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Risky Tweets in Quiet Times: Social Media Attention and Bank Deposit Flows

By *Yong Kyu Gam, Chunbo Liu, Yongxin Xu*

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Yong Kyu Gam[§]

University College Dublin

Chunbo Liu [‡]

Shanghai International Studies University

Yongxin Xu [†]

Monash University

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[§] College of Business, University College Dublin. Email: kevin.gam@ucd.ie

[‡] School of Business and Management, Shanghai International Studies University. Email: bernard.cliu@shisu.edu.cn

[†] Monash Business School, Monash University. Email: yongxin.xu@monash.edu

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ABSTRACT

Does social media attention affect bank deposit flow sensitivity to performance absent systemic crises? Using data on U.S. commercial banks from 2009 to 2022, we show that heightened Twitter attention increases the sensitivity of non-core deposit outflows—but not core deposit outflows—to deteriorating bank performance. This effect is stronger for banks with greater liquidity mismatch and when Twitter discussions receive more engagement among users. The results remain robust for transparent banks and after controlling for negative social media sentiment. Our findings suggest that social media heightens depositors' awareness of peer attention to banks, amplifying deposit outflow sensitivity to weak fundamentals even during calm periods.

Keywords: Social media, Bank deposits, Bank fragility, Liquidity transformation

JEL Codes: D83, G01, G21

Introduction

The Silicon Valley Bank (SVB) failure in March 2023 triggered new debates on the underlying mechanisms by which a bank's asset losses lead to depositors' panic runs on the bank. Jiang, Matvos, Piskorski, and Seru (2023) develop a theoretical model and demonstrate that a combination of a bank's asset losses, low capital, and, importantly, high uninsured leverage can lead to self-fulfilling solvency runs on the bank, as exemplified by the SVB case. While the financial soundness of individual banks is crucial, factors beyond bank-specific signals—particularly those shaping depositors' concerns—may also play a significant role in bank runs, as suggested by Diamond and Dybvig (1983).

One of the most noteworthy phenomena in the course of the SVB failure was a large spike in communication on Twitter about SVB's financial troubles.[1] Cookson, Fox, Gil-Bazo, Imbet, and Schiller (2026) find that U.S. regional banks with more Twitter conversations experienced larger stock market losses following the collapse of SVB in March 2023. Patrick McHenry, the chairman of the U.S. House Financial Services Committee, referred to the SVB collapse as "the first Twitter fueled bank run" in the press release (March 12, 2023).[2] Is the SVB episode an isolated incident, or does it reflect a more fundamental relationship between social media attention and bank fragility? Using data from 2009 to 2022—predating the SVB episode—we examine whether deposit withdrawals respond more drastically to deteriorating bank fundamentals when banks receive more attention from social media, even in the absence of a system-wide banking failure.

[1] We use the term "Twitter" throughout this paper, as our sample period (2009-2022) predates the platform's rebranding to "X" in July 2023.
[2] See the press release titled "McHenry Statement on Regulator Actions Regarding Silicon Valley Bank" (March 2023) for more details.

Theory suggests that deposit outflows from banks could originate from weak fundamentals but can also be exacerbated by depositors' beliefs that others will withdraw their deposits in response to the signals (Goldstein and Pauzner 2005; Goldstein 2012). Chen, Goldstein, Huang, and Vashishtha (2024) empirically show that banks indeed face more severe deposit outflows in response to deteriorated performance when their liquidity transformation is subject to higher fragility. This suggests that deposit outflows are driven not only by banks' weak fundamentals but also by depositors' fears that others will withdraw funds in response to negative signals, ultimately depleting banks' resources due to liquidity mismatches. Specifically, findings in Chen et al. (2024) suggest that a depositor's incentive to withdraw funds depends on both noisy signals about bank fundamentals and the performance threshold at which depositors choose to withdraw their funds. They document that this threshold rises with the degree of liquidity transformation, increasing depositors' fears and susceptibility to deposit outflows.

The threshold of bank performance at which depositors decide to withdraw may be influenced by the level of public attention the bank receives on social media. Increased public scrutiny can shape depositors' expectations about how quickly and effectively negative, bank-specific signals spread among peers—and, in turn, how sensitive those peers will be to a bank's fundamentals. This can create fears that the bank might deplete its liquidity due to sudden deposit withdrawals by peer depositors in response to negative, bank-specific signals, potentially leading to self-fulfilling outcomes, as described by Diamond and Dybvig (1983). Building on this background, we examine whether social media attention accelerates deposit outflows following the disclosure of poor bank performance and explore the social media-induced strategic complementarity. Critically, we analyze this phenomenon during the periods preceding the collapse of SVB in March 2023 to assess whether it reflects a general pattern rather than a case unique to the SVB crisis.

To address this research question, we use a sample of U.S. banks from 2009 to 2022 with quarterly financial information. We rely on the ticker of bank holding companies to identify bank-related discussions on Twitter. Hence, our sample covers banks controlled by listed bank holding companies. To measure social media attention towards banks, we count the number of tweets that mention stock tickers of their parent bank holding companies for the last two quarters (*t-2* and *t-1*). In each quarter, we sort banks to top, middle, and bottom terciles based on tweet counts from the previous two quarters. Following the framework by Chen et al. (2024), we analyze changes in non-core deposits over a two-quarter period (from the end of *t-1* to the end of *t+1*), scaled by the banks' lagged total assets (as of the end of *t-1*), in relation to lagged quarter bank profitability (as of the quarter *t-1*), measured by returns on equity (ROE). Since our sample primarily covers periods without systemwide banking fragility—between the Global Financial Crisis of 2008 and the SVB collapse in 2023—we focus on flows of non-core deposits rather than uninsured deposits, some of which are classified as core deposits and generally remain insensitive to bank performance during non-crisis periods.[3] [4] To quantify the impact of social media attention on the sensitivity of deposit flows to bank performance (deposit-flow-performance sensitivity), we examine how such sensitivity differs among banks belonging to the three social media attention groups. Specifically,

[3] For example, Chen et al. (2024) use a sample spanning January 1994 to December 2016, which covers the 2008 financial crisis.

[4] In the Uniform Bank Performance Report (UBPR) in the U.S., core deposits are defined as the sum of the following items: all transaction accounts, non-transaction money market deposit accounts, non-transaction other savings deposits, and non-transaction time deposits up to the deposit insurance limit, minus fully insured brokered deposits. Sheehan (2013) documents that core deposits are expected to remain in banks for many years and meet the definitions of a stable source of funds set by the Financial Standard Accounting Board and Basel III standard. Non-core deposits are calculated by deducting core deposits from total deposits.

using banks with low attention as the base case, we interact the two dummies indicating banks having medium or high levels of attention from Twitter users with banks' ROEs (as of quarter *t-1*).

By regression analyses, we first confirm that banks' non-core deposit flows are sensitive to their profitability. As banks' performance deteriorates, they are more likely to face a significant decrease in their non-core deposits in the following quarter. Important to our study, the sensitivity of non-core deposit flows to ROE is stronger for banks in the middle or top tercile of Twitter exposure than those in the bottom tercile. In terms of the economic magnitude, the deposit-flow-performance sensitivity for non-core deposits is higher by 41% and 74% for the banks in middle and top tercile groups, respectively, than for those in bottom tercile. It is important to note that our results are robust to the addition of bank fixed effects as well as time-varying macroeconomic and bank level control variables such as S&P 500 index returns, effective federal funds rates, capital ratios, size, asset compositions, and funding structures of each bank in our models. In addition, the magnifying effect of bank Twitter exposure on deposit-flow-performance sensitivity is observed only when banks face worse-than-normal profitability, while such effect is muted during periods of higher-than-normal performance. Further, the interaction effects of banks' ROEs and their Twitter exposure vanish when we focus on core deposits, which are largely insensitive to bank performance due to deposit insurance or potential bank switching costs. Regarding total deposits, we find evidence that social media attention tends to make overall deposit flows more sensitive to bank performance, consistent with our findings for non-core deposits.

Our results indicate that depositors' awareness of increased peer scrutiny of banks through social media raises concerns that these peers are sensitive to bank performance and that their withdrawals could lead to liquidity shortages. This concern about potential liquidity depletion can be a source of self-fulfilling deposit outflows from banks. To test this mechanism, we run splitsample tests by sorting banks based on the liquidity risks they face. We measure banks' liquidity risks using two indicators: their reliance on non-core deposits for funding and the ratio of liquid assets to total assets. If increased social media attention generates fears that a bank might face a liquidity shortage due to a higher risk of deposit outflows, our regression results should be stronger for banks with higher liquidity risks. Consistent with this prediction, we find the magnifying effect of social media attention on deposit-flow-performance sensitivity is significantly stronger for banks that rely more heavily on non-core deposits or hold a smaller fraction of liquid assets—conditions that could potentially lead to severe liquidity shortage in the event of large-scale deposit withdrawals.

A key condition for our mechanism to work is the coordination among depositors through interactions on social media. Twitter discussions that engage more users are supposed to exert more impact on deposit outflows when bank performance deteriorates. To evaluate this role, we leverage two features of Twitter posts, i.e., *retweets* and *likes* below the text of each tweet, and measure the degree of user engagement using the number of *retweets* and *likes* per tweet during the last two quarters. We then categorize banks with a similar level of social media attention into two subgroups based on user engagement. Our findings show that the interaction effects are more significant for banks with higher numbers of *retweets* or *likes* among Twitter-exposed banks. This suggests that tweets with greater engagement serve as additional key indicators of public attention toward a bank, offering insights beyond what performance data alone reveals about the bank's fundamentals and ultimately increasing depositors' sensitivity to poor performance.

Social media attention toward banks may simply reflect the more efficient transmission of information about bank fundamentals, thereby increasing depositors' sensitivity to performance directly, regardless of the awareness of their peers' susceptibility to deposit outflows. To test this alternative hypothesis, we rerun our baseline regression for more transparent banks and those with lower transparency, separately (Chen, Goldstein, Huang, and Vashishtha 2022). If social media merely serves as a more efficient means of information transmission without affecting awareness of other depositors' responses, then the incremental effect of social media attention should be minimal for transparent banks. In contrast to this prediction, we continue to find that the deposit flow sensitivity to performance increases with banks' social media attention, even for banks with a higher level of transparency.

Our baseline results may partly capture the impact of sentiment among Twitter users, as heated discussions could coincide with negative sentiment that can drive deposit outflows. To examine whether the content of social media, such as words that reveal a negative sentiment, drives our results, we introduce a new variable that captures the abnormal change in negative sentiment about the bank on Twitter in quarter *t* relative to the prior two quarters (Cookson, Niessner, and Schiller 2025), along with its interaction with ROE, as controls. We find that when the tone of Twitter discussions turns more negative, non-core deposits are indeed more severely withdrawn in response to poor bank performance. However, the coefficient on the interaction between social media attention and ROE remains robust, and the economic magnitude of social media attention's effect is more than three times that of negative sentiment. These results suggest that social media attention affects deposit flows through channels beyond sentiment, with the attention effect being the dominant mechanism.

Social media attention is not randomly assigned across banks, which means our results could be subject to endogeneity concerns (e.g., omitted variable bias). To address these concerns, we first rely on propensity-score matching to pair banks in the top tercile of Twitter exposure with banks in the bottom tercile, based on a battery of bank attributes that determine their attractiveness to social media users. Our baseline results continue to hold among the matched sample of banks. As the second exercise, we use the relaxation of the character space limit in Twitter (140 to 280) in November 2017—introduced to stimulate user activity—as an exogenous shock to banks' Twitter exposure. We find that banks with low Twitter exposure before the shock faced more tweets after the relaxation of the character limit, which further enhanced the sensitivity of their non-core deposit flows to performance.

Our results survive several robustness tests. First, they remain robust when continuous variables for Twitter exposure are employed, shorter (1 quarter) or longer (3-4 quarters) windows are adopted to count the number of tweets on banks, and returns on assets are used as the bank performance indicators instead of ROEs. We confirm that our results are not explained by a potential association between *ex-ante* social media attention and subsequent sentiment or performance, as we find no evidence that Twitter exposure predicts bank ROEs or abnormal negative sentiment in the following quarters. Finally, our findings show that deposit outflows from banks with high social media attention are not driven by reductions in deposit interest rates following weak performance.

Our study contributes to several strands of literature. First, our paper is closely related to the studies of Chen et al. (2022, 2024), who find that uninsured deposit flows are more sensitive to bank performance when the banks are more transparent or their liquidity transformation is subject to higher fragility. Our paper makes an important contribution to their studies by finding that social media attention is an additional key driver that amplifies the sensitivity of deposit flows to bank performance. Our study is also highly related to Artavanis, Paravisini, Robles-Garcia, Seru, and Tsoutsoura (2019), who document that two-third of a large Greek bank's deposit withdrawals is driven by the bank's deteriorating fundamentals and the remaining part is due to the changes in expectation of other depositors' potential runs on the bank. Similarly, in our study, we address both fundamental-based and panic-based deposit withdrawals from banks. We document the direct effect of bank performance on deposit flows and show that this effect is intensified by social media attention, which can influence depositors' expectations about how others might react to poor bank performance. Broadly, our study is a part of the literature that analyses the underlying drivers of large-scale deposit outflows. One strand of research focuses on *panic-based run* (e.g., Diamond & Dybvig, 1983; Iyer and Puri 2012; Keister, 2016; Allen et al., 2018). Another strand highlights a *fundamental-based run* (e.g., Gorton, 1988; Chari & Jagannathan, 1988; Jacklin & Bhattacharya, 1988; Allen & Gale, 1998).

We also contribute to the growing literature regarding the role of social media in capital markets. Focusing on stock markets, earlier studies show that social media contain valuable information (e.g., Antweiler and Frank 2004; Das and Chen 2007; Chen, De, Hu, and Hwang 2014; Bartov, Faurel, and Mohanram 2018; Da and Huang 2020). However, recent theoretical works have also pointed out the adverse effect of social media in terms of facilitating the spread of investor behavioral biases (e.g., Hirshleifer 2020; Han, Hirshleifer, and Walden 2022; Pedersen 2022). Empirically, Cookson, Engelberg, and Mullins (2023) discovered that equity investors on social networks, such as StockTwits, tend to engage more with posts that confirm their pre-existing beliefs. To the best of our knowledge, we are among the first, along with Cookson et al. (2026), to document the adverse effect of social media on financial intermediaries, banks in particular. However, while Cookson et al. (2026) focus on social media's role during the acute crisis period of March 2023, we examine whether these effects persist during normal times, providing evidence that social media represents an ongoing structural vulnerability rather than merely a crisis catalyst. Specifically, their study shows that during the run period following the SVB collapse, regional banks in the top tercile of pre-run Twitter exposure experienced greater losses in stock market value. Additionally, social media amplifies the sensitivity of deposit flows to balance sheet risks for these banks. Our study complements theirs by showing that, even outside of the relatively rare bank run periods, social media continues to influence deposit flows beyond capital market returns, thereby affecting bank stability through a nexus of fundamental and panic-induced deposit flows.

