Investor Attention to Bank Risk During the Spring 2023 Bank Run

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Abstract

We examine how investors' perception of bank balance sheet risk evolved before and during the March-April 2023 bank run. 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 the market's perception of bank risk shifted in both the time series and the cross-section. From January 2022 to February 2023, the factor betas were mostly insignificant but, after the bank run started, they became positive and significant for all banks on average. Surprisingly, most of the increase in betas occurred in the week before the bank run started and, in the cross-section, for large banks or banks that were subsequently downgraded or put on downgrade watch by rating agencies during the run. These results suggest that investors focused on a limited set of banks, either due to limited attention or because they had a naive prediction model.

Keywords: Bank run, information sensitivity, limited attention, balance sheet beta, uninsured deposits, unrealized losses

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1 Introduction

The bank run that started in March 2023 in the US transpired unusually rapidly, with historically high 1-day deposit withdrawal rates for Silicon Valley Bank (SVB) and Signature Bank of New York (SBNY) occurring on March 9 and 10 (see Figure 1), suggesting that depositors became aware of bank liquidity risk quite suddenly. So how did depositors process information about bank risk before and during the bank run? This is an important question because bank run dynamics are intimately related to depositor information. For example, in the global games approach, depositors have slightly noisy information about bank fundamentals and, in equilibrium, even a panic run is related to these fundamentals (Goldstein and Pauzner (2005)). In these models, the runs occur instantaneously but, historically, runs have duration (Correia, Luck and Verner (2023)). During the run period, do investors quickly incorporate all relevant information, or, due to limited attention, do they update their priors only when the information is salient (Huberman and Regev (2001) and, relatedly, overweight certain types of information (e.g., market information, as in Peng and Xiong (2006))? If the latter, then the resulting price dynamics make it harder for market participants and regulators to assess bank risk and respond appropriately. While there is evidence of limited investor attention in financial markets (Hirshleifer (2015)), there is less evidence of how investors attend to bank risk, particularly in the context of a bank run.

This paper studies how the market's perception of bank risk, as reflected in bank stock prices, evolved before and during the bank run in March and April of 2023. How did these risk perceptions change as the informational environment changed – for example, as the relative emphasis on different banks and their risk exposures shifted? To what extent did stock prices incorporate relevant and readily available information about bank balance sheet risk before the run, going back to 2022Q1 when the Fed started to raise interest rates?

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 the prior quarter. To mitigate any mechanical findings, we exclude failed and downgraded banks from the factor construction procedure and we exclude SVB, SBNY, and Silvergate Bank from all analyses in the paper. First Republic Bank (FRC) is also omitted after April 28 (as it failed before the market opened on May 1). To capture the post-run informational environment, we make use of announcements by credit rating agencies. Specifically, Moody's put some banks on downgrade *watch* on March 14, and, during the week between April 14 and April 21, these and other regional banks were downgraded. We form bank groups based on these announcements, as well as groups of non-downgraded regional and stress-tested banks. Comparing the balance sheet factor betas of these different groups allows us to understand how investors perceived bank risk during the bank run in both the time series and the cross-section of banks and their risk exposures.

Our main results are illustrated in Figure 2, which shows the estimates of betas before and during the bank run for factors constructed from asset shares of uninsured deposits (denoted UID; see Panel A) and of unrealized losses on securities in held-to-maturity (HTM) and available-for-sale (AFS) accounts (denoted *Losses*; see Panel B). These characteristics are widely recognized as being central to the March-April 2023 bank run (see, for example, Acharya, Richardson, Schoenholtz and Tuckman (2023)). Panel A shows that the UID factor beta was insignificant in January and February of 2023 but became positive and significant during the bank run (March 1-May 5). Panel B shows similar results for the *Losses* factor. In other words, during the bank run, investors required return compensation for systematic UID and *Losses* risk whereas, just before the run, they did not, consistent with these factors becoming more information sensitive (Dang, Gorton and Holmstrom (2018)).

We next examine banks mentioned in rating agency announcements (denoted "event banks") during the bank run. We show that neither the downgrade watch announcements on March 14 nor the actual downgrades of several banks between April 14 and 21 were informative as the abnormal returns of event banks were insignificantly different from zero on the announcement day. Whether we estimate announcement day returns relative to a normal period (January-February, 2023) or to a period immediately before the announcements (to exclude any crisis effects), these results remain true. Nevertheless, Figure 2 shows that the UID and *Losses* betas of *only* event banks were positive and significant, whether estimated between March 1 and April 13, or from April 21 to May 5. In contrast, the betas of other regional banks remained insignificant as did the betas of stress-tested banks (the baseline group in the regressions and so indicated by the stand-alone $Factor$ estimate). This is surprising since, similar to event banks, non-downgraded regional banks exhibited higher balance sheet risk – such as higher *Losses* in 2022Q4 (see Table 1). For robustness, we conduct a "leave-one-out" analysis by excluding event banks one by one and re-estimating the regressions, and find that the magnitude and standard errors of the point estimates are very similar to the original results. These results suggest that investors focused on a limited set of banks, whether due to limited attention or because they predicted the same set of banks to fail as rating agencies.

To test these hypotheses, we estimate bank-by-bank regressions for 10-day periods before and after rating announcements. We find that the increases in betas after March 1 mostly occurred in the first week of March, just prior to the bank run. There is little evidence of a post-announcement boost in the betas, thus ruling out the idea that investors with limited attention coordinated on the announcements. Further, the betas of stress-tested banks also increased sharply but not those of non-downgraded regionals in the first week of March, suggesting that investors' prediction models were not sophisticated. For example, investors might have predicted large banks to fail (since the non-downgraded regionals were generally smaller in size than either the event banks or the stress-tested banks; see Table 1). Subsequently, some of these banks turned out to be risky (i.e., the event banks) while others did not (i.e., the stress-tested banks). Alternatively, investors with limited attention might simply have focused on large banks. Therefore, our results do not rule out either that investors operated with limited attention or that they had a naive prediction model.

