

NO. 1095
APRIL 2024

REVISED
MARCH 2025

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Federal Reserve Bank of New York Staff Reports, no. 1095

April 2024; revised March 2025

<https://doi.org/10.59576/sr.1095>

Abstract

We examine how investors' perceptions of bank balance sheet risk evolved before and during the bank run in March-April 2023. To do so, we estimate the covariance ("beta") of bank excess stock returns with returns on factors constructed from long-short portfolios sorted on shares of uninsured deposits and unrealized losses on securities. We find that investor perception of bank risk shifted, as the factor betas are insignificant before the bank run but become positive and significant during the run. In the cross-section, increases in the betas occurred for a limited set of banks and cannot be predicted by balance sheet risk in Q3 or Q4 of 2022. Instead, we find evidence that published bank news coordinated investor actions: they are informative to stock investors and significantly affect factor betas during the bank run, even three days after publication. In particular, for banks downgraded by rating agencies during the run, news arrivals increased (decreased) the share of factor betas that responded positively (negatively) to news. These results suggest that stock market investors have limited ability to discipline banks in a timely fashion during a bank run.

JEL classification: G01, G12, G14, G21

Key words: bank run, information sensitivity, limited attention, balance sheet beta, uninsured deposits, unrealized losses

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This paper presents preliminary findings and is being distributed to economists and other interested readers solely to stimulate discussion and elicit comments. The views expressed in this paper are those of the author(s) and do not necessarily reflect the position of the Federal Reserve Bank of New York or the Federal Reserve System. Any errors or omissions are the responsibility of the author(s).

To view the authors' disclosure statements, visit https://www.newyorkfed.org/research/staff_reports/sr1095.html.

1 Introduction

The bank run that started in March 2023 in the US transpired at an unusually rapid pace, with historically high 1 day deposit withdrawal rates for Silicon Valley Bank (SVB) and Signature Bank of New York (SBNY) (see Figure A.1), suggesting that depositors were “sleepy” (Drechsler, Savov, Schnabl and Wang (2024)). Other interested parties to potentially discipline banks are: bondholders (Morgan (2002)), X users (Cookson, Fox, Gil-Bazo, Imbet and Schiller (2023)), bank supervisors (Gopalan and Granja (2023)) and large depositors (Cipriani, Eisenbach and Kovner (2024)).

This paper studies whether stock market investors were “awake” and disciplined banks during the bank run of Spring 2023. Specifically, we examine how the stock market’s perception of bank balance sheet risk (“bank risk” from now on) evolved as the informational environment changed. Did investors promptly update their beliefs about bank risk using available information such as regulatory reports that show rising unrealized losses for most banks starting in 2022Q1 (see Figure 1)? Alternatively, did they coordinate based on public signals (such as news articles) to focus on a few banks, whether risky or not, either due to limited attention (Hirshleifer (2015)) or higher-order beliefs (Morris and Shin (2002))? Indeed, Correia, Luck and Verner (2024) show that bank failures are preceded by several months of persistently deteriorating fundamentals, suggesting limited attention of investors. Since asset price dynamics are distorted when investors overreact due to higher-order beliefs (Allen, Morris and Shin (2008)) or limited attention (Peng and Xiong (2006) and Van Nieuwerburgh and Veldkamp (2010)), the issue is of import for investors and regulators who need to accurately assess bank risk during a run.

To measure bank risk, we estimate balance sheet “betas”—the covariance of bank excess stock returns with returns on factors constructed from long-short portfolios based on several bank balance sheet characteristics in 2022Q3. To mitigate any mechanical findings, we exclude failed and downgraded banks when constructing factors and SVB, SBNY, and Silvergate Bank (SI) from *all* of our analyses.

Figure 2 shows the estimates of factor betas in standard deviation (SD) units before and during the bank run for factors constructed from asset shares of uninsured deposits (denoted *UID*) and unrealized losses on securities in held-to-maturity (HTM) and available-for-sale (AFS) accounts (denoted *Losses*) — characteristics widely recognized as being central to the Spring 2023 bank run (see, for example, Acharya, Richardson, Schoenholtz and Tuckman (2023)). The *UID* and *Losses* factor betas were insignificant in January and February of 2023 but became positive and significant during the bank run (March 1-May 5). Similar results obtain for 2 other factors based on the asset share of cash and the Tier 1 capital ratio (CET1). In other words, investors were insensitive to these bank risks before the run and became more sensitive to them during the run.

To consider the cross-sectional distribution of the factor betas, we form bank groups based on rating announcements during the run. *Event banks* consist of those put on downgrade watch by Moody’s on March 14 or downgraded between April 14 and April 21. We also form groups based on non-downgraded regional (denoted “regionals”) and US stress-tested banks (denoted STBs). We find that the share of all banks with positive and significant *UID* and *Losses* betas increased from less than 15% before the run to almost 40% during the run; for event banks, the corresponding share increased from less than 10% to 50%. However, increases in the betas are weakly correlated with bank risk in 2022Q3 or 2022Q4.

If bank risk in 2022 does not fully explain beta increases during the run, how else did investors decide which banks to focus on? We examine whether public news arrivals in 2023 allowed investors to coordinate on updating their beliefs about the increased risk of these banks during the run, either due to higher-order beliefs (Allen et al. (2008)) or due to limited attention. To do so, we consider two measures: a count of publications on the sample banks and announcement dates for ratings downgrades during the run.

We first consider *Pubcount* or bank publication counts divided by assets (to remove a size effect induced by greater coverage of larger banks). We show that *Pubcount* is informative to stock market investors. During the run, news affects event bank returns negatively. In

contrast, *Pubcount* and bank returns are positively correlated for all bank groups before the run. The significant effects of publications remain even after 2 days, suggesting that stale news was salient, as in Huberman and Regev (2001), perhaps due to limited attention.

We induce time- and bank-variation in the factor betas by interacting *Pubcount* with the balance sheet factors, and denote the estimated coefficient as the “news beta.” The news betas are insignificant before the run but positive and highly significant during the run. These effects are long-lasting and persistent, consistent with the idea that publications allow coordination among investors when they update their estimates of bank risk. Such coordination results in investors becoming more information sensitive during the run (Dang, Gorton and Holmstrom (2018)).

Considering the cross-sectional distribution of the news betas, we find that during the run, there is a sharply lower incidence of publications reducing the factor betas, consistent with a paucity of good news that improves investor perceptions of bank risk. Conversely, for event banks, there is a greater incidence of publications increasing the factor betas, thereby enhancing investor perception of their risk.

Finally, we investigate whether rating announcements also coordinate investor attention. We find that the abnormal returns of event banks were insignificantly different from zero on rating announcement days, implying that no new information (not already incorporated in stock prices) were released on these days, consistent with Norden and Weber (2004). However, investors may coordinate on even uninformative public signals due to higher-order beliefs (Allen et al. (2008)). Our evidence is not supportive of this hypothesis. We find that the betas mostly increased in the first week of March, *before* the rating announcements, thus ruling out the idea that investors coordinated on the announcements. For coordination purposes, the daily flow of publications may have been more salient than the episodic arrival of rating announcements in a fast-moving information environment.

Contributions and related literature. Our estimates of balance sheet betas using high-frequency data provide new insights into the evolution of bank risk during the bank run of Spring 2023. Jiang, Matvos, Piskorski and Seru (2023) analyze the interest rate risk of U.S. bank assets and find that the market value of bank assets is \$2.2 trillion lower than suggested by their book value of assets accounting for loan portfolios held to maturity. ? show that the liquidity risk of banks increases with interest rates. A run equilibrium is absent at low interest rates but it appears when rates rise because the deposit franchise comes to dominate the value of the bank. Haddad, Hartman-Glaser and Muir (2023) argues that the exposure of bank values to interest rate risk can be insensitive most of the time but highly responsive when asset losses become salient. They find evidence consistent with this non-linearity during the rate increase of 2022 and 2023, culminating with the failure of SVB. Granja (2023) finds that banks with lower capital ratios, higher shares of run-prone uninsured depositors, and greater exposures to interest rate risks were more likely to reclassify securities to HTM during 2021 and 2022. While our examination of uninsured deposits and unrealized losses is common to this literature, our focus on when and how much these balance sheet risks are incorporated into stock market prices is new.

We build on the literature that studies the importance of information and communication to bank run dynamics. In the global games approach, depositors have noisy information about bank fundamentals which influences their incentives to run (Goldstein and Pauzner (2005)). Investors’ attention to information on bank risk is likely to improve the disciplining of opaque banks (Morgan (2002) and Granja (2013)). More recently, Cookson et al. (2023) show that during the SVB run period, banks with higher pre-run Twitter exposure lost more stock market value, and experienced greater deposit outflows during 2023Q1. Similar to Cookson et al. (2023), our paper studies how stock prices reflect information arrival. However, we use rating announcements instead of Twitter feeds and study return comovements rather than returns. We show that return comovements reflect bank risk while Cookson et al. (2023) find that the effect of tweets on returns is unexplained by unrealized losses and

uninsured deposits. Moreover, we provide new evidence on how investors attend to bank risk in the context of a bank run.

We further contribute to this literature by showing that investors are mainly sensitive to information on bank risks that are most salient at the time and affect prices by modulating investors' limited attention. Our result that *uninformative* news publications increase bank betas is consistent with a behavioral explanation of inattention, whereby publicity draws attention to neglected firms and risks (Klibanoff, Lamont and Wizman (1998), Huberman and Regev (2001), Barber and Odean (2008) and Barber, Huang, Odean and Schwarz (2022)). While the behavioral literature typically investigates the effect of media attention on returns, we also examine rating announcements and betas. Research on the rational allocation of attention finds that investors allocate more attention to common, relative to firm-specific, factors (e.g., Barberis and Shleifer (2003), Peng and Xiong (2006) and Kacperczyk, Van Nieuwerburgh and Veldkamp (2014)). We do not examine the relative comovements between common and firm-specific news but instead, address how the factor betas vary in the cross-section and time-series.

Our paper is related to research on the informativeness of credit ratings. Inaccurate credit ratings were identified as key contributors to the Great Financial Crisis due to conflicts of interest and rating shopping leading to biased ratings (e.g., Skreta and Veldkamp (2009)). However, Goldstein and Yang (2019) argue that independent research by rating agencies might reduce price efficiency if it focuses on information that the market is good at aggregating. In our paper, even when credit ratings do not convey new information, they may allow investors with limited attention to focus on salient banks.

While not the main focus of our paper, we also examine bank stock returns mainly to test for the informativeness of rating announcements. Choi, Goldsmith-Pinkham and Yorulmazer (2023) find that bank stock returns are correlated with uninsured deposit shares and unrealized losses on HTM securities. They argue that the stock market partially anticipated risks from reliance on uninsured deposits. We find that return spillovers mostly affected a limited

set of event banks and for limited periods before and during the bank run.¹ For example, after the rate hikes in March and May of 2022, returns of banks with high *Losses* turned negative but stabilized by January 2023. Different from Choi et al. (2023), we examine the covariance of bank excess stock returns with balance sheet factor returns.

The paper is organized as follows. In section 2, we discuss the data, hypotheses, and methodology. The informativeness of credit ratings is examined in section ???. Results on the evolution of bank balance sheet betas during Spring 2023 are in section ???. Section ??? reviews investor attention to bank risk in 2022. Section 6 concludes. The appendices contain additional information about our data and sample, robustness checks on our main results, and additional results not reported in the paper.

2 Data, Hypotheses and Methodology

We describe the data in section 2.1 (further details are in appendix A.) Our methodology for defining the different bank groups, and estimating the factor betas are described in section 2.2. We develop hypotheses in section 2.3.1 and specify the regressions in section 2.3.2.

2.1 Data

We use daily cum-dividend stock returns from the Center for Research in Security Prices (CRSP) database for the period January 3, 2022 to May 5, 2023. The end date of the sample is chosen to occur 2 weeks after the April 21 downgrade announcements, so that we have an adequate sample size for estimating the post-announcement betas. Bank balance sheet data is from the FR Y-9C and Call Reports, and is matched to the stock price data by mapping the ticker symbols to RSSD identifiers. Appendix A.2 details how we do this.

In our analyses, we exclude banks that failed during the *estimation sample* as well as Silvergate Bank which announced its liquidation in early March. Among failed banks, we

¹Our during the run results are not strictly comparable to Choi et al. (2023) since we distinguish between pre-crisis and crisis period effects while the latter estimate average effects from February to March 2023.

always omit SVB and SBNY. First Republic Bank (FRC) is also omitted after April 28 (as it failed before the market opened on May 1). Separately, banks on downgrade watch or downgraded are also excluded when constructing our *factors*, as further discussed in section 2.2.2. We omit failed banks for two reasons. First, we are interested in how investors evaluate the risk of surviving banks during the bank run. Second, the failed banks have limited data in the relevant sample. For example, when our estimation sample is from March 1 to April 14, limited data is available for Silvergate, SVB, and SBNY that were all liquidated or failed between March 8 and 12.² Similarly, when our estimation sample is from April 21 to May 5, there is little data for FRC.

Since we focus on the effects of information arrival on the market’s perception of bank balance sheet risk, we ensure that the estimation of the factor betas is based on balance sheet data *only when they become available to market participants*, which we assume is following the last submission date for Call Reports (approximately 1 month after the end of the reporting quarter). For example, since the submission deadline for the 2022Q3 Call Report was October 30, 2022, we assume that investors become aware of the 2022Q3 balance sheets starting on October 31, 2022. Then, following January 30, 2023 – when the 2022Q4 Call Reports were due – we assume that investors became informed of the 2022Q4 balance sheet data. Table A.1 in the appendix lists the Call Report submission deadlines in our sample.

Measures of news arrivals We gather data on two proxy measures of news arrivals: bank publication counts and credit rating announcements during the bank run. Daily counts of publications regarding our sample banks are from Bloomberg NewsHeat and available for the entire sample. We normalize the series by bank assets since larger banks are typically more news-worthy and denote this series as *Pubcount*. Absent normalization, publication counts could mainly indicate a size effect. Notably, publications are counted as long as they appear till 11:59 PM on that day. Since after-hour publications affect returns the following day, we

²Silvergate announced its intent to wind down operations and voluntarily liquidate on March 8. SVB and SBNY went into receivership on March 10 and March 12, respectively.

show results using both contemporaneous values and 2-day moving averages of *PubCount*. We have also used a 1-day lagged value of *Pubcount* instead of contemporaneous values (since the latter affects tomorrow’s returns) and found qualitatively similar results.

We collect rating information from Moody’s Ratings and Assessment Reports Directory³ and targeted internet searches for news articles between March 1, 2023 and May 5, 2023. We ignore ratings affirmations and upgrades, focusing only on negative rating announcements (i.e., downgrade watches and downgrades) as these are most closely related to the bank run.

The first rating announcements occurred on March 14, 2023, when Moody’s placed 6 banks on downgrade watch,⁴⁵ highlighting the banks’ reliance on uninsured deposit funding and their unrealized losses on AFS and HTM securities portfolios which could be realized if the banks were forced to sell these assets to meet deposit outflows.⁶ One of these banks, INTRUST Financial Corporation, is not publicly traded and thus not in our sample. Another bank in this group, FRC, was subsequently downgraded on March 17 (issuer rating) and again on April 21 (preferred shares). On April 14, Fitch downgraded PacWest Bancorp, and S&P downgraded Schwab on April 19. On April 21, Moody’s downgraded 11 banks including all 6 that were previously on downgrade watch plus 5 new banks. The downgrade announcements on April 21 emphasized broader risks to the US banking sector, particularly regional banks, including a reduction in deposits, higher funding costs, and interest rate losses on fixed-rate assets that increase their “liquidity and capital risks.”⁷ Section A.4 in the appendix lists the event banks flagged by the various rating announcements.

³See <https://www.moodys.com/reports/ratings-assessments-reports>.

⁴Silvergate, SVB and SBNY were downgraded prior to their failures or liquidation.

⁵Moody’s released the downgrade watch announcement after market close on Monday, March 13. Since we use daily equity data, we treat March 14 as the date of the announcement

⁶For example, when placing Comerica on downgrade, Moody’s states that “Today’s rating action reflects Comerica’s high reliance on more confidence sensitive uninsured deposit funding, its high amount of unrealized losses in its available-for-sale (AFS) securities portfolio . . . In addition, if it were to face higher-than-anticipated deposit outflows, the bank could need to sell assets, thus crystallizing unrealized losses on its AFS securities . . .” See Comerica downgrade watch notice.

⁷See for example UMB Financial downgrade and Associated Banc-Corp downgrade.

2.2 Methodology

We discuss our methods for forming bank groups (section 2.2.1) and the bank balance sheet risk factors (section 2.2.2).

2.2.1 Formation of Bank Groups

Banks are divided into groups. First, *event banks* are those mentioned in two rating announcements in March and April, and comprised of the following 12 banks.

- The *March Downgrade Watch (DGW)* group, which includes 5 banks put on downgrade watch by Moody’s on March 14 (see appendix A.4 for the bank list).
- The *April Only DG* group, which includes 7 more banks that rating agencies downgraded between April 14 and April 21 (listed in appendix A.4).⁸

In addition, we define non-event regional banks (simply ”regional banks” from now on), and non-event stress-tested banks (henceforth STBs) as follows:

- The *regional bank* group comprises of 38 banks in the KRX index (listed in appendix A.4) that were not on DGW in March or downgraded in April.⁹
- The *STB* group includes 21 large banks that participated in the Federal Reserve stress tests of 2022 and listed in the KBW index (see appendix A.4) after excluding Schwab and US Bancorp, which were downgraded on April 19 and April 21, respectively.

2.2.2 Bank Balance Sheet Risk Factors

Uninsured deposits are widely considered to have been a main source of risk during the 2023 crisis due, in part, to the concentration of these deposits among certain sectors and the inability of banks to raise interest rates enough to attract new deposit inflows. A related

⁸An additional 6 banks were downgraded by Moody’s on April 21; 5 of these were previously on downgrade watch in March and 1 is not publicly traded.

⁹5 regional banks were downgraded in April.

risk arose from concerns over *unrealized losses* in banks’ security holdings, which triggered further outflows of uninsured deposits. While liquidity buffers are supposed to cushion deposit shocks, interest rate increases since 2022 led to unrealized losses on liquid AFS and HTM securities such as Treasuries, adding to financial distress.¹⁰ *Cash depletions* may further contribute to deposit outflows, as when SBNY lost large amounts of cash in 2022 (FDIC (2023)). Indeed, Lee and Sarkar (2023) argue that some banks experienced cash shortages in 2022 as the aggregate amount of bank reserves declined, prompting unusually high borrowing frequencies (for a non-crisis period) from the Fed’s discount window facility. Thus, the bank run in 2023 may have been, in part, a continuation of prior liquidity concerns due to monetary policy tightening. High capital reserves might offset these risk factors.¹¹

Motivated by these considerations, we construct bank risk factors based on the following.

- *UID*, or uninsured deposits as % of assets
- *Losses*, or unrealized losses on AFS + HTM securities as % of assets
- *Cash*, or cash % as of assets
- *CET1*

The bank risk factors are constructed as follows. First, we drop the banks in the downgrade watch and downgraded groups since they are likely to have the most extreme returns, and thus potentially lead to a mechanical correlation between their returns and the factor returns. We sort the remaining banks by each of the above variables, using Call Report and FR Y-9C data for the previous quarter, assuming that these reports become available following their last submission dates. We form 3 portfolios (High, Medium, Low), calculate market capitalization-weighted average stock returns of banks in each portfolio each day, and then

¹⁰We use AFS + HTM losses instead of just HTM losses because banks can (and often do) strategically reclassify AFS securities as HTM (Fuster and Vickery (2023)). Further, for banks with assets of at least \$50 billion, Basel III rules require AFS losses to be reflected in CET1.

¹¹The reported *CET1* may overstate the available capital as it does not incorporate unrealized HTM losses. Separately, we have also used a factor based on adjusting CET1 for unrealized losses. These unreported results are in-between those based on the *Losses* and CET1 factors.

take the difference in average returns of the highest minus the lowest terciles (High – Low). We take the negative of cash and CET1 to have a consistent interpretation across characteristics: that is, greater values indicate potentially higher balance sheet risk. To illustrate our methodology for constructing factor returns for 2023Q1, since the Call Reports filing deadlines for 2022Q4 and 2023Q1 are January 30, 2023, and April 30, 2023, respectively, we use 2022Q3 balance sheets to construct factor returns for January 1 to 30, 2023, and 2022Q4 balance sheets to calculate factor returns for January 31, 2023, to April 30, 2023. Table A.1 lists the various dates relevant to our analysis. Figure A.2 illustrates how the Call Reports submission dates map to the calculation of factor returns.

While we account for the Fama-French size factor SMB, bank size may be an additional risk factor potentially orthogonal to SMB (Gandhi and Lustig (2015)). Accordingly, we construct a bank size factor $BSizeF$ using portfolio returns of the smallest size tercile minus the largest size tercile of banks.

2.3 Hypotheses and Regression Specifications

In section 2.3.1, we develop hypotheses regarding the expected changes in abnormal returns and the factor betas, conditional on news arrivals. In section 2.3.2, we specify regressions to test our hypotheses.