The rest of the paper is organized as follows. Section 1 provides the theoretical motivation. Section 2 describes the data sources and provides summary statistics of the sample. Section 3 presents the empirical results. Section 4 provides additional analyses. Section 5 concludes.

1. Theoretical Motivation

In this study, we explore how social media attention toward banks influences the sensitivity of deposit flows to their performance. Prior studies have shown that deposit outflows are typically driven by deteriorating bank performance and fundamentals (e.g., Allen & Gale, 1998; Chari & Jagannathan, 1988). In such cases, worsening bank performance directly raises depositor concerns about the safety of their funds, ultimately leading to deposit outflows. In contrast, Diamond and Dybvig (1983) show that a self-fulfilling panic run can happen regardless of a bank's fundamentals, due to coordination failures among depositors arising from the bank's liquidity mismatch between its assets and liabilities. In these situations, depositors' concerns are driven primarily by the fear that others will withdraw their funds in response to a bank's poor performance—leading to liquidity depletion before they have a chance to act—rather than by the performance signals themselves, ultimately resulting in deposit outflows. Next, Goldstein and Pauzner (2005) and Goldstein (2012) integrate the two mechanisms discussed above and suggest that, while deposit outflows typically begin with weak fundamentals, strategic complementarities among depositors can amplify these outflows. In line with these suggestions, Chen et al. (2024) empirically document that the sensitivity of deposit flows to bank performance varies with bank-specific characteristics, such as the extent of liquidity transformation, which may foster strategic complementarity among depositors.

While bank-specific characteristics are crucial in determining deposit flow sensitivity to performance, the context surrounding depositors may also play a significant role. In this study, we specifically focus on the role of social media attention. Motivated by the so-called "Twitter fueled bank run" observed during the SVB collapse, we examine social media attention toward banks as a potential factor influencing depositors' withdrawal decisions and, consequently, the sensitivity of deposit flows to bank performance—even during periods without systemwide banking fragility before SVB's collapse. If social media attention indeed affects the sensitivity of deposit flows to performance, what is the underlying mechanism? Is it primarily because high social media attention fosters strategic complementarities among depositors, or simply because depositors are better informed about deteriorating bank fundamentals through social media?

First, social media may affect depositors by rapidly disseminating bad news, making it easier for them to recognize banks' financial problems without searching through multiple news sources (e.g., Blankespoor, Miller, and White 2014). This swift transmission of negative financial information via social media alone might lead depositors to develop growing concerns about banks' financial stability and subsequently withdraw their funds. Under this scenario, bank-specific negative information, effectively circulated through social media, is key to depositors' decision to withdraw their funds. If this is the primary mechanism, the role of social media is expected to diminish for already transparent banks, since depositors can easily access bank-specific negative signals even without social media. In other words, under this mechanism, the influence of social media is pronounced only for opaque banks that are not well covered by other information sources.

Second, the role of social media may extend beyond simply transmitting bank-specific bad news to individual depositors, due to its potential externalities.[5] High social media attention may heighten individual depositors' concerns about their peers' behaviors in response to poor bank performance, as these depositors also recognize that signals of deteriorating performance rapidly spread through the entire depositor network and can potentially influence deposit flows. We can explain this mechanism through the theoretical model proposed by Chen et al. (2024). According to their model, depositors' decision to withdraw funds is influenced by noisy signals about the bank's financial health and by a specific performance threshold that triggers withdrawal. This threshold is affected by various factors, such as the bank's liquidity mismatch (Chen et al., 2024). In our context, we posit that social media attention may affect this performance threshold by influencing depositors' awareness of public scrutiny directed at the banks. We predict that social media provides additional context beyond bank-specific financial information, such as the extent to which other depositors are paying attention to the bank and their perceptions of negative news about its fundamentals. Concerned about other depositors' potential reactions to deteriorating bank fundamentals, depositors may become more attuned to poor bank performance and more likely to withdraw their deposits when banks are more frequently discussed on social media.

Without social media, depositors could only observe peers' responses through a limited pool of sources, such as close friends, nearby colleagues, and news media interviews. Traditionally, recognizing peers' panicked reactions to a bank's financial problems required physically visiting bank branches or ATMs to see lines of people withdrawing their deposits. Consequently, without a bank's social media exposure, peer attention to the bank becomes harder to detect, which may

[5] Prior studies regarding the effect of social media on equity markets also show that social media can proxy both "attention" and "sentiment". For example, Cookson, Lu, Mullins, and Niessner (2024) show that the number (tone) of discussions on social media negatively (positively) predicts next-day stock returns.

ease individual depositors' concerns about potential reactions from others. In contrast, with the vast number of active social media users today, depositors can now receive and update information about their peers' concerns on a large scale and in real time through social media, without needing to observe long lines at bank branches or ATMs. With rapid updates on peers' negative responses, depositors may feel compelled to rush to withdraw money, fearing that others will quickly deplete the bank's resources. If a bank is already widely discussed on social media, individual depositors are likely to pay closer attention to its fundamentals and respond quickly to negative signals—driven primarily by concerns about peers' prompt reactions. Such withdrawals are driven more by changing expectations about peers' behavior in response to poor performance at banks with high social media attention than by the efficient dissemination of deteriorating fundamentals through social media.[6] This is closely related to the mechanism described by the self-fulfilling bank panic (e.g., Diamond and Dybvig 1983; Iyer and Puri 2012; Keister, 2016).

2. Data and Summary Statistics

2.1 Data source and variable construction

This section describes our data sources and key variable construction. Our sample consists of a quarterly panel of publicly traded U.S. banks for the period of 2009 to 2022. We compile data from several sources as described below.

Bank financial statements: We rely on Uniform Bank Performance Report (UBPR) provided by the Federal Financial Institutions Examination Council for banks' financial statements. Our key dependent variables, including Δ*Noncore*, Δ*Core*, and Δ*Deposits*, are obtained from the

[6] It has been shown that social media can play a role in coordination. For example, Enikolopov, Makarin, and Petrova (2020) show that the use of social media in Russia leads to more protest activity, which is not explained by spreading information critical of the government but by reducing coordination costs.

UBPR. Δ*Noncore* is the change in the balance of non-core deposits, defined as the difference between total deposits and core deposits, over a two-quarter period from the previous quarter-end (*t-1*) to the following quarter-end (*t+1*), scaled by the lagged quarter-end total assets (*t-1*). Δ*Core* represents the change of core deposits, which include transaction accounts, non-transaction money market deposit accounts, and insured non-transaction time deposits, scaled by the lagged total assets, for the same two-quarter periods.[7] Δ*Deposit* is defined as the change of the total amount of domestic and foreign deposits, scaled by lagged total assets, for the same two-quarter window. Because our sample mainly represents non-crisis periods between the 2008 Global Financial Crisis and the 2023 SVB collapse, we focus on the movements of non-core deposits rather than uninsured deposits, some of which are categorized as core deposits and are typically insensitive to bank performance during non-crisis times. *ROE*, the main proxy for bank performance of this paper, is defined as net income as a percentage of average bank equity capital as of the previous quarter-end (*t-1*) and is available from the UBPR. We include a set of bank-level control variables, including capital ratios, size, asset compositions, funding structures, and off-balance sheet items, which are all available from UBPR. Those control variables are as of the previous quarter-end (*t-1*), and winsorized at 1% and 99% level. Variable definitions are provided in Appendix Table A1.

Social media: Banks can be mentioned on social media (e.g., Twitter) in various forms. For instance, Twitter users can use the full name of a bank, such as First Republic Bank, or they can simply use the usual abbreviation of it (i.e., FRB) when referring to the bank in their tweets. Relying on bank names, either in the form of full names or in abbreviations, has several disadvantages. First, considering the character limit of Twitter, the use of abbreviations is prevalent.

[7] Core deposits are deposits that bank management considers a stable source of funds (Financial Accounting Standards Board, November 2010). Details are from here: https://www.kansascityfed.org/banking/community-banking-bulletins/highlight-banks-turn-to-noncore-borrowings-as-funding-profiles-shift/

However, finding the commonly used abbreviation is nontrivial and subject to errors. Second, some abbreviations can easily represent other entities than the bank itself.[8] Third, many banks in the U.S. are named in a similar fashion. Therefore, we follow Cookson et al. (2026) and use the "*$ + ticker*" format to locate mentions of stocks of the corresponding holding company of the bank. For each bank, we trace back to its parent bank holding company (BHC) using the Summary of Deposits provided by the Federal Deposit Insurance Corporation. Using the ticker of BHC stocks, we are able to retrieve tweets that mention these stocks at least once during the sample period. For robustness, we also collect the tweets containing the full names of banks. Robustness tests in Section 4.2 generate consistent results even after these tweets are included in the calculation of banks' social media attention.

During the period from 2007 Q1 to 2022 Q3, we are able to extract tweets covering 733 BHC stocks. As tweets were quite sparse in the earlier periods, we drop the period between 2007 Q1 and 2009 Q2 to ensure a fairly large number of banks with nonzero tweets. We then aggregate tweets to the ticker-quarter level and match quarterly Twitter volume to bank-level data provided by UBPR. Following prior studies (e.g., Acharya and Mora, 2015), we exclude banks with total assets smaller than $100 million. To ameliorate the impact of bank mergers and acquisitions, we also exclude bank-quarter observations for which the growth of assets is larger than 10%. Requiring non-missing values for key variables, the main sample comprises 23,444 bank-quarter observations that span the period from 2009 Q3 to 2022 Q3, covering 861 publicly listed banks.[9]

2.2. Summary statistics

Table 1 reports the summary statistics of our main variables used in this paper. As shown in

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[8] For instance, Seacoast National Bank is sometimes referred to as "Seacoast," which also refer to a geographical seacoast, implying a completely different entity.

[9] We use bank deposit data up to the last quarter of 2022. However, as the proxy for deposit growth at quarter t is computed using two periods of data (i.e., $t-1$ and $t+1$), the sample period eventually ends at the third quarter of 2022.

Panel A, the social media attention is based on 4,039,584 bank-related tweets over the sample period. A topic analysis of these tweets using Gemini 1.5 Flash indicates that the majority of Twitter discussions focus on bank fundamentals (e.g., ROE, asset quality, and non-performing loans) or stock prices. About 8% of tweets are related to the governance and management teams of banks. The rest spans topics related to financial services, regulation, and advertising. A substantial share of tweets merely express attention to the banks without containing meaningful content; Gemini categorizes these as "Others."

[Insert Table 1 here]

According to Table 1 Panel B, the average bank is mentioned about 283 times by Twitter users during the last two quarters. The median number of tweets equals 82, suggesting a right-skewed distribution of the number of Twitter discussions. The standard deviation is also as large as 931, meaning a wide dispersion of tweet volume on the bank level. Of course, the effect of an additional 30 tweets for a bank that already receives substantial attention on Twitter (e.g., those in the 75th percentile) could differ significantly from that for the effect for a bank in the 25th percentile. To account for the potential nonlinearity embedded in the effect of interest, following prior studies (e.g., Cookson et al. 2026), we categorize banks into terciles based on the average number of tweets mentioning the stock of the BHC and create two dummies indicating the second and the third tercile, using banks in the first tercile of Twitter discussions as the base case.

The growth of total deposits—measured as deposit flows over two quarters scaled by lagged total assets—is 6.22% on average, with a median of 4.16%. The growth of core deposits is similar to that of total deposits, probably because of their dominance in banks' sources of financing. According to the mean of *%Noncore*, the average bank has 13.1% of its deposits financed by non-core deposits, with the remaining financed by core deposits. The growth of non-core deposits, however, exhibits quite a different pattern. On average, banks in our sample period lose 0.57% of non-core deposits annually. The growth of non-core deposits is also widely dispersed, with the standard deviation equal to 7.27%.

Panel A of Figure 1 depicts the average number of BHC stock-related tweets for banks in each tercile during the period from the third quarter of 2009 to the fourth quarter of 2022. The number of tweets is expressed in thousands. Evidently, the within-quarter variation in Twitter volume is driven almost entirely by differences between the first tercile of banks and the rest. The distribution justifies using the two dummies identifying the first and second tercile banks as proxies for social media attention. In Panel B of Figure 1, we compute the average number of tweets for banks that differ in assets. Using cutoffs adopted by prior studies (Berger and Bouwman 2009; Beatty and Liao 2011), we use $500 million as the cutoff for medium-sized banks and $3 billion as the cutoff for big banks. Unsurprisingly, big banks received substantially more attention on Twitter. However, we cannot spot a sizeable difference in Twitter discussions between medium-sized and small banks. To account for the impact of bank size on attention from social media users, we control for the impact of bank assets in all regressions in this study.

[Insert Figure 1 here]

3. Empirical design and results

3.1 Model

Following prior studies (e.g., Acharya and Mora, 2015; Chen et al., 2022), we model deposit flows as a function of a variety of bank-level attributes that could affect depositors' decisions. Particularly, we examine how the sensitivity of deposit flows to bank performance varies between banks that have differential exposure to social media (e.g., Twitter). The empirical model is specified as follows:

$$\Delta deposit_{i,t} = \beta_1 ROE_{i,t-1} + \beta_2 ROE_{i,t-1} \times Medium\_Twitter_{i,t-1} + \beta_3 ROE_{i,t-1} \times High\_Twitter_{i,t-1} + \beta_4 Medium\_Twitter_{i,t-1} + \beta_5 High\_Twitter_{i,t-1} + \sum_{j=1}^{K} \theta_j x_{i,j,t-1} + \sum_{j=1}^{K} \rho_j ROE_{i,t-1} \times x_{i,j,t-1} + \sum_{h=1}^{L} \gamma_h z_{h,t} + \alpha_i + \varepsilon_{i,t} \quad (1)$$

where the dependent variable $\Delta deposit_{i,t}$ represents the growth in the deposit balance (i.e., non-core, core, and total deposit) of bank *i* at quarter *t*. Following Acharya and Mora (2015), we measure deposit growth as the difference in deposit balance between quarter *t-1* and that of quarter *t+1*, scaled by bank assets at *t-1*. Looking ahead for one period, instead of using deposit balance at the end of the current quarter (i.e., quarter *t*), is to account for the fact that depositors are only able to get access to banks' earnings figures with a lag of 30 days (Badertscher et al. 2018). We then scale the absolute two-period difference in deposit balance using bank assets as of the last quarter (i.e., quarter *t-1*). Our results, however, are not sensitive to how we scale the change in deposit flows, as indicated by robustness tests in Section 4.2. We measure banks' performance using last quarter's ROE (i.e., quarter *t-1*), which is defined as earnings divided by the average book value of equity (Chen et al. 2022, 2024). Therefore, the coefficient β_1 captures the sensitivity of deposit flows to bank performance.