Did investors pay attention to information about bank risks in 2022, such as regulatory reports (showing that average *Losses* of regional banks increased monotonically before peaking in 2022Q3 and remained high in 2022Q4; see Figure 5), credit rating agency warnings of "emerging risks for U.S. regional banks" in June 2022.[1] and deposit outflows? To address this question, we examine rolling window betas over 2022. Regarding unrealized losses, regulatory reports indicated that their shares increased after the Fed raised rates by 25bp on March 17, 50bp on May 5, and 75bp on June 16 (see Figure 5). We find that the average *Losses* beta became significant on August 19 (corresponding to the estimation window starting on June 27) but turned insignificant after December 14 and remained so through the end of February 2023. Considering deposit outflow news, we find that the average UID beta was significant at times during 2022Q2 and 2022Q4, but only sporadically so, suggesting that concerns about deposit outflows from specific banks[2] did not spread to the banking sector broadly. These results indicate that, despite the rising risk of *Losses* for all banks in 2022, investors were only intermittently sensitive to it in 2022, suggesting a pattern of investor attention starting from before the bank run in March 2023.

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. Drechsler, Savov, Schnabl and Wang (2023) 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

[1]See "Silicon Valley Bank's Distress Wasn't Reflected in Credit Ratings," *The Wall Street Journal*, March 17, 2023.

[2]For example, SVB suffered deposit outflows in 2022, albeit at a slow pace, that continued through February 2023 (FRB (2023b)). SBNY lost deposits as reports scrutinized its involvement with the crypto industry during the crypto winter of 2022 (FDIC (2023)). On November 15, 2022, SBNY was forced to announce that deposits from FTX and related crypto entities were a minor share of its overall deposits.

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 (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, Fox, Gil-Bazo, Imbet and Schiller (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.

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 (i.e., due to inclusion in rating announcements) and affect prices by modulating investors' limited attention. Our result that *uninformative* rating announcements 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 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 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.[3]. 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 3. Results on the evolution of bank balance sheet betas during Spring 2023 are in section 4. Section 5 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.

[3]Our post-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.

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.1 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 always omit SVB and SBNY and, depending on the estimation period, FRC. 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.[4] 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

[4] Silvergate 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.

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.

We also gather data on rating announcements to proxy for the arrival of information during the bank run. We collect this information from Moody's Ratings and Assessment Reports Directory[5] 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) since the latter is 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,[6][7] 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.[8] 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,

[5]See `https://www.moodys.com/reports/ratings-assessments-reports`.

[6]Silvergate, SVB and SBNY were downgraded prior to their failures or liquidation.

[7]Moody'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

[8]For 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.

including a reduction in deposits, higher funding costs, and interest rate losses on fixed-rate assets that increase their "liquidity and capital risks."[9] Section A.3 in the appendix lists the event banks flagged by the various rating announcements.

2.2 Methodology

We describe 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: those mentioned in the rating announcements ("event banks"), non-event regional banks, and non-event stress-tested banks. Membership in these groups depends on the event. Thus, *after* the downgrade watch on March 14 but *before* the ratings downgrades on April 14, the groups are:

- The *March Downgrade (DG) Watch* group includes 5 banks that were put on a downgrade watch by Moody's on March 14 (see appendix A.3 for the bank list). As these banks typically had relatively high UID (see Table 1), investors concerned about deposit risk may have considered the downgrade watch to be salient information in March.

- The *Other Regional Bank* group includes 43 banks in the KRX index that are not in the *March DG Watch* group.

- The *Stress-Tested Bank* group includes 23 large banks that participated in the Federal Reserve stress tests of 2022 and were also listed in the KBW index (see appendix A.3).

After the April 21 downgrade announcements, the relevant groups are as follows:

- The *DG* group includes 11 banks that were downgraded between April 14 and April 21. 4 of these banks (after excluding FRC) were previously on downgrade watch, and 7

[9]See for example UMB Financial downgrade and Associated Banc-Corp downgrade.

more banks that rating agencies downgraded between during this period (denoted the *April Only DG* group and listed in appendix A.3). The *April Only DG* banks typically had relatively high *Losses* (see Table 1). Given heightened concerns about unrealized losses of regionals in April, investors may have considered the downgrades salient.

- The *Non-DG Regional Bank* group is a subset of the *Other Regional Bank* after excluding the 5 regional banks downgraded in April. There were 38 such banks in the KRX index, and these are listed in appendix A.3.

- The *Non-DG Stress-Tested Bank* group is a subset of the *Stress-Tested Bank* group 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 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. In this view, 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

[10]We 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.

factors. However, the reported Tier 1 capital ratio *CET1* may overstate the available capital as it does not incorporate unrealized HTM losses.

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 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 3 illustrates how the Call Reports submission dates map to the calculation of factor returns.

Table 1 reports the means of balance sheet characteristics as of 2022Q4 for each of our bank groups. For comparison purposes, we also show SVB, SBNY, and Silvergate. The

March DG Watch banks were large, with average assets close to \$100B. So were the 7 additional banks downgraded in April (the *April Only DG* banks), with average assets of almost \$200B. By comparison, SVB had assets of \$212B and SBNY had assets of \$110B, whereas Silvergate was smaller with assets of \$11B. The non-downgraded stress-tested banks, of course, were the largest with average assets of almost \$850B. By comparison, the non-downgraded regional banks were smaller, with average assets of \$34B. The *March DG Watch* banks had the highest UID in our sample (about 60% versus 37% for stress-tested banks), topped only by SVB and SBNY. These banks, along with the *April Only DG* and non-DG regional banks, also had the highest unrealized loss shares (2.6% or higher versus 2.1% for stress-tested banks) in our sample behind SVB and SBNY. The *March DG Watch*, *April Only DG* and *Non-DG Regional* groups also had the lowest cash shares (4% or lower versus 12% for stress-tested banks). CET1 was similar across sample banks except the *March DG Watch* banks and Silvergate which had relatively low and high levels of CET1, respectively. Overall, based on 2022Q4 information, the most salient risks appeared to have been uninsured deposits for banks distressed in March and unrealized losses and cash shares for regional banks (whether downgraded or not) in April. Indeed, the overall balance sheet risk of non-downgraded and downgraded regional banks does not appear to be materially different at any time in 2022 (see Figure 5).