2.3.1 Hypotheses Development

To the extent that the betas reflect stock market investors’ perception of bank risk, they should increase on average for all banks during the bank run, especially for factors based on uninsured deposits and losses on securities – balance sheet characteristics most salient in the bank run. In the cross-section, banks with higher balance sheet risk in 2022 are expected to experience greater increases in their betas.

Hypothesis 1: Crisis effect on beta. (a) In the time series, the factor betas increase on average following the bank run. (b) In the cross-section, betas of banks with greater balance

sheet risk in 2022 increase more.

Bank risk may vary with bank-specific news during the run if the news contains information new to stock investors. If publications are informative, then they should be significantly correlated with bank abnormal returns. Further, if they mostly convey negative news during the run (as is likely to be the case for event banks) then more publications are likely to be associated with higher balance sheet betas. Similarly, if ratings are informative, then we expect that event bank abnormal returns to fall with DGW or downgrade announcements, as in Norden and Weber (2004). Moreover, downgraded bank betas are expected to increase relative to those of non-downgraded banks.

Hypothesis 2: News is informative of bank risk and returns during bank run. After rating announcements or publications during bank run, abnormal returns of event banks decrease and their balance sheet betas increase relative to non-event banks.

Even if news is uninformative for some banks, investors may coordinate on it due to limited attention or higher-order beliefs, and then update their priors on the risk of those banks.¹² If so, the betas of these banks may change with news even when their returns do not. For publications, the beta changes occur when investors read them. For ratings, the timing of beta changes is tied to the announcements which coordinate investor actions.

Hypothesis 3: News coordinates investor beliefs about bank risk during the run. Following news arrivals, balance sheet betas of banks increase during the run even when their abnormal returns are unaffected.

2.3.2 Regression Specifications

Beta and Crisis To facilitate the comparison of beta estimates across banks and factors, we *standardize* all continuous variables to have mean zero and standard deviation 1 whenever we estimate the factor betas. To test hypothesis 1(a) on how the crisis affects the betas on

¹²The implication of limited attention on abnormal returns is ambiguous. Salience theory argues that extreme returns indicate information salience (see, for example, Bordalo, Gennaioli and Shleifer (2012) and Bordalo, Gennaioli and Shleifer (2022)) but in our application, inclusion in the rating announcements or publications may indicate salience even absent any effect on returns.

average, we estimate panel regressions of bank excess returns on the factors:

$$\begin{aligned}
Y_{i,t} = & \alpha_0 + \alpha_i + \beta_1 Pre_t \times Factor_t + \beta_2 Post_t \times Factor_t \\
& + \beta_3 Pre_t \times BSizeF_t + \beta_4 Post_t \times BSizeF_t \\
& + \sum_{j=1}^5 \delta_j FF_{j,t} + \delta_6 Log(MVE)_{i,t-1} + \epsilon_{it}
\end{aligned} \tag{1}$$

where Y is the stock return for bank i minus the 3-month Treasury bill rate on day t . Pre is a dummy variable equal to 1 for January-February 2023 and $Post$ equals 1 from March 1 to May 5, 2023. The regressors are the bank balance sheet factors (UID , $Losses$, Cash or CET1), the bank size factor $BSizeF$, the (lagged) log of the bank's market value of equity (MVE), and the 5 Fama-French factors. α_i indicates a bank fixed effect. Hypothesis 1(a) states that $\beta_2 > \beta_1$: sensitivity to the factor increases after the bank run.

To test Hypothesis 1(b) — whether beta changes are related to bank risk — we estimate regression (1) *bank-by-bank*, and report balance sheet values in 2022q3 sorted by whether a bank's beta increased significantly during the run. We also estimate a cross-section regression to predict increases in during the run betas with balance sheet values as of 2022q3:

$$\begin{aligned}
Y_{i,F} = & \alpha_{0,F} + \sum_{j=1}^4 \alpha_{i,j,F} CLV_{i,j,2022q3} \\
& + \alpha_{5,F} UID_{i,2022q3} + \alpha_{6,F} Losses_{i,2022q3} + \alpha_{7,F} UID_{i,2022q3} \times Losses_{i,2022q3} \\
& + \alpha_{8,F} Pubcount_{i,2022q3} + \epsilon_{i,F}
\end{aligned} \tag{2}$$

where Y_i is an indicator variable equal to 1 if $bank_i$ experienced a significant increase in its factor beta F during the run, where $F=UID$, $Losses$, Cash, CET1. $CLV_{i,j}$ are the 4 variables that Correia et al. (2024) found to be significant in predicting bank failures: Asset growth, $\frac{NetIncome}{Assets}$, $\frac{TimeDeposits}{Deposits}$ and the interaction of the last two variables. We also include UID , $Losses$ and the interaction between them and, finally, as an alternative to the risk explanation, we include the normalized publication counts $Pubcount$.

Informativeness of Publications. We estimate bank abnormal returns $AR_{i,t}$ as the residual from regressing bank returns on the 5 Fama-French factors using data for the first 3 quarters of 2022. Details are in appendix C.1. To examine whether publication counts are informative, we estimate:

$$\begin{aligned}
AR_{i,t} = & \alpha_i + \sum_{k=1}^3 \phi_k AR_{i,t-k} \\
& + \eta_0 PubCount_{i,t} \times Pre_t + \sum_{k=1}^2 \eta_k BankGroup_k \times PubCount_{i,t} \times Pre_t \\
& + \gamma_0 PubCount_{i,t} \times Post_t + \sum_{k=1}^2 \gamma_k BankGroup_k \times PubCount_{i,t} \times Post_t + \epsilon_{it} \quad (3)
\end{aligned}$$

In additional specifications, we use 2-day and 3-day moving averages of *PubCount* to allow for a delayed effect of publications that came out after market-close. *Pre* (*Post*) is defined as before. *BankGroup_k* is either *Event* or *Regional* that are dummy variables equal to 1 for event or non-downgraded regional banks, respectively. The STBs are the control group. Lagged returns are included to allow for short-run return momentum. Since this is a dynamic panel, we estimate using the 2-step GMM, implemented with the Arellano and Bond (1991) estimator. Robust standard errors are reported. Publications are informative pre-run if η_0 is significant. Further, during the run, assuming that news is bad on average, particularly for event banks, we expect that $\gamma_0 < 0$ and $\gamma_k < 0$ for the *Event* bank group.

Publications and beta. We augment specification 1 and interact *PubCount* with the factors (effectively making the factor betas varying with time, as in Avramov and Chordia (2006), as well as across banks). All regression variables are standardized.

$$\begin{aligned}
Y_{i,t} = & \alpha_i + \beta_1 PubCount_{i,t} \times Pre_t + \beta_2 BankFactor_t \times Pre_t + \beta_3 BankFactor_t \times PubCount_{i,t} \times Pre_t \\
& + \gamma_1 PubCount_{i,t} \times Post_t + \gamma_2 BankFactor_t \times Post_t + \gamma_3 BankFactor_t \times PubCount_{i,t} \times Post_t \\
& + \sum_{j=1}^5 \delta_j FF_{j,t} + \delta_6 Log(MVE)_{i,t-1} + \epsilon_{it} \quad (4)
\end{aligned}$$

In additional specifications, we use 2-day and 3-day moving averages of *PubCount*. If news coordinates investor actions, then we expect that β_3 or γ_3 to be significant. The sign depends on whether the news is risk decreasing (increasing), implying a negative (positive) sign. During the run, we expect that $\gamma_3 > 0$.

To examine the cross-section distribution of the news betas (i.e. β_3 and γ_3), we re-estimate specification (4) bank-by-bank. Since the event banks are known to experience negative news, we expect that $\gamma_3 > 0$ for most event banks but insignificant for most STBs: news will have a stronger effect on the betas of more event banks as compared to the STBs.

Informativeness of ratings. We estimate rating announcement day returns using panel regressions of bank abnormal returns $AR_{i,t}$ on announcement dummies as follows:

$$\begin{aligned}
AR_{i,t} = & \alpha_i + \sum_{k=1}^n \phi_k AR_{i,t-k} \\
& + \eta_0 Day0_{i,t} + \sum_{k=1}^m \eta_k BankGroup_k \times Day0_{i,t} \\
& + \gamma_0 Day[1,3]_{i,t} + \sum_{k=1}^m \gamma_k BankGroup_k \times Day[1,3]_{i,t} + \epsilon_{it}
\end{aligned} \tag{5}$$

The regression is estimated separately for the March (using the March sample) and April announcements (using the April sample). We use 3 (8) lags of the dependent variable for the March (April) announcements; the additional lags for the April announcements is to account for the possible effects of the April 14 downgrades on the April 21 announcements. Also, as banks have different announcement days, we estimate the April regression in *event time*. *Day0* and *Day[1,3]* are dummy variables equal to 1 on the day of and 3 trading days after the announcement date, respectively. There are 2 bank groups ($m = 2$) in March: the *March DGW* group and *Regionals*. There is another group ($m = 3$) in April: the *April Only DG* group. *Regionals* is a dummy variable equal to 1 for regional banks not downgraded at the time of announcements. The control group consists of STBs not downgraded at the time

of announcements. The regression is estimated using the 2-step GMM with the Arellano and Bond (1991) estimator. Hypothesis 2 implies that $\eta_k < 0$ and significant for the *March DGW* (*April Only DG*) group in March (April).

Informativeness of BTFP. Specification 5 is also used to estimate the effects of the BTFP announcement. *Day0* is March 13 and we use 3 lags of the dependent variable. And we use *Day*[1,4] instead of *Day*[1,3].

Ratings and coordination To test for coordination on the announcements, we test whether the betas of event banks increased just after announcements and not before. We estimate the following regression bank-by-bank before and after announcements:

$$\begin{aligned}
Y_{i,t} = & \alpha_i + \gamma_{i,1} BSizeF_t \times Pre + \gamma_{i,2} BSizeF_t \times Post \\
& + \beta_{i,0} BankFactor_t + \sum_{k=1}^5 \beta_{i,k} Period_{k,t} \times BankFactor_t \\
& + \sum_{k=1}^5 \zeta_{i,k} Period_{k,t} + \sum_{j=1}^5 \delta_{i,j} FF_{j,t} + \delta_{i,6} Log(MVE)_{i,t-1} + \epsilon_{it}
\end{aligned} \tag{6}$$

where $Period_{k,t}$ are dummy variables equal to 1 during 5 periods in March 1-May 5: 9 trading days before and after the March and April announcements, and days omitted from these periods. January-February is the reference period. Thus, for banks put on downgrade watch on March 14, the periods are March 1-13 ($k = 1$) and March 14 - 24 ($k = 2$). For banks downgraded in April, since the first downgrade occurs on April 14, the pre-event period is March 31 – April 13 ($k = 3$). The post-event period ($k = 4$) is d to $d + 8$ days, where d is the downgrade date (April 14, 19 or 21). $k = 5$ indicates the omitted periods: March 27-30 for all banks and, in addition, April 27-May 5 for banks with April 14 announcements, April 14-18 and May 2-5 for banks with April 19 announcements, April 14-20 and May 4-5 for banks with April 21 announcements.

3 Crisis Effects on Bank Balance Sheet Betas

If investor perception of bank risk is reflected in the factor betas, then the betas are expected to be positive and significant and increase during the bank run, indicating enhanced investor risk sensitivity. We first examine if the betas increased during the run on average, and then characterize the distribution of betas across banks.

Descriptive statistics of balance sheet risk in 2022Q3-Q4 Panel A of Table 1 reports the medians of balance sheet characteristics as of 2022Q3 for each of our bank groups. For reference, we also show statistics for the failed banks excluded from our sample: SIVB, SBNY, and SI. The *March DGW* banks were large, with median assets greater than \$80B. The *April Only DG* banks were of similar size as regionals — to be expected, since 5 of 7 banks in this group are regionals. The STBs were, of course, the largest with median assets of more than \$300B. By comparison, SVB and SBNY were larger than the median sample bank (except the STBs) while SI was smaller. The *March DGW* banks had the highest shares of uninsured deposits and *Losses* in our sample, topped only by the failed banks. The *April Only DG* banks had relatively high loss shares but average uninsured deposits shares. The cash shares were relatively low for the *March DGW* banks and high for STBs. CET1 was relatively low for event banks and high for regionals. In 2022Q4 (panel B), the median uninsured deposits, *Losses* and cash shares are somewhat lower, while CET1 is somewhat higher relative to 2022Q3, but the relative bank risk is similar between groups.

Overall, based on 2022Q3 and 2022Q4 information, bank risk was generally lowest for STBs and highest for the *March DGW* group. However, the balance sheet risk was not materially different for the non-DG and DG regional banks.¹³ Also, except for the *March DGW* group, bank excess returns are negative in 2022 Q3 but revert in Q4, suggesting that stock investors did not anticipate bank run risk in 2022Q4.

¹³This is based on comparing non-DG regionals with the *April Only* group but we have verified the result by considering the five downgraded regionals separately.

Average beta before and during the bank run To examine whether the betas increased after the bank run, we estimate regression (1) for January to May 5 of 2023, interacting the factors with before- and during-the-run dummies. Since the variables are standardized, the coefficients are in SD units.

Table 2 and Figure 2 show the results. Prior to the run, all balance sheet betas are insignificant except for cash which is weakly significant. During the run, all betas are positive and highly significant, except that the *UID* beta is significant at the 10% level of confidence. However, the *UID* beta was negative before the run and is 0.11 SD afterwards, so the change in the beta is economically meaningful. Similarly, the *Losses* beta is insignificant before the run and 0.09 SD afterwards and significant at the 5% level of confidence. The bank size factor is mostly insignificant before the run but becomes positive and significant during the run (except in the cash factor regression), even after accounting for the SMB factor. This result is consistent with investor perception of government guarantees for large bank shareholders in crisis, as shown in Gandhi and Lustig (2015) and Antill and Sarkar (2018). All 5 Fama-French factors, except RMW, are significant. The lagged bank MVE is negatively related to bank excess returns but not significant.

Cross-section of betas How widespread was the increase in the betas, and how was it related to bank risk? We evaluate the cross-sectional distribution of the changes in betas by estimating the specification (1) *bank-by-bank*. Figure 3 shows scatter plots of the beta estimates before the run (horizontal axis) against during the run (vertical axis). Estimates for the event banks are shaded orange. More estimates are likely to be negative or zero before the run and to be positive during the run. Further, there is a greater incidence of scatters above the 45-degree line, implying that the betas increase in size during the run. These patterns are more pronounced for event banks.

Table 3) reports the share and mean of the beta conditional on being *positive* and *significant* (henceforth “*positive betas*”). Consider results for the *UID* (Panel A) and *Losses*

(Panel B) factors. The share of positive betas increases for all bank groups during the run. For example, for the *UID* factor, the share of positive betas of event banks increases from 0% pre-run to 50% during the run. The corresponding increases for regionals and STBs are from 0.18% and 14%, respectively, before the run to 0.32% and 43%, respectively, during the run. However, as these shares range from 24% to 50%, only a narrow set of banks is perceived as risky during the run. For some of these banks, beta increases are large as is apparent from Figure 3, and also indicated by the large mean positive betas relative to the unconditional means. For example, for the *UID* factor, the means of the unconditional beta and the positive beta are 0.17 SD and 0.47 SD, respectively, for STBs during the run.

For the *Cash* and CET1 factors (Panels C and D of the table), the share and mean of positive betas of event banks increase during the run, as with the other factors. The share also increases for regionals but the mean positive beta declines, implying that the beta increases were small during the run. For STBs, both the share and mean of positive betas *decline* during the run. Since shares and means of positive Cash and CET1 betas of STBs were high even before the bank run relative to their *UID* and *Losses* betas, this result may indicate a reallocation of investor attention from more traditional risks to novel risks that became salient during the run, consistent with "attention externality" (Bordalo et al. (2022)).¹⁴

Bank risk in 2022 and changes in beta Does the cross-section of beta increases during the run reflect bank risk in 2022? Appendix tables B.2 (for the *UID* and *Losses* factors) and B.3 (for the *Cash* and CET1 factors) report the median values of balance sheet characteristics in 2022Q3 of banks with significantly higher betas during the run (i.e., banks with significantly positive betas during the run *and* insignificant or negative pre-run betas). For the full sample, banks with higher betas during the run had higher median uninsured deposits and unrealized losses than other banks and these differences were significant for all factors other than *CET1*, based on exact p-values from a Wilcoxon test to compare medians

¹⁴A choice set that renders a good's attribute more salient causes the decision maker to attach a higher weight to the good's attribute in that choice set. It also causes the decision maker to attach a *lower* weight to attributes that, in the same choice set, are not salient (Natenzon (2019), Bordalo et al. (2012)).

(see Appendix section B.2 for more detail). However, results are not always consistent when considering bank groups. For example, for the *UID* and *Losses* factors, event banks with higher betas during the run had more uninsured deposits and losses and lower excess returns, but also more cash and CET1, with no change statistically significant.

To more formally consider the predictive power of 2022Q3 balance sheet variables for changes in beta during the run, we estimate the cross-section regressions specified in equation(2). The results for the *UID* beta and the *Losses* beta are shown in Table 4. Considering the *UID* beta (Panel A), the first two columns show results using the specification in Correia et al. (2024) for predicting bank failures. All predictors are significant but, except for the net income share, their signs are contrary to expectations. After adding the shares of uninsured deposits and losses and their interaction, the adjusted R^2 doubles and the root mean square error (RMSE) decreases, but the new regressors are all insignificant. For the *Losses* beta (Panel B) or the Cash and CET1 betas (Table B.4 in the appendix), no variable is significant. The *Event* banks have the highest RMSE on average for predicting any factor, consistent with the weak association of bank risk in 2022Q3 with their beta increases noted earlier. The RMSE is lowest for regionals on average when predicting the *UID* beta but similar for regionals and STBs when predicting the *Losses* beta.

Figure ?? shows scatter plots of a dummy variable equal to 1 for significant increases in the factor betas during the run against their predicted values from the regression. For all factors, the scatters are generally far from the 45 degree line, indicating the poor predictive power of 2022Q3 balance sheet information for increases in bank risk in 2023.

As robustness, we used the 2022Q4 values of the regressors and found none significant. We also included additional prediction variables found to be relevant for the SVB crisis in the literature (e.g., see Cipriani et al. (2024)), such as Commercial Real Estate (CRE) loans and borrowings from Federal Home Loan Banks (FHLB), but did not find the 2022Q3 values of these variables to be significant.

Discussion We conclude that while the factor betas increased on average during the run, this was true for less than 60% of the banks. How did investors decide which banks became risky during the run? Beta increases occurred during the run for a large share of banks that were eventually downgraded but otherwise, they were weakly associated with bank balance sheet risk in 2022Q3 or Q4. Did investors recognize as salient only news that materialized in 2023? In the next sections, we consider measures of public information arrival during the crisis and examine whether investors mainly attended to salient banks by coordinating on these public signals, either due to limited attention or higher-order beliefs.

4 Do Publications Coordinate Investor Attention to Bank Risk?

In this section, we examine whether publications coordinated investor attention to particular banks. We do so by allowing the factor betas to vary over time and by bank with the publication counts.

Descriptive statistics of abnormal returns and publications. Panel A of Table 5 shows the distribution of 100 times *Pubcount* (i.e. the publication counts normalized by assets in \$B) in 2022Q3, by bank group. The median count is between 6% and 7% for most groups except for the *March DGW* banks which have a median count of 3%. Thus, the riskiest *Event* banks were not the most news-worthy in 2022Q3. The distribution of *Pubcount* is similar In 2022Q4 (Panel B of Table C.1 in the appendix).

Figure 5 plots the *standardized* value of *Pubcount* for different bank groups. It shows considerable daily variation, suggesting that even banks with low *average* media coverage experience periods of intensive publicity. Also plotted are bank abnormal returns (the dotted lines), estimated relative to the market model using specifications C.1 and (C.2), and cumulated from January 1, 2023. Through March 8, just before the crisis, *Pubcount* was

steady for all groups while abnormal returns declined moderately, ranging from 5% to 10% for all banks except STBs (which had positive cumulated returns). *Pubcount* spiked on March 13, especially for the *March DGW* group. This is expected since, although the DGW announcement was made after market close on March 13, our measure includes any publication occurring before 11:59 PM. *Pubcount* also increases on March 13 for the *April DG* group and even for the STBs (but with *Pubcount* less than 0.8 SD versus more than 2 SD for the event banks). However, the regionals do not experience unusual media interest at this time. Between March 9 and March 13, event bank stock price declines accelerated, while regional bank and STB returns fell by 3% and 1%, respectively. News flows then die down until event banks experience another surge of media interest starting on April 17 (the start of the April downgrades), which continues to the end of the sample. Shortly after, non-DG regional banks start to generate media attention that lasts till the end of April, as do STBs, with interest in the latter peaking on April 20. Event bank stock price declines continued at a gentler pace after March 13 so that by the end of the sample, the cumulated returns were about -50% for *March DGW* banks and -30% for *April Only DG* banks. By comparison, regional bank returns were steady after March 13 except for occasional dips, decreasing only by another -3% through the end of the sample. Finally, STB cumulated returns turned negative on March 17 and remained so through April 13, but were positive on May 5. The figure suggests that the number of publications is associated with bank risk events during the run while its correlation with returns appears to be weaker outside of the event banks.