Social media attention is defined as the average number of tweets mentioning the ticker of the BHC during quarters *t-1* and *t-2*.[10] We then divide banks into three terciles based on the number of Twitter mentions in the last two quarters, and create two dummies, i.e., $Medium\_Twitter_{i,t-1}$ and $High\_Twitter_{i,t-1}$, which indicate banks in the middle and top terciles, respectively.[11] These

[10] Our results are also robust to counting ticker-relevant tweets using shorter (e.g., 1 quarter) or longer (3-4 quarters) horizons. Details are provided in Section 4.2.

[11] The probability of sample banks switching to a different tercile of Twitter exposure equals 17%.

two dummies are further interacted with bank ROE. Measuring social media attention in terciles has several advantages. First, it ameliorates the concern of measurement errors in banks' social media exposure. Second, it accounts for the possibility of nonlinearities in the effect of social media attention on the deposit-flow-performance sensitivity. The coefficients of the interaction terms, β_2 and β_3, represent the incremental sensitivity of deposit flows to performance for banks in the middle and top terciles of social media attention, relative to the sensitivity for those in the bottom tercile, captured by β_1.

Following prior studies (e.g., Acharya and Mora 2015; Chen et al. 2022), we include a standard set of bank-level control variables ($x_{i,j,t-1}$) that may affect deposit flows, including the standard deviation of write-offs, capital ratio, wholesale funding, unused commitments, the fraction of real estate loans, and total assets (in its natural log). To isolate the effect of social media attention on deposit-flow-performance sensitivity, we also interact these control variables with the proxy for bank performance (i.e., ROE) in our main specification. Next, we include time-varying macroeconomic variables ($z_{h,t}$) in the model, namely S&P 500 index returns and effective federal funds rates, both defined for the current quarter to address the trend embedded in aggregate deposit flows as well as the activeness of social media. Lastly, banks with certain attributes (e.g., brand, founder charisma, and culture) are probably more popular among certain groups of depositors and could be more heatedly discussed on social media. We account for the effect of these persistent bank-level characteristics by controlling for bank fixed effects (α_i). Standard errors are clustered on the bank level.

3.2 Baseline results

Before presenting the linear regression results, we first estimate the sensitivity of deposit flows to bank performance using semiparametric estimation. Following Chen et al. (2024), we center ROE on its median and apply the Robinson's (1988) estimator with Gaussian local kernel regressions. Panel (a) of Figure 2 plots the estimates for core and non-core deposit flows, separately. Two patterns emerge from the figure. First, non-core deposit flows exhibit a much larger sensitivity to bank performance, compared with core deposit flows. Second, non-core depositors do not react to changes in bank performance in the above-median ROE spectrum, while they tend to withdraw their funds from banks in response to worsening ROE when bank performance is worse than usual. In Panel (b), we contrast the non-core deposit flow-performance sensitivity of banks with the highest level of Twitter exposure with that of banks with the lowest level of Twitter exposure. Apparently, there is virtually no difference in the deposit flow-performance sensitivity between these two groups of banks when ROE is above median. However, non-core depositors of banks with higher exposure to social media react substantially stronger to deteriorating bank performance than their low-exposure counterparts when bank ROE is below median.

[Insert Figure 2 here]

Table 2 presents the baseline regression results. Before estimating Eq. (1), we first examine a simple model that relates non-core deposit flows to bank performance. As shown in Column (1), we obtain a positive and statistically significant coefficient of ROE, indicating that non-core depositors tend to withdraw from their bank accounts when bank performance deteriorates.

[Insert Table 2 here]

In Column (2), as our baseline regression of Eq. (1), we interact ROE and each of the medium and top tercile dummy variables for Twitter exposure. In Column (2), we further control for the interactions between various bank characteristics (e.g., size and capital ratio) and ROE to account for the heterogeneous sensitivity of non-core deposit flows to bank performance across different types of banks. ROE continues to load significantly positively. The coefficient of ROE can be interpreted as the sensitivity of non-core deposit flows to performance for an average bank (in terms of the aforementioned bank characteristics) that has the lowest level of social media attention. Important for our study, the interactions between ROE and the two dummies indicating a medium and high level of social media attention are positive with high statistical significance. In terms of economic magnitude, banks with a medium level of Twitter discussions have a non-core deposit-flow-performance sensitivity that is 41% higher than the base case in relative terms. Social media attention magnifies the sensitivity of non-core deposit flows to bank performance with an even larger degree once we focus on banks with the largest amount of Twitter discussions. Non-core deposits in these banks are 74% more sensitive to bank performance in relative terms than the reference.

In Column (3), as a robustness check, we control for market-wide fluctuations in non-core deposit flows and bank performance by including year-quarter fixed effects, which absorb the two macroeconomic control variables (i.e., S&P 500 index returns and effective federal funds rates).[12] In general, the coefficient estimates are close to those in Column (2). The estimated effect of social media attention on deposit-flow-performance sensitivity is even larger in relative terms. Being in the top tercile for social media attention is associated with a 173% greater deposit-flow-performance sensitivity compared to the bottom tercile group. Overall, the results in this section imply that non-core deposit flows are more sensitive to bank performance when banks are discussed more on Twitter.

In Appendix Table A2, we further examine the effects of banks' Twitter exposure on the sensitivity of deposit flows to performance by categorizing tweets by topics. We distinguish among

[12] Following Chen et al. (2022, 2024), we do not control for year-quarter fixed effects in the rest of our analyses. However, all the results remain qualitatively similar when year-quarter fixed effects are included in the regressions.

Twitter discussions on three major topics, including fundamentals, stock price-related content, and other topics. We then categorize banks into three terciles based on the number of Twitter discussions on each topic that mention bank holding companies over the previous two quarters. Consistent with the baseline specification, we construct dummies indicating medium or high levels of social media attention for each topic and interact these dummies with ROE. Two findings emerge. First, regardless of the topic, social media attention is consistently associated with a higher sensitivity of non-core deposit flows to performance, suggesting that the amplification mechanism operates broadly across different types of Twitter discussions. Second, the coefficient for the interaction between ROE and dummies for the intensity of Twitter discussions on stock prices has the largest magnitude, implying that stock price-related tweets have the strongest effect on the reactions of depositors to bank performance. Stock price movements are continuously updated, immediately visible, and require minimal financial expertise to understand, which likely make price-related tweets particularly effective at heightening depositors' awareness of peer concerns about bank performance. This interpretation aligns with Cookson et al. (2026), who find that investment-specific tweets preceded general discussions during the SVB run, suggesting that stock-market-oriented tweets serve as early warning signals that amplify depositor concerns.

A key prediction of bank deposit flow theory is that the effect of interest should be observed only in the spectrum of bank performance below the normal level. In fact, Chen et al. (2024) show that uninsured deposits are sensitive to bank ROA, but this sensitivity vanishes as bank ROA is above the median. We also expect that the heightened deposit-flow-performance sensitivity among banks with greater Twitter exposure is driven by quarters of relatively poor performance, during which social media may amplify depositors' concerns about the safety of their funds. To test this conjecture, we categorize bank-quarter observations into two sub-groups based on whether bank

ROE is lower than the sample median. We rerun baseline regressions using the two sub-samples and present the results in Table 3. Consistent with our prediction, the interactions between ROE and the dummies for different levels of social media attention are significant only in the poor performance subsample, as reported in Column (2). [13]

[Insert Table 3 here]

3.3 Core and total Deposits

Do core depositors' differential reactions to news in bank fundamentals across varying levels of social media attention differ from those of non-core depositors? In our setting, two possibilities arise. One possibility is that core depositors may not respond to deteriorating bank performance, as their funds are largely protected by deposit insurance (Diamond and Dybvig 1983) and they may face high bank switching costs (Sheehan 2012). Consequently, they have little incentive to change their behavior in response to poor bank performance, no matter how heatedly the bank is discussed on social media. The other possibility, however, hinges on the response of banks experiencing poor performance. Managers of poorly performing banks may detect the spread of negative sentiment on social media, which is probably triggered by bad earnings news, and decide to counteract potential outflows of large non-core deposits by attracting more core deposits. In this case, banks with high social media attention may have an incentive to secure small deposits as a substitute for the outflow of large deposits (Chen et al. 2022, 2024). Lastly, even in the absence of any counteraction from banks, depositors may voluntarily reallocate their deposits across different ownership categories within the same bank, leading to an increase in core deposits and a reduction in non-core deposits.

[13] In Table A3 of the Appendix, we incorporate year-quarter fixed effects into the regressions for subsamples with above-median and below-median ROE, resulting in consistent findings.

Column (1) of Table 4 presents the results of regressions using the flow of core deposits as the dependent variable. All other regression specifications are the same as in Table 2 Column (2). Consistent with our second and third predictions, both interaction terms are negative, suggesting that core deposit flows increase in response to weak bank fundamentals, particularly when banks have moderate or high social media attention. However, the coefficient of the interaction term for *ROE* × *High_Twitter* is statistically insignificant, while the coefficient for *ROE* × *Medium_Twitter* is strongly significant.

[Insert Table 4 here]

In Column (2), we examine how the sensitivity of total deposit flows to bank performance varies with social media attention. Similar to the results for non-core deposits, banks with a high level of social media attention exhibit greater deposit-flow-performance sensitivity compared to banks with the lowest level of attention.[14] Banks in the second attention tercile do not exhibit a significantly different deposit-flow-performance sensitivity compared with the reference group, possibly due to the offsetting effects of social media attention on non-core versus core deposits.

3.4 The economic mechanism

3.4.1 The role of liquidity mismatch

In this section, we investigate the economic mechanism that drives our results. According to the classical Diamond and Dybvig (1983) model, depositors have more incentives to withdraw when they expect others to be running on the bank due to the bank's liquidity transformation. A recent study by Chen et al. (2024) also documents that uninsured deposit flows become more sensitive to bank performance as banks engage in greater liquidity transformation. In our setting,

[14] In Table A4 of the Appendix, we include year-quarter fixed effects in the regressions for core and total deposits, and the results remain consistent.

we expect non-core deposit outflows following performance declines for banks with high social media attention to be more pronounced as banks exhibit greater liquidity mismatches. We employ two proxies that capture the degree of liquidity mismatch on both the asset and liability sides. The first proxy, *%Noncore*, is defined as the proportion of non-core deposits relative to total deposits. The second proxy, *LiquidAssets*, represents the ratio of liquid assets to total assets. Liquid assets are defined as the sum of cash and securities, which include Treasury, Agency, and Municipal securities. Banks with a higher proportion of non-core deposits or a lower proportion of liquid assets are defined as engaging in greater liquidity transformation on the liability and asset sides, respectively.

Banks are categorized into two subsamples based on these two liquidity mismatch proxies. Table 5 reports the results of regressions based on subsamples sorted by liquidity mismatch. According to the coefficient estimates in Columns (2) and (3), the effects of interest are significant for banks with a higher proportion of non-core deposits and those with a lower proportion of liquid assets. Notably, the magnitude of the *ROE* × *High_Twitter* interaction coefficient is 0.142 in Column (2) and 0.114 in Column (3), which is substantially larger than the estimates from the full sample. This finding suggests that intense social media discussions tend to prompt non-core depositors to withdraw funds more aggressively from poorly performing banks, particularly when banks rely more heavily on non-core deposits or hold a smaller proportion of liquid assets relative to total assets. For banks more reliant on core deposits or holding sufficient liquid assets, the deposit-flow-performance sensitivity varies insignificantly or only weakly with social media attention, as shown in Columns (1) and (4).

[Insert Table 5 here]

Overall, the findings in this section strongly support the idea that the amplification effect of social media attention on bank deposit flow-performance sensitivity is deeply rooted in liquidity mismatch. Particularly, we find that the composition of both deposits and assets is more critical when analyzing non-core deposit outflows following deteriorating bank performance, consistent with Jiang et al. (2023).

3.4.2 The effect of social media user engagement

As discussed in the theoretical motivation section, social media's role may extend beyond quickly transmitting bank-specific information that potentially assists depositors' decision regarding fund withdrawal. It may also convey information about how rapidly peer depositors receive news as well as how these depositors might respond to bad news. Consequently, for banks with greater social media attention, non-core depositors may be more easily "awakened" by the visibility of peer attention and concerns, heightening their own concerns about the safety of their funds and prompting withdrawals—similar to the depositor run dynamics observed at SVB. In the end, as suggested by Jiang et al. (2023), the fraction of non-core depositors who are "awakened" determines whether a bad-performing bank fails.

Directly pinning down this mechanism from our sample is challenging. Instead, we test it indirectly by leveraging the engagement among social media users via tweets. Specifically, we rely on two basic features of Twitter, i.e., *retweets* and *likes*, to gauge the extent of user engagement for each tweet in our sample. Tweets that receive more *retweets* or *likes* arguably engage users more effectively and hence are more likely to amplify concerns about peer depositors' attentions and sentiments toward the bank. For each bank, we compute the average number of *retweets* and *likes* for all tweets mentioning the bank during quarters *t-2* and *t-1*. We further categorize banks in the *Medium_Twitter* group into two subgroups based on the average number of *retweets* or the average number of *likes*. The dummy variable *Medium_LessRetweet* (*Medium_MoreRetweet*) takes the value of one for banks in the second tercile of Twitter exposure with an average number of *retweets* below (above) the median. Similarly, the dummy variable *Medium_LessLike* (*Medium_MoreLike*) equals one for banks with a medium level of Twitter discussions and an average number of *likes* below (above) the median. A similar categorization is applied to banks belonging to the *High_Twitter* group.

We rerun the baseline regressions using the finer categorization of banks based on how influential Twitter discussions are. The coefficient estimates reported in Column (1) of Table 6 reveal that such categorization is insightful. Among banks in the medium group of total Twitter discussions, those for which relevant tweets receive more *retweets* exhibit greater sensitivity of non-core deposit flows to performance than those with fewer *retweets*. Among banks in the *High_Twitter* group, the impact of Twitter discussions on the deposit-flow-performance is of a larger magnitude when these tweets receive more *retweets*. Specifically, the non-core deposit-flow-performance sensitivity of banks that belong to the *High_MoreRetweet* is 97% higher than that of the base group, compared with a 43% difference for the *High_LessRetweet* group. A similar pattern can be observed when using the intensity of *likes* as the proxy for the influence of tweets, as reported in Column (2) of Table 6.