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 the informativeness of rating announcements. In section 2.3.2, we specify regressions to test our hypotheses.

2.3.1 Hypotheses Development

Suppose that rating announcements reveal information about bank risk not previously in stock prices. Following Norden and Weber (2004), we expect that, in the time series, event bank *abnormal returns* fall after downgrade watches or downgrades. Moreover, the announcement effects should be incremental to any general crisis effects, implying that event bank returns fall more than non-event bank returns. Further, to incorporate the new information, we expect that the event bank betas increase relative to any increase in the betas of non-event banks.

Hypothesis 1: Ratings are informative of event banks. After rating announcements, (i) event banks' abnormal returns decrease in the absolute and relative to non-event banks, and (ii) their balance sheet betas increase relative to non-event banks.

Even if ratings are uninformative, they may nevertheless act as a coordination device by drawing investor attention to the risk exposures of event banks, thereby affecting their betas. This is likely to happen if investors have limited attention and only react to salient information – in this case, the bank names flagged in the rating announcement. The 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 may indicate salience even absent any effect on returns.

Hypothesis 2: Rating announcements coordinate limited attention of investors. Following rating announcements, the betas of event banks increase relative to non-event banks, even if announcement day abnormal returns do not decrease significantly.

2.3.2 Regression Specifications

To test hypothesis 1 about rating informativeness, we first compute bank abnormal returns relative to the Fama-French 5-factor model. We also include the excess return on the regional bank index (KBRW-RF) to account for crisis effects on the announcement day returns.

$$R_{i,t} = \alpha_{0,i} + \sum_{j=1}^{5} \delta_{j,i} FF_{j,t} + \delta_{6,i}(KBWR_t - RF_t) + \epsilon_{it} \tag{1}$$

R_{it} 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).[11]

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

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

We conduct event studies by estimating panel regressions of bank abnormal returns on time dummies for event banks only, as follows:

$$AR_{i,t} = \alpha_0 + \alpha_i + \eta_0 Post[-1] + \gamma_0 Post0 + \gamma_1 Post[1,4] + \gamma_2 Post[5,9] + \phi AR_{i,t-1} + \epsilon_{it} \quad (3)$$

The lagged return is included to allow for return reversals, given that on some crisis days, banks exhibit strongly negative returns. All panel regressions include bank-fixed effects α_i. The time variable t indicates *event time*. Thus, $Post[-1]$ is a dummy variable equal to 1 on the day before the event; $Post0$ is a dummy variable equal to 1 on the event date; $Post[x, y]$ are dummy variables indicating days x to y since the event. The post-event window is 10 days since the announcement. There are 2 specifications for the pre-event window. In one, the pre-event period is January and February of 2023 which is free from crisis effects. Since the announcement day returns may reflect crisis effects during the omitted period, we also estimate another version using the pre-announcement period as the pre-event window. Note that, if the regional bank index captures the crisis effect adequately, the estimates should be robust across the two specifications (another robustness check based on estimating equation (4) is discussed below). Thus, for the March 14 downgrade watches, the pre-event window is March 1-12 (alongside a dummy variable for March 13). For the April downgrades, we use March 27 as the bank's pre-downgrade day as the pre-event window. Hypothesis 1 implies that $\gamma_0 < 0$ and significant.

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

We estimate equation (3) separately for the March 14 announcement, consisting of a panel of 5 banks, and for the downgrade announcements of 11 banks between April 14 and 21. For the downgrade announcements in April, we further estimate the announcement effects separately for the banks on downgrade watch (the *March DG Watch* group) and the remaining banks (the *April Only DG* group).

$$\begin{aligned}
AR_{i,t} =&\alpha_0 + \alpha_i + \eta_0(March\,DG\,Watch \times Post[-1]) + \xi_0(April\,DG \times Post[-1]) \\
&+ \gamma_0(March\,DG\,Watch \times Post0) + \lambda_0(April\,DG \times Post0) \\
&+ \gamma_1(March\,DG\,Watch \times Post[1,4]) + \lambda_1(April\,DG \times Post[1,4]) \\
&+ \gamma_2(March\,DG\,Watch \times Post[5,9]) + \lambda_2(April\,DG \times Post[5,9]) \\
&+ \phi AR_{i,t-1} + \epsilon_{it} \qquad (4)
\end{aligned}$$

If markets are efficient, then γ_0 is insignificant in equation (4) — i.e., there is no announcement effect for the *March DG Watch* banks in April, as in Norden and Weber (2004) — but $\lambda_0 < 0$ and significant if downgrades of the *April Only DG* banks are informative.

To test our hypotheses about the effect of ratings on bank betas, we estimate panel regressions of bank excess returns for various samples (e.g. pre- or post-bank run), obtaining the betas as coefficients of regressors involving the bank balance sheet factor, as follows:

$$\begin{aligned}
Y_{i,t} =&\alpha_0 + \alpha_i + \beta BankFactor_t + \sum_{j=1}^{5} \delta_j FF_{j,t} + \delta_6 Log(MVE)_{i,t-1} \\
&+ \sum_{k=1}^{2} \gamma_k BankFactor_t \times BankGroup_k + \epsilon_{it} \qquad (5)
\end{aligned}$$

where Y is the stock return for bank i minus the 3-month Treasury bill rate on day t. The regressors include one of the bank balance sheet factors (UID, *Losses*, Cash or CET1) and the (lagged) log of the bank's market value of equity (MVE), in addition to the Fama-French factors and a bank fixed effect. If β is higher post- versus pre-crisis, this implies greater risk sensitivity after the bank run. Moreover, if $\gamma_k > 0$, then this implies that investors are even more sensitive to the risk of banks in group k, as compared to stress-tested banks.

