member of the startup community, as constructed in Section 2.1.2. Contagion Tweet' and Run Tweet' indicate if the tweet contains at least one token in the contagion and run behavior dictionaries respectively. 'High Balance Sheet Risk' indicates if the bank belongs to the top 50 banks with highest bank balance sheet risk (MTM losses × uninsured deposits). We exclude observations for which the traded volume associated with the last price in the window before the tweet or the first price in the window after the tweet is zero. In all regressions, we include fund fixed effects. Standard errors are reported in parenthesis and doubled clustered at the bank-day level. ***, , and * denote statistical significance at the 1%, 5%, and 10% significance level, respectively.

$$\Delta p_{i,t} = a + b \times \text{VADER Pos (z)}_{it} + c \times \text{VADER Neg (z)}_{it} + \gamma_i + \epsilon_{i,t}$$

	(1) $\Delta p_{i,t}$	(2) $\Delta p_{i,t}$	(3) $\Delta p_{i,t}$	(4) $\Delta p_{i,t}$	(5) $\Delta p_{i,t}$	(6) $\Delta p_{i,t}$
VADER Pos(z)	-0.12	-0.07	-1.56	-1.45	-1.54	-0.36
	(0.22)	(0.22)	(1.62)	(1.64)	(1.79)	(1.25)
VADER Neg(z)	-2.06***	-2.00***	-2.90	-2.80	-3.44	-6.69***
	(0.37)	(0.38)	(2.54)	(2.75)	(2.28)	(1.88)
Startup Flag		3.76**	5.52			
		(1.70)	(12.08)			
VADER Pos(z) × Startup Flag		-1.91*	9.66			
		(1.08)	(9.76)			
VADER Neg(z) × Startup Flag		-2.55**	-24.96***			
		(1.26)	(7.69)			
Contagion Tweet				44.96		
				(39.24)		
VADER Pos(z) × Contagion Tweet				23.24		
				(25.51)		
VADER Neg(z) × Contagion Tweet				-30.86**		
				(15.11)		
Run Tweet					-3.24	
					(8.77)	
VADER Pos(z) × Run Tweet					5.80	
					(8.39)	
VADER Neg(z) × Run Tweet					-1.41	
					(10.76)	
VADER Pos(z) × High Balance Sheet Risk						-1.24
						(2.58)
VADER Neg(z) × High Balance Sheet Risk						3.99
						(3.48)
Constant	-1.18	-1.26	-29.68***	-29.56***	-29.34***	-29.81***
	(1.08)	(1.06)	(5.49)	(5.59)	(5.53)	(5.32)
Observations	1086469	1086469	37940	37940	37940	37940
R^2 (%)	1.05	1.06	2.4	2.41	2.39	2.39
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Sample	All	All	$\geq$ Mar09	$\geq$ Mar09	$\geq$ Mar09	$\geq$ Mar09