[Insert Table 6 here]

Overall, the findings based on users' feedback in the form of *retweets* and *likes* suggest that the engagement among social media users is probably driving the differential non-core deposit-flow-performance sensitivity that is documented in the baseline regression. Hence, they lend further support to the mechanism whereby social media conveys information about peers' attention to the bank beyond bank-specific signals, which becomes a key source of depositors' concerns about the safety of their funds when the bank's performance deteriorates.

3.4.3 The role of bank transparency

The first mechanism suggested in the theoretical motivation section is that social media (e.g., Twitter) simply act as more efficient information transmitters, making information on bank performance accessible to a larger number of depositors at a lower cost. The premise behind this explanation is that, before the era of social media, high information acquisition costs hindered depositors from monitoring bank performance. The emergence of large social media platforms has reduced these costs for non-core depositors, increasing their awareness of bank performance. As a larger portion of non-core depositors regularly access bank performance figures via social media, the deposit flow becomes more sensitive to bank performance. Directly testing this hypothesis is challenging as the opinions of Twitter users are typically intertwined with fragmented information about BHC stocks (e.g., earnings per share and stock prices). As an indirect test, we exploit the variation in bank transparency, based on the conjecture that information acquisition cost would be lower for more transparent banks. If the information transmission channel holds, we should expect a less pronounced effect for more transparent banks, as the role of social media in information transmission will be limited for these banks.

Following Chen et al. (2022), we adopt the R-squared (i.e., *R2*) of the regression of write-offs on various bank performance indicators and bank capital ratio as the proxy for bank transparency.[15] Intuitively, it captures how well current income figures predict future bank asset quality and can proxy for the ease of acquiring information regarding bank asset performance (Dang et al., 2017). For banks with a high *R2*, large depositors can rely more on earnings figures, and do not have to incur additional costs to acquire information on banks' solvency. We then rerun the baseline

[15] Specifically, for each bank in each quarter, the current amount of write-offs is regressed on loan loss provisions, earnings before loan loss provisions and the change in non-performing loans—all defined for both the previous quarter and two quarters prior—as well as the capital ratio from the previous quarter. See Section 2.1 of Chen et al. (2022) for details on the calculation.

regressions using subsamples that are formed based on bank transparency.

Table 7 reports the coefficient estimates for subsamples. The interactions between ROE and dummies for a medium and high level of social media attention are significant in both subsamples, with the difference in coefficients being statistically insignificant. These results are in sharp contrast to the implication that social media acts solely as an information transmitter.[16] Put differently, as suggested by the second mechanism in the theoretical motivation section, social media may play a role beyond merely rapidly transmitting bank-specific information among users in influencing depositors' decisions to withdraw their funds.

[Insert Table 7 here]

3.4.4 The role of Twitter sentiment

The content on social media may play a critical role in driving the heightened sensitivity of deposit flows to performance. In other words, the significant association between *ex-ante* social media attention and the sensitivity of deposit flows to performance may be driven by the negative sentiment embedded in high levels of social media activity following the release of poor performance. If this is the case, depositors' concerns about potential outflows by their peers are likely influenced more by negative Twitter sentiment about the banks in response to poor performance than by overall depositor attention beforehand.

To evaluate to what extent our baseline findings are driven by the sentiment channel, we run a horse race between the attention to and the sentiment of social media discussions. We first construct a proxy for the degree of negative sentiment on Twitter toward each bank. Following prior research (e.g., Cookson et al. 2025), negative sentiment for each bank-quarter is defined as

[16] In Table A5, we directly control for the impact of bank transparency (*R2*) by including the proxy of transparency and the interaction of transparency and bank performance in the regression. Our main effect remains unchanged.

the difference between the proportion of tweets mentioning the bank with a negative tone and those with a positive tone during that quarter. Using sentiment during quarter *t-1* and *t-2* as the normal level of sentiment, we calculate abnormal sentiment (denoted as *Abn_sentiment*) as the difference in negative sentiment between quarter *t* and that in the two preceding quarters.[17] We then sort banks into terciles based on abnormal sentiment and construct two dummies, *Medium_abn_sentiment* and *High_abn_sentiment*, indicating banks in the second and third terciles, respectively. These variables, along with their interactions with ROE, are incorporated into Eq. (1).

The results are presented in Table 8. In Column (1), we include a continuous variable for abnormal sentiment, *Abn_sentiment*, and its interaction term with ROE in the regression, excluding variables related to social media attention. As predicted, we find a positive and significant interaction term, indicating that an increase in negative sentiment tends to amplify the sensitivity of deposit flows to performance. In Column (2), we run a horse race by including proxies for sentiment and social media attention in the same regression. For social media attention, we include *Ln(Tweets)*, which represents the natural logarithm of the number of tweets mentioning the bank over the previous two quarters. We find that both (negative) sentiment and attention significantly increase the sensitivity of deposit flows to performance. More importantly, the impact of social media attention is stronger than that of sentiment in terms of the economic magnitude. When negative sentiment in tweets is increased by one standard deviation, banks' deposit-flow-performance sensitivity tends to rise by 0.014 (0.171×0.084). In comparison, one standard deviation increase in Twitter exposure is associated with a 0.046 (1.649×0.028) increase in deposit-

[17] The calculated abnormal sentiment has a mean of -0.0014, and a standard deviation of 0.1708. The minimum equals -1.8, and the maximum equals 1.6667. Results are qualitatively similar if the normal levels of sentiment are computed using tweets posted during a longer window (e.g., the past four quarters). Note that sample size declines to 20,881 for sentiment analysis as banks without any mentions on Twitter are excluded from the sample.

flow-performance sensitivity,[18] which is 3.3 times as large as the effect of negative sentiment.

[Insert Table 8 here]

In Columns (3) and (4), we replace the continuous abnormal sentiment measure with two dummy variables (*Medium_abn_sentiment* and *High_abn_sentiment*) indicating the second and third terciles of abnormal sentiment. We continue to find that both higher abnormal sentiment and greater social media attention amplify the sensitivity of deposit flows to performance.[19] Moreover, as indicated by the coefficient estimates in Column (4), the increase in deposit-flow-performance sensitivity from the first to the third tercile of attention is much larger than that observed when moving from the first to the third tercile of sentiment. Overall, these findings indicate that the effect of social media attention on deposit flows cannot be subsumed into the implications of sentiment. Rather, the potential for heightened attention from peer depositors—reflected in higher Twitter exposure—plays a crucial role in shaping depositors' concerns about the safety of their funds in the bank.

4 Additional analyses

4.1 Alleviating endogeneity concerns

4.1.1 Results based on propensity-score matching

Banks that are discussed more on social media (e.g., Twitter) and those that do not have as much exposure to social media might differ in many dimensions. In particular, heated discussions on social media could be due to changes in banks' asset quality. In this case, social media attention is simply capturing the impact of the cash-generating potential of bank assets. Moreover, it is also

[18] For the sample used in Table 8, *Ln(Tweets)* has a mean of 4.464 and a standard deviation of 1.649.
[19] In Table A6, we examine the relationship between a bank's abnormal sentiment on Twitter in the current quarter (*t*) and its social media exposure over the previous two quarters (*t-2* to *t-1*). We find no evidence that heightened *ex-ante* social media exposure predicts increased negative abnormal sentiment in the subsequent quarter.

possible that banks with more exposure to social media are more visible or more transparent. As documented in Cookson et al. (2026), more exposed banks may experience increased stock trading activity or stronger price reactions, which could, in turn, amplify deposit outflows. Such omitted variables tend to generate biased coefficient estimates.

As the first step in alleviating these endogeneity concerns, we create a matched sample by pairing each bank in the third tercile of Twitter exposure with one bank in the first tercile. Specifically, banks are matched based on the basic bank characteristics that are included in our baseline regression, as well as several characteristics that could determine the attractiveness of banks to Twitter users. In particular, we match on the two-quarter cumulative return of the bank holding company stocks, considering that stock price movements attract social media discussions. We use one-to-one nearest-neighborhood matching without replacement with a caliper of 0.01, requiring common support for the propensity scores. The matching yields a sample of 4,731 bank-quarter observations. As shown in Panel A of Table 9, the matching performs quite successfully. The difference in bank attributes across the two groups of banks becomes minimal after the matching, with two-tailed *t*-tests unable to reject the null of no significant difference at the 10% level in all rows.

[Insert Table 9 here]

We rerun the baseline regressions using the matched sample and present the results in Panel B. Note that banks in the second tercile of Twitter exposure are dropped before the matching process, and banks in the first tercile continue to be the base case. The coefficient estimate of *ROE* × *High_Twitter* is statistically significant, with the magnitude similar to that obtained using the original sample.

4.1.2 Character limit expansion as an exogenous shock

To further address the potential endogeneity concerns, we exploit the plausibly exogenous increase in social media exposure following the lift of the character limit per tweet that became effective in early November 2017. Twitter started out with a character limit of 140. According to official data from Twitter, about 9% of tweets in English hit the 140-character limit.[20] Even though this fraction seems small, it does not account for the tweets that could have been sent if the users had more space. An internal study of Twitter found that given the fraction of users reaching the character limit, the word limit has to reach 274 to make 99% of English tweets viable, and relaxing the character limit could bring in more Twitter users.[21] In light of these findings, Twitter launched a test in September 2017 with a small group of users worldwide, allowing them to tweet with a doubled character limit, i.e., 280 characters. The test results reveal that these users found it easier to tweet and received more engagement (e.g., retweets, likes, and @mentions), even though a great majority of tweets remained brief and did not exceed the previous 140-character limit. The test program rolled out to all Twitter users in English on November 7, 2017.[22]

We trace Twitter discussions on bank stocks back to the six quarters prior to the relaxation of the character limit in the fourth quarter of 2017, and divide banks into two groups based on the number of Twitter discussions. We then run a difference-in-differences model that estimates the impact of relaxing the character limit on the activeness of Twitter users. The model is specified as follows.

$$Ln(Tweets_{i,t}) = \gamma_1 Low\_PreTwitter_i + \gamma_2 Low\_PreTwitter_i \times After_t + \sum_j \theta_j x_{i,j,t-1} + \sum_j \rho_j ROE_{i,t-1} \times x_{i,j,t-1} + \alpha_i + \mu_t + \varepsilon_{i,t} \quad (2)$$

[20] See the article "Tweeting Made Easier" (X Blog, November 2017) for details.
[21] See the article "Our discover of cramming" (X Engineering, November 2017) for details.
[22] See the article "Twitter is officially doubling the character limit to 280" (The Washington Post, November 2017) for details.

The dependent variable is the number of tweets at the current quarter for each bank (in its natural log). The variable *Low_PreTwitter* equals one if the bank stock has lower-than-median Twitter discussions during the six quarters before the character limit relaxation. *Low_PreTwitter* is interacted with the dummy *After*, which indicates the period after the character limit relaxation. The regression includes bank-level control variables ($x_{i,j,t-1}$) and their interactions with ROE, as well as bank (α_i) and year-quarter (μ_t) fixed effects.

The sample period spans the six quarters before and after the event (i.e., from 2016 Q2 to 2019 Q2), excluding the event quarter itself. As shown in Panel A of Table 10, the *Low_PreTwitter* × *After* interaction has a positive coefficient and is significant at 1% level. In terms of economic magnitude, the number of Twitter discussions for banks in the lower-than-median group increased by nearly 38% six quarters after the doubling of the character limit. This finding implies that relaxing character limits increased users' propensity to express their opinions via Twitter, with this effect being more pronounced for banks that previously received less social media attention.

[Insert Table 10 here]

Utilizing character limit relaxation as an exogenous shock to banks' social media attention, we then run a reduced form regression with bank performance interacted with the treatment status of banks and a dummy indicating the post-event sample period. Panel B reports the results of the triple-differences regressions. Column (1) includes macroeconomic variables, and Column (2) controls for year-quarter fixed effects. The triple interaction term loads significantly positively in both columns. In terms of the economic magnitude, banks with lower-than-median Twitter discussions experience more than a two-fold increase in their non-core deposit-flow-performance sensitivity following the character limit relaxation, compared to the pre-period.[23]

[23] According to Column (1) of Table 10 Panel B, the deposit-flow-performance sensitivity for banks with lower-than-

One potential concern that could invalidate the inference is the presence of pre-existing upward trends in performance-deposit-flow sensitivity among banks that received less Twitter coverage prior to the event. To test for the existence of potential pre-trends, we follow Edmans et al. (2017) and construct two dummies indicating the two quarters prior to the event. We then fully interact these two dummies as well as the *After* dummy with the *ROE* × *Low_PreTwitter* interaction.[24] As shown in Column (1) of Panel C, none of the triple interactions for the pre-event periods are statistically significant, suggesting that treated banks are unlikely to exhibit upward trends in performance-deposit-flow sensitivities prior to the event. Column (2) examines the dynamics of the treatment effect after the event. We define two time dummies: one indicating the quarter immediately following the event (*Quarter t+1*) and the other indicating the remaining five quarters of the post-event period (*Quarter t+2 afterward*). We find the coefficient on *Quarter t+1* is statistically insignificant, while the coefficient on *Quarter t+2 afterward* is statistically positive at the 5% level. These results suggest that it takes one quarter for the expansion of the character limit of Twitter to affect the sensitivity of non-core depositors' reaction to bank performance.

Overall, results from the matching exercise and the quasi-natural experiment help alleviate potential endogeneity concerns inherent in our empirical design, enhancing our confidence in making causal inferences.

4.2 Robustness test

In this section, we conduct several robustness tests. First, we show that the baseline findings continue to hold when we measure social media attention over alternative horizons. As shown in

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median Twitter discussions is 0.115, which is the sum of coefficients for *ROE* (0.285) and *ROE* × *Low_PreTwitter* (-0.170), in the pre-period. Following the relaxation of the character limit, the sensitivity for these banks increases to 0.272, which is the sum of coefficients for *ROE* (0.285), *ROE* × *Low_PreTwitter* (-0.170), and *ROE* × *Low_PreTwitter* × *After* (0.157), representing a 136.5% increase in relative terms.

[24] Note that we only present coefficients for main interaction terms for brevity, although *ROE*, the *Low_PreTwitter* dummy and time dummies are fully interacted.