If we find that β is on average higher post-crisis, based on estimating equation 5, this may be due to the crisis or the rating announcements, or both. To better estimate the higher-frequency announcement effects, and also to more fully account for bank heterogeneity (e.g. banks were downgraded on different days), we turn to the following bank-by-bank regressions:

$$
\begin{aligned}
Y_{i,t} =& \alpha_i + \beta_{i,0} BankFactor_t + \sum_{j=1}^{5} \delta_{i,j} FF_{j,t} + \delta_{i,6} Log(MVE)_{i,t-1} + \sum_{k=1}^{4} \zeta_{i,k} Period_{k,t} \\
&+ \sum_{k=1}^{4} \beta_{i,k} Period_{k,t} \times BankFactor_t + \epsilon_{it}
\end{aligned} \tag{6}
$$

where $Period_{k,t}$ is a dummy variable equal to 1 for 10-days days before and since the announcements. Thus, for banks put on DG watch on March 14, the periods are March 1-13 ($k = 1$) and March 14 - 24 ($k = 2$). For banks downgraded in April, the pre-event period is March 27 – April 13 ($k = 3$). The post-event period ($k = 4$, after which the sample ends) is d to $d + 9$ days, where d is the downgrade date — April 14, 19 or 21. For $d = 19, 21$, the days April 14 to $d - 1$ are omitted from the sample. For banks that were not actually downgraded, we use a placebo date of April 21, by which date all our sample banks were downgraded. The omitted period is January through February of 2023. All other variables are defined in the same way as in equation 5.

To aid in the comparison of estimates across banks, we standardize all continuous variables to have mean zero and standard deviation 1. An announcement effect (Hypothesis 1) implies that the post-event βs ($\beta_{i,2}$ and $\beta_{i,4}$) are higher than the pre-event βs ($\beta_{i,1}$ and $\beta_{i,3}$) for the March DG watches and April DGs, respectively, while they are unchanged for non-event banks. In contrast, hypothesis 2 implies no change in the betas between the pre- and post-event periods for any bank.

3 Are Credit Ratings Informative?

Section 3.1 reports descriptive statistics for abnormal bank returns around key dates in our sample. Section 3.2 examines the rating announcement effects on abnormal returns.

3.1 Bank Abnormal Equity Returns: Descriptive Statistics

Table 2 shows the daily means of abnormal returns for different bank groups around information events. Panel A adjusts the returns for the 5 Fama-French factors only. Panel B also adjusts for the regional bank index return, as in specifications 1 and (2). SVB, SBNY, and Silvergate are included only as points of 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 DG Watch* banks, we show results with and without FRC.

Panel A, columns 1-2, of Table 2 shows minimal declines in bank stock prices, relative to the market model, in January-February or March 1-8 of 2023, except for Silvergate. 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 *March DG Watch* banks had daily mean abnormal returns of around –8% on these days, similar to the *April Only DG* banks, while the *Non-DG Regional* banks and the *Non-DG Stress-Tested* banks' abnormal returns fell between 1% and 2% on March 9 but reverted on March 10. On March 13, abnormal returns of the *March DG Watch* banks fell more than 30% while the *April Only DG* bank stocks fell about 8% and the regionals and stress-tested banks fell by about 2%. The downgrade watches were announced after the market-close on March 13. On March 14, the event banks exhibit *positive* returns, indicative of return reversals. In the 9 days following the March event (March 15-27), there were moderate declines (once FRC is excluded) of less than 5% cumulatively for some event banks and the stress-tested banks. 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 (April 14, 19, and 21), announcement effects were zero to moderate. On April 14 and 21, the *March DG Watch* banks fell about 1%-2% while the *April Only DG* and regional banks fell by about 1%. Stock prices increased for all banks on April 19 (when Schwab was downgraded) and for stress-tested banks on all announcement days. In the 10 days after the last downgrade on April 21 (April 24-May 5), *March DG Watch* banks fell another 12% while the *April Only DG* groups fell a further 5%, perhaps an effect of FRC's failure on May 1. However, when FRC is excluded from the *March DG Watch* banks (see the row labeled "ex-FRC"), the decline in *March DG Watch* bank stocks is almost halved.

Figure 4 plots the abnormal returns with (solid lines) and without (dotted line) adjusting for the regional bank index. Comparing the two series, we find that while the adjustment makes little difference to abnormal returns pre-run (i.e., January-March 8 2023), it boosts abnormal returns during the bank run, suggesting that the crisis effect is mitigated, as intended. For example, Panel B of Table 2 reports that, on March 9, the *Non-DG Regional* banks and the *Non-DG Stress-Tested* banks had *positive* abnormal returns versus a reduction of 1% to 2% in Panel A.

Since the March and April bank groups contain few banks, outliers may influence the results. Accordingly, we report in Table B.1 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.

3.2 Bank Abnormal Returns: Announcement Day Effects

Results from estimating equations 3 and 4 are shown in Table 3. Panel A shows results for the March 14 event. The first column shows results using January-February of 2023 as the pre-event window. We find that the announcement day abnormal returns are insignificantly different from zero for the *March DG Watch* group on the event date (Post0), with no further significant effects over the following 9 days. In contrast, returns on March 13 (denoted Post[-1]) are highly negative and significant, indicating the crisis effect. The coefficient on the lagged abnormal return is negative, albeit insignificant, suggesting return reversals. Column 2 shows results using March 1-12 as the pre-event window. The results are qualitatively and quantitatively similar, indicating that adjusting for the regional bank index was successful in separating the announcement effect from broader crisis effects. Panel B of the table shows results for the April downgrade announcements. The pre-event sample is either January to February 2023 (columns 1-3) or March 27 to the pre-downgrade day (columns 4-6). In both cases, we observe an insignificant announcement effect for all downgraded banks and the *March DG Watch* group. *March DG Watch* bank returns are negative and significant on days 5 to 9 after announcements, possibly an effect of the failure of FRC on May 1.

4 Crisis and Announcement Effects on Bank Balance Sheet Betas

In this section, we evaluate the question posed in the introduction: How did the betas evolve since the bank run for different risk factors and bank groups? Betas might change due to the *onset* of the bank run and the arrival of information *during* the run. Accordingly, in section 4.1, we first examine whether post-crisis betas increased relative to their pre-crisis values. Then, in section 4.2, we investigate how betas changed as information about bank risk (in the form of rating announcements) further increased the betas of event banks.