Publication effects on returns. If the publications contain price-relevant information, then we expect bank's abnormal returns to be significantly affected on the day of publications. However, if the publication occurs after market hours, then returns may not be affected till the day after (as with the *March DGW* announcement). Also, if the salience of the news is not immediately apparent, then the publication might affect returns with a lag (as in Huberman and Regev (2001)). Thus, we also show results using the 2- and 3-day moving

average of *Pubcount*.¹⁵ Finally, the *sign* of the news effect may differ before versus during the run as, in the latter case, the content of the articles is likely to be more negative on average, implying a *negative* correlation with returns.

Results from estimating specification (3) are shown in Table 6. The first 4 columns show results from contemporaneous news effects. All 3 AR terms are negative and significant, indicating strong short-run negative momentum. The results in columns 1 and 2 show that, on average, news and abnormal returns are uncorrelated before the run but significantly and negatively associated during the run. After interacting news with the bank groups (columns 3-4), we find that, before the run, news has a significant and positive effect on abnormal returns of STBs and a smaller, but still significant and positive, effect on event banks and regionals. During the run, news affects event bank returns negatively, regional bank returns positively while STB returns are unaffected. These results remain when we use the 2-day and 3-day moving average of publications (columns 5-8), with the exception that, during the run, news no longer has a significant effect on returns of regionals. After 3 days, the effect of news on abnormal returns during the run becomes insignificant but the pre-run effect remains positive for all bank groups.

The significant effect of publications on returns even after 2 days suggests that investors react to news only after it becomes salient, perhaps due to their limited attention capacity. Further, the weaker effect of stale news during the run suggests that investors are quicker to pay attention during periods of adversity, consistent with the literature.¹⁶ Finally, the negative (insignificant) effect of news during the run on event bank (STB) returns indicates that the publication *counts* are informative of bank risk.

¹⁵Using lagged *Pubcount* allows only past information to affect current returns but at the cost of omitting the most salient news arriving on the same day. Results are similar to those reported with this alternative specification.

¹⁶For example, Bordalo et al. (2012) and Bordalo et al. (2022)) argue that extreme returns indicate information salience. Further, Gabaix and Laibson (2001) suggest that slow updating of consumption (e.g. due to decision or attention allocation costs) leads to a downward bias in the measured covariance between consumption growth and returns. If households adjust consumption quicker after large stock return shocks, then the covariance is increasing in the size of return shocks.

Publication effects on betas. The continuous flow of news causes variation over time and across banks in the betas, as reflected in specification (4), where we interact the publication counts with the factors. Results for the *UID* and *Losses* betas are reported in Table 7. Estimates for the 5 FF factors and the MVE are not reported to maintain brevity. The results for the *UID* beta (Panel A of the table) show a striking difference in the effect of news on the betas before versus during the run (last 2 rows of table). Considering the contemporaneous effect of publications (columns 1-2), news has a negative and insignificant effect on the betas before the run but a positive and highly significant effect during the run. As in Table 2, the stand-alone factor betas are insignificant pre-run and positive and significant during the run. The additional effect of news during the run increases up to at least 3 days following publications; for example, 3 days after publications, the news beta (i.e., the coefficients on the *News*Factor* regressor) is about the same or higher than the factor beta (last 2 columns of the table). Finally, after accounting for the factors, news does not directly affect returns. Panel B shows that similar results obtain for the *Losses* beta, with the exception that, when using the contemporaneous *Pubcount*, the news beta is only weakly significant during the run (column 1). Pre-to-post-run changes in the news betas are significant at the 5% level, based on a Wald test, indicating that news arrivals increase investor risk perception of banks.

By comparison with the *UID* and *Losses* betas, the effect of publications on the cash and CET1 betas during the run is qualitatively similar but more muted in magnitude and significance (see Table C.2 in the Appendix). For example, during the run, the statistical significance of the news beta is only weakly significant in 3 of 6 specifications, and the news beta is small relative to the factor beta. Indeed, the pre/post changes in the news betas are statistically insignificant, based on a Wald test.

These results suggest that publications facilitate coordination among investors when updating their estimates of bank risk, thereby making them more information-sensitive (Dang et al. (2018)). The long-lasting and persistent effect of news on bank risk, even when news

is not directly informative about returns, is consistent with the limited attention capacity of investors. Moreover, the stronger evidence of news effects relating to (the relatively novel) *UID* and *Losses* risks is consistent with attention externality, as previously discussed.

Cross-section of news betas The cross-section of news betas is informative of news content. In particular, for event banks, we expect bad (good) news to increase (decrease) investor perception of bank risk during the run, implying positive (negative) news betas. Conversely, for STBs, we expect small and insignificant news betas, given its greater visibility.

To obtain the cross-section, we estimate specification (4) bank-by-bank. Figure 6 shows scatter plots of estimates of the *UID* and *Losses* factor betas (x-axis) and news betas (y-axis) before the run (left panel) and during the run (right panel). Scatters above (below) the 45 degree line show greater (lesser) reliance on news to coordinate investor perceptions of bank risk. Estimates for the event banks are shaded orange. During the run, most scatters move to the positive quadrant, consistent with the previously observed shift in the factor betas from negative to positive values and, in addition, with a reduced incidence of negative estimates of the news beta. Also, the scatters become more concentrated around the 45 degree line during the run, implying that about half of beta increases is news-related. For the cash and CET1 factors (see Figure C.1 in the appendix), there is also a shift to the positive quadrant, but the scatters tend to mess below the 45 degree line during the run, implying a weaker reliance on news to update beliefs on these more traditional risks.

In Table 8, we characterize the distributions of *significant* news betas, separately for positive and negative estimates. For all factors, the share of negative and significant news betas (“negative news beta”) decrease. For example, considering the *UID* factor (Panel A), the share of negative news betas for all (event) banks decrease from 24% (33%) before the run to 4% (0%) during the run. The corresponding numbers for regionals (STBs) are 21% (24%) before the run and 5% (5%) during the run. The only exception is that the share of negative news betas of STBs increase slightly for the *Losses* factor (Panel B), but

these numbers are small both before and during the run. The result indicates a decrease in the incidence of risk-reducing news during the run for all groups, and particularly for event banks. The share of positive news betas increases during the run for *event* banks for all factors, indicating a higher incidence of risk-increasing news. For example, the share of positive news betas related to the *Losses* factor (Panel B) increases from 0% before the run to 50% during the run. However, this is sporadically true for other bank groups.

In summary, investor perception of bank risk is closely tied to news arrivals during the run. In particular, news during the run is less likely to lower the factor betas and improve investor perceptions of bank risk. In addition, for event banks, news is also more likely to increase the factor betas and enhance investor perceptions of bank risk during the run. Finally, changes in the news betas are weakly associated with balance sheet values of bank groups in 2022Q3 or 2022Q4 (see Tables C.3 and C.4 in the appendix), reinforcing the interpretation of news as coordination devices.

5 Do Rating Announcements Coordinate Investor Attention to Bank Risk?

The strong effect of publications on beta changes of event banks raises the possibility that rating announcements coordinated investor attention to these banks. In this section, we examine this issue, by assessing how the factor betas changed around rating announcements. We begin by assessing rating announcement effects, and then examining the role of ratings as coordination devices.

Announcement effects on returns Table D.1 in the appendix shows the daily means of abnormal returns for different bank groups around crisis and rating events. On March 13, abnormal returns of the *March DGW* banks fell more than 30%, returns of the *April Only DG* banks fell about 8% and returns of the regionals and STBs fell by about 2%. Following

announcement of the DGW after market close on March 13, the event banks exhibit *positive* returns on March 14, indicative of return reversals. On the downgrade dates of April 14 and 21, the *March DGW* banks fell about 1%-2% while the *April Only DG* and regional banks fell by about 1%. However, stock prices increased for all banks on April 19 when Schwab was downgraded. *STBs* had positive returns on all announcement days in April. The descriptive statistics suggest no negative effect on returns of the March announcements and some negative effects of the April announcements.

To test the informativeness of ratings more formally, we estimate specification 5 and show the results in Table 9. On March 14, abnormal returns are significant but positive for all banks (columns 1-2). Returns continue to increase in the next 3 trading days. Columns 3-4 show that both the *March DGW* group and the regionals have *positive* returns while relative to these groups, *STBs* (the control group) have negative returns. These results are consistent with the descriptive statistics shown in Table D.1. For the April downgrade announcements, and for all banks, the announcement effect is once again significantly positive and returns increase further in the next 3 trading days. However, the last 2 columns show that announcement-day returns are significantly negative for *April Only DG* banks, as well as for *STBs* but not for regionals. Returns are also negative for the *March DGW* group, implying a market inefficiency since we expect all information to be impounded in March when the watch was announced (Norden and Weber (2004)). As we find negative announcement effects for the event banks in April but not in March, the results indicate that the April downgrade announcements, but not the March DGW announcements, were informative.

Do Rating Announcements Coordinate Investor Attention? If the rating announcements act as coordination devices for investors with limited attention, then the betas of event banks should only change after announcements and not before. To identify the announcement effects on the betas, we estimate specification (6) be.

Figure 7 shows scatter plots of estimates (in SD units) of the *UID* and *Losses* factor

betas before (x-axis) and after (y-axis) announcements, separately for the March (left panel) and April (right panel) announcements. Estimates for the event banks are shaded orange. For both announcements, the mass of scatters is similar above and below the 45-degree line, indicating little change in the betas around these events. For the event banks, the betas mostly lie below the 45-degree line in March, but above it in April, implying higher betas for event banks after the April announcements but not after the March announcements.

The mean of betas around announcements is shown in Figure 8. For the *UID* factor, mean betas are mostly negative in January-February 2023. In the pre-announcement period of March 1-13, the mean β increases for all banks, ranging from 0.12 SD units (for regionals) to 0.53 SD units (for *March DGW* banks). After the March announcements, we find no further increases in the mean betas for any bank. In the post-April announcement period, the betas increase for the *April Only DG* banks relative to the pre-announcement period. Thus, the April (but not the March) announcements are followed by higher average betas for event banks. The results are similar for the *Losses* factor (Panel B) and the Cash and CET1 factors (shown in Figure D.1 in the appendix).

Shares of significantly positive betas are shown in Table 10. Panel A of the table shows the results for the *UID* factor. In the pre-March announcement period (columns 3-4), the share of positive betas exceeds 29% for all groups and is 80% for *March DGW* banks. All shares are lower after the March announcements. After the April announcements, the shares of positive betas increase for the *April Only DG* banks relative to the pre-April announcement period — this is also true for the Cash factor but not for the other factors. To rule out crisis effects, we re estimate the regression after excluding the crisis period of March 9-13, and continue to find similar results (see Table D.2 in the appendix).

Discussion There is some evidence that the April announcements coordinated investor attention: for event banks, returns decrease, the average beta increases for all factors and the share of positive betas increases for 2 factors after announcements. Also, the betas of

regionals (with similar risk profiles as the event banks in 2022) did not increase, suggesting that investors may have coordinated on the announcement events, independent of bank fundamentals. There is no evidence of coordination for the March announcements as returns increase and the betas increase before, and not after announcements.

6 Conclusion

We investigate whether stock market investors disciplined banks during the Spring 2023 bank run. To this end, we study how investor perception of bank risk evolved in 2022 and 2023. To measure bank risk, we estimate balance sheet “betas”— the covariance of bank excess stock returns with returns on factors constructed from long-short portfolios based on bank balance sheet characteristics, such as the shares of uninsured deposits (*UID*) or unrealized losses (*Losses*) on AFS and HTM securities, to assets in 2022Q3.

We find that the betas were insignificant in January and February of 2023 but became positive and significant during the bank run. Thus, investors displayed heightened sensitivity to bank risk during the run (Dang et al. (2018)). In the cross-section of banks, we find that the betas increased significantly for a limited set of banks (about 30% for *Losses* and 40% for *UID*), and that increases in the beta was weakly correlated with bank risk. Finally, balance sheet risk in 2022Q3 or 2022Q4 does not predict higher betas during the bank run.

How did investors select banks to focus on, if these were not the most risky banks? We examine whether the arrival of public information allowed investors to coordinate their actions, either due to higher-order beliefs (Allen et al. (2008)) or due to limited attention.

To do so, we first consider *Pubcount* or the publication counts divided by assets (to remove a size effect induced by larger banks tending to be more newsy). We show that *Pubcount* is informative to stock market investors during the run as news affects returns of event banks (i.e., those banks downgraded in April) negatively. Further, news betas (or the correlation of bank returns and *Pubcount* times the balance sheet factors) are insignificant effect before the

run but positive and highly significant effect during the run. Cross-section analysis shows that higher betas during the run is due to a reduced incidence of risk-mitigating news (i.e., news arrivals associated with lower betas). These effects are long-lasting and persistent, even when news is not directly informative of returns, consistent with the idea that publications allow coordination among investors when they update their estimates of bank risk.

Do rating announcements also coordinate investor attention? The March rating announcements were not informative and the betas increased in the first week of March, *before* the announcements, thus ruling out the idea that investors coordinated on the March announcements. There is some evidence that the April announcements were informative and were followed by higher betas.

The limited ability of investors to process the variety of information available during a bank run may have both positive and negative consequences. It potentially makes price dynamics more noisy, which poses challenges to market participants and policymakers. However, limited attention may also limit contagion to a broader set of banks. Indeed, the results indicate that contagion was limited in breadth (i.e., the number of banks affected) and time, although this effect is difficult to disentangle from the effects of government support.¹⁷

¹⁷Metrick and Schmelzing (2024)) find that government actions around the March runs were unusual in their policy mix and size.

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Table 1: **Bank Characteristics as of 2022Q3 and 2022Q4**

Panel A: 2022Q3							
Bank Group	Number	Assets \$B	Unins. Dep. % of Assets	Losses % of Assets	Cash % of Assets	CET1 %	Excess Ret. %
April Only DG	7	38.05	43.27	3.34	3.82	9.86	0.01
March DGW	5	84.34	65.28	3.68	2.70	9.61	-0.10
STBs	21	303.57	42.49	2.37	8.37	10.33	-0.16
Regional Banks	38	26.90	46.86	2.57	3.13	11.54	0.05
All Sample Banks	71	43.73	46.68	2.62	4.04	10.98	-0.02
SBNY	1	114.47	85.32	2.87	10.12	10.11	-0.17
SI	1	15.47	77.75	6.58	12.20	40.72	0.16
SIVB	1	212.87	75.48	8.79	6.32	12.13	0.06
Panel B: 2022Q4							
Bank Group	Number	Assets \$B	Unins. Dep. % of Assets	Losses % of Assets	Cash % of Assets	CET1 %	Excess Ret. %
April Only DG	7	39.41	41.38	2.88	2.98	9.92	0.08
March DGW	5	85.65	62.17	2.46	2.23	9.65	-0.15
STBs	21	301.45	42.13	2.23	7.99	10.60	0.09
Regional Banks	38	27.56	45.92	2.48	2.93	11.62	0.07
All Sample Banks	71	43.92	44.85	2.46	3.84	10.92	0.07
SBNY	1	110.36	75.63	2.91	5.49	10.41	-0.26
SI	1	11.36	33.77	1.00	40.28	42.12	-1.48
SIVB	1	211.79	74.01	8.35	6.14	12.05	-0.72

Note: The table shows the median values of balance sheet characteristics for four bank groups, reported as of 2022Q3 and 2022Q4. SVB, SBNY, SI are not in the sample but shown for reference. *Losses* are differences between par and fair values of AFS and HTM securities. The *March DGW* group includes banks put on DG watch in March. The *April Only DG Banks* group includes banks downgraded between April 14 and 28. The *regional banks* (STB) group consists of non-DG regional (US stress-tested) banks. Banks in the various groups are listed in appendix A. *DG*=Downgraded. *Unins.Dep.* = Uninsured Deposits. *Ret.* = returns.

Table 2: **Bank Balance Sheet Factor Betas: Before and During the Bank Run**

	Factor=UID		Factor=Losses		Factor=Cash		Factor=CET1	
	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE
Factor*Pre	-0.03	0.08	0.07	0.07	0.12*	0.07	0.10	0.07
Factor*Post	0.11*	0.06	0.09**	0.04	0.17***	0.05	0.13***	0.05
BankSize Factor*Pre	0.10*	0.06	0.08	0.05	0.03	0.06	0.07	0.05
BankSize Factor*Post	0.11**	0.04	0.14***	0.05	0.05	0.05	0.10**	0.04
Mkt-Rf	0.42***	0.03	0.43***	0.04	0.42***	0.04	0.42***	0.03
SMB	0.13***	0.03	0.12***	0.03	0.12***	0.03	0.13***	0.03
HML	0.48***	0.06	0.49***	0.04	0.46***	0.05	0.45***	0.05
RMW	-0.02	0.04	-0.01	0.04	-0.03	0.04	-0.02	0.04
CMA	-0.23***	0.06	-0.24***	0.06	-0.21***	0.06	-0.21***	0.06
Log Bank MVE_Lag1	-0.04	0.03	-0.04	0.03	-0.04	0.03	-0.04	0.03
Obs	6101		6101		6101		6101	
Adj R2	0.59		0.59		0.59		0.59	
Bank FE	YES		YES		YES		YES	

Note: This table shows results from estimating regression (1) for the period January 3 to May 5, 2023. The pre-(post-) run dummy variable *Pre* (*Post*) equals 1 before (since) March 1, 2023. The factors are constructed from long-short portfolios based on 2022Q3 asset shares of uninsured deposits (*UID*), unrealized losses on AFS and HTM securities (*Losses*), cash as shares of assets, and the common equity tier one ratio CET1. The *negative* of the cash and CET1 factor returns is used for consistency with the other factors. Downgraded and failed banks are excluded from the factor construction. SVB, SBNY and Silvergate are not included in the regressions. All variables are standardized to have mean zero and unit standard deviation. Standard errors (in parentheses) are robust and clustered by date. Stars represent statistical significance: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table 3: **Cross-Section of Bank Balance Sheet Betas: Before and During the Bank Run**

Panel A: Factor=UID							
	Pre-Run			Post-Run			
	N	Avg β	% $\beta > 0$ & $p \leq 0.05$	Avg $\beta > 0$ & $p \leq 0.05$	Avg β	% $\beta > 0$ & $p \leq 0.05$	Avg $\beta > 0$ & $p \leq 0.05$
All Banks	71	-0.04	0.14	0.40	0.12	0.38	0.42
Event Banks	12	-0.03	0.00	NA	0.28	0.50	0.47
Regional Banks	38	-0.06	0.18	0.41	0.04	0.32	0.31
STBs	21	0.00	0.14	0.38	0.17	0.43	0.47
Panel B: Factor=Losses							
	Pre-Run			Post-Run			
	N	Avg β	% $\beta > 0$ & $p \leq 0.05$	Avg $\beta > 0$ & $p \leq 0.05$	Avg β	% $\beta > 0$ & $p \leq 0.05$	Avg $\beta > 0$ & $p \leq 0.05$
All Banks	71	0.06	0.10	0.30	0.09	0.31	0.28
Event Banks	12	0.04	0.08	0.28	0.17	0.42	0.37
Regional Banks	38	0.07	0.03	0.26	0.07	0.24	0.19
STBs	21	0.07	0.24	0.31	0.09	0.38	0.32
Panel C: Factor=Cash							
	Pre-Run			Post-Run			
	N	Avg β	% $\beta > 0$ & $p \leq 0.05$	Avg $\beta > 0$ & $p \leq 0.05$	Avg β	% $\beta > 0$ & $p \leq 0.05$	Avg $\beta > 0$ & $p \leq 0.05$
All Banks	71	0.11	0.31	0.57	0.18	0.52	0.48
Event Banks	12	0.03	0.17	0.38	0.38	0.58	0.63
Regional Banks	38	0.05	0.18	0.50	0.09	0.55	0.35
STBs	21	0.27	0.62	0.63	0.22	0.43	0.60
Panel D: Factor=CET1							
	Pre-Run			Post-Run			
	N	Avg β	% $\beta > 0$ & $p \leq 0.05$	Avg $\beta > 0$ & $p \leq 0.05$	Avg β	% $\beta > 0$ & $p \leq 0.05$	Avg $\beta > 0$ & $p \leq 0.05$
All Banks	71	0.09	0.30	0.40	0.14	0.37	0.37
Event Banks	12	0.03	0.25	0.25	0.25	0.58	0.43
Regional Banks	38	0.05	0.18	0.37	0.08	0.29	0.26
STBs	21	0.20	0.52	0.46	0.18	0.38	0.46

Note: This table summarizes the results of estimating equation (1) bank by bank, from January 1 to May 5, 2023. We show the mean β , the percentage of banks with a positive and significant β , and the mean of β conditional on being positive and significant, by bank group before and during the run periods. All variables in the regression are standardized to have mean zero and unit standard deviation. Event banks had ratings downgrades in April; all other bank groups exclude downgraded banks. *STBs*=Non-downgraded US stress-tested banks. Banks in the various groups are listed in appendix A.