Table 11 Panel A, we find similar results using social media attention computed over one, three, and four quarters leading up to the end of quarter *t-1*. Second, as mentioned in Section 2.2, in our baseline regressions, we construct terciles of tweet volume to account for potential nonlinearities in the effect of interest and to correct for potential measurement errors in social media attention. As a robustness check, we use the original values of tweet volume as the proxy for social media attention and present the corresponding regression results in Panel B. The interaction between ROE and the number of tweets (in its natural log) is significant across all columns (with different numbers of quarters to calculate the social media attention), with a fairly large economic magnitude.[25] Third, we include tweets that only contain bank names without mentioning stock tickers when computing banks' social media attention. As explained in Section 2.1, due to abbreviations, it is impractical to exhaust all tweets that mention the names of banks. We locate tweets that contain the *full* name of banks, which adds an additional 320,000 tweets to the calculation of social media attention. Panel C presents the results based on both dummies (Column (1)) and the number of tweets (in the natural log) (Column (2)) as proxies for social media attention. Our baseline results continue to hold.

[Insert Table 11 here]

In Panel D, we test whether our baseline results are sensitive to alternative proxies for deposit growth. In the first column, we scale the difference in non-core deposits between quarter *t+1* and the current quarter by total assets in the current quarter *t.* In the second column, we scale non-core deposit growth by total deposits lagged one quarter (*t-1*). In the last column, we focus on the subset of non-core deposits (i.e., uninsured time deposits) and compute the growth of this type of deposits

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[25] Take the coefficient estimate of the interaction in Column (2) as an example. A one standard deviation increase in the number of tweets (approximately 1.78) is associated with a 50% ($1.78 \times 0.022 / 0.079$) increase in deposit-flow-performance sensitivity in relative terms.

in a manner that is consistent with our baseline specification (from *t-1* to *t+1*). Our results are insensitive to the calculation of deposit growth. Lastly, we switch to another proxy for bank performance (i.e., ROA). As shown in Panel E, banks with more social media attention exhibit a significantly larger sensitivity of non-core deposit flows to ROA, and the economic magnitude is quite close to that estimated using ROE as the proxy for bank performance.

4.3 Alternative explanations

Prior studies have shown that social media contains useful information for investors to evaluate their equity investments (e.g., Chen, De, Hu, and Hwang 2014). Therefore, one alternative explanation of our results is that banks' social media attention simply captures private information on banks' true performance, and the observed effect is unrelated to depositors' concerns about peers' attention on banks. To examine this alternative explanation, we examine the predictability of social media attention on bank performance in Table A7 in the Appendix. In Columns (1) and (2), the dependent variable is contemporaneous ROE (as of quarter *t*), which has not been disclosed when we calculate the social media attention (i.e., the number of tweets from quarters *t-2* to *t-1*). In Columns (3) and (4), the dependent variable is the next period ROE (as of quarter *t+1*). In Columns (1) and (3), we use indicator variables, *Medium_Twitter* and *High_Twitter*, to proxy for the social media attention as used in our baseline regressions. In Columns (2) and (4), we use *Ln(Tweets)*, which is the natural log of the number of tweets, as the measure of social media attention. We include lagged four quarters' ROEs in our regressions to control for the autocorrelation among banks' performance. As can be seen in this table, no matter which proxy is used to measure social media attention, its coefficient is statistically insignificant, when we use either contemporaneous ROE or next-period ROE. These results suggest that social media attention does not predict undisclosed performance, against the alternative explanation.

Another possible explanation for our findings is that banks with high exposure to social media may react to poor performance by lowering their deposit interest rates to restore profitability through reduced funding costs, ultimately triggering significant deposit outflows. In this scenario, the primary driver of outflows would be the search for higher deposit interest rates elsewhere, rather than withdrawals in response to poor bank performance. To test this alternative hypothesis, we use deposit interest rate data from RateWatch and financial statements. The results are presented in Table A8 in the Appendix. In Columns (1) and (2), the dependent variables are the bank-quarter average interest rates on 24-month certificates of deposit with a $10,000 account size, measured in the current quarter and sourced from RateWatch. In Columns (3) and (4), the outcome variables, derived from financial statement data, are the deposit interest income as a proportion of total deposits for the quarter. In Columns (1) and (3), we find a negative association between the ROE as of *t-1* and deposit interest rates at *t*, indicating that poor performance leads to higher deposit interest rates in the following quarter. Combined with the results in Column (1) of Table 2, this suggests that the rising interest rates following poor performance can be attributed to banks' efforts to respond to deposit outflows after weak performance. In Columns (2) and (4), crucial to our study, the interaction terms *ROE × Medium_Twitter*, and *ROE × High_Twitter* are statistically insignificant. These results indicate that banks with medium or high exposure to social media do not reduce their deposit interest rates following poor performance, relative to banks with low social media exposure. Thus, we find no evidence that deposit outflows are driven by lower deposit interest rates after poor performance.

5. Conclusion

In this paper, we examine how social media attention amplifies banks' deposit outflow sensitivity to performance even in times without any systemic banking crisis. Using a sample preceding the SVB crisis, we show that as banks face more discussions on Twitter, they tend to experience more severe outflows of their non-core deposits when encountering deteriorated performance. The results are stronger for banks with heavy reliance on non-core deposits and with low asset liquidity. This amplification persists even for transparent banks, suggesting that social media's role extends beyond efficient information transmission. We find strong evidence suggesting that social media heightens depositors' awareness of their peers' attention to banks, which amplifies depositors' concerns about potential liquidity depletion and fears about bank fragility, and potential monetary losses, ultimately increasing deposit flow sensitivity to weak fundamentals.

From this research, we provide empirical evidence that "Twitter fueled deposit outflows" are not unique to the recent SVB episode but reflect a general pattern in the U.S. banking sector. We conclude that social media attention is indeed a real risk factor that may continuously shake banking sector stability with respect to banks' liquidity transformation, even outside the special case of SVB collapse. As social media becomes increasingly pervasive in financial markets, understanding and addressing these structural vulnerabilities is crucial. Addressing how to protect the banking sector from these ongoing risks introduced by social media represents an important avenue for future research and policy developments.

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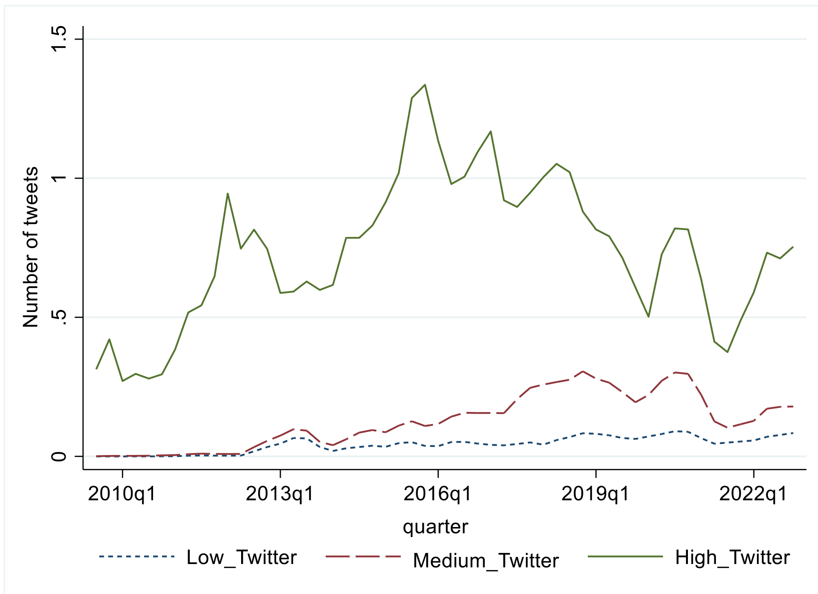
Figure 1: The number of BHC stock-related tweets over time

This figure depicts the number of BHC stock-related tweets for different groups of banks during the period from the third quarter of 2009 to the third quarter of 2022. For each bank, we calculate the average number of tweets mentioning the stock of its holding company during quarters t-2 and t-1. Each quarter, we categorize banks into terciles based on the two-quarter Twitter volume. Panel A shows the average number of (two-quarter) tweets for banks in each tercile. Panel B shows the Twitter volume for banks with different sizes. The number of tweets is in thousands.

Panel A: Banks in terciles of social media exposure



Panel B: Banks with different sizes

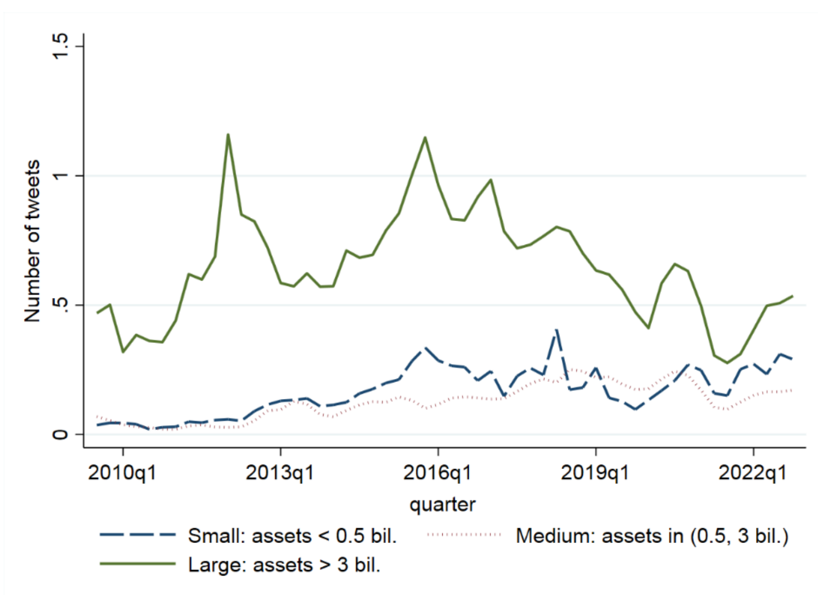
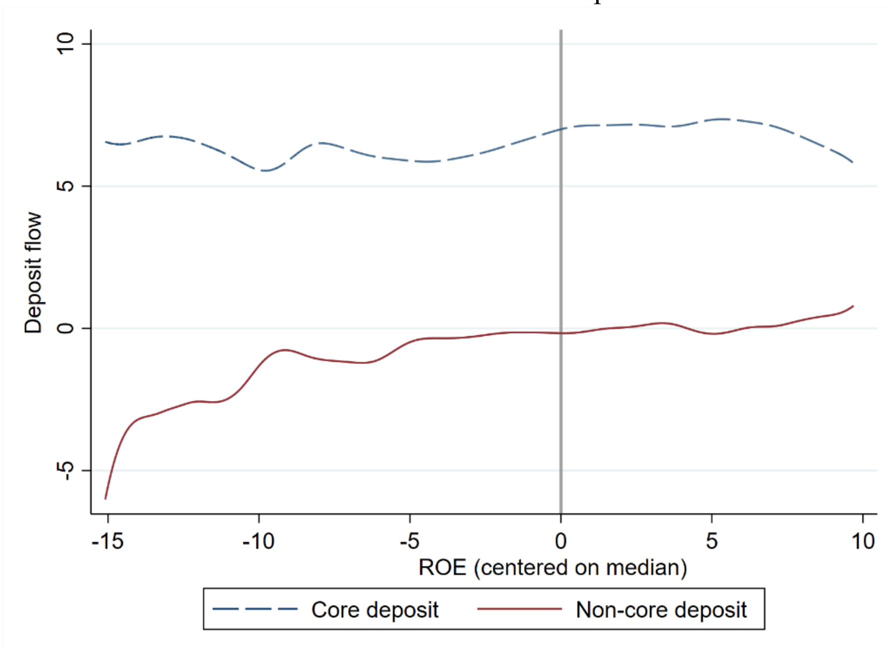


Figure 2: Semiparametric estimates of the flow-performance relation

This figure depicts the semiparametric estimates of the deposit flow-performance relation using Robinson's (1988) estimator implemented using Gaussian local kernel regressions. Panel A plots the estimates for core and non-core deposit flows, separately. Panel B plots the estimates for the non-core deposit flow for banks in the top and bottom terciles of Twitter exposure. Deposit flows are defined as the change in deposit balance between quarter *t+1* and *t-1*, scaled by bank assets in quarter *t-1*.

Panel A: Core versus non-core deposit flow



Panel B: Subsample of Twitter exposure

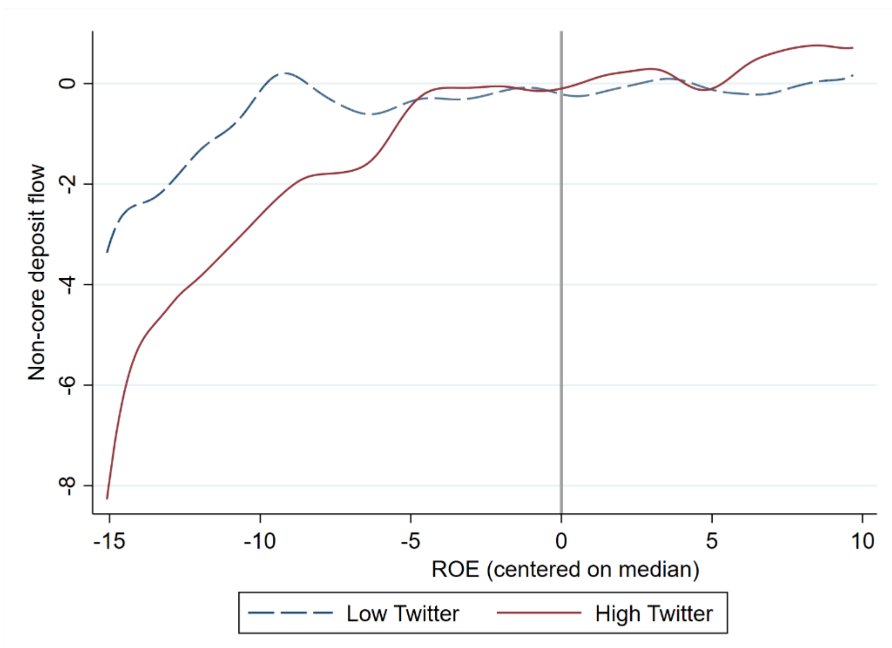


Table 1: Summary statistics

This table reports the summary statistics of main variables used in this paper. Detailed variable definitions can be found in Table A1.