4.1 Crisis Effects on Bank Balance Sheet Betas

If the market was cognizant of balance sheet risks, then the factor betas are expected to be positive and significant even before the bank run. Thus, we start by estimating the factor betas from regression (5) (but without the factor times bank group interactions) for January to February of 2023, the two months prior to the bank run. Table 4 shows the results.

The betas for CET1 and cash are positive and significant, while those for UID and *Losses* are insignificant. Of the 5 Fama-French factors, the betas with respect to market excess returns, size, and value are significant in all cases. The lagged bank MVE is negatively and significantly related to bank excess returns in all cases. Overall, immediately before the bank run, stock market investors were attuned to the risk emanating from lower levels of the more "traditional" factors (capital and cash) but not to higher levels of the two factors (UID and *Losses*) that became central during the bank run.

Do bank stock returns become more sensitive to balance sheet risks during the bank run? In Table 5, we estimate regression (5) without the bank factor times group interactions for March 1 to May 5, 2023. In sharp contrast to the pre-run period, the UID and *Losses* betas are now positive and statistically significant. The cash and CET1 betas remain significant as was the case before the run. The significance and magnitude of these results are robust to excluding FRC during the entire sample period as shown in appendix table B.2. Hence, these results indicate a shift in investors' risk perceptions from before the crisis, consistent with increased sensitivity to UID and *Losses* risks following an information shock (Dang et al. (2018)).

An alternative explanation for the results in Table 5 is that there is more overlap between banks in the long-short portfolios of different factors during the run as compared to before the run. In particular, the composition of the long and short portfolios for the UID and *Losses* factors may have moved closer to that of the cash and CET1 factors during the run. But the results in Table A.2 in appendix A show that, for each factor pair, the number of overlapping banks in the long portfolio plus the number of such banks in the short portfolio is stable, thereby ruling out the alternative hypothesis.

4.2 Announcement Effects on Bank Balance Sheet Betas

How did investor perceptions change in the cross-section of banks and their risk exposures (e.g. uninsured deposits vis-a-vis unrealized losses) as information about bank risk arrived during the run? To evaluate these questions, we include in the regression the interactions of the factors with the *March DG Watch* and *Other Regional* bank groups, while the stress-tested banks are the omitted group. To consider time variation in factor exposures, we estimate regression (5) from March 1 to April 13, just before the onset of the crisis and inclusive of the March 14 announcements, but before the downgrade announcements starting on April 14. The results are illustrated in Figure 2 for the UID and *Losses* factors; the related tables for these factors, and also for the Cash and CET1 factors, are reported in the appendix Table C.1. We find that the UID and *Losses* betas are positive and highly significant when interacted with the *March DG Watch* bank dummy. In contrast, the betas are insignificant when interacted with *Other Regional* banks and also for the stress-tested banks (as indicated by the standalone factor). Similar results hold for the Cash and CET1 factors (see Table C.1). Thus, the increase in factor betas in the month after the bank run started is narrowly confined to the event banks.

To check the robustness of our results to members of the *March DG Watch* group, we report in Figure C.1 the results from a "leave-one-out" analysis. Specifically, we exclude member banks one at a time from the *March DG Watch* group, re-estimate the regressions, and report the new beta coefficients and 95% confidence intervals. We find that the magnitude and standard errors of the point estimates are very similar to the baseline results in Table C.1. The factor betas are positive and significant at the 5% level of confidence for the *March DG Watch* group but insignificant for all other banks. One particular concern is that the results may be entirely driven by FRC, which was downgraded on March 17 after being placed on downgrade watch on March 14. However, the exclusion of FRC does not dampen the significance of the estimated beta for the *March DG Watch* group. Therefore, our results are robust to the exclusion of specific members of the *March DG Watch* group.

Did investors become concerned about more banks or particular risks as information about bank risk arrived – for example, about the unrealized losses of regional banks more broadly? To address this question, we estimate regression (5) from April 21 to May 5. On

April 21, nine – mostly regional – publicly traded banks were downgraded. In their reports, rating agencies emphasized the weakness of the US banking sector from rising rates and pointed to the recent failures of regional banks.[12] We estimate the regression after including interactions of the factors with the *DG banks* (i.e., those downgraded on April 14, 19 or 21 but excepting FRC), and the *Non-DG Regional* banks, with the *Non-DG stress-tested* banks as the omitted group. The results, in Panel A of the appendix Table C.2, show that the betas for the *DG* banks are positive and significant for all factors; however, the factor betas for the *Non-DG Regional* banks are insignificant, except for the cash beta which is weakly significant at the 10% level.[13] A "leave-one-out" analysis shows that our results are robust to membership in the *DG* group (see Figure C.2).

The significance of the factor betas of downgraded banks may reflect the continuing salience of banks put on the downgrade watch in March, rather than the salience of the newly downgraded banks in April. To address this issue, we show results separately for downgraded banks previously on downgrade watch (i.e. the *March DG Watch* group) and those that were not (i.e. the *April Only DG* group). We find (see Figure 2 for the UID and *Losses* factors and Panel B of the appendix Table C.2 for all factors) that all the factor betas are significant for both groups.

While the significant betas of the event banks are suggestive of the salience of the rating announcements for investors' risk perceptions, they could also be due to sophisticated investors predicting the same subset of risky regional banks as rating agencies. To better estimate the higher-frequency announcement effects, and also to more fully account for bank heterogeneity (e.g. banks were downgraded on different days), we estimate the bank-by-bank regressions specified in equation (6).

Summary statistics of the results are shown in Table 6, with estimates reported in stan-

[12]For example, when downgrading UMB on April 21, Moody's states that "...the banking system faces rising funding and profitability pressures related to the significant and rapid tightening in monetary policy, which has led to a reduction in US banking system deposits and higher funding costs...the recent failures of two sizeable US regional banks have shaken depositor confidence, especially among uninsured depositors." See UMB downgrade.