Table 4: Predicting Increases in *UID* and *Losses* Betas During the Run

Panel A: Predicting Increases in the <i>UID</i> Beta During the Run						
	Estimate	SE	Estimate	SE	Estimate	SE
Asset Growth	-0.06*	0.03	-0.05	0.04	-0.04	0.04
<i>NetInc</i>	-0.20*	0.10	-0.16	0.12	-0.16	0.12
<i>TimeDep</i>	-0.37**	0.17	-0.32	0.20	-0.31	0.20
<i>NetInc</i> \times <i>TimeDep</i>	0.47*	0.25	0.49*	0.26	0.47*	0.26
UID			0.08	0.16	0.08	0.16
Losses			0.07	0.37	0.07	0.36
UID*Losses			0.05	0.38	0.06	0.38
Pubcounts					-0.05	0.03
Intercept	0.25***	0.05	0.25***	0.05	0.25***	0.05
Obs	71		71		71	
Adj R2	0.08		0.17		0.17	
Root MSE, All Banks	0.42		0.40		0.40	
Root MSE, Event Banks	0.50		0.47		0.47	
Root MSE, STBs	0.48		0.46		0.45	
Root MSE, Regionals	0.31		0.29		0.28	

Panel B: Predicting Increases in the <i>Losses</i> Beta During the Run						
	Estimate	SE	Estimate	SE	Estimate	SE
Asset Growth	0.00	0.06	0.01	0.05	0.00	0.05
<i>NetInc</i>	-0.01	0.09	0.03	0.08	0.03	0.08
<i>TimeDep</i>	-0.07	0.16	-0.04	0.18	-0.06	0.18
<i>NetInc</i> \times <i>TimeDep</i>	0.01	0.17	0.05	0.20	0.07	0.20
UID			0.19	0.16	0.20	0.16
Losses			0.24	0.34	0.24	0.34
UID*Losses			-0.19	0.37	-0.19	0.37
Pubcounts					0.07	0.11
Intercept	0.21***	0.05	0.21***	0.05	0.21***	0.05
Obs	71		71		71	
Adj R2	-0.03		0.07		0.09	
Root MSE, All Banks	0.42		0.40		0.39	
Root MSE, Event Banks	0.50		0.42		0.42	
Root MSE, STBs	0.35		0.32		0.33	
Root MSE, Regionals	0.39		0.38		0.37	

Note: The table shows results from a cross-section regression of an indicator for banks with higher during the run *UID* and *Losses* betas on their balance sheet values as of 2022Q3. *Losses* are differences between par and fair values of AFS and HTM securities. *Event Banks* include banks put on downgrade (DG) watch in March or downgraded in April. The *Regionals* (STB) bank group consists of non-downgraded regional (US stress-tested) banks. We report heteroscedasticity-consistent standard errors (SE) based on MacKinnon and White (1985). ***(**)* indicate statistical significance at the 1%(5%)10% level. $UID = \frac{Uninsured\ deposits}{Assets}$. $NetInc = \frac{Net\ Income}{Assets}$. $TimeDep = \frac{Time\ Deposits}{Deposits}$. DG=Downgraded.

Table 5: **Bank Publication Counts and OMO Shares**

Panel A: PUBCOUNT, 2022Q3							
Bank Group	Number	Mean	Min	P25	P50	P75	Max
All Sample Banks	71	13.65	0.36	3.56	6.02	14.05	755.98
April Only DG	7	16.49	0.67	4.32	6.75	17.29	580.82
March DGW	5	7.32	0.49	2.37	3.41	7.98	106.44
STBs	21	10.68	0.36	3.28	5.84	14.21	269.41
Regional Banks	38	15.60	0.91	3.74	6.38	14.55	755.98
SBNY	1	4.56	0.87	0.87	1.75	3.49	48.92
SI	1	40.31	6.47	6.47	19.40	45.26	355.59
SIVB	1	5.62	0.47	2.35	3.29	6.34	42.28
Panel B: OMO SHARE, 2022Q4							
Bank Group	Number	Mean	Min	P25	P50	P75	Max
All Sample Banks	71	16.76	1.67	9.41	15.50	22.63	54.73
April Only DG	7	23.17	6.77	9.41	20.69	31.14	54.73
March DGW	5	14.49	2.71	5.00	20.84	20.90	23.00
STBs	21	17.06	1.67	13.66	17.00	20.90	29.72
Regional Banks	38	15.71	4.10	7.93	13.93	22.63	38.04
SBNY	1	21.40	21.40	21.40	21.40	21.40	21.40
SI	1	50.10	50.10	50.10	50.10	50.10	50.10
SIVB	1	51.08	51.08	51.08	51.08	51.08	51.08

Note: The table shows the distribution of 100*publication counts, normalized by assets in \$B, in 2022Q3 (Panel A) and the asset share of OMO collateral in 2022Q4 (Panel B). SVB, SBNY, Silvergate are not in the sample but shown for reference. The *March DGW* group includes banks put on DG watch in March. The *April Only DG Banks* group includes banks downgraded between April 14 and 28. The *regional banks* (STB) group consists of non-DG regional (US stress-tested) banks. Banks in the various groups are listed in appendix A. *DG*=Downgraded.

Table 6: Effect of News on Bank Abnormal Returns: Before and during the run

	News=Pubcount		News=Pubcount		News=Pubcount_MA2		News=Pubcount_MA3	
	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE
News*Pre	-0.01	0.05	3.03***	0.30	3.07***	0.40	4.78***	0.62
News*Event Banks*Pre			-2.80***	0.34	-0.57	0.51	-2.72***	0.66
News*Regionals*Pre			-2.29***	0.30	-1.91***	0.37	-3.25***	0.59
News*Post	-1.39***	0.03	0.10	0.22	0.42	0.39	0.66	0.47
News*Event Banks*Post			-1.67***	0.24	-1.15***	0.44	-0.35	0.51
News*Regionals*Post			0.70***	0.24	-0.01	0.39	0.51	0.47
Y_lag1	-0.29***	0.00	-0.31***	0.00	-0.25***	0.00	-0.24***	0.00
Y_lag2	-0.08***	0.00	-0.11***	0.00	-0.04***	0.00	-0.04***	0.00
Y_lag3	-0.13***	0.00	-0.18***	0.00	-0.10***	0.00	-0.12***	0.00
Obs	5,888		5,888		5,888		5,888	
RMSE	3.06		3.08		3.19		3.28	
Bank FE	YES		YES		YES		YES	

Note: The table shows the effect of *Pubcount* (i.e. a bank's publication counts divided by assets) on abnormal bank stock returns (in %) from January 3, 2023 to May 5, 2023 for different banks groups. *Y_lagx* denotes an AR term with a lag of *x* days. *Pubcount-MAx* is the moving average of *Pubcount* over *x* days. Bank abnormal returns are calculated according to equations (C.1) and (C.2). The pre- (post-) run dummy variable *Pre* (*Post*) equals 1 before (since) March 1, 2023. The *Event* dummy is 1 for banks on downgrade watch in March or downgraded in April. The *Regionals* dummy is 1 for non-downgraded regional banks. Non-downgraded US STBs are the control group. The estimation method is the 2-step GMM, implemented using the Arellano and Bond (1991) estimator. Robust standard errors are reported. ***(**)* indicate statistical significance at the 1%(5%)10% level. *RMSE*=Root Mean-Squared Error.

Table 7: **Effect of News on *UID* and *Losses* Betas: Before and during the run**

Panel A: UID Factor						
	News=Pubcount		News=Pubcount_MA2		News=Pubcount_MA3	
	Estimate	SE	Estimate	SE	Estimate	SE
Factor*Pre	-0.03	0.08	-0.02	0.08	-0.03	0.08
Factor*Post	0.10*	0.05	0.10*	0.06	0.11*	0.06
Banksiz Factor*Pre	0.10*	0.06	0.13**	0.05	0.14**	0.06
Banksiz Factor*Post	0.11***	0.04	0.11***	0.04	0.11**	0.04
News*Pre	0.03	0.03	0.02	0.03	0.05	0.04
News*Post	0.03	0.03	0.03	0.04	0.01	0.04
News*Factor*Pre	-0.04	0.05	-0.03	0.05	-0.05	0.06
News*Factor*Post	0.05**	0.03	0.08**	0.04	0.10**	0.05
Obs	6101		6030		5959	
Adj R2	0.59		0.60		0.60	
FF5 and Bank MVE?	YES		YES		YES	
Bank FE	YES		YES		YES	
Panel B: Losses Factor						
	News=Pubcount		News=Pubcount_MA2		News=Pubcount_MA3	
	Estimate	SE	Estimate	SE	Estimate	SE
Factor*Pre	0.10	0.06	0.04	0.07	0.04	0.07
Factor*Post	0.15***	0.05	0.07**	0.03	0.07**	0.03
Banksiz Factor*Pre	0.03	0.06	0.12***	0.04	0.12**	0.05
Banksiz Factor*Post	0.06	0.05	0.14***	0.04	0.14***	0.04
News*Pre	0.01	0.03	0.02	0.03	0.04	0.03
News*Post	0.03	0.03	0.05	0.03	0.02	0.04
News*Factor*Pre	0.06	0.06	-0.03	0.05	-0.04	0.05
News*Factor*Post	0.05*	0.03	0.12***	0.03	0.11***	0.04
Obs	6101		6030		5959	
Adj R2	0.59		0.60		0.60	
FF5 and Bank MVE?	YES		YES		YES	
Bank FE	YES		YES		YES	

Note: This table shows results from estimating regression (4) for the period January 3 to May 5, 2023. *Pubcount* is a bank's publication counts divided by assets. *Pubcount-MAx* is the moving average of *Pubcount* over *x* days. The pre- (post-) run dummy variable *Pre* (*Post*) equals 1 before (since) March 1, 2023. The factors are constructed from long-short portfolios based on 2022Q3 asset shares of uninsured deposits (*UID*) and unrealized losses on AFS and HTM securities (*Losses*). Downgraded and failed banks are excluded from the factor construction. SVB, SBNY and Silvergate are not included in the regressions. All variables are standardized to have mean zero and unit standard deviation. Standard errors (in parentheses) are robust and clustered by date. Stars represent statistical significance: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table 8: **Cross-Section of Bank News Betas: Before and During the Bank Run**

Panel A: Factor=UID					
	Pre-Run			Post-Run	
	N	% $\beta > 0$	% $\beta < 0$	% $\beta > 0$	% $\beta < 0$
		& $p \leq 0.05$	& $p \leq 0.05$	& $p \leq 0.05$	& $p \leq 0.05$
All Banks	71	0.21	0.24	0.30	0.04
Event Banks	12	0.17	0.33	0.58	0.00
STBs	21	0.14	0.24	0.33	0.05
Regional Banks	38	0.26	0.21	0.18	0.05
Panel B: Factor=Losses					
	Pre-Run			Post-Run	
	N	% $\beta > 0$	% $\beta < 0$	% $\beta > 0$	% $\beta < 0$
		& $p \leq 0.05$	& $p \leq 0.05$	& $p \leq 0.05$	& $p \leq 0.05$
All Banks	71	0.13	0.14	0.23	0.06
Event Banks	12	0.00	0.17	0.50	0.00
STBs	21	0.24	0.05	0.10	0.10
Regional Banks	38	0.11	0.18	0.21	0.05
Panel C: Factor=Cash					
	Pre-Run			Post-Run	
	N	% $\beta > 0$	% $\beta < 0$	% $\beta > 0$	% $\beta < 0$
		& $p \leq 0.05$	& $p \leq 0.05$	& $p \leq 0.05$	& $p \leq 0.05$
All Banks	71	0.21	0.17	0.23	0.06
Event Banks	12	0.00	0.17	0.58	0.00
STBs	21	0.19	0.29	0.19	0.10
Regional Banks	38	0.29	0.11	0.13	0.05
Panel D: Factor=CET1					
	Pre-Run			Post-Run	
	N	% $\beta > 0$	% $\beta < 0$	% $\beta > 0$	% $\beta < 0$
		& $p \leq 0.05$	& $p \leq 0.05$	& $p \leq 0.05$	& $p \leq 0.05$
All Banks	71	0.25	0.14	0.25	0.08
Event Banks	12	0.08	0.17	0.58	0.00
STBs	21	0.19	0.14	0.19	0.10
Regional Banks	38	0.34	0.13	0.18	0.11

Note: This table summarizes the results of estimating equation (4) bank by bank, from January 1 to May 5, 2023. We show the mean news β (i.e. the coefficient on the *Factor* \times *News* regressor) and the percentage of banks with a significant news β with either positive or negative estimates, by bank group before and during the run periods. All variables in the regression are standardized to have mean zero and unit standard deviation. Event banks are those with ratings downgrades in April. *STBs* are non-downgraded US stress-tested banks. Banks in the various groups are listed in appendix A.

Table 9: **Effect of Rating Announcements on Bank Abnormal Returns**

	Day 0 = March 14				Day 0 = April 14, 19 or 21			
	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE
Day 0	1.27***	0.03	-3.80***	0.15	0.04***	0.01	-1.76***	0.02
Day 0*March DGW			20.87***	0.39			-1.38***	0.08
Day 0*Regionals			5.08***	0.20			2.62***	0.03
Day 0*April Only DG							0.44***	0.08
Day [1,3]	0.26***	0.02	-0.68***	0.06	0.13***	0.01	0.21***	0.04
Day [1,3]*March DGW			-1.35***	0.20			-6.77***	0.09
Day [1,3]*Regionals			1.46***	0.07			-0.30***	0.04
Day [1,3]*April Only DG							2.55***	0.16
Obs	1,486		1,482		1,197		1,191	
RMSE	4.39		4.43		2.87		2.87	
Lags of Dependent Variable	YES		YES		YES		YES	
Bank FE	YES		YES		YES		YES	

Note: This table shows the effects of rating announcements on March 14 and April 14, 19 or 21 of 2023 on bank abnormal returns based on estimating equation 5. Day 0 is the event date and Day[1,3] denotes the 3 trading days after the event date. The sample is March 1-31 for March announcements and April 1-28 for April announcements. Bank abnormal returns are calculated according to equations (C.1) and (C.2). The *March DGW* group banks were put on downgrade watch on March 14 and downgraded in April. The *April Only DG* group includes banks downgraded between April 14 and 21. The *Regionals* dummy is 1 for regional banks not downgraded at the time of announcements. STBs not downgraded at the time of announcements are the control group. The estimation method is the 2-step GMM, implemented using the Arellano and Bond (1991) estimator. Robust standard errors are reported. Stars represent statistical significance: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$. *DGW*=Downgrade watch. *DG*=Downgrades.

Table 10: **Shares of Significant Betas Around Rating Announcements**

Panel A: Factor=UID					
		March Announcement		April Announcements	
		Pre	Post	Pre	Post
	N	% $\beta > 0$	% $\beta > 0$	% $\beta > 0$	% $\beta > 0$
		& $p \leq 0.05$	& $p \leq 0.05$	& $p \leq 0.05$	& $p \leq 0.05$
All Banks	71	38.03	23.94	32.39	22.54
April Only DG	7	57.14	42.86	28.57	42.86
March DGW	5	80.00	20.00	20.00	20.00
STBs	21	38.10	23.81	23.81	28.57
Regionals	38	28.95	21.05	39.47	15.79
Panel B: Factor=Losses					
		March Announcement		April Announcements	
		Pre	Post	Pre	Post
	N	% $\beta > 0$	% $\beta > 0$	% $\beta > 0$	% $\beta > 0$
		& $p \leq 0.05$	& $p \leq 0.05$	& $p \leq 0.05$	& $p \leq 0.05$
All Banks	71	39.44	7.04	9.86	5.63
April Only DG	7	57.14	14.29	0.00	0.00
March DGW	5	80.00	0.00	20.00	0.00
STBs	21	38.10	0.00	4.76	9.52
Regionals	38	31.58	10.53	13.16	5.26
Panel C: Factor=Cash					
		March Announcement		April Announcements	
		Pre	Post	Pre	Post
	N	% $\beta > 0$	% $\beta > 0$	% $\beta > 0$	% $\beta > 0$
		& $p \leq 0.05$	& $p \leq 0.05$	& $p \leq 0.05$	& $p \leq 0.05$
All Banks	71	35.21	16.90	19.72	14.08
April Only DG	7	57.14	14.29	0.00	14.29
March DGW	5	100.00	40.00	40.00	40.00
STBs	21	28.57	19.05	14.29	23.81
Regionals	38	26.32	13.16	23.68	5.26
Panel D: Factor=CET1					
		March Announcement		April Announcements	
		Pre	Post	Pre	Post
	N	% $\beta > 0$	% $\beta > 0$	% $\beta > 0$	% $\beta > 0$
		& $p \leq 0.05$	& $p \leq 0.05$	& $p \leq 0.05$	& $p \leq 0.05$
All Banks	71	30.99	15.49	26.76	11.27
April Only DG	7	57.14	14.29	28.57	28.57
March DGW	5	60.00	0.00	20.00	20.00
STBs	21	28.57	14.29	28.57	14.29
Regionals	38	23.68	18.42	26.32	5.26

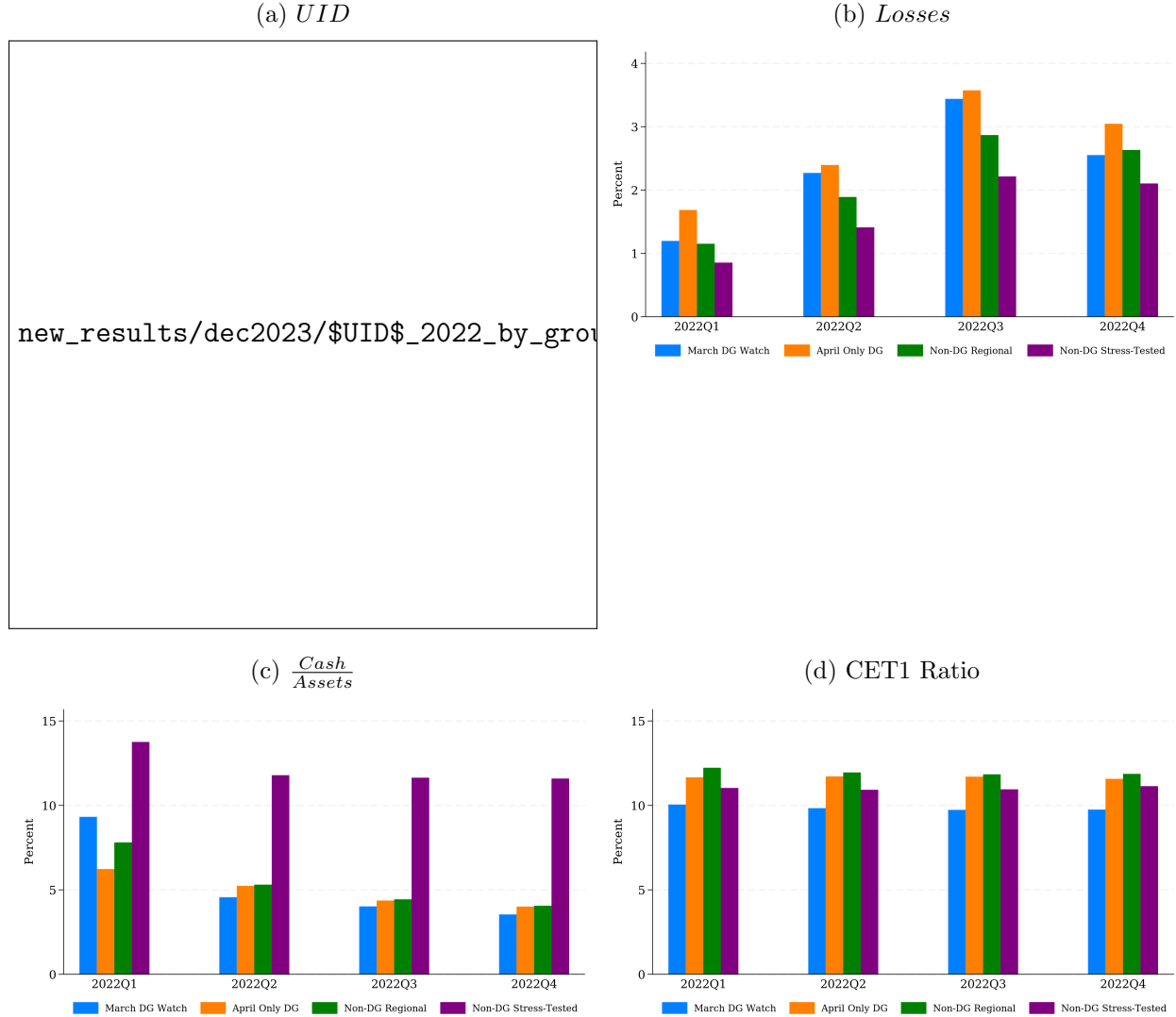
Note: This table summarizes the results of estimating equation (6) bank by bank, from January 1 to May 5, 2023. We show the share of banks with a significantly positive β by bank group before and after the March and April rating announcements. The *March DGW* group banks were put on downgrade watch on March 14 and downgraded in April. The *April Only DG* group includes banks downgraded between April 14 and 21. All variables in the regression are standardized to have mean zero and unit standard deviation. Banks in the various groups are listed in appendix A. *DGW*=Downgrade watch. *DG*=Downgrades.