Panel A: The topic composition of tweets

Topics	#Tweets	%Tweets
Fundamentals	888,709	22.0%
Stock prices	1,462,330	36.2%
Governance	331,246	8.2%
Financial services	4,4435	1.1%
Regulation	4,4435	1.1%
Advertisement	5,6554	1.4%
Others	1,211,875	30%
Total	4,039,584	100%

Panel B: Bank characteristics

Variables	N	Mean	P25	Median	P75	S.D.
Twitter	23,444	283.263	17.000	81.500	224.500	930.842
ΔNoncore	23,444	-0.573	-1.751	-0.093	1.530	7.267
ΔCore	23,444	6.842	-0.380	4.246	10.967	13.293
ΔDeposit	23,444	6.225	-0.862	4.159	10.644	13.972
ROE	23,444	7.391	5.490	8.650	11.600	10.514
Std_WriteOff	23,444	0.535	0.106	0.260	0.634	0.728
Capital_Ratio	23,444	0.159	0.125	0.139	0.159	0.129
Wholesale_funding	23,444	0.070	0.023	0.042	0.079	0.094
RealEstate_Loans	23,444	0.723	0.639	0.778	0.869	0.213
Ln(Assets)	23,444	14.746	13.572	14.406	15.707	1.774
Unused_Commitments	23,444	0.180	0.125	0.172	0.221	0.094
Deposit_Rate	23,444	0.160	0.065	0.122	0.215	0.133
%Noncore	23,444	0.132	0.041	0.084	0.162	0.154
%LiquidAssets	23,444	0.204	0.117	0.180	0.263	0.130
R2	22,522	0.320	-0.003	0.427	0.744	0.512

Table 2: Social Media Attention and Non-core Deposit Flow-Performance Sensitivity

This table presents the results of regressions that examine how the sensitivity of deposit flows to bank performance varies with social media attention. The dependent variable Δ*Noncore* is defined as two-period (i.e., between *t+1* and *t-1*) change in non-core deposits scaled by bank assets as of the end of last quarter. Banks are categorized into three terciles based on the average number of Twitter discussions on their bank holding companies during the two-quarter period prior to the current quarter. The dummy variable *Medium_Twitter* (*High_Twitter*) equals one for banks in the second (third) tercile of Twitter discussions. In Columns (2) and (3), the interactions between bank characteristics (i.e., *Std_WriteOff*, *Capital_Ratio*, *Wholesale_funding*, *RealEstate_Loans*, *Ln(Assets)*, *Unused_Commitments*, and *Deposit_Rate*) and ROE are included in the regressions as controls. Macroeconomic controls are included in Columns (1) and (2), while Column (3) controls for year-quarter fixed effects. Bank fixed effects are controlled in every specification. Detailed variable definitions can be found in Table A1. Standard errors, shown in parentheses, are adjusted for clustering on the bank level. ***, ** and * denote significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)
Dependent variable	ΔNoncore	ΔNoncore	ΔNoncore
ROE	0.080***	0.134	0.033
	(0.010)	(0.142)	(0.113)
ROE × Medium_Twitter		0.055***	0.016
		(0.017)	(0.015)
ROE × High_Twitter		0.099***	0.057***
		(0.022)	(0.018)
Medium_Twitter	0.056	-0.374*	-0.040
	(0.151)	(0.201)	(0.173)
High_Twitter	0.059	-0.760***	-0.560**
	(0.220)	(0.271)	(0.228)
Std_WriteOff	0.087	-0.044	-0.194
	(0.172)	(0.151)	(0.141)
Capital_Ratio	-3.659**	-3.881**	-1.306
	(1.829)	(1.756)	(1.334)
Wholesale_funding	-31.174***	-38.396***	-17.323***
	(6.502)	(4.073)	(3.181)
RealEstate_Loans	-1.066	-2.107	-1.453
	(2.620)	(2.101)	(1.725)
Ln(Assets)	-2.017***	-1.681***	-1.414***
	(0.269)	(0.238)	(0.328)
Unused_Commitments	6.694**	7.983***	8.304***
	(2.642)	(2.960)	(2.624)
Deposit_Rate	-12.519***	-12.414***	-8.447***
	(1.907)	(1.421)	(1.787)
Bank characteristics × ROE	No	Yes	Yes
Macro-variable controls	Yes	Yes	No
Bank FE	Yes	Yes	Yes
Year-quarter FE	No	No	Yes
Observations	23,444	23,444	23,444
Adj. R-squared	0.228	0.244	0.376

Table 3: High versus Low ROE

This table presents the results of regressions that examine how the sensitivity of non-core deposit flows to bank performance varies with social media attention for subsamples with above-median and below-median ROE, separately. The dependent variable Δ*Noncore* is defined as two-period (i.e., between *t+1* and *t-1*) change in non-core deposits scaled by bank assets as of the end of last quarter. Bank characteristics interacted with ROE, as well as macro-economic controls and bank fixed effects are controlled in every specification. Standard errors, shown in parentheses, are adjusted for clustering on the bank level. ***, ** and * denote significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)
Dependent variable	ΔNoncore	ΔNoncore
ROE	-0.080	0.404**
	(0.284)	(0.174)
ROE × Medium_Twitter	-0.027	0.055**
	(0.046)	(0.021)
ROE × High_Twitter	-0.001	0.113***
	(0.065)	(0.027)
Medium_Twitter	0.593	-0.435**
	(0.576)	(0.208)
High_Twitter	0.358	-0.672**
	(0.836)	(0.292)
Std_WriteOff	0.360	-0.105
	(0.427)	(0.155)
Capital_Ratio	-4.184	-7.054***
	(7.058)	(2.447)
Wholesale_funding	-38.215***	-54.157***
	(6.686)	(4.585)
RealEstate_Loans	-2.079	-1.908
	(2.741)	(2.415)
Ln(Assets)	-1.704***	-1.964***
	(0.340)	(0.349)
Unused_Commitments	10.157*	4.671
	(5.660)	(3.389)
Deposit_Rate	-16.092***	-9.709***
	(2.908)	(1.672)
ROE is below median?	No	Yes
Bank characteristics × ROE	Yes	Yes
Bank FE	Yes	Yes
Macro-variable controls	Yes	Yes
Observations	11,728	11,716
Adj. R-squared	0.118	0.339

Table 4: Core and Total Deposit Flows

This table presents the results of regressions that examine how the sensitivity of deposit flows to bank performance varies with social media attention. The dependent variable in Column (1) is core deposit flows that are computed as the two-period change in insured deposits scaled by bank assets as of the last quarter. We compute the change in total deposits in a similar manner and present the corresponding results in Column (2). The interactions between bank characteristics and ROE are included in both specifications. Bank fixed effects are also included. Standard errors, shown in parentheses, are adjusted for clustering on the bank level. ***, ** and * denote significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)
Dependent variable	ΔCore	ΔDeposit
ROE	-0.321	-0.163
	(0.227)	(0.216)
ROE × Medium_Twitter	-0.077***	0.002
	(0.026)	(0.027)
ROE × High_Twitter	-0.026	0.084***
	(0.032)	(0.031)
Medium_Twitter	1.105***	0.530
	(0.338)	(0.339)
High_Twitter	0.401	-0.442
	(0.485)	(0.495)
Std_WriteOff	-2.834***	-2.883***
	(0.285)	(0.298)
Capital_Ratio	5.435*	1.129
	(3.262)	(2.388)
Wholesale_funding	60.684***	13.720***
	(6.278)	(5.017)
RealEstate_Loans	-11.598***	-13.225***
	(3.211)	(2.796)
Ln(Assets)	-2.717***	-4.497***
	(0.417)	(0.414)
Unused_Commitments	4.951	13.604**
	(5.380)	(5.793)
Deposit_Rate	8.481***	-4.079**
	(2.169)	(1.951)
Bank characteristics × ROE	Yes	Yes
Bank FE	Yes	Yes
Macro-variable controls	Yes	Yes
Observations	23,444	23,444
Adj. R-squared	0.151	0.127

Table 5: The Role of Bank Liquidity Mismatch

This table presents results of regressions that examine how the impact of social media attention on non-core deposit-flow-performance sensitivity varies among banks with differential levels of liquidity mismatch. The first proxy of liquidity mismatch, *%Noncore*, is defined as the fraction of non-core deposits. The second proxy, *%LiquidAssets*, represents the fraction of liquidity assets out of total assets. Banks are categorized into two subsamples (i.e., *Low* versus *High*) based on these two liquidity mismatch proxies. Bank characteristics interacted with ROE, as well as macro-economic controls and bank fixed effects are controlled in every specification. Standard errors, shown in parentheses, are adjusted for clustering on the bank level. ***, ** and * denote significance at the 1%, 5%, and 10% levels, respectively.

Partition variable	%Noncore		%LiquidAssets	
Subsample	Low	High	Low	High
	(1)	(2)	(3)	(4)
ROE	0.094	0.225	0.058	-0.025
	(0.158)	(0.188)	(0.199)	(0.164)
ROE × Medium_Twitter	0.028	0.080***	0.059**	0.047**
	(0.018)	(0.025)	(0.025)	(0.023)
ROE × High_Twitter	0.023	0.142***	0.114***	0.060**
	(0.022)	(0.033)	(0.034)	(0.027)
Medium_Twitter	-0.100	-0.817**	-0.348	-0.458*
	(0.214)	(0.319)	(0.318)	(0.252)
High_Twitter	0.020	-1.509***	-1.404***	-0.140
	(0.281)	(0.425)	(0.435)	(0.305)
Std_WriteOff	-0.053	-0.428*	-0.206	0.048
	(0.153)	(0.239)	(0.229)	(0.200)
Capital_Ratio	-2.570**	-2.706	-6.820***	2.254
	(1.042)	(3.077)	(1.312)	(2.111)
Wholesale_funding	-55.734***	-39.032***	-38.636***	-43.592***
	(7.290)	(4.643)	(4.849)	(6.487)
RealEstate_Loans	-0.112	-0.147	-4.755*	-0.122
	(1.739)	(2.850)	(2.533)	(2.651)
Ln(Assets)	-0.999***	-2.713***	-1.981***	-1.881***
	(0.223)	(0.427)	(0.353)	(0.314)
Unused_Commitments	0.316	10.830**	6.070*	7.962*
	(2.644)	(4.513)	(3.328)	(4.474)
Deposit_Rate	-10.162***	-12.408***	-12.176***	-11.768***
	(1.880)	(1.866)	(1.989)	(1.938)
Equal coefficient for ROE × Medium_Twitter?	*p*-value = 0.058		*p*-value = 0.541	
Equal coefficient for ROE × High_Twitter?	*p*-value = 0.002		*p*-value = 0.087	
Bank characteristics × ROE	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes
Macro-variable controls	Yes	Yes	Yes	Yes
Observations	11,655	11,789	11,723	11,721
Adj. R-squared	0.307	0.263	0.271	0.239

Table 6: The Role of Social Media User Engagement

This table examines whether the effect of Twitter discussions on the non-core deposit-flow-performance sensitivity depends on the degree of engagement of Twitter users. For every bank, we compute the average number of *retweets* and *likes* during the two-quarter period in which we compute social media attention. Banks that belong to the *Medium_Twitter* group are categorized into subgroups, first based on *retweets* (i.e., *Medium_LessRetweet* and *Medium_MoreRetweet*), and then based on *like* intensity (i.e., *Medium_LessLike* and *Medium_MoreLike*). A similar categorization is applied to the *High_Twitter* group. Bank characteristics interacted with ROE, as well as macro-economic controls and bank fixed effects are controlled in every specification. Standard errors, shown in parentheses, are adjusted for clustering on the bank level. ***, ** and * denote significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)
Dependent variable	ΔNoncore	ΔNoncore
ROE	0.140	0.131
	(0.142)	(0.142)
ROE × Medium_LessRetweet	0.052***	
	(0.019)	
ROE × Medium_MoreRetweet	0.065***	
	(0.020)	
ROE × High_LessRetweet	0.060**	
	(0.026)	
ROE × High_MoreRetweet	0.136***	
	(0.024)	
ROE × Medium_LessLike		0.051***
		(0.018)
ROE × Medium_MoreLike		0.065***
		(0.023)
ROE × High_LessLike		0.093***
		(0.024)
ROE × High_MoreLike		0.105***
		(0.025)
Bank characteristics	Yes	Yes
Bank characteristics × ROE	Yes	Yes
Bank FE	Yes	Yes
Macro-variable controls	Yes	Yes
Observations	23,444	23,444
Adjusted R-squared	0.244	0.245

Table 7: The Role of Bank Transparency

This table presents results of regressions that examine how the impact of social media attention on non-core deposit-flow-performance sensitivity varies among banks with differential levels of transparency. The proxy for bank performance, *R2*, is defined as the R-squared of the regression of write-offs on several bank performance indicators as well as bank capital ratio, following Chen et al. (2022). Banks are categorized into two subsamples (i.e., Low versus High) based on their levels of transparency. Bank characteristics interacted with ROE, as well as macro-economic controls and bank fixed effects are controlled in every specification. Standard errors, shown in parentheses, are adjusted for clustering on the bank level. ***, ** and * denote significance at the 1%, 5%, and 10% levels, respectively.