[13]Estimates for the control variables are not reported in the table to save space.

dard deviation (SD) units. The bank-by-bank estimates are shown in Figures C.3-C.6 in the appendix. Panel A of the table shows results when including the immediate bank run period of March 9-13. Consider the results for the UID factor. For the March DG watch pre-event period (column 1), we find that most betas are positive and significant at the 5% level of confidence or below for most banks, including (surprisingly) the stress-tested group. The median increase in β, relative to January-February 2023, ranges from 0.45 SD units (for stress-tested banks) to 0.60 SD units (for DG watch banks). A notable exception is the *Other Regionals* group with a median increase in β of just 0.13 SD units with less than 27% of banks having significant estimates. Turning to the post-DGW announcement period of March 14-27, we find no further increases in the betas, and with lower shares of significant estimates, indicating no effects from the March DG watch announcements. Once again, the *Other Regionals* group is an exception, with a greater median increase in β and share of significant estimates, as compared to the pre-event period. The results for March 27-April 13 (the pre-April DG period) are similar to the March 14-27 period, with similar changes in β and shares of significant estimates. In the post-April DG period, the median changes in β and shares of significant estimates increase relative to the pre-event period for all banks, possibly reflecting the effects of the impending failure of FRC. For the other factors, most of the post-crisis increase in β changes and significance occurs in the first two weeks of March, with little further increases. Overall, these results provide little evidence that either the March DGW or the April DG announcements affected the betas.

Was the increase in β during March 1-13 mostly due to the immediate effect of the bank run? In Panel B of Table 6, we re-estimate regression (6) after excluding the immediate crisis period of March 9-13. The answer is no, as we continue to find that increases in β and its significance mainly occur during March 1-8.[14] Moreover, the median increase in β during

[14]One reason why the betas are similar even when excluding the March 9-13 period may have been the announcement of the Federal Reserve's Bank Term Funding Program (BTFP) on March 12 which allowed banks to delay the realization of losses on underwater liquid securities. The BTFP allowed banks to borrow against the full face value of securities with maturity of up to one year, that are eligible for purchase by the Federal Reserve Banks in open market operations, such as U.S. Treasuries, U.S. agency securities, and U.S. agency mortgage-backed securities (see BTFP announcement. However, this rationale does not explain

this pre-crisis period is typically greater than in all later periods. This result suggests that stock market investors updated their beliefs of balance sheet risk of the same group of banks as later flagged in rating agency announcements, and in addition of stress-tested banks, in the week before the bank run.

Discussion. These results suggest that the rating changes were not salient to investors and they did not affect their perceptions of bank risk, consistent with their uninformative nature. Indeed, stock market investors updated their beliefs about the same set of banks as rating agencies, and up to a month before the actual announcements. One explanation for this result is that stock market investors were skilled in identifying risky banks. Thus, they identified the same banks as the rating agencies and generally ignored the regional banks not downgraded or put on downgrade watch. However, the betas of stress-tested banks also increased in the week before the bank run, suggesting that the prediction models of stock investors were not sophisticated. For example, they may have focused mainly on large banks – indeed, the non-downgraded regional banks were on average smaller than the event banks and the stress-tested banks (see Table 1), while having similar levels of *Losses* and UID (albeit with more cash and CET1).

An alternative explanation for these findings is that investors had limited attention capacity, although they did not use the rating announcements to coordinate on the set of risky banks. Instead, investors may have paid attention only to large banks; thus, bank size may have acted as a coordination device for investor attention.

4.3 Additional Investigations

As an additional exercise, we report results for the *CET1 with losses* factor in appendix D. *CET1 with losses* is defined as the hypothetical CET1 ratio if AFS + HTM losses were realized and the factor is constructed similarly to the others (see appendix D for more details). These results fall in between those for *Losses* and $CET1$, as to be expected. In

the *differential* effects between non-downgraded regionals and event banks since both groups were eligible to access the BTFP.

January and February 2023, the *CET1 with losses* factor beta is positive and significant, similar to CET1 (Table D.2). After the start of the run but before the April downgrade announcements, the beta remains positive and significant but only for the *March DG Watch* banks (Tables D.3 and D.4). Finally, for the post-downgrade announcement sample, the *CET1 with losses* factor beta is positive and significant for the downgraded banks but not for the non-downgraded regionals (Table D.5).

5 Investor Attention in 2022

Is there evidence of limited investor attention before the bank run? For example, were investors sensitive to interest rate risk after the Fed raised rates in 2022? To provide context for our analysis of bank risk in 2022, section 5.1 describes the balance sheet characteristics and returns of the bank groups in that year. In section 5.2, we evaluate the second question posed in the introduction: How did the bank balance sheet factor betas evolve *prior* to the run around potentially salient events?

5.1 Bank Balance Sheet Characteristics and Returns in 2022

Figure 5 shows how UID, *Losses*, cash and CET1 evolved over 2022. The *March DG Watch* (*April Only DG*) banks consistently had the highest UID (*Losses*). Notably, while *Losses* of all banks spiked in 2022Q3 (as interest rates jumped in the first half of 2022), that of non-downgraded regional banks became the second highest in Q4, as previously discussed. The non-stress-tested banks had relatively low cash shares, typically less than half of that of the stress-tested banks. The *March DG Watch* banks had the lowest CET1 ratio, with stress-tested banks also having relatively low CET1. Overall, the *March DG Watch* (stress-tested) banks were most (least) risky across the majority of balance sheet characteristics, while the *April Only DG* banks and non-downgraded regionals had high exposure to *Losses* and cash risk. Since balance sheet information for all banks was publicly available as early as April 30, 2022 – the deadline for filing the Call Report for 2022Q1 – investors could have become aware of these bank risks early in 2022.

Figure 6 plots the cumulated abnormal returns for the different bank groups, after dropping SVB, SBNY, and Signature banks. Vertical drop lines indicate the Call Report filing deadlines for Q1, Q2 and Q3 of April 30, June 30, and October 30, respectively, along with the 75bp rate hike on June 16, and the failure of the crypto entity FTX on November 11. There is limited evidence that bank stock prices reacted *persistently* to news events before the bank run. For example, between March 17 and May 5 of 2022, the Fed hiked rates by a cumulative 75bp. During this period, the returns of *April Only DG* banks – that had the highest *Losses* (see Figure 5) – fell a cumulated 14% but returns of other bank groups fell far less, between 4% and 7%. By the end of May, bank stock prices had partially reverted with *April Only DG* bank returns gaining 5% since May 5. Similarly, between June 16, when the Fed hiked rates by 75bp, and July 8, the week after the filing deadline for the 2022Q2 Call Report, bank stock returns – including those of *April Only DG* banks – were mostly stable. In 2022Q4, amidst deposit outflows and the "crypto winter", returns of the *March DG Watch* banks – which had the highest UID (see Figure 5) – fell 10% but share prices of all other banks mostly improved, even as SVB, SBNY and Signature bank returns declined between 30% and 137% cumulatively.