Table 11: **Effect of BTFP Announcement on Bank Abnormal Returns**

	Day 0 = March 13				Placebo Day 0 = March 9			
	Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE
Day 0	-9.33***	0.07	20.07***	1.38	-0.73***	0.02	-20.32***	1.70
Day 0*OMO share 2022Q4	0.20***	0.01	-1.44***	0.08	-0.09***	0.00	1.05***	0.09
Day 0*Event Banks			-67.18***	1.28			19.42***	1.80
Day 0*Event Banks*OMO share 2022Q4			2.73***	0.08			-1.27***	0.10
Day 0*Regional Banks			-18.29***	1.81			21.03***	2.08
Day 0*Regional Banks*OMO share 2022Q4			1.37***	0.10			-1.20***	0.11
Obs	1,486		1,482		1,486		1,482	
RMSE	4.24		4.26		4.34		4.42	
Lag Dependent Variables	YES		YES		YES		YES	
Bank FE	YES		YES		YES		YES	

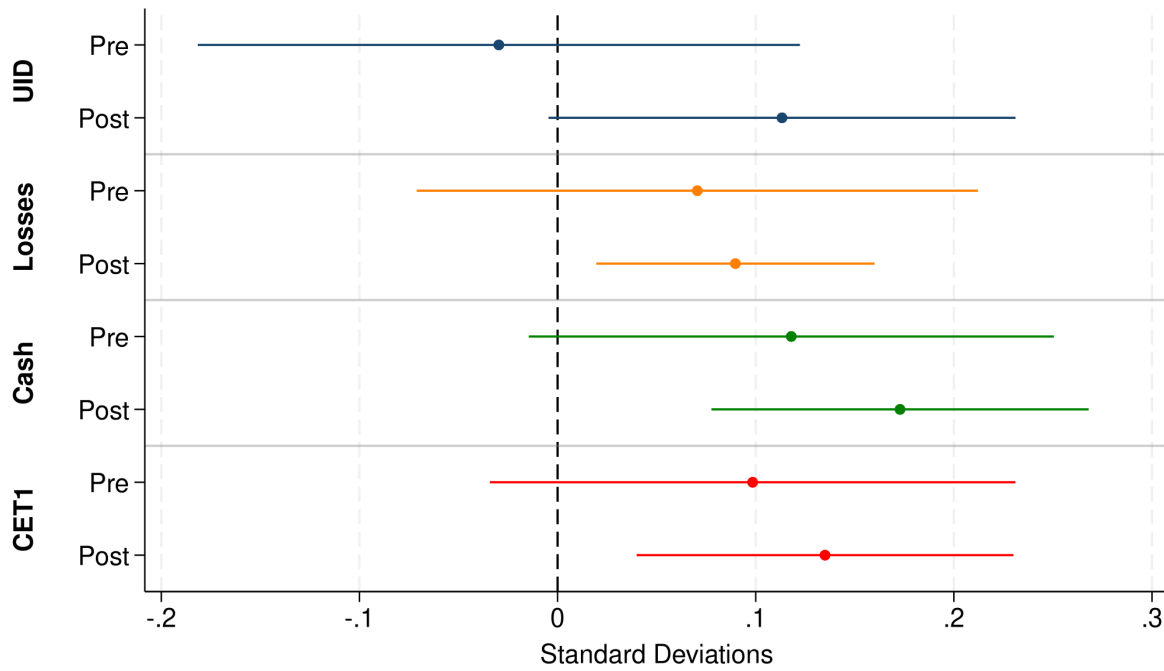
Note: This table shows the effects of the announcement of the Fed's BTFP liquidity facility on March 13 on bank abnormal returns based on estimating specification 5. Also shown is a placebo test using March 9 as the announcement date. *OMO* refers to collateral eligible for open market operations. Day 0 is the event date and Day[1,4] denotes the 4 trading days after the event date. The sample is March 1-31. Bank abnormal returns are calculated according to equations (C.1) and (C.2). The *Event Banks* include the *March DGW* and the *April Only DG* groups that were put on watch in March and downgraded in April. The *Regionals* dummy is 1 for non-downgraded regional banks. STBs are the control group. The estimation method is the 2-step GMM, implemented using the Arellano and Bond (1991) estimator. Robust standard errors are reported. Stars represent statistical significance: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$. *DGW*=Downgrade watch. *DG*=Downgrades.

Figure 1: Bank Balance Sheet Characteristics in 2022, by Bank Group



Note: This table shows the average values of bank balance sheet characteristics for the four bank groups throughout 2022. We do not show the average values for 2023Q1 because the deadline for Call Report submission was April 30, 2023—after the end of our sample. The ratios are reported in %. *UID* is the asset share of uninsured deposits. *Losses* is the asset share of unrealized losses on AFS and HTM securities. The *March DGW* group includes banks put on DG watch in March. The *April Only DG* group includes banks downgraded between April 14 and 21. The *Non-DG Resional (Stress-Tested)* group consists of non-downgraded regional (US stress-tested) banks. Banks in the various groups are listed in appendix A. Banks in the various groups are listed in appendix A. *DG*=Downgraded.

Figure 2: **Evolution of Factor Betas Before and During the Run**



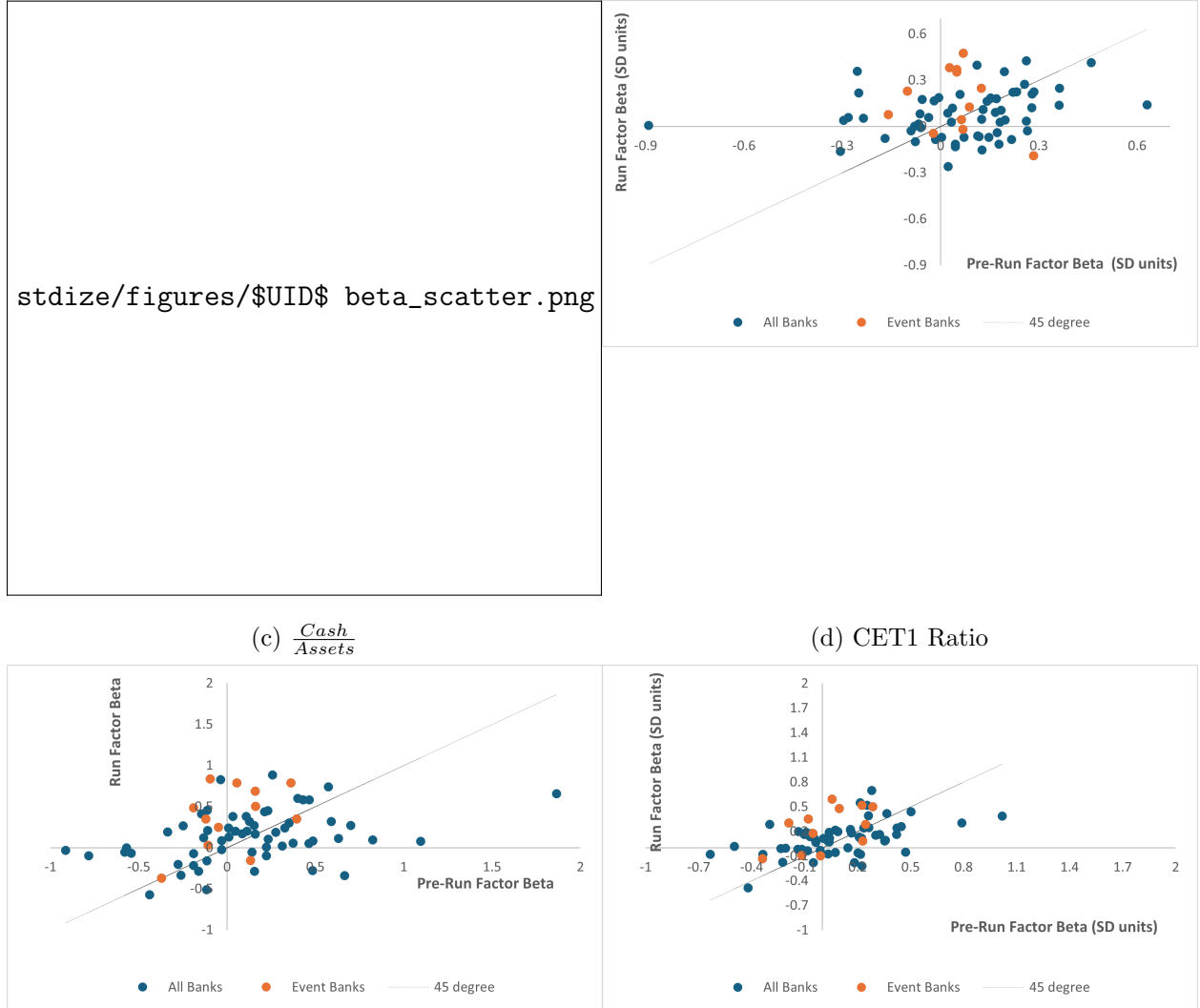
Note: This figure plots point estimates and 95% confidence intervals.

Note: This figure shows the point estimates and 95% confidence intervals from estimating regression (1) for the period January 3 to May 5, 2023. These results can also be found in Table 2. The pre- (post-) run dummy variable *Pre* (*Post*) equals 1 before (since) March 1, 2023. The factors are constructed from long-short portfolios based on 2022Q3 asset shares of uninsured deposits (*UID*), unrealized losses on AFS and HTM securities (*Losses*), cash as shares of assets, and the common equity tier one ratio CET1. The *negative* of the cash and CET1 factor returns is used for consistency with the other factors. Downgraded and failed banks are excluded from the factor construction. SVB, SBNY and Silvergate are not included in the regressions. All variables are standardized to have mean zero and unit standard deviation. Standard errors (used to calculate confidence intervals) are robust and clustered by date.

Figure 3: **Bank Balance Sheet Betas Before and During the Run**

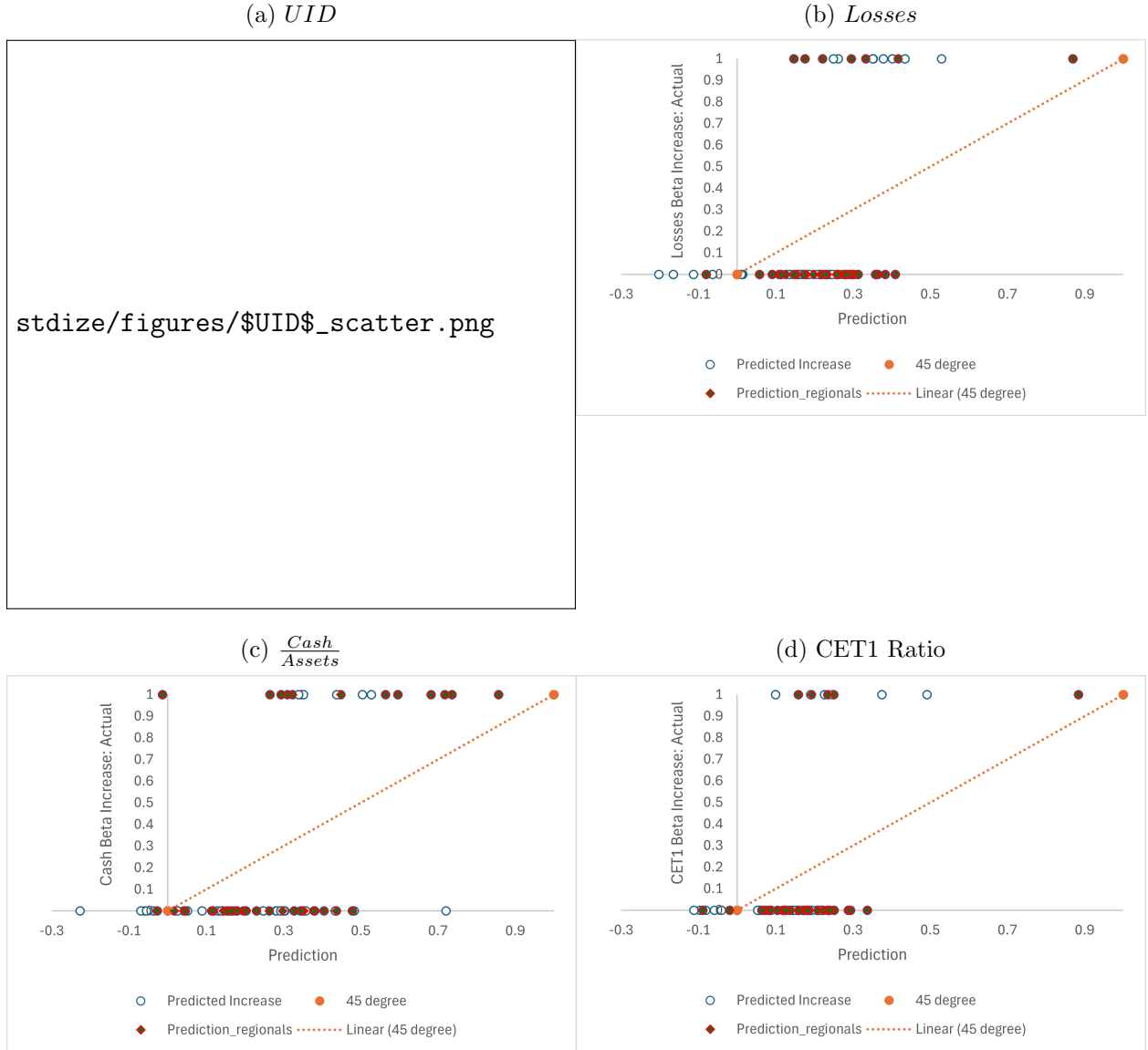
(a) *UID*

(b) *Losses*



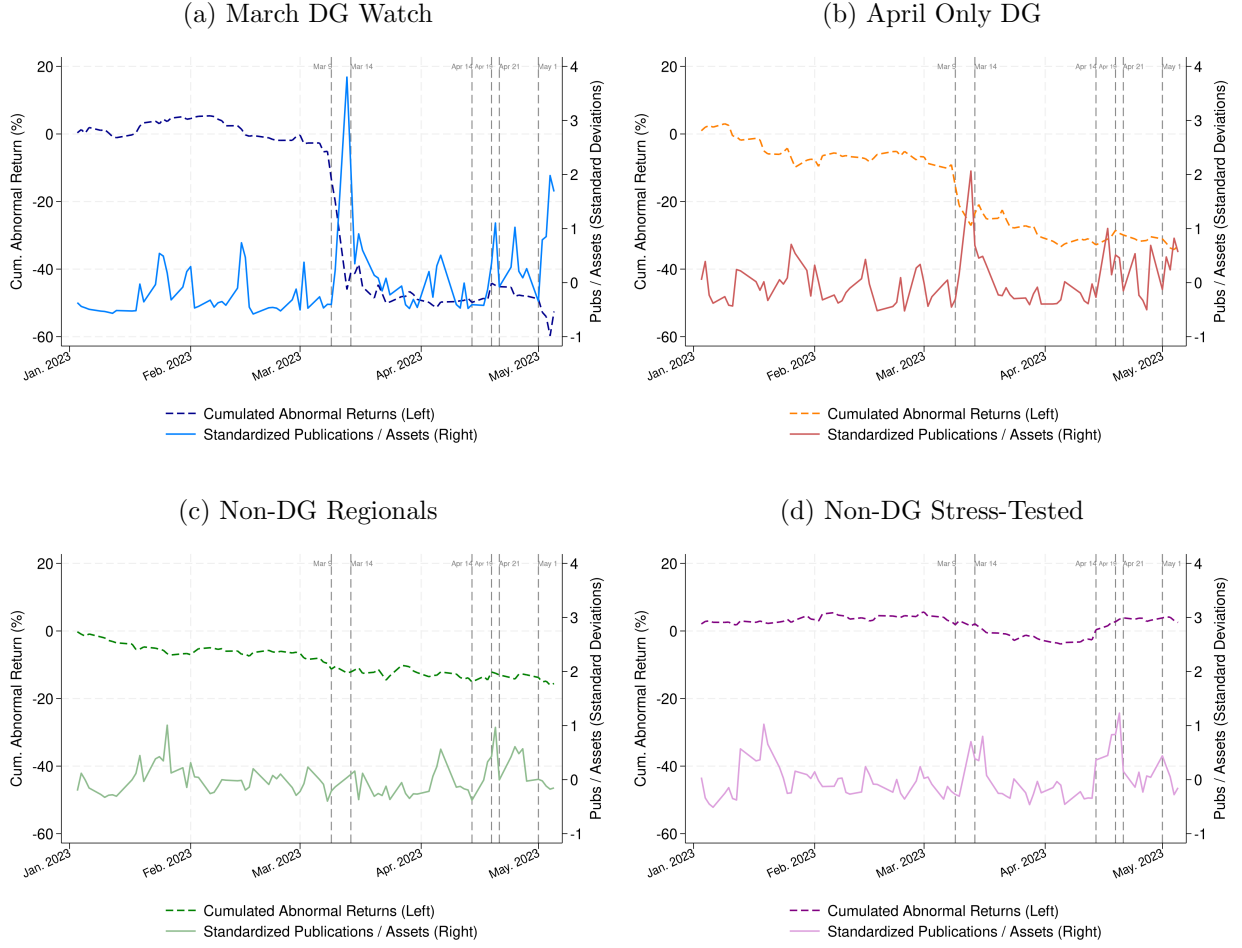
Note: These figures shows scatter plots of factor beta estimates before the run (horizontal axis) versus during the run (vertical axis), obtained by estimating specification (1) bank-by-bank. Colored dots indicate the estimates for the *event* banks (i.e. banks downgraded by rating agencies in April). *UID* is the asset share of uninsured deposits. *Losses* is the asset share of unrealized losses on AFS and HTM securities.

Figure 4: Predicting during the run Increases in Bank Balance Sheet Betas



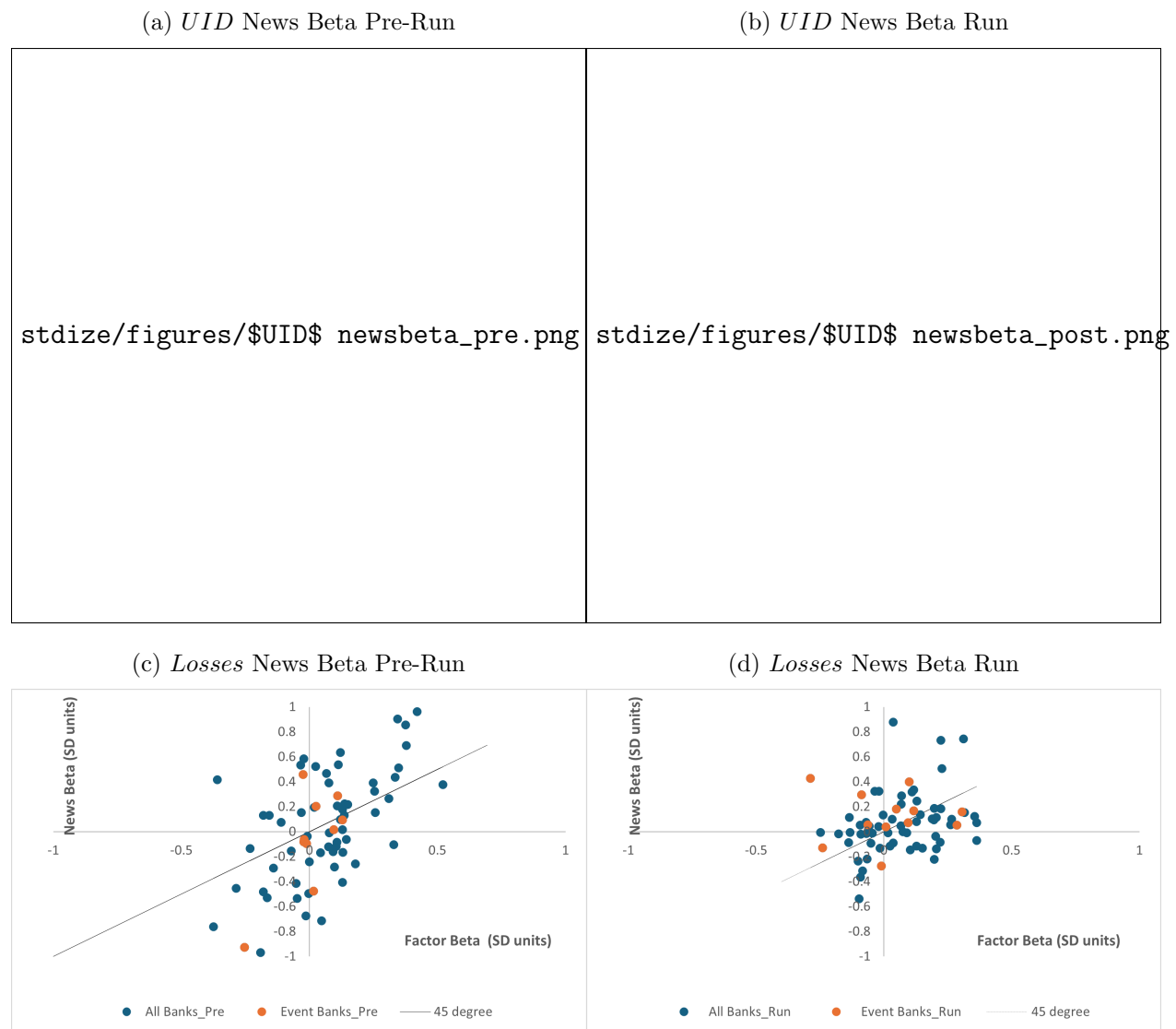
Note: These figures shows scatter plots of actual versus predicted increases in during the run factor betas. The vertical axis plots a dummy variable equal to 1 for banks with significant during the run increases in their factor betas. The horizontal axis shows estimates from the regression (2). Colored dots indicate the estimates for the *non-downgraded Regional* banks. *UID* is the asset share of uninsured deposits. *Losses* is the asset share of unrealized losses on AFS and HTM securities.