Subsample	Low R2	High R2
	(1)	(2)
Dependent variable	ΔNoncore	ΔNoncore
ROE	0.127	0.124
	(0.216)	(0.206)
ROE × Medium_Twitter	0.069***	0.073***
	(0.025)	(0.021)
ROE × High_Twitter	0.117***	0.093***
	(0.029)	(0.029)
Medium_Twitter	-0.233	-0.852***
	(0.283)	(0.269)
High_Twitter	-0.475	-1.120***
	(0.381)	(0.373)
Std_WriteOff	-0.057	-0.293*
	(0.204)	(0.171)
Capital_Ratio	-7.870**	-4.569**
	(3.300)	(1.803)
Wholesale_funding	-47.476***	-39.701***
	(4.834)	(4.301)
RealEstate_Loans	2.442	-1.727
	(2.611)	(2.005)
Ln(Assets)	-1.669***	-1.887***
	(0.299)	(0.324)
Unused_Commitments	12.480***	3.885
	(4.545)	(3.718)
Deposit_Rate	-12.619***	-12.355***
	(1.820)	(1.880)
Equal coefficient for ROE × Medium_Twitter?	*p*-value = 0.962	
Equal coefficient for ROE × High_Twitter?	*p*-value = 0.520	
Bank characteristics × ROE	Yes	Yes
Bank FE	Yes	Yes
Macro-variable controls	Yes	Yes
Observations	11,276	11,246
Adj. R-squared	0.282	0.280

Table 8: The Role of Social Media Sentiment

This table presents results of regressions that examine the impact of social media sentiment on the sensitivity of non-core deposit flows to bank performance. The (negative) sentiment of tweets for each bank stock-quarter is defined as the difference between the proportion of tweets mentioning the stock in that quarter with a negative tone and the proportion of tweets with a positive tone. Abnormal sentiment (*Abn_sentiment*) is calculated as the sentiment of tweets posted in the current quarter minus the average sentiment of tweets posted during the last two quarters. Each quarter, banks are categorized into three terciles based on their levels of abnormal sentiment. The dummy variables *Medium_abn_sentiment* and *High_abn_sentiment* indicate banks in the second and third terciles, respectively. *Ln(Tweets)* represents the number of tweet mentions in the last two quarters. Bank characteristics interacted with ROE, as well as macro-economic controls and bank fixed effects are controlled in every specification. Standard errors, shown in parentheses, are adjusted for clustering on the bank level. ***, ** and * denote significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)
Dependent variable	ΔNoncore	ΔNoncore	ΔNoncore	ΔNoncore
ROE	0.030	0.058	0.014	0.116
	(0.128)	(0.126)	(0.127)	(0.131)
ROE × Abn_sentiment	0.083***	0.084***		
	(0.030)	(0.030)		
ROE × Ln(Tweets)		0.028***		
		(0.007)		
ROE × Medium_abn_sentiment			0.030*	0.032*
			(0.018)	(0.018)
ROE × High_ abn_sentiment			0.047**	0.038**
			(0.019)	(0.018)
ROE × Medium_Twitter				0.032*
				(0.019)
ROE × High_Twitter				0.096***
				(0.025)
Abn _sentiment	-0.246	-0.238		
	(0.364)	(0.363)		
Ln(Tweets)		-0.110		
		(0.089)		
Medium_ abn_sentiment			-0.089	-0.117
			(0.186)	(0.187)
High_ abn_sentiment			-0.312	-0.232
			(0.196)	(0.191)
Medium_Twitter				-0.396**
				(0.198)
High_Twitter				-0.919***
				(0.278)
Bank characteristics	Yes	Yes	Yes	Yes
Bank characteristics × ROE	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes
Macro-variable controls	Yes	Yes	Yes	Yes
Observations	20,881	20,881	20,881	20,881
Adjusted R-squared	0.189	0.192	0.189	0.191

Table 9: Results based on a PSM-matched Sample

This table presents the results of regressions using a PSM-matched sample. Banks that belong to the third tercile of Twitter discussions are matched with those in the first tercile (i.e., *Low_Twitter*) using the basic bank characteristics as well as the two-quarter cumulative return of the bank holding company stocks (*Return*), the R-squared generated from Chen et al. (2022) regressions of write-offs (*R2*), and the fraction of noncore deposits (*%Noncore*). Panel A shows the mean of bank characteristics for the two groups of banks after matching, as well as the *p*-values associated with two-tailed *t*-tests that compare the mean of the two groups. Panel B presents the results of non-core deposit-flow-performance sensitivity regressions using the matched sample. The interactions between bank characteristics and ROE, as well as bank fixed effects are controlled in both specifications. Column (1) controls for macroeconomic variables, and Column (2) includes year-quarter fixed effects. Standard errors, shown in parentheses, are adjusted for clustering on the bank level. ***, ** and * denote significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Mean of bank characteristics for two matched samples

Bank characteristics	Low_Twitter	High_Twitter	difference	*t*-stat.
Std_WriteOff	0.641	0.625	-0.016	-0.68
Capital_Ratio	0.156	0.158	0.002	0.45
Wholesale_funding	0.068	0.066	-0.002	-0.46
RealEstate_Loans	0.736	0.740	0.004	0.87
Ln(Assets)	14.405	14.351	-0.054	-1.36
Unused_Commitments	0.179	0.177	-0.002	-0.51
Deposit_Rate	0.172	0.165	-0.007	-1.40
Return	0.035	0.044	0.009	1.04
R2	0.341	0.323	-0.018	-1.26
%Noncore	0.129	0.128	-0.001	-0.39

Panel B: Regressions using the matched sample

	(1)	(2)
Dependent variable	ΔNoncore	ΔNoncore
ROE	-0.174	-0.235
	(0.208)	(0.165)
ROE × High_Twitter	0.074***	0.052***
	(0.025)	(0.019)
High_Twitter	0.212	0.045
	(0.442)	(0.380)
Std_WriteOff	-0.271	-0.300*
	(0.179)	(0.162)
Capital_Ratio	-10.015***	-3.596**
	(1.820)	(1.647)
Wholesale_funding	-50.800***	-22.995***
	(5.334)	(4.739)
RealEstate_Loans	-0.618	-1.839
	(2.453)	(2.339)
Ln(Assets)	-1.923***	-1.458***
	(0.476)	(0.533)
Unused_Commitments	7.838*	5.418
	(4.628)	(4.176)
Deposit_Rate	-8.964***	-3.515
	(2.401)	(3.664)
Bank characteristics × ROE	Yes	Yes
Macro-variable controls	Yes	No
Bank FE	Yes	Yes
Year-quarter FE	No	Yes
Observations	4,641	4,641
Adj. R-squared	0.354	0.491

Table 10: Character Limit Expansion as an Exogenous Shock

This table presents the results of regressions in which the character limit expansion that became effective in early November of 2017 is used as an exogenous shock to banks' Twitter exposure. The sample period spans the six quarters before and after the event (i.e., from 2016 Q2 to 2019 Q2), excluding the event quarter itself. The dependent variable in Panel A is the number of tweets in the current quarter for each bank (in its natural log). *Low_PreTwitter* is a dummy variable that equals one if the bank has lower-than-median Twitter discussions during the four-quarter period prior to the announcement of character limit expansion, and zero otherwise. *After* equals one if it is after the fourth quarter of 2017. In Panel B, we further interact the DID terms in Panel A with bank ROE. Column (1) includes macroeconomic variables, and Column (2) controls for year-quarter fixed effects. Panel C tests for the existence of potential pre-trends in performance-deposit-flow sensitivity. Note that we only present coefficients for main interaction terms for brevity, although *RO E*, the *Low_PreTwitter* dummy and time dummies are fully interacted. Standard errors, shown in parentheses, are adjusted for clustering on the bank level. ***, ** and * denote significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Word limit expansion and Twitter volumes

Dependent variable	Ln(Tweets)
Low_PreTwitter	-1.784***
	(0.512)
Low_PreTwitter × After	0.378***
	(0.069)
Bank characteristics	Yes
Bank characteristics × ROE	Yes
Bank FE	Yes
Year-quarter FE	Yes
Observations	5,111
Adj. R-squared	0.847

Panel B: Character limit relaxation and deposit-flow-performance sensitivity

	(1)	(2)
Dependent variable	ΔNoncore	ΔNoncore
ROE	0.285	0.300
	(0.280)	(0.280)
ROE × Low_PreTwitter	-0.170***	-0.175***
	(0.060)	(0.060)
Low_PreTwitter	2.664***	2.952***
	(0.920)	(0.907)
ROE × After	-0.122**	-0.140***
	(0.049)	(0.052)
Low_PreTwitter × After	-1.462*	-1.506*
	(0.814)	(0.808)
ROE × Low_PreTwitter × After	0.157**	0.155**
	(0.073)	(0.073)
After	-0.996*	
	(0.567)	
Bank characteristics	Yes	Yes
Bank characteristics × ROE	Yes	Yes
Bank FE	Yes	Yes
Macro-variable controls	Yes	No
Year-quarter FE	No	Yes
Observations	5,111	5,111
Adj. R-squared	0.098	0.106

Panel C: Testing for pre-trends

	(1)	(2)
Dependent variable	ΔNoncore	ΔNoncore
ROE	0.300	0.322
	(0.278)	(0.273)
ROE × Low_PreTwitter	-0.181***	-0.188***
	(0.058)	(0.059)
ROE × Low_PreTwitter × Quarter *t-2*	0.023	
	(0.193)	
ROE × Low_PreTwitter × Quarter *t-1*	-0.110	
	(0.180)	
ROE × Low_PreTwitter × After	0.160**	
	(0.077)	
ROE × Low_PreTwitter × Quarter *t+1*		0.050
		(0.158)
ROE × Low_PreTwitter × Quarter *t+2* afterward		0.177**
		(0.088)
Bank characteristics	Yes	Yes
Bank characteristics × ROE	Yes	Yes
Bank FE	Yes	Yes
Year-quarter FE	Yes	Yes
Observations	5,111	5,111
Adj. R-squared	0.105	0.106

Table 11: Robustness Tests

This table presents the results of several robustness tests. In Panel A, we recalculate the average number of tweets in different horizons (i.e., one-, three-, and four-quarter horizons), and construct new dummies of the degree of social media attention based on the newly calculated tweet amount. Panel B adopts a continuous version of social media attention. In Panel C, we also consider tweets that mention the names of banks. Panel D adopts several alternative proxies for non-core deposit growth. Panel E uses ROA as the proxy for bank performance. Standard errors, shown in parentheses, are adjusted for clustering on the bank level. ***, ** and * denote significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Alternative horizons used when counting relevant tweets

	(1)	(2)	(3)
Number of quarters	1	3	4
Dependent variable	ΔNoncore	ΔNoncore	ΔNoncore
ROE	0.112	0.061	0.080
	(0.142)	(0.143)	(0.144)
ROE × Medium_Twitter	0.017	0.047***	0.036*
	(0.016)	(0.017)	(0.018)
ROE × High_Twitter	0.058***	0.048**	0.069***
	(0.021)	(0.021)	(0.022)
Medium_Twitter	-0.056	-0.028	0.205
	(0.180)	(0.202)	(0.223)
High_Twitter	-0.225	0.113	-0.231
	(0.249)	(0.269)	(0.284)
Bank characteristics	Yes	Yes	Yes
Bank characteristics × ROE	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes
Macro-variable controls	Yes	Yes	Yes
Observations	23,444	23,444	23,444
Adj. R-squared	0.243	0.243	0.244

Panel B: Total number of tweets as the proxy for social media attention

	(1)	(2)	(3)	(4)
Number of quarters	1	2	3	4
Dependent variable	ΔNoncore	ΔNoncore	ΔNoncore	ΔNoncore
ROE	0.062	0.079	0.071	0.065
	(0.136)	(0.136)	(0.136)	(0.137)
ROE × Ln(Tweets)	0.016***	0.022***	0.019***	0.019***
	(0.005)	(0.005)	(0.005)	(0.005)
Ln(Tweets)	0.131*	0.049	0.086	0.056
	(0.069)	(0.072)	(0.073)	(0.073)
Bank characteristics	Yes	Yes	Yes	Yes
Bank characteristics × ROE	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes
Macro-variable controls	Yes	Yes	Yes	Yes
Observations	23,444	23,444	23,444	23,444
Adj. R-squared	0.245	0.245	0.245	0.244

Panel C: Including tweets mentioning bank names

	(1)	(2)
Dependent variable	ΔNoncore	ΔNoncore
ROE	0.078	0.068
	(0.140)	(0.136)
ROE × Medium_Twitter	0.053***	
	(0.018)	
ROE × High_Twitter	0.066***	
	(0.021)	
Medium_Twitter	-0.409*	
	(0.220)	
High_Twitter	-0.562**	
	(0.262)	
ROE × Ln(Tweets)		0.021***
		(0.005)
Ln(Tweets)		0.032
		(0.075)
Bank characteristics	Yes	Yes
Bank characteristics × ROE	Yes	Yes
Bank FE	Yes	Yes
Macro-variable controls	Yes	Yes
Observations	23,444	23,444
Adj. R-squared	0.243	0.245

Panel D: Alternative proxies for deposit growth

	(1)	(2)	(3)
Dependent variable	Scaled by current total assets	Scaled by lagged deposits	Growth of uninsured time deposits
ROE	0.105	-0.468	0.188*
	(0.088)	(1.198)	(0.113)
ROE × Medium_Twitter	0.031**	0.434***	0.067***
	(0.013)	(0.129)	(0.013)
ROE × High_Twitter	0.039***	0.709***	0.079***
	(0.014)	(0.141)	(0.017)
Medium_Twitter	-0.173	-2.139	-0.481***
	(0.135)	(1.833)	(0.151)
High_Twitter	-0.107	-3.529	-0.347*
	(0.169)	(2.690)	(0.208)
Bank characteristics	Yes	Yes	Yes
Bank characteristics × ROE	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes
Macro-variable controls	Yes	Yes	Yes
Observations	23,444	23,292	23,444
Adj. R-squared	0.151	0.107	0.345

Panel E: ROA as the proxy for performance

	(1)	(2)
Dependent variable	ΔNoncore	ΔNoncore
ROA	0.582***	0.747***
	(0.195)	(0.233)
ROA × Medium_Twitter	0.635***	
	(0.200)	
ROA × High_Twitter	0.785***	
	(0.214)	
Medium_Twitter	-0.508**	
	(0.224)	
High_Twitter	-0.636**	
	(0.279)	
ROA × Ln(Tweets)		0.098**
		(0.048)
Ln(Tweets)		0.075
		(0.068)
Bank characteristics	Yes	Yes
Bank characteristics × ROA	Yes	Yes
Bank FE	Yes	Yes
Macro-variable controls	Yes	Yes
Observations	23,444	23,444
Adj. R-squared	0.248	0.248

Appendix

Risky Tweets in Quiet Times:
Social Media Attention and Bank Deposit Flows

Table A1: Variable definitions

Variables	Definitions
Ln(Tweets)	The average number of tweets mentioning the stock ticker of the bank holding company during quarter t-2 and t-1.
Medium_Twitter	A dummy variable that equals one for banks for which the average number of tweets mentioning the stock ticker of the corresponding BHC during quarter t-2 and t-1 is in the second tercile of quarterly sample distribution, and zero otherwise
High_Twitter	A dummy variable that equals one for banks for which the average number of tweets mentioning the stock ticker of the corresponding BHC during quarter t-2 and t-1 is in the third tercile of quarterly sample distribution, and zero otherwise
Abn_sentiment	Calculated as the sentiment of tweets posted in the current quarter minus the average sentiment of tweets posted during the last two quarters, where the (negative) sentiment of tweets for each bank stock-quarter is defined as the difference between the proportion of tweets mentioning the stock in that quarter with a negative tone and the proportion of tweets with a positive tone
Medium_abn_sentient	A dummy variable that equals one for banks for which the abnormal (negative) sentiment of tweets mentioning the stock ticker of the corresponding BHC during quarter t is in the second tercile of quarterly sample distribution, and zero otherwise
High_abn_sentiment	A dummy variable that equals one for banks for which the abnormal (negative) sentiment of tweets mentioning the stock ticker of the corresponding BHC during quarter t is in the third tercile of quarterly sample distribution, and zero otherwise
ΔNoncore	The balance change of non-core deposits for two-quarter periods from the previous quarter-end (t-1) to the following quarter-end (t+1), scaled by the lagged quarter-end total assets (t-1).
ΔCore	The change of core deposits, which include transaction accounts, non-transaction money market deposit accounts, and insured non-transaction time deposits, scaled by the lagged quarter-end total assets (t-1).
ΔDeposit	The change of total deposits for two-quarter periods from the previous quarter-end (t-1) to the following quarter-end (t+1), scaled by the lagged quarter-end total assets (t-1).
ROE	Net income as a percentage of average bank equity capital as of the previous quarter-end (t-1).
Std_WriteOff	Standard deviation of write-offs measured over the period from quarter t-12 to t-1, scaled by average total loans for the previous 12 quarters.
Capital_Ratio	Total risk-based capital to risk-weighted assets.
Wholesale_funding	Wholesale funding as a share of total assets. Wholesale funds are the sum of large time deposits, deposits booked in foreign offices, subordinated debt and debentures, gross federal funds purchased, repos, and other borrowed money.
RealEstate_Loans	Real estate loans (loans secured by real estate) scaled by total loans.
Ln(Assets)	The natural logarithm of bank total assets.
Unused_Commitments	Unused commitment scaled by the sum of total loans and unused commitment.
Deposit_Rate	Interests on deposits over total deposits.
%Noncore	The fraction of non-core deposits out of total deposits.
%LiquidAssets	The fraction of liquid assets (cash and securities) out of total deposits.
R2	The R-squared of a regression that regresses the current amount of write-offs on loan loss provisions, earnings before loan loss provisions, and the change in non-performing loans, all of which are defined both on the last quarter and two quarter prior to the current quarter, as well as last quarter's capital ratio, using the past 12 quarters of data. See Section 2.1 of Chen et al. (2022) for details of calculation.
Return	Cumulative return of the bank holding company stocks during the period from quarter t-

Variables	Definitions
	2 to t-1.
Low_PreTwitter	A dummy variable that equals one if the bank has lower-than-median Twitter discussions during the four-quarter period prior to the announcement of character limit expansion in November 2017 by Twitter, and zero otherwise.