In summary, the return dynamics in 2022 suggest some concerns with unrealized losses during 2022Q1 and deposit flights during 2022Q4 as banks with the highest *Losses* or UID faced downward pressure on their returns. But, these concerns had eased by January 2023.

5.2 Bank Balance Sheet Factor Betas in 2022

To better understand the dynamics of the factor betas in 2022, Figure 7 plots the beta coefficients and 95% confidence intervals from estimating regression 5, without the factor times bank group interactions, for a *rolling* window of 39 trading days starting on January 3, 2022. The window length was chosen to span the period from January 3 to February 28 of 2023 (the sample used in Table 4). The dates on the x-axis represent the end date of the rolling window. The factors are constructed using balance sheets from the quarter before the start of the rolling window and after the Call Report filing deadline (see Figure 3). The vertical drop lines are the same as those in Figure 6.

Were investors aware of bank risks in 2022? Panel A of Figure 7 shows the dynamics of factor betas in 2022. Between March 17 and May 5 of 2022 when the Fed hiked rates by a cumulative 75bp, the *Losses* beta was statistically insignificant. However, following the Fed hike rates on June 16 by 75bp, the *Losses* beta became significant on August 19 (corresponding to the estimation window starting on June 27); it remained significant through December 14 before turning insignificant and remaining so through the end of February 2023. The UID beta became positive and significant at the end of March and remained so till May 20; it became significant again on September 9, remaining as such through February 3, 2023 (corresponding to the estimation window starting on December 8, 2022), after which it became insignificant. The cash beta also became significant on September 9, and remained so through the end of February 2023. The CET1 beta became positive and significant on October 18, later than the other factors, and also remained significant through the end of February 2023. Thus, before the bank run, while investors were intermittently sensitive to "novel" risks from high levels of UID and *Losses* in 2022, their concerns appear to have disappeared as 2023 approached.

Considering the evidence from the return and beta dynamics in 2022, we conclude that investors paid temporary attention to specific balance sheet risks (e.g. uninsured deposits risk) as they received salient information but their attention dissipated in short order. In other words, limited investor attention is consistent with bank risk dynamics both in 2022 and during the bank run of Spring 2023.

6 Conclusion

This paper studies how the market's perception of bank risk, as reflected in bank stock prices, evolved in 2022 and during the bank run in the Spring of 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 several bank balance sheet characteristics in the prior quarter.

We find that the UID and $Losses$ factor betas were insignificant in January and February of 2023 but became positive and significant during the bank run that started in March. Thus, in contrast to the pre-run period, investors required compensation for systematic UID and $Losses$ risk, consistent with heightened sensitivity to these risks (Dang et al. (2018)).

We next examine how investors reacted to information about bank risk during the run. On March 14, Moody's put some banks on downgrade watch. We show that these announcements were *not* informative as event bank abnormal returns were not significantly different from zero on the announcement day. After the start of the run, the UID and $Losses$ betas of *only* these banks were positive and significant, while the beta of other regional banks remained insignificant — even though these banks had similar risk profiles. When several banks (not previously on watch) were downgraded between April 14 and 21, their announcement day returns were also not significantly different from zero but once again their betas were positive and significant following the announcements. These results show that investors paid attention to a limited set of banks during the bank run. A "leave-one-out" analysis shows that the results are robust to excluding specific event banks. The results are also not due to increased overlaps between banks constituting the portfolios used to create the factors.

Bank-level estimates of betas around the rating announcement days show that the increase in beta after March 1 mainly occurred during the first week of March, before the onset of the bank run. In the cross-section, the betas of event banks *and* large stress-tested banks increased in March 1-8 but those of non-downgraded regional banks did not. We suggest that these results could be either attributed to investors having a naive prediction model (e.g.

based only size, since non-downgraded regionals were smaller banks) or to limited attention capacity (where size acts to coordinate investor attention).

In 2022, as the Fed raised rates, regulatory and credit agency reports, and deposit outflows, revealed information about balance sheet risks. We examine rolling window betas over 2022 and find that investors were only intermittently sensitive to high levels of UID and $Losses$ in 2022 – further reinforcing the interpretation of limited investor attention.

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.[15]

[15]Metrick 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 Balance Sheet Characteristics as of 2022Q4, by Bank Group**

	Number of Banks	Assets ($B)	$\frac{Unin.Dep.}{Assets}$	$\frac{Losses}{Assets}$	CET1	$\frac{Cash}{Assets}$
SVB	1	211.79	74.01	8.35	12.05	6.14
SBNY	1	110.36	75.63	2.91	10.41	5.49
Silvergate	1	11.36	33.77	1.00	42.12	40.28
March DG Watch Banks	5	98.82	60.72	2.55	9.75	3.54
April Only DG Banks	7	196.72	40.14	3.05	11.57	4.00
Non-DG Regional Banks	38	34.05	45.19	2.63	11.86	4.05
Non-DG Stress-Tested Banks	21	846.77	36.71	2.10	11.14	11.59

Note: The table shows the average values of bank balance sheet characteristics for SVB, SBNY, Silvergate and four bank groups, reported as of 2022Q4. The ratios are reported in %. *Losses* are differences between par and fair values of AFS and HTM securities. The $March\, DG\, Watch$ group includes banks put on downgrade (DG) watch in March. The *April Only DG Banks* group includes banks downgraded between April 14 and 28. 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. $Unin.Dep.$ = Uninsured Deposits.