Figure 5: Cumulated Abnormal Returns and Standardized Publication Counts



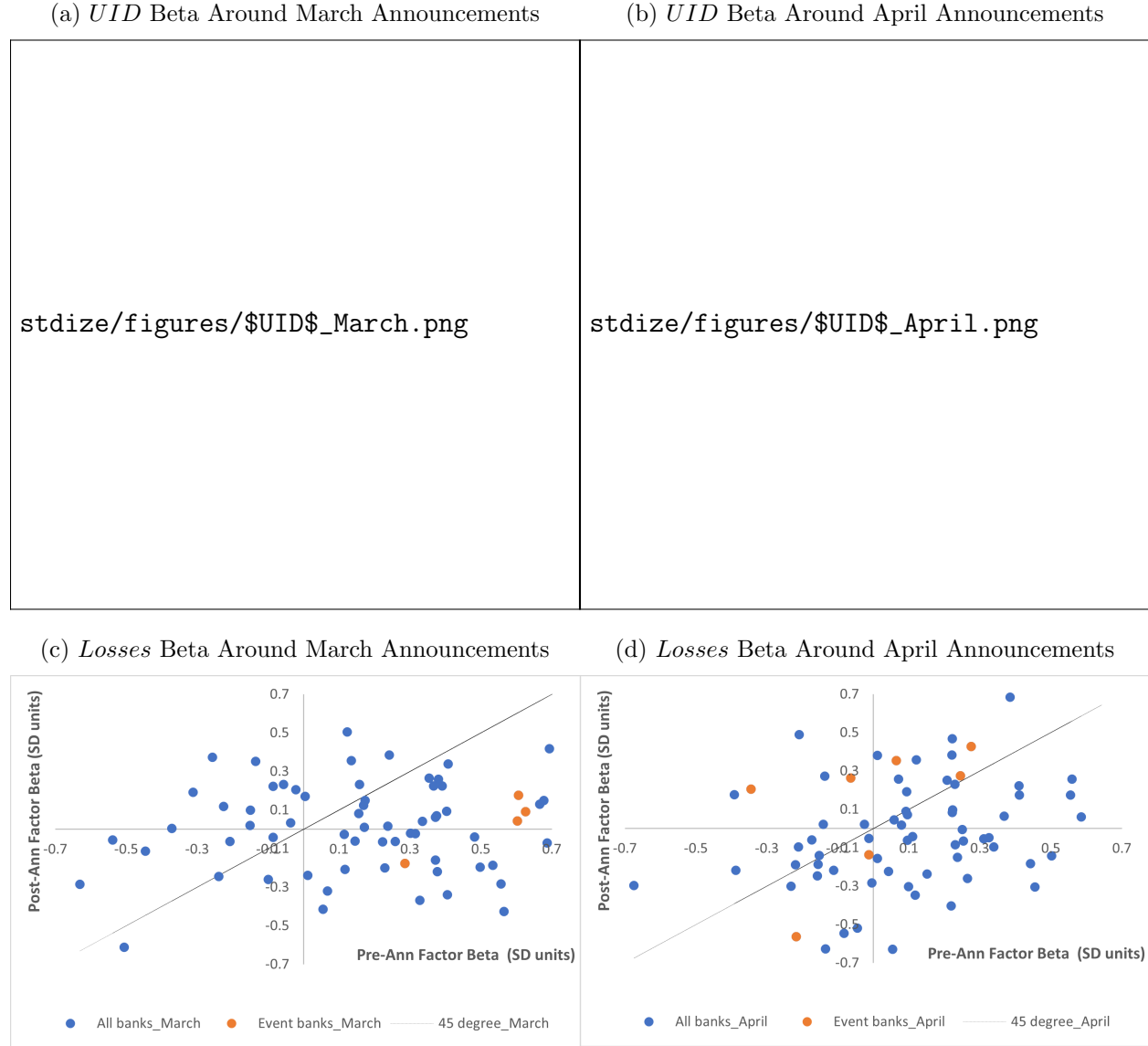
Note: This figure plots the time series of news publications over assets and value-weighted cumulated returns by bank group. News publications over assets are first standardized to have mean zero and unit standard deviation for each bank over the period Jan. – May 5 of 2023. The figure shows the unweighted average by bank group of the standardized series. Abnormal returns for each bank are calculated according to equations (C.1) and (C.2). We then take the value-weighted average of abnormal returns for each day by bank. Finally, we calculate cumulative returns for each group g 's time series as $CAR_{g,t} = \left(\prod_{s=3\text{Jan}2023}^t AR_{g,s} \right) - 1$

Figure 6: Bank Balance Sheet and News Betas Before and During the Run: *UID* and *Losses* Factors



Note: These figures shows scatter plots of *UID* and *Losses* factor β estimates (horizontal axis) versus news β estimates (vertical axis) before the run (left panel) and during the run (right panel), obtained by estimating specification (4) bank by bank from January 1 to May 5, 2023. The news β is the coefficient on the $Factor \times News$ regressor. Colored dots indicate the estimates for the *event* banks (i.e. banks downgraded by rating agencies in April). *UID* is the asset share of uninsured deposits. *Losses* is the asset share of unrealized losses on AFS and HTM securities.

Figure 7: **Bank Balance Sheet Betas Before and After Rating Announcements: *UID* and *Losses* Factors**



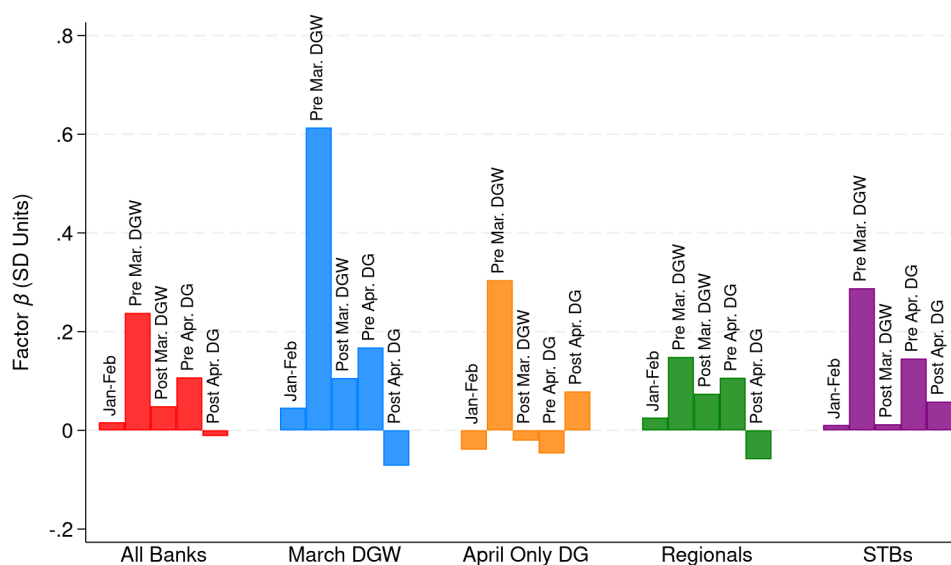
Note: These figures shows scatter plots of *UID* and *Losses* factor β estimates before (horizontal axis) and after (vertical axis) rating announcements, for March (left panel) and April (right panel) announcements, obtained by estimating specification (6) bank by bank from January 1 to May 5, 2023. Colored dots indicate the estimates for the *event* banks (i.e. banks on downgrade watch in March or downgraded in April by rating agencies). *UID* is the asset share of uninsured deposits. *Losses* is the asset share of unrealized losses on AFS and HTM securities.

Figure 8: **Average Betas Around Rating Announcements: *UID* and *Losses* Factors**

(a) *UID* Beta



(b) *Losses* Beta

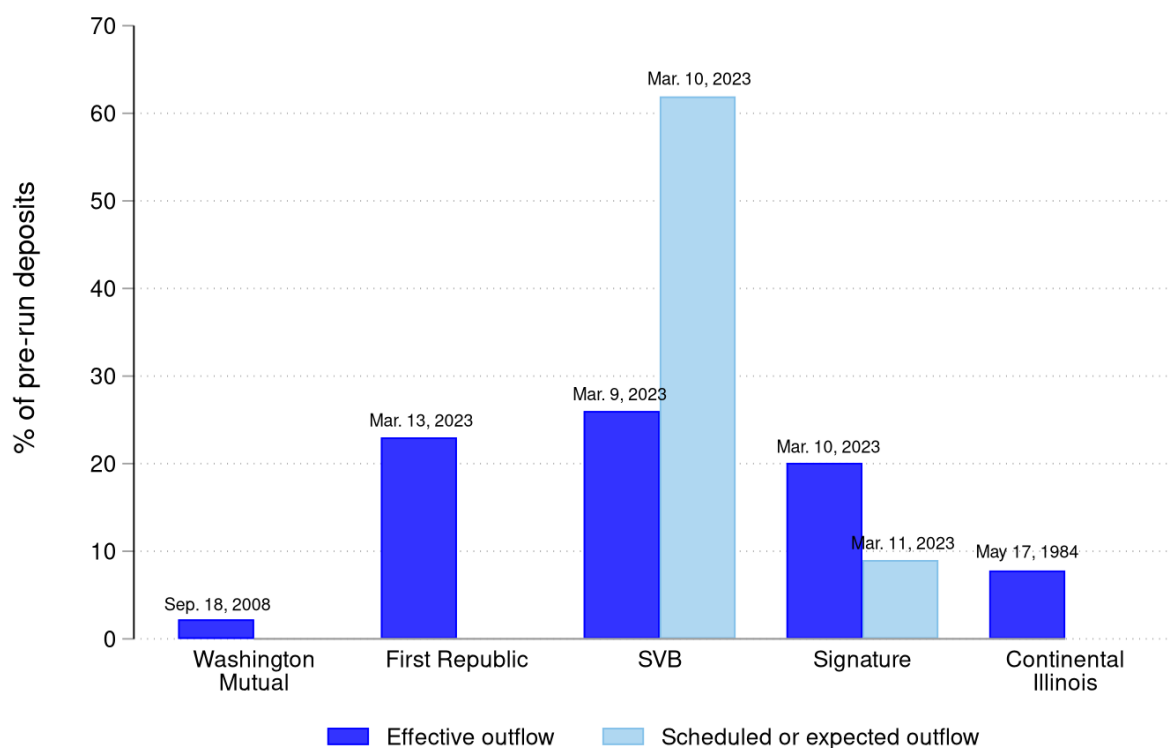


Note: These figures summarize the results of estimating equation (6) bank by bank, from January 1 to May 5, 2023. We show the average β for all banks in a given group and period before and after the March and April rating announcements. We directly estimate the β for the Jan.-Feb. period. For the remaining periods, we estimate the change in the beta relative to Jan.-Feb. For these periods, we plot the sum of

A Appendix A: Data

A.1 Peak Deposit Withdrawals During Bank Runs

Figure A.1: Peak 1-Day Deposit Withdrawal Rates



Note: The figure shows the 1-day peak deposit withdrawals as a percent of pre-run deposits, and the associated dates, for select banks during the March 2023 bank run, and for Continental Illinois and Washington Mutual. Banks are sorted by inflation adjusted assets from left (highest) to right (lowest). The data is from FRB (2023) and Rose (2023).

A.2 Linking Balance Sheet and Stock Data

We start with a list of 74 bank stock tickers, which include the 71 stock in our four groups along with SVB, SBNY and Silvergate. We use this list of tickers to obtain stock returns, market capitalization, permanent company code (PERMCO) and entity name from CRSP. We then merge this list of PERMCOs to the Federal Reserve Bank of New York’s PERMCO-RSSD crosswalk for all PERMCO-RSSD mappings that have an end date after the start of our sample (January 3, 2022).¹⁸ This crosswalk matches with 71 of the 74 banks.¹⁹ For the remaining three banks, we manually map them to an RSSD using the following procedure. We take the entity name from CRSP and paste it into the Federal Financial Institutions Examination Council’s (FFIEC) RSSD Lookup tool.²⁰ Each of the three entity names yields only one result in the FFIEC data which gives us the RSSD of the bank. Having obtained a mapping from bank stocks to RSSDs, we are able to map the returns data to balance sheet data from Call Reports and FR Y-9C filings.

A.3 Call Report Submission Deadlines

To sort banks into the long-short portfolios, we use balance sheet data from the previous quarter, starting the day after the submission deadline for the previous quarter’s Call Report until the submission deadline of the next Call Report. The submission deadlines and dates for which we use the Call Reports are listed in Table A.1. An illustration of how the Call Reports submission dates inform the calculation of factor returns is in Figure A.2.

Table A.1: Call Report Submission Deadlines

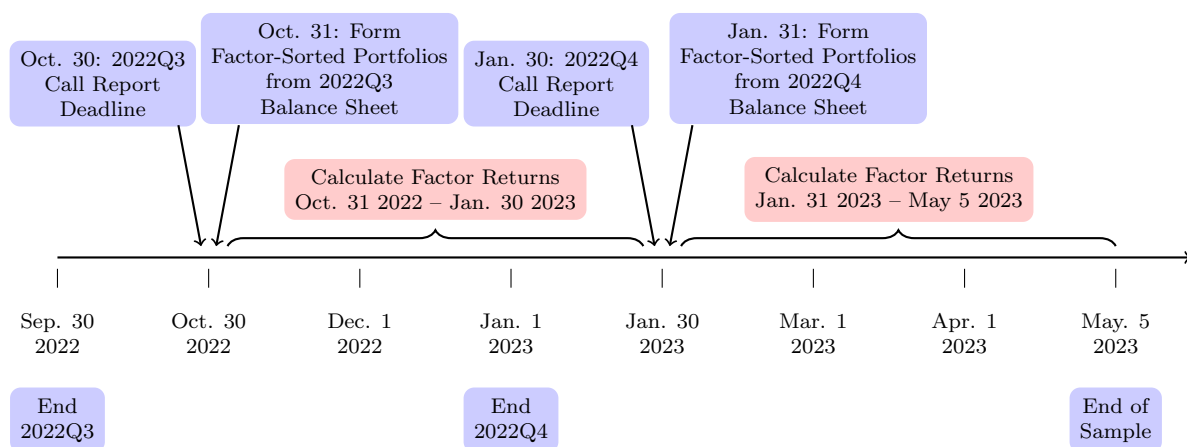
Call Report Quarter	Submission Deadline	Factor Return Dates
2021Q3	October 30, 2021	January 1, 2022 – January 30, 2022
2021Q4	January 30, 2022	January 31, 2022 – April 30, 2022
2022Q1	April 30, 2022	May 1, 2022 – July 30, 2022
2022Q2	July 30, 2022	July 31, 2022 – October 30, 2022
2022Q3	October 30, 2022	October 31, 2022 – January 30, 2023
2022Q4	January 30, 2023	January 31, 2023 – April 30, 2023
2023Q1	April 30, 2023	N/A

¹⁸Available here: https://www.newyorkfed.org/research/banking_research/crsp-frb

¹⁹The three unmatched banks are Cadence Bank, Eastern Bankshares Inc, and Bank OZK,

²⁰Available here: <https://www.ffiec.gov/NPW>

Figure A.2: Call Report Submission Dates and Construction of Factor Returns



Note: The figure illustrates how the Call Report submission dates inform the calculation of factor returns.

A.4 Bank Group Members

A.4.1 March Downgrade Watch and April Downgrade Banks

Banks in the KBW regional banking Index (KRX) as of Jan. 2023 have an asterisk next to their name.

1. First Republic Bank (FRC): placed on downgrade watch on March 14 and its preferred stock rating downgraded on April 21 by Moody's; failed on May 1.
2. Zions Bancorporation, National Association (ZION): placed on downgrade watch on March 14 and downgraded on April 21 by Moody's.
3. Comerica Incorporated (CMA): placed on downgrade watch on March 14 and downgraded on April 21 by Moody's.
4. UMB Financial Corporation* (UMBF): placed on downgrade watch on March 14 and downgraded on April 21 by Moody's.
5. Western Alliance Bancorporation (WAL): placed on downgrade watch on March 14 and downgraded on April 21 by Moody's.

A.4.2 April Only Downgrades

Banks in the KBW regional banking Index (KRX) as of Jan. 2023 have an asterisk next to their name.

1. PacWest Bancorp* (PACW): downgraded by Fitch on April 14.
2. The Charles Schwab Corporation (SCHW): downgraded by S&P on April 19.
3. US Bancorp (USB): downgraded by Moody's on April 21.
4. Associated Banc-Corp* (ASB): downgraded by Moody's on April 21.
5. Banks of Hawaii Corporation* (BOH): downgraded by Moody's on April 21.
6. First Hawaiian, Inc.* (FHB): downgraded by Moody's on April 21.
7. Washington Federal, Inc.* (WAFD): downgraded by Moody's on April 21.

There were 6 other banks downgraded by Moody's on April 21, of which one is not publicly traded (Intrust), and five others (FRC, Zions, Comerica, UMB Financial, and Western Alliance) are in the March downgrade watch group.

A.4.3 Non-Downgraded regional banks

Our sample contains 38 regional banks not in the March downgrade watch or April Only Downgrades group, consisting of those that are listed in the KRX index.

1. First Financial Bancorp. (FFBC)
2. CVB Financial Corp. (CVBF)
3. Brookline Bancorp, Inc. (BRKL)
4. Hope Bancorp, Inc. (HOPE)
5. Glacier Bancorp, Inc. (GBCI)
6. First Citizens BancShares, Inc. (FCNC.A)
7. Hancock Whitney Corporation (HWC)
8. Eastern Bankshares, Inc. (EBC)
9. Fulton Financial Corporation (FULT)
10. United Community Banks, Inc. (UCBI)
11. Cullen/Frost Bankers, Inc. (CFR)
12. First Interstate BancSystem, Inc. (FIBK)
13. SouthState Corporation (SSB)
14. Synchrony Financial (SYF)
15. Independent Bank Corp. (INDB)
16. Old National Bancorp (ONB)
17. Cadence Bank (CADE)
18. Prosperity Bancshares, Inc. (PB)
19. BOK Financial Corporation (BOKF)
20. Commerce Bancshares, Inc. (CBSH)
21. Home Bancshares, Inc. (HOMB)
22. Pacific Premier Bancorp, Inc. (PPBI)
23. Ameris Bancorp (ABCB)
24. First Commonwealth Financial Corporation (FCF)

25. BankUnited, Inc. (BKU)
26. Texas Capital Bancshares, Inc. (TCBI)
27. Bank OZK (OZK)
28. Simmons First National Corporation (SFNC)
29. Synovus Financial Corp. (SNV)
30. First Financial Bankshares, Inc. (FFIN)
31. Atlantic Union Bankshares Corporation (AUB)
32. Trustmark Corporation (TRMK)
33. Pinnacle Financial Partners, Inc. (PNFP)
34. Cathay General Bancorp (CATY)
35. Wintrust Financial Corporation (WTFC)
36. WSFS Financial Corporation (WSFS)
37. F.N.B. Corporation (FNB)
38. United Bankshares, Inc. (UBSI)

A.4.4 STBs

This group includes 21 of the 34 banks that were part of the 2022 Federal Reserve stress tests that were also in the KBW index and not in the March downgrade watch or April Only Downgrades.²¹

1. Ally Financial Inc. (ALLY)
2. American Express Company (AXP)
3. Bank of America Corporation (BAC)
4. Bank of Mellon New York Corporation (BK)
5. Capital One Financial Corporation (COF)
6. Citigroup Inc.(C)
7. Citizens Financial Group, Inc. (CFG)
8. Discover Financial Services (DFS)

²¹For the full list of STBs see Table 2 of "2022 Federal Reserve Stress Test Results," available at 2022 stress test results.

9. Fifth Third Bancorp (FITB)
10. Goldman Sachs Group, Inc. (GS)
11. Huntington Bancshares Incorporated (HBAN)
12. JPMorgan Chase & Co. (JPM)
13. Keycorp (KEY)
14. M&T Bank Corporation (MTB)
15. Morgan Stanley (MS)
16. Northern Trust Corporation (NTRS)
17. PNC Financial Services Group, Inc. (PNC)
18. Regions Financial Corporation (RF)
19. State Street Corporation (STT)
20. Truist Financial Corporation (TFC)
21. Wells Fargo & Company (WFC)

B Appendix B: Crisis Effects on Bank Betas

B.1 Overlap of Banks in Long/Short Factor Portfolio Groups

Table B.1 shows the degree of overlap in the long and short buckets for each factor. The buckets are reconstructed upon the submission deadline of the quarterly Call Report. For the given factor pair, each cell shows the number of banks that are in the long portfolio for both factors plus the number of banks that are in the short portfolio for both factors. Since there are 20 banks in each of the long portfolio and the short portfolio, the maximum overlap is 40 banks, which would occur if the long and short portfolios for two factors were identical in bank composition. For *UID* and *Losses* the long portfolio is the tercile with the highest values, and for Cash and CET1 the long portfolio is the lowest tercile.