Table A2: The Effect of the Twitter Discussion Topics

This table presents the results of regressions that examine how the sensitivity of deposit flows to bank performance varies with Twitter discussions on different topics. The dependent variable Δ*Noncore* is defined as two-period (i.e., between *t+1* and *t-1*) change in non-core deposits scaled by bank assets as of the end of last quarter. We first distinguish between Twitter discussions on different topics, including fund amental- and stock price-related tweets as well as tweets on other topics. We then categorize banks into three terciles based on the number of Twitter discussions on each topic that mention bank holding companies during the previous two quarters. "Other" includes tweets on governance, financial services, regulation, advertisement, and unclassified tweets (i.e., all topics except fundamentals and stock prices). Bank characteristics interacted with ROE, as well as bank and year quarter fixed effects are controlled in every specification. Standard errors, shown in parentheses, are adjusted for clustering on the bank level. ***, ** and * denote significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)
Dependent variable	ΔNoncore	ΔNoncore	ΔNoncore
ROE	0.096	0.135	0.078
	(0.142)	(0.140)	(0.138)
ROE × Medium_Twitter_Fundamental	0.041**		
	(0.018)		
ROE × High_Twitter_Fundamental	0.050**		
	(0.023)		
ROE × Medium_Twitter_StockPr		0.047**	
		(0.018)	
ROE × High_Twitter_StockPr		0.095***	
		(0.021)	
ROE × Medium_Twitter_Other			0.034**
			(0.017)
ROE × High_Twitter_Other			0.044**
			(0.019)
Bank characteristics	Yes	Yes	Yes
Bank characteristics × ROE	Yes	Yes	Yes
Macro-variable controls	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes
Observations	23,444	23,444	23,444
Adj. R-squared	0.243	0.244	0.243

Table A3: Heterogeneity with respect to Bank Performance with Quarter Fixed Effects

This table presents the results of regressions that examine how the sensitivity of deposit flows to bank performance varies with social media attention for samples with above-median and below-median ROE, separately. The dependent variable Δ*Noncore* is defined as two-period (i.e., between *t+1* and *t-1*) change in non-core deposits scaled by bank assets as of the end of last quarter. Bank characteristics interacted with ROE, as well as bank and year quarter fixed effects are controlled in every specification. Standard errors, shown in parentheses, are adjusted for clustering on the bank level. ***, ** and * denote significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)
Dependent variable	ΔNoncore	ΔNoncore
ROE	-0.150	0.213
	(0.268)	(0.153)
ROE × Medium_Twitter	0.020	-0.003
	(0.042)	(0.019)
ROE × High_Twitter	0.040	0.047**
	(0.065)	(0.022)
Medium_Twitter	-0.093	-0.024
	(0.524)	(0.179)
High_Twitter	-0.327	-0.559**
	(0.809)	(0.243)
ROE is below median?	No	Yes
Bank characteristics × ROE	Yes	Yes
Bank FE	Yes	Yes
Year-quarter FE	Yes	Yes
Observations	11,728	11,716
Adj. R-squared	0.203	0.489

Table A4: Results of Core and Total Deposit Flows with Quarter Fixed Effects

This table presents the results of regressions that examine how the sensitivity of deposit flows to bank performance varies with social media attention. The dependent variable in Column (1) is core deposit flows that are computed as the two-period change in insured deposits scaled by bank assets as of the last quarter. We compute the change in total deposits in a similar manner and present the corresponding results in Column (2). The interactions between bank characteristics and ROE are included in both specifications. Bank and quarter fixed effects are also included. Standard errors, shown in parentheses, are adjusted for clustering on the bank level. ***, ** and * denote significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)
Dependent variable	ΔCore	ΔDeposit
ROE	-0.139	-0.095
	(0.195)	(0.213)
ROE × Medium_Twitter	-0.029	0.005
	(0.023)	(0.026)
ROE × High_Twitter	0.022	0.085***
	(0.027)	(0.030)
Medium_Twitter	0.586**	0.432
	(0.294)	(0.323)
High_Twitter	0.293	-0.266
	(0.436)	(0.481)
Bank characteristics × ROE	Yes	Yes
Bank FE	Yes	Yes
Year-quarter FE	Yes	Yes
Observations	23,444	23,444
Adj. R-squared	0.265	0.192

Table A5: Controlling for Earnings Quality

This table presents the result of the regression that examines the impact of social media attention on non-core deposit-flow-performance sensitivity, explicitly controlling for the impact of earnings quality. Our proxy for earnings quality, *R2*, is defined as the R-squared of the regression of write-offs on several bank performance indicators as well as bank capital ratio, following Chen et al. (2022). The interactions between bank characteristics and ROE, as well as bank fixed effects are controlled in both specifications. Standard errors, shown in parentheses, are adjusted for clustering on the bank level. ***, ** and * denote significance at the 1%, 5%, and 10% levels, respectively.

	(1)
Dependent variable	ΔNoncore
ROE	0.182
	(0.145)
ROE × Medium_Twitter	0.070***
	(0.016)
ROE × High_Twitter	0.107***
	(0.022)
Medium_Twitter	-0.545***
	(0.198)
High_Twitter	-0.857***
	(0.269)
ROE × R2	0.006
	(0.016)
R2	0.040
	(0.175)
Bank characteristics	Yes
Bank characteristics × ROE	Yes
Macro-variable controls	Yes
Bank FE	Yes
Observations	22,522
Adj. R-squared	0.248

Table A6: Social Media Discussions and Sentiment

This table presents results of regressions that examine the association between Twitter attention and sentiment. The (negative) sentiment of tweets for each bank stock-quarter is defined as the difference between the proportion of tweets mentioning the stock in that quarter with a negative tone and the proportion of tweets with a positive tone. Abnormal sentiment (*Abn_sentiment*) is further calculated as the sentiment of tweets posted in the current quarter minus the average sentiment of tweets posted during the last two quarters. It has been multiplied by 100 to ease exposition. Standard errors, shown in parentheses, are adjusted for clustering on the bank level. ***, ** and * denote significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)
Dependent variable	Abn_sentiment	Abn_sentiment	Abn_sentiment	Abn_sentiment
Ln(Tweets)	-0.210	-0.179		
	(0.219)	(0.220)		
Medium_Twitter			0.090	0.091
			(0.501)	(0.501)
High_Twitter			0.125	0.187
			(0.565)	(0.567)
ROE (*t-1*)	-0.020	-0.041	-0.019	-0.040
	(0.023)	(0.026)	(0.023)	(0.026)
ROE (*t-2*)		0.052**		0.053**
		(0.026)		(0.026)
ROE (*t-3*)		-0.019		-0.018
		(0.026)		(0.026)
ROE (*t-4*)		0.051**		0.051**
		(0.024)		(0.024)
Std_WriteOff	0.016	0.250	-0.008	0.233
	(0.256)	(0.254)	(0.255)	(0.254)
Capital_Ratio	-0.361	-0.328	-0.225	-0.211
	(1.128)	(1.183)	(1.136)	(1.193)
Wholesale_funding	-2.647	-3.061	-2.948	-3.319
	(2.342)	(2.354)	(2.320)	(2.329)
RealEstate_Loans	-0.858	-0.503	-0.956	-0.574
	(1.270)	(1.267)	(1.277)	(1.275)
Ln(Assets)	0.158	0.182	0.030	0.060
	(0.367)	(0.366)	(0.357)	(0.357)
Unused_Commitments	1.793	1.293	1.609	1.137
	(2.365)	(2.381)	(2.364)	(2.379)
Deposit_Rate	1.952	2.678	2.231	2.940*
	(1.800)	(1.813)	(1.773)	(1.785)
Bank FE	Yes	Yes	Yes	Yes
Year-quarter FE	Yes	Yes	Yes	Yes
Observations	20,771	20,771	20,771	20,771
Adj. R-squared	0.0980	0.0986	0.0979	0.0986

Table A7: Social Media Discussions and Bank Performance

This table presents results of regressions that examine whether the effect of social media on the deposit-flow-performance sensitivity can be explained by the predictability of social media attention on bank performance. In Columns (1) and (2), the dependent variable is contemporaneous ROE, which has not been disclosed when we calculate the number of social media discussions (i.e., the number of tweets in quarter *t -1* and *t-2*). In Columns (3) and (4), the dependent variable is the next period ROE. We include lagged ROE in our regressions to control for the autocorrelation among banks' performance. Standard errors, shown in parentheses, are adjusted for clustering on the bank level. ***, ** and * denote significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)
Dependent variable	ROE (*t*)	ROE (*t+1*)	ROE (*t*)	ROE (*t+1*)
Medium_Twitter	-0.244	-0.068		
	(0.212)	(0.168)		
High_Twitter	-0.412	-0.205		
	(0.295)	(0.230)		
Ln(Tweets)			-0.053	-0.045
			(0.089)	(0.073)
ROE (*t*)		0.175***		0.175***
		(0.017)		(0.017)
ROE (*t-1*)	0.259***	0.124***	0.260***	0.124***
	(0.021)	(0.014)	(0.021)	(0.014)
ROE (*t-2*)	0.149***	0.076***	0.149***	0.076***
	(0.018)	(0.011)	(0.018)	(0.011)
ROE (*t-3*)	0.097***	0.068***	0.097***	0.068***
	(0.015)	(0.013)	(0.015)	(0.013)
ROE (*t-4*)	0.067***		0.067***	
	(0.016)		(0.016)	
Std_WriteOff	0.694***	0.490**	0.695***	0.492**
	(0.220)	(0.191)	(0.220)	(0.191)
Capital_Ratio	-5.323***	-4.838***	-5.337***	-4.871***
	(1.302)	(1.184)	(1.318)	(1.203)
Wholesale_funding	2.975	1.203	3.029	1.293
	(2.060)	(2.263)	(2.107)	(2.276)
RealEstate_Loans	-4.232***	-4.599***	-4.210***	-4.562***
	(1.071)	(1.234)	(1.081)	(1.240)
Ln(Assets)	-1.572***	-1.546***	-1.610***	-1.555***
	(0.358)	(0.344)	(0.373)	(0.348)
Unused_Commitments	4.878**	4.399**	4.945**	4.457**
	(2.046)	(2.030)	(2.043)	(2.031)
Deposit_Rate	-10.064***	-7.651***	-10.083***	-7.691***
	(1.852)	(1.591)	(1.883)	(1.620)
Bank FE	Yes	Yes	Yes	Yes
Year-quarter FE	Yes	Yes	Yes	Yes
Observations	23,322	23,322	23,322	23,322
Adj. R-squared	0.610	0.603	0.610	0.603

Table A8: Effects on Deposit Interest Rates

This table presents the results of regressions that examine how the sensitivity of deposit interest rates to bank performance varies with social media attention. In Columns (1) and (2), the dependent variable, *CD rate (t)*, is the bank-quarter average interest rates for certificates of deposit with a 24-month maturity and an account size of $10,000, measured in the current quarter. In Columns (3) and (4), the dependent variable, *Deposit rate (t)*, is the deposit interest income as a proportion of total deposits for the quarter. Standard errors, shown in parentheses, are adjusted for clustering on the bank level. ***, ** and * denote significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)
Dependent variables	CD rate (*t*)	CD rate (*t*)	Deposit rate (*t*)	Deposit rate (*t*)
ROE	-0.001**	0.006	-0.020**	-0.042
	(0.000)	(0.007)	(0.009)	(0.090)
ROE × Medium_Twitter		0.001		0.010
		(0.001)		(0.007)
ROE × High_Twitter		-0.000		0.013
		(0.001)		(0.012)
Medium_Twitter	-0.035***	-0.042***	-0.189**	-0.257**
	(0.011)	(0.011)	(0.088)	(0.108)
High_Twitter	-0.048***	-0.048***	-0.314**	-0.400**
	(0.016)	(0.016)	(0.130)	(0.172)
Std_WriteOff	0.010	0.006	0.029	0.031
	(0.011)	(0.011)	(0.081)	(0.077)
Capital_Ratio	-0.712**	-0.751***	-0.324	-0.467
	(0.292)	(0.291)	(2.453)	(2.315)
Wholesale_funding	1.433***	1.490***	5.283	7.123**
	(0.180)	(0.178)	(3.294)	(3.127)
RealEstate_Loans	0.366***	0.428***	2.430**	2.667***
	(0.127)	(0.127)	(1.112)	(0.945)
Ln(Assets)	-0.168***	-0.161***	-1.015***	-1.026***
	(0.019)	(0.019)	(0.175)	(0.177)
Unused_Commitments	-0.061	-0.056	-2.736*	-4.381**
	(0.193)	(0.194)	(1.646)	(2.094)
Deposit_Rate	2.695***	2.618***	79.476***	78.670***
	(0.092)	(0.087)	(3.337)	(3.307)
Bank characteristics × ROE	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes
Macroeconomic controls	Yes	Yes	Yes	Yes
Observations	18,173	18,173	23,443	23,443
Adj. R-squared	0.750	0.751	0.925	0.926

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