Table B.1: **Overlap of Banks in Factor Groups**

2021Q3					2021Q4				
	Losses	UID	Cash	CET1		Losses	UID	Cash	CET1
Losses	Losses
UID	12	.	.	.	UID	10	.	.	.
Cash	12	15	.	.	Cash	15	16	.	.
CET1	14	14	14	.	CET1	13	14	16	.

2022Q1					2022Q2				
	Losses	UID	Cash	CET1		Losses	UID	Cash	CET1
Losses	Losses
UID	16	.	.	.	UID	16	.	.	.
Cash	22	17	.	.	Cash	22	15	.	.
CET1	14	11	13	.	CET1	15	13	18	.

2022Q3					2022Q4				
	Losses	UID	Cash	CET1		Losses	UID	Cash	CET1
Losses	Losses
UID	17	.	.	.	UID	15	.	.	.
Cash	22	18	.	.	Cash	22	16	.	.
CET1	13	14	15	.	CET1	14	12	15	.

Note: This table shows the degree of overlap in the long and short buckets for each factor. The buckets are reconstructed upon the submission deadline of the quarterly Call Report. For the given factor pair, each cell shows number of banks that are in the long portfolio for both factors plus the number of banks that are in the short portfolio for both factors. Since there are 20 banks in each the long portfolio and the short portfolio, the maximum overlap is 40 banks, which would occur if the long and short portfolios for two factors are identical in bank composition. For *UID* and *Losses* the long portfolio is the tercile with the highest values, and for *Cash* and *CET1* the long portfolio is the lowest tercile.

B.2 2022Q3 Balance Sheet Values of Banks with Increases in Factor Betas During the Run

Do increases in beta during the run reflect bank risk in the cross-section? To answer this question, Table B.2 reports the median values of balance sheet characteristics in 2022Q3 of banks with significantly higher betas during the run (i.e., banks with significantly positive betas during the run *and* insignificant or negative pre-run betas). A Wilcoxon test is used

to compare the medians and exact p-values are reported.²² Panel A of the table reports statistics for the *UID* factor. At the 5% level of significance, the 18 banks with higher *UID* betas during the run had higher median uninsured deposits and unrealized loss shares compared to other banks. This result also holds when considering increases in the *Losses* beta (Panel B of Table B.2) and the *Cash* beta but not the *CET1* beta (see Table B.3). However, results are not consistent across bank groups. Thus, event banks with increased betas during the run were larger, had more uninsured deposits and losses, but also more cash and similar CET1, with no difference being statistically significant. Of the STBs, increases in the *UID* and *Losses* betas during the run occurred for those banks with significantly higher losses, lower cash and lower CET1, but this result does not hold for the Cash and CET1 betas. For the regionals, increased *UID* and cash betas during the run occurred for banks with more uninsured deposits, but also with *more* cash or CET1.

²²The standard asymptotic p-values are likely invalid due to the small sample sizes. The computation of exact values is based on exact conditional inference for contingency tables (Agresti (1992)).

Table B.2: **2022Q3 Balance Sheet Values of Banks with Increases in *UID* and *Losses* Betas During the Run**

Panel A: Factor=UID							
	N	Assets (\$B)	Unin. Dep %	Losses %	Cash %	CET1 %	Eret %
All Banks, Beta<0 or insig	53	38.05	44.53	2.45	4.40	11.02	2.09
All Banks, Beta>0 & sig	18	94.62*	55.85**	3.64**	3.93	9.96	1.97
Event Banks, Beta<0 or insig	6	31.46	50.93	2.78	3.06	9.64	2.23
Event Banks, Beta>0 & sig	6	86.41*	61.76	4.00	6.06	9.79	1.79
Non-DG STB, Beta<0 or insig	15	444.23	35.78	1.86	10.50	10.98	2.82
Non-DG STB, Beta>0 & sig	6	207.69	45.80	3.40**	3.29**	9.29***	2.25
Non-DG Regionals, Beta<0 or insig	32	26.48	45.42	2.57	3.13	11.14	1.81
Non-DG Regionals, Beta>0 & sig	6	33.50	60.95**	2.93	6.96	13.12**	2.12
Panel B: Factor=Losses							
	N	Assets (\$B)	Unin. Dep %	Losses %	Cash %	CET1 %	Eret %
All Banks, Beta<0 or insig	56	43.21	44.20	2.45	4.53	11.06	2.08
All Banks, Beta>0 & sig	15	47.70	51.99***	3.68**	3.33	10.25	1.95
Event Banks, Beta<0 or insig	7	38.05	50.30	2.95	3.29	9.65	2.09
Event Banks, Beta>0 & sig	5	84.34	65.21	4.32	5.69	9.93	1.74
Non-DG STB, Beta<0 or insig	18	365.76	38.90	2.01	9.66	10.68	2.74
Non-DG STB, Beta>0 & sig	3	190.23	48.28	3.93***	2.75**	9.12***	2.46
Non-DG Regionals, Beta<0 or insig	31	29.05	44.53	2.52	3.09	11.73	1.82
Non-DG Regionals, Beta>0 & sig	7	23.69	49.93*	3.35	3.33	11.08	2.02

Note: This table shows the median balance sheet values and excess returns in 2022Q3 of banks with increases in their *UID* and *Losses* factor betas after the bank run for 3 bank groups. The ratios are reported as % of assets in 2022Q3. *Losses* are differences between par and fair values of AFS and HTM securities. The *Event* banks were downgraded during the bank run. The *regionals (STB)* group consists of non-downgraded regional (US stress-tested) banks. Banks in the various groups are listed in appendix A. ***(**)* indicate statistical significance at the 1%(5%)10% level based on a Wilcoxon test with exact computation of p-values. *DG*=Downgraded. *Unin.Dep.* = Uninsured Deposits. *Eret*=excess returns. *Sig*=Significant. *Insig*=Insignificant.

Table B.3: **2022Q3 Balance Sheet Values of Banks with Increases in Cash and CET1 Betas During the Run**

Panel A: Factor=Cash							
	N	Assets (\$B)	Unin. Dep %	Losses %	Cash %	CET1 %	Eret %
All Banks, Beta<0 or insig	52	43.21	44.20	2.44	4.12	10.78	2.05
All Banks, Beta>0 & sig	19	47.70	51.99***	3.68***	4.04	11.10	1.97
Event Banks, Beta<0 or insig	7	38.05	50.30	2.95	3.82	9.65	1.96
Event Banks, Beta>0 & sig	5	84.34	58.32	4.55	2.83	9.93	1.85
Non-DG STB, Beta<0 or insig	19	225.14	42.03	2.15	8.37	10.62	2.67
Non-DG STB, Beta>0 & sig	2	488.20	46.32	3.62*	16.67	9.53	1.95
Non-DG Regionals, Beta<0 or insig	26	26.90	44.50	2.44	2.93	11.27	1.81
Non-DG Regionals, Beta>0 & sig	12	27.11	51.15**	3.36	4.27*	12.13	2.10
Panel B: Factor=CET1							
	N	Assets (\$B)	Unin. Dep %	Losses %	Cash %	CET1 %	Eret %
All Banks, Beta<0 or insig	60	44.45	44.93	2.57	3.84	10.90	2.04
All Banks, Beta>0 & sig	11	37.85	49.93	3.68	5.57	11.10	1.97
Event Banks, Beta<0 or insig	7	41.40	50.30	2.95	3.29	9.61	1.96
Event Banks, Beta>0 & sig	5	69.16	65.21	4.32	5.69	11.18	1.85
Non-DG STB, Beta<0 or insig	20	365.76	42.26	2.40	8.29	10.24	2.62
Non-DG STB, Beta>0 & sig	1	197.96	49.27	0.92	13.97	10.75	3.04
Non-DG Regionals, Beta<0 or insig	33	26.73	46.68	2.52	3.09	11.73	1.82
Non-DG Regionals, Beta>0 & sig	5	34.57	48.84	3.29	5.12	11.10	3.50

Note: This table shows the median balance sheet values and excess returns in 2022Q3 of banks with increases in their *Cash* and *CET1* factor betas after the bank run for 3 bank groups. The ratios are reported as % of assets in 2022Q3. *Losses* are differences between par and fair values of AFS and HTM securities. The *Event* banks were downgraded during the bank run. The *regionals (STB)* group consists of non-downgraded regional (US stress-tested) banks. Banks in the various groups are listed in appendix A. ***(**)* indicate statistical significance at the 1%(5%)10% level based on a Wilcoxon test with exact computation of p-values. *DG*=Downgraded. *Unin.Dep.* = Uninsured Deposits. *Eret*=excess returns. *Sig*=Significant. *Insig*=Insignificant.

Table B.4: Predicting Increases in Cash and CET1 Betas During the Run

Panel A: Predicting Increases in Post-Run Cash Beta						
	Estimate	SE	Estimate	SE	Estimate	SE
Asset Growth	0.05	0.08	0.06	0.08	0.06	0.08
<i>NetInc</i>	-0.13	0.13	-0.08	0.11	-0.09	0.11
<i>TimeDep</i>	-0.37*	0.20	-0.30	0.20	-0.31	0.21
<i>NetInc</i> \times <i>TimeDep</i>	0.40	0.34	0.42	0.32	0.43	0.32
UID			0.10	0.16	0.10	0.17
Losses			0.13	0.36	0.13	0.36
UID*Losses			0.03	0.39	0.03	0.39
Pubcounts					0.05	0.12
Intercept	0.27***	0.06	0.27***	0.06	0.27***	0.06
Obs	71		71		71	
Adj R2	0.04		0.18		0.18	
Root MSE, All Banks	0.44		0.40		0.40	
Root MSE, Event Banks	0.48		0.44		0.44	
Root MSE, Non-DG STB	0.36		0.32		0.32	
Root MSE, Non-DG Regionals	0.43		0.39		0.39	
Panel B: Predicting Increases in Post-Run CET1 Beta						
	Estimate	SE	Estimate	SE	Estimate	SE
Asset Growth	0.04	0.07	0.05	0.07	0.05	0.07
<i>NetInc</i>	0.01	0.10	0.04	0.08	0.03	0.08
<i>TimeDep</i>	-0.12	0.09	-0.12	0.13	-0.15	0.13
<i>NetInc</i> \times <i>TimeDep</i>	0.04	0.13	0.08	0.17	0.11	0.17
UID			0.17	0.15	0.17	0.15
Losses			0.22	0.36	0.22	0.36
UID*Losses			-0.24	0.38	-0.25	0.38
Pubcounts					0.08	0.09
Intercept	0.15***	0.04	0.15***	0.05	0.15***	0.05
Obs	71		71		71	
Adj R2	0.00		0.03		0.07	
Root MSE, All Banks	0.36		0.36		0.35	
Root MSE, Event Banks	0.53		0.48		0.49	
Root MSE, Non-DG STB	0.24		0.23		0.23	
Root MSE, Non-DG Regionals	0.33		0.33		0.31	

Note: The table shows results from a cross-section regression of an indicator for banks with higher during the run cash and CET1 betas on its balance sheet values as of 2022Q3. *Losses* are differences between par and fair values of AFS and HTM securities. *Event Banks* include banks put on down-grade (DG) watch in March or downgraded in April. The *Non-DG Regional (STB)* group consists of non-downgraded regional (US stress-tested) banks. We report heteroscedasticity-consistent standard errors (SE) based on MacKinnon and White (1985). ***(**)* indicate statistical significance at the 1%(5%)10% level. $UID = \frac{Uninsured\ deposits}{Assets}$. $NetInc = \frac{Net\ Income}{Assets}$. $TimeDep = \frac{Time\ Deposits}{Deposits}$. DG=Downgraded.

C Appendix C: Publication Counts

Table C.1: **Bank Publication Counts in 2022Q4 and OMO Shares in 2022Q3**

Panel A: OMO, 2022Q3							
Bank Group	Number	Mean	Min	P25	P50	P75	Max
All Sample Banks	71	16.99	1.76	10.06	16.37	23.02	53.82
April Only DG	7	23.65	6.73	10.06	23.05	32.14	53.82
March DGW	5	15.10	2.54	5.16	21.72	21.76	24.34
STBs	21	17.01	1.76	13.05	17.03	21.69	30.20
Regional Banks	38	16.01	4.11	8.69	15.06	21.28	38.76
SBNY	1	20.21	20.21	20.21	20.21	20.21	20.21
SI	1	48.50	48.50	48.50	48.50	48.50	48.50
SIVB	1	52.12	52.12	52.12	52.12	52.12	52.12
Panel B: PUBCOUNT, 2022Q4							
Bank Group	Number	Mean	Min	P25	P50	P75	Max
All Sample Banks	71	14.78	0.18	3.56	6.39	15.43	316.14
April Only DG	7	18.87	0.36	4.24	8.14	20.34	288.89
March DGW	5	8.38	0.47	1.48	3.50	8.86	101.27
STBs	21	10.40	0.18	2.69	5.92	13.74	269.32
Regional Banks	38	17.29	0.91	3.83	7.04	17.60	316.14
SBNY	1	6.31	0.91	1.81	3.62	7.25	36.24
SI	1	182.33	8.81	44.03	140.90	281.80	651.66
SIVB	1	6.55	0.47	2.83	4.72	7.08	53.83

Note: The table shows the distribution of the asset share of OMO collateral in 2022Q3 (Panel A) and 100*publication counts, normalized by assets in \$B, in 2022Q4 (Panel B). SVB, SBNY, Silvergate are not in the sample but shown for reference. The *March DGW* group includes banks put on DG watch in March. The *April Only DG Banks* group includes banks downgraded between April 14 and 28. The *regional banks* (STB) group consists of non-DG regional (US stress-tested) banks. Banks in the various groups are listed in appendix A. *DG*=Downgraded.

C.1 Estimating Bank Abnormal Returns

We compute bank abnormal returns relative to the Fama-French 5-factor model using 2022 data.

$$R_{i,t} = \alpha_{0,i} + \sum_{j=1}^5 \delta_{j,i} FF_{j,t} + \epsilon_{it} \quad (\text{C.1})$$

$R_{i,t}$ is the stock return for bank i at time t . FF_j denotes one of the 5 Fama-French factors (i.e., the market excess return RM-RF, SMB, HML, RMW and CMA).²³

²³Data for the Fama-French factors are downloaded from the Kenneth R. French data library (FFData). We thank Kenneth French for use of the data.

Let $\hat{\alpha}_{0,i}$ and $\hat{\delta}_{j,i}$, $i = 1, \dots, 6$ be the coefficients from estimating equation (C.1) for 2022. Then, for day t in 2023, the abnormal returns $AR_{i,t}$ for bank i are defined as:

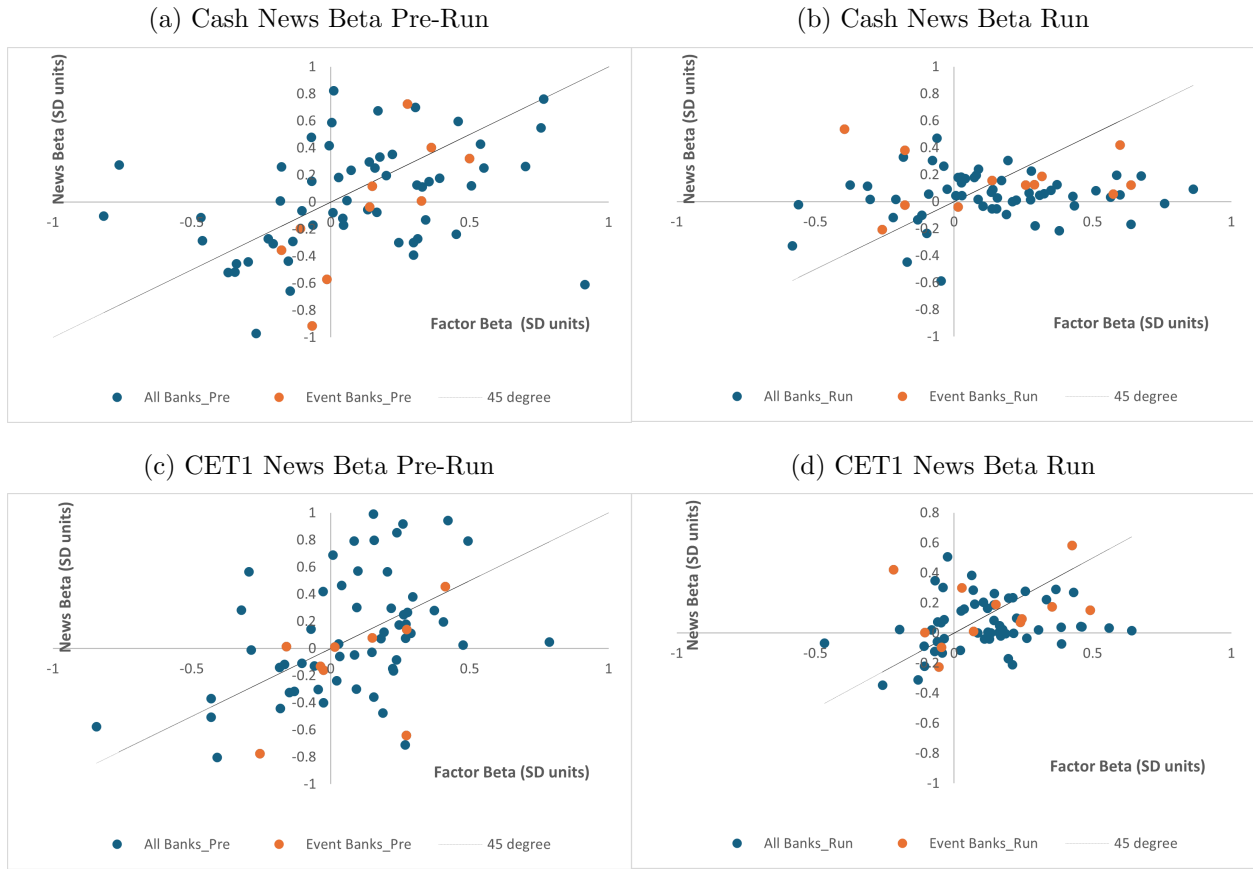
$$AR_{i,t} = R_{i,t} - \hat{\alpha}_{0,i} - \sum_{j=1}^5 \hat{\delta}_{j,i} FF_{j,t} - \hat{\delta}_{6,i} (KBWR_t - RF_t) \quad (\text{C.2})$$

Table C.2: **Effect of News on Cash and CET1 Factor Betas: Before and during the run**

Panel A: Cash Factor						
	News=Pubcount		News=Pubcount_MA2		News=Pubcount_MA3	
	Estimate	SE	Estimate	SE	Estimate	SE
Factor*Pre	0.10	0.06	0.08	0.07	0.08	0.07
Factor*Post	0.15***	0.05	0.15***	0.05	0.16***	0.05
Banksize Factor*Pre	0.03	0.06	0.08	0.05	0.08	0.06
Banksize Factor*Post	0.06	0.05	0.06	0.05	0.05	0.05
News*Pre	0.01	0.03	0.00	0.03	0.02	0.03
News*Post	0.03	0.03	0.04	0.04	0.02	0.04
News*Factor*Pre	0.06	0.06	0.08*	0.04	0.08	0.05
News*Factor*Post	0.05*	0.03	0.08**	0.04	0.09*	0.04
Obs	6101		6030		5959	
Adj R2	0.59		0.60		0.60	
FF5 and Bank MVE?	YES		YES		YES	
Bank FE	YES		YES		YES	
Panel B: CET1 Factor						
	News=Pubcount		News=Pubcount_MA2		News=Pubcount_MA3	
	Estimate	SE	Estimate	SE	Estimate	SE
Factor*Pre	0.09	0.07	0.07	0.06	0.08	0.08
Factor*Post	0.12***	0.05	0.12***	0.05	0.13***	0.05
Banksize Factor*Pre	0.07	0.05	0.11**	0.04	0.10**	0.05
Banksize Factor*Post	0.11**	0.04	0.11***	0.04	0.10**	0.04
News*Pre	0.01	0.03	0.00	0.03	0.01	0.04
News*Post	0.04	0.03	0.04	0.04	0.02	0.04
News*Factor*Pre	0.04	0.07	0.06	0.06	0.07	0.07
News*Factor*Post	0.06**	0.02	0.08**	0.03	0.08*	0.04
Obs	6101		6030		5959	
Adj R2	0.59		0.60		0.60	
FF5 and Bank MVE?	YES		YES		YES	
Bank FE	YES		YES		YES	

Note: This table shows results from estimating regression (4) for the period January 3 to May 5, 2023. *Pubcount* is a bank's publication counts divided by assets. *Pubcount-MA x* is the moving average of *Pubcount* over x days. The pre- (post-) run dummy variable *Pre* (*Post*) equals 1 before (since) March 1, 2023. The factors are constructed from long-short portfolios based on 2022Q3 asset shares of cash and the common equity tier one ratio CET1. The *negative* of the cash and CET1 factor returns is used for consistency with the other factors. Downgraded and failed banks are excluded from the factor construction. SVB, SBNY and Silvergate are not included in the regressions. All variables are standardized to have mean zero and unit standard deviation. Standard errors (in parentheses) are robust and clustered by date. Stars represent statistical significance: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Figure C.1: Bank Balance Sheet and News Betas Before and During the Run: Cash and CET1 Factors



Note: These figures shows scatter plots of cash and CET1 factor β estimates (horizontal axis) versus news β estimates (vertical axis) before the run (left panel) and during the run (right panel), obtained by estimating specification (4) bank by bank from January 1 to May 5, 2023. The news β is the coefficient on the $Factor \times News$ regressor. Colored dots indicate the estimates for the *event* banks (i.e. banks downgraded by rating agencies in April).

C.2 Balance Sheet Risk in 2022 and Changes in News Beta During the Bank Run

Table C.3 reports median balance sheet values as of 2022Q3 for banks with increases in their news betas (i.e. with negative or insignificant news betas pre-run and significantly positive news betas during the run). For the *UID* (*Losses*) factor, reported in Panel A (B), we find that, considering all banks, banks with higher news betas during the run had significantly greater uninsured deposits but also more cash (lower CET1). Table C.4 reports similar results for the cash and CET1 factors. Thus, news-induced risk perceptions of investors are weakly correlated with actual balance sheet risk as reflected in 2022Q3 or 2022Q4 balance sheets.

Table C.3: **2022Q3 Balance Sheet Values of Banks with Increases in News Betas During the Run: *UID* and *Losses* Factors**

Panel A: Factor=UID							
	N	Assets (\$B)	Unin. Dep %	Losses %	Cash %	CET1 %	PubCount %
All Banks, No Change in News Beta	53	42.69	44.30	2.45	3.82	10.98	7.63
All Banks, Higher News Beta	18	68.66	50.18**	3.04	6.38*	10.90	7.74
Event Banks, No Change in News Beta	6	53.61	46.29	2.70	2.99	9.64	8.78
Event Banks, Higher News Beta	6	62.87	57.06	4.00	5.82	9.79	7.77
Non-DG STB, No Change in News Beta	15	225.14	42.03	1.86	8.21	10.62	4.73
Non-DG STB, Higher News Beta	6	365.76	48.35	2.80	18.85	10.24	6.40
Non-DG Regionals, No Change in News Beta	32	29.73	46.01	2.75	3.13	11.14	8.03
Non-DG Regionals, Higher News Beta	6	18.45*	49.17	2.44	3.77	12.89*	17.05
Panel B: Factor=Losses							
	N	Assets (\$B)	Unin. Dep %	Losses %	Cash %	CET1 %	PubCount %
All Banks, No Change in News Beta	56	45.70	44.50	2.57	4.53	11.09	8.14
All Banks, Higher News Beta	15	41.40	51.56**	2.93	2.79	9.98*	7.25
Event Banks, No Change in News Beta	6	121.58	42.78	3.15	3.55	9.76	8.78
Event Banks, Higher News Beta	6	55.28	61.76**	4.00	4.26	9.77	7.77
Non-DG STB, No Change in News Beta	19	427.95	42.49	2.37	8.37	10.62	6.06
Non-DG STB, Higher News Beta	2	175.04	38.88	2.88	15.81	9.63	4.97
Non-DG Regionals, No Change in News Beta	31	29.05	47.04	2.62	3.33	11.73	10.44
Non-DG Regionals, Higher News Beta	7	19.95	45.33	2.33	1.98	10.37	7.63

Note: This table shows the median balance sheet values and publication counts (*PubCount*) in 2022Q3 of banks with increases in their news betas (i.e. the coefficient on $Pubcount \times Factor$) associated with the *UID* and *Losses* factors after the bank run. These are banks with negative or insignificant news betas pre-run and significantly positive news betas during the run. The balance sheet values are reported as % of assets in 2022Q3. *Losses* are differences between par and fair values of AFS and HTM securities. The *Event* group includes banks put on DG watch in March and those downgraded between April 14 and 28. The *regionals* (*STB*) group consists of non-downgraded regional (US stress-tested) banks. Banks in the various groups are listed in appendix A. ***(**)* indicate statistical significance at the 1%(5%)10% level based on a Wilcoxon test with exact computation of p-values. *DG*=Downgraded. *Unin.Dep.* = Uninsured Deposits.

Table C.4: **2022Q3 Balance Sheet Values of Banks with Increases in News Betas During the Run: Cash and CET1 Factors**

Panel A: Factor=Cash							
	N	Assets (\$B)	Unin. Dep %	Losses %	Cash %	CET1 %	PubCount %
All Banks, No Change in News Beta	56	44.45	44.20	2.57	3.94	11.05	7.85
All Banks, Higher News Beta	15	41.40	51.07***	2.88	4.40	10.33	6.66
Event Banks, No Change in News Beta	5	38.05	42.29	2.95	3.29	9.86	9.52
Event Banks, Higher News Beta	7	69.16	58.32	3.68	5.69	9.65	7.25
Non-DG STB, No Change in News Beta	18	264.35	42.26	2.26	8.29	10.38	6.16
Non-DG STB, Higher News Beta	3	1,555.99	48.28	2.88	8.83	10.33	6.02
Non-DG Regionals, No Change in News Beta	33	29.05	45.33	2.88	3.18	11.35	9.14
Non-DG Regionals, Higher News Beta	5	17.19*	50.20	2.42	2.79	12.05	6.12
Panel B: Factor=CET1							
	N	Assets (\$B)	Unin. Dep %	Losses %	Cash %	CET1 %	PubCount %
All Banks, No Change in News Beta	56	44.45	44.38	2.48	3.94	10.90	7.65
All Banks, Higher News Beta	15	41.40	51.56**	3.61**	4.76	11.18	7.25
Event Banks, No Change in News Beta	5	38.05	43.27	2.95	3.29	9.65	8.04
Event Banks, Higher News Beta	7	69.16	58.32	4.32	5.69	9.93	8.30
Non-DG STB, No Change in News Beta	18	264.35	42.26	2.26	9.43	10.38	6.16
Non-DG STB, Higher News Beta	3	1,160.03	48.28	2.88	8.08	10.33	6.02
Non-DG Regionals, No Change in News Beta	33	30.41	46.68	2.62	3.18	11.18	9.14
Non-DG Regionals, Higher News Beta	5	19.71**	50.20	2.46	2.79	13.49**	6.12

Note: This table shows the median balance sheet values and publication counts (*PubCount*) in 2022Q3 of banks with increases in their news betas (i.e. the coefficient on $Pubcount \times Factor$) associated with the cash and CET1 factors after the bank run. These are banks with negative or insignificant news betas pre-run and significantly positive news betas during the run. The balance sheet values are reported as % of assets in 2022Q3. The *Event* group includes banks put on DG watch in March and those downgraded between April 14 and 28. The *regionals (STB)* group consists of non-downgraded regional (US stress-tested) banks. Banks in the various groups are listed in appendix A. ***(**)* indicate statistical significance at the 1%(5%)10% level based on a Wilcoxon test with exact computation of p-values. *DG*=Downgraded. *Unin.Dep.* = Uninsured Deposits.

D Appendix D: Credit Ratings

D.1 Informativeness of ratings

Descriptive statistics of returns Table D.1 shows the daily means of abnormal returns for different bank groups around crisis and rating events. SVB, SBNY, and Silvergate are included for comparison. Observations for SVB and SBNY stock prices are dropped after they went into receivership on March 10 and March 12, respectively. For the *March DGW* banks, we show results with and without FRC. On March 9 and 10, the first 2 days of the bank run, failed bank abnormal returns plunged between 12% and 56% per day. The event banks had daily mean abnormal returns of between -7% and -8% on these days. The *Non-DG Regional* banks and the *STBs*’ abnormal returns fell between 1% and 2% on March 9 but reverted on March 10. On March 13, abnormal returns of the *March DGW* banks fell more than 30% while the *April Only DG* bank stocks fell about 8% and the regionals and STBs fell by about 2%. Following the announcement of downgrade watches after the close of markets on March 13, the event banks exhibit *positive* returns on March 14, indicative of return reversals, and suggesting that the announcement likely did not contain new information to stock market investors. In the 12 days before the first downgrade announcement on April 14 (March 28-April 13), the *April Only DG* banks and regionals declined between 4% and 7% cumulatively while other bank stocks were stable. On the downgrade dates of April 14 and 21, the *March DGW* banks fell about 1%-2% while the *April Only DG* and regional banks fell by about 1%. However, stock prices increased for all banks on April 19 when Schwab was downgraded. *STBs* had positive returns on all announcement days in April. These patterns are qualitatively robust when FRC is excluded from the *March DGW* banks (see the row labeled “ex-FRC”), with the decline in *March DGW* bank stocks in the 10 days after the last downgrade on April 21 (April 24-May 5) is almost halved.

Since the March and April bank groups contain few banks, outliers may influence the results. Accordingly, we report in Table ?? of the appendix the daily means of the value-weighted *median* abnormal returns and find robust results. We conclude that there is little evidence that markets anticipated bank risk events in 2023 before the run and, after March 13, spillovers were mostly limited to the small set of event banks on some rating announcement days and following the failure of FRC. Even for the event banks, there does not appear to be a robust association between rating events and returns.

Table D.1: Daily Means of Abnormal Stock Returns, by Bank Group

	1/3 – 2/28	3/1 – 3/8	3/9	3/10	3/13	DG Watch 3/14	3/15 – 3/27	3/28 – 4/13	PACW DG 4/14	4/17 – 4/18	SCHW DG 4/19	4/20	Moody's DGs 4/21	4/24 – 5/5
SVB	0.37	-0.80	-53.81	-57.81
SBNY	-0.14	-1.32	-5.90	-18.05
Silvergate	-0.51	-12.64	-34.27	-3.08	-5.31	-12.25	0.44	-2.36	-1.97	-1.64	5.42	2.08	-7.18	-0.94
March DG Watch Banks	-0.02	-0.73	-8.63	-7.69	-32.57	9.49	-1.27	-0.07	-2.34	0.67	9.92	-1.17	-0.71	-1.16
March DG Watch Banks Ex-FRC	0.06	-0.56	-5.35	-4.90	-23.24	2.98	0.18	-0.04	-2.23	1.04	9.60	-1.21	-1.26	-0.70
April Only DG Banks	-0.17	-0.42	-7.01	-6.77	-7.52	4.85	-0.51	-0.55	-1.32	1.91	2.47	-1.26	-0.68	-0.47
Non-DG Regional Banks	-0.16	-0.59	-1.89	0.87	-2.12	0.32	0.26	-0.34	-1.42	0.35	2.74	-0.39	-0.60	-0.29
Non-DG Stress-Tested Banks	0.14	-0.41	-0.89	1.15	-1.52	0.65	-0.37	-0.12	3.07	1.07	0.18	0.77	0.36	-0.13

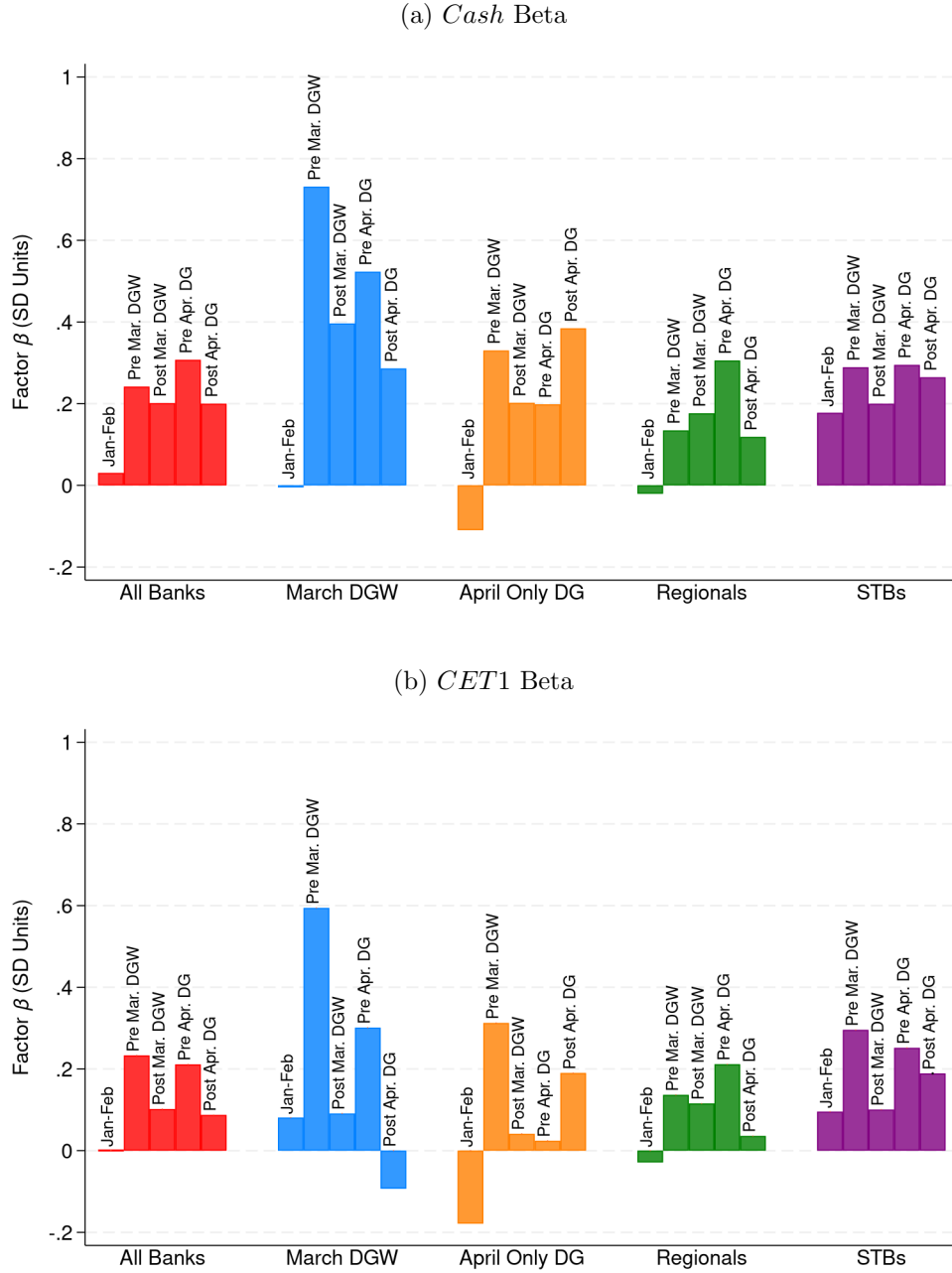
Note: The table shows market value-weighted average abnormal bank stock returns (in %) from January 3, 2023 to May 5, 2023 for different banks groups and sample periods. Abnormal returns for each bank and day are calculated according to equations (C.1) and (C.2) in Appendix C. The table reports the daily market capitalization weighted average of abnormal returns across all banks in a given group. In the *March DGW* group, First Republic Bank (FRC) is dropped on and after May 1, 2023. We also show the *March DGW* group *excluding* FRC throughout the entire sample. The *April Only DG Banks* group includes banks downgraded between April 14 and 21. The *Non-DG Regional (Stress-Tested) Banks* groups consist of non-downgraded regional (US stress-tested) banks. Banks in the various groups are listed in appendix A. *DG*=Downgraded.

Table D.2: Changes in Bank Betas Around Rating Announcements: Excluding March 9-13

Panel A: Factor=UID										
	N	Mean β Jan-Feb	March Announcement				April Announcements			
			Pre		Post		Pre		Post	
			$\Delta\beta$ wrt Jan-Feb	% $\beta > 0$ & $p \leq 0.05$	$\Delta\beta$ wrt Jan-Feb	% $\beta > 0$ & $p \leq 0.05$	$\Delta\beta$ wrt Jan-Feb	% $\beta > 0$ & $p \leq 0.05$	$\Delta\beta$ wrt Jan-Feb	% $\beta > 0$ & $p \leq 0.05$
All Banks	71	-0.09	0.60	46.48	0.31	26.76	0.38	32.39	0.30	28.17
April Only DG	7	-0.20	0.71	42.86	0.51	57.14	0.46	28.57	0.61	57.14
March DGW	5	0.05	0.31	60.00	0.22	20.00	0.40	40.00	0.17	20.00
STBs	21	-0.06	0.66	47.62	0.34	28.57	0.35	23.81	0.41	38.10
Regionals	38	-0.11	0.58	44.74	0.27	21.05	0.38	36.84	0.20	18.42
Panel B: Factor=Losses										
	N	Mean β Jan-Feb	March Announcement				April Announcements			
			Pre		Post		Pre		Post	
			$\Delta\beta$ wrt Jan-Feb	% $\beta > 0$ & $p \leq 0.05$	$\Delta\beta$ wrt Jan-Feb	% $\beta > 0$ & $p \leq 0.05$	$\Delta\beta$ wrt Jan-Feb	% $\beta > 0$ & $p \leq 0.05$	$\Delta\beta$ wrt Jan-Feb	% $\beta > 0$ & $p \leq 0.05$
All Banks	71	0.01	0.76	53.52	0.04	7.04	0.08	7.04	-0.02	5.63
April Only DG	7	-0.05	0.88	57.14	0.03	14.29	0.01	0.00	0.13	0.00
March DGW	5	0.05	0.15	20.00	0.05	0.00	0.13	20.00	-0.13	0.00
STBs	21	0.01	0.93	76.19	0.01	0.00	0.12	0.00	0.06	9.52
Regionals	38	0.02	0.72	44.74	0.06	10.53	0.07	10.53	-0.07	5.26
Panel C: Factor=Cash										
	N	Mean β Jan-Feb	March Announcement				April Announcements			
			Pre		Post		Pre		Post	
			$\Delta\beta$ wrt Jan-Feb	% $\beta > 0$ & $p \leq 0.05$	$\Delta\beta$ wrt Jan-Feb	% $\beta > 0$ & $p \leq 0.05$	$\Delta\beta$ wrt Jan-Feb	% $\beta > 0$ & $p \leq 0.05$	$\Delta\beta$ wrt Jan-Feb	% $\beta > 0$ & $p \leq 0.05$
All Banks	71	0.04	0.04	9.86	0.21	23.94	0.32	26.76	0.22	14.08
April Only DG	7	-0.08	0.92	28.57	0.37	14.29	0.38	14.29	0.56	14.29
March DGW	5	0.01	0.49	40.00	0.39	40.00	0.50	40.00	0.28	60.00
STBs	21	0.19	-0.17	4.76	0.05	19.05	0.15	19.05	0.12	14.29
Regionals	38	-0.02	-0.06	5.26	0.25	26.32	0.37	31.58	0.20	7.89
Panel D: Factor=CET1										
	N	Mean β Jan-Feb	March Announcement				April Announcements			
			Pre		Post		Pre		Post	
			$\Delta\beta$ wrt Jan-Feb	% $\beta > 0$ & $p \leq 0.05$	$\Delta\beta$ wrt Jan-Feb	% $\beta > 0$ & $p \leq 0.05$	$\Delta\beta$ wrt Jan-Feb	% $\beta > 0$ & $p \leq 0.05$	$\Delta\beta$ wrt Jan-Feb	% $\beta > 0$ & $p \leq 0.05$
All Banks	71	0.01	0.54	60.56	0.13	21.13	0.21	25.35	0.12	12.68
April Only DG	7	-0.15	0.71	71.43	0.24	14.29	0.20	28.57	0.37	28.57
March DGW	5	0.08	0.16	60.00	0.05	40.00	0.24	20.00	-0.14	20.00
STBs	21	0.10	0.55	61.90	0.04	14.29	0.16	23.81	0.13	19.05
Regionals	38	-0.03	0.56	57.89	0.18	23.68	0.24	26.32	0.10	5.26

Note: This table summarizes the results of estimating equation (6) bank by bank, from January 1 to May 5, 2023 but excluding the crisis period of March 9-13. We show the mean β in January-February (the reference period), along with the mean change in β relative to the reference period, and the share of banks with a significantly positive β , by bank group before and after the March and April rating announcements. The *March DGW* group banks were put on downgrade watch on March 14. The *April Only DG Banks* group includes banks downgraded between April 14 and 21. All variables in the regression are standardized to have mean zero and unit standard deviation. Banks in the various groups are listed in appendix A. *DGW*=Downgrade watch. *DG*=Downgrades.

Figure D.1: **Average Betas Around Rating Announcements: Cash and CET1 Factors**



Note: These figures summarize the results of estimating equation (6) bank by bank, from January 1 to May 5, 2023. We show the average β for all banks in a given group and period before and after the March and April rating announcements. We directly estimate the β for the Jan.-Feb. period. For the remaining periods, we estimate the change in the beta relative to Jan.-Feb. For these periods, we plot the sum of the average Jan.-Feb. β and the average change relative to Jan.-Feb. The *March DGW* group banks were put on downgrade watch on March 14 and downgraded in April. The *April Only DG* group includes banks downgraded between April 14 and 21. All variables in the regression are standardized to have mean zero and unit standard deviation. Banks in the various groups are listed in appendix A. *DGW*=Downgrade watch. *DG*=Downgrades.