Table 2: **Daily Means of Abnormal Stock Returns, by Bank Group**

Panel A: Relative to FF 5-Factor Model

	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	Moodys' DGs 4/21	4/24 – 5/5
SVB	0.43	-0.78	-54.13	-57.86	.	.	.	.	.	.	.	.	.	.
SBNY	-0.06	-1.22	-5.88	-17.97	.	.	.	.	.	.	.	.	.	.
Silvergate	0.21	-12.06	-35.07	-3.91	-5.59	-10.68	1.11	-1.64	-1.65	-1.00	6.09	2.32	-6.66	-0.41
March DG Watch Banks	-0.03	-0.71	-8.44	-7.47	-32.49	9.43	-1.24	-0.05	-2.26	0.69	9.93	-1.27	-0.72	-1.15
March DG Watch Banks Ex-FRC	0.08	-0.53	-5.46	-4.87	-23.26	3.02	0.22	-0.02	-2.15	1.07	9.62	-1.36	-1.28	-0.70
April Only DG Banks	-0.16	-0.44	-7.36	-6.99	-7.70	5.01	-0.47	-0.56	-1.29	1.86	2.43	-1.50	-0.79	-0.52
Non-DG Regional Banks	-0.12	-0.58	-2.07	0.72	-2.22	0.44	0.30	-0.32	-1.40	0.36	2.76	-0.50	-0.63	-0.29
Non-DG Stress-Tested Banks	0.12	-0.44	-1.09	0.98	-1.68	0.69	-0.38	-0.15	3.05	1.02	0.15	0.62	0.28	-0.18

Panel B: Relative to FF 5-Factors and Regional Bank Index

	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	Moodys' DGs 4/21	4/24 – 5/5
SVB	0.55	-0.18	-51.30	-57.80	.	.	.	.	.	.	.	.	.	.
SBNY	0.06	-0.60	-3.00	-17.91	.	.	.	.	.	.	.	.	.	.
Silvergate	0.32	-11.56	-32.71	-3.86	-3.62	-10.97	1.23	-1.27	-0.01	-1.19	3.97	2.49	-6.23	-0.12
March DG Watch Banks	0.03	-0.37	-6.78	-7.43	-30.82	9.19	-1.11	0.31	-0.66	0.50	7.86	-1.11	-0.31	-0.84
March DG Watch Banks Ex-FRC	0.19	0.01	-2.90	-4.81	-21.10	2.70	0.35	0.38	-0.36	0.86	7.30	-1.19	-0.82	-0.38
April Only DG Banks	-0.10	-0.14	-5.97	-6.96	-6.54	4.84	-0.40	-0.34	-0.33	1.75	1.19	-1.41	-0.54	-0.35
Non-DG Regional Banks	-0.02	-0.06	0.37	0.78	-0.20	0.14	0.43	0.06	0.29	0.15	0.57	-0.33	-0.19	0.01
Non-DG Stress-Tested Banks	0.18	-0.18	0.11	1.01	-0.69	0.54	-0.32	0.04	3.87	0.92	-0.92	0.71	0.49	-0.03

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 (1) and (2). We then take the daily market capitalization weighted average of abnormal returns across all banks in a given group. The table reports the average of daily observations for the bank-groups. In the $March\,DG\,Watch$ group, First Republic Bank (FRC) is dropped on and after May 1, 2023. We include and additional row for the $March\,DG\,Watch$ 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 3: **Abnormal Returns for Event Banks**

Panel A: March Event Banks

	Relative to: Jan. – Feb.	Relative to: Mar. 1 – 12
Post[-1]	-29.378***	-29.005***
	(0.201)	(1.767)
Post[0]	0.181	3.080
	(6.983)	(7.324)
Post[1,4]	-4.289	-2.500
	(3.516)	(3.825)
Post[5,9]	0.318	2.195
	(1.537)	(1.930)
Lag Ab. Ret.	-0.237	-0.200
	(0.237)	(0.251)
Constant	0.150	-1.653
	(0.132)	(1.024)
Obs	250	95
Adj R2	0.433	0.385
Bank FE	YES	YES

Panel B: April Event Banks

	Relative to: Jan. – Feb.			Relative to: March 27 – day before DG		
	All April Event Banks	Post × March DG Watch	Post × April Only DG	All April Event Banks	Post × March DG Watch	Post × April Only DG
Post[-1]	-0.547	-1.229***	-0.003	-0.945	-2.004	-0.048
	(0.427)	(0.274)	(0.669)	(1.022)	(2.608)	(0.764)
Post[0]	0.047	0.146	-0.042	-0.295	-0.566	-0.073
	(0.221)	(0.465)	(0.475)	(0.308)	(0.755)	(0.481)
Post[1.4]	-1.320	-3.160	-0.037	-1.678	-3.905	-0.061
	(1.116)	(2.773)	(0.401)	(1.126)	(2.829)	(0.413)
Post[5,9]	-2.687***	-6.431***	-0.459	-3.127***	-7.403***	-0.506
	(0.929)	(2.058)	(0.416)	(0.996)	(2.220)	(0.434)
Lag Ab. Ret.	0.044	0.028	-0.119*	0.025	0.013	-0.212***
	(0.301)	(0.376)	(0.062)	(0.267)	(0.326)	(0.072)
Constant	0.095	0.099		0.430	0.416	
	(0.082)	(0.079)		(0.303)	(0.288)	
Obs	596	596		325	325	
Adj R2	0.062	0.119		0.043	0.099	
Bank FE	YES	YES		YES	YES	

Note: This table shows the results of estimating equations (3) and (4). Post[0] is the event date and Post[-1] is one day before the event date. Panel A shows the results for the March 14 event. The first (second) column uses January–February of 2023 (March 1–12) as the pre-event window, Panel B shows the results for the April downgrade announcements. The pre-event window is either January–February of 2023 (columns 1–3) or March 27 to the pre-downgrade day (columns 4–6). Standard errors (in parentheses) are robust and clustered by date. Stars represent statistical significance: *$p < 0.1$; **$p < 0.05$; ***$p < 0.01$.

Table 4: **Bank Balance Sheet Factor Beta: January to February 2023**

	Factor=%UID	Factor=% Losses	Factor=% Cash	Factor = CET1
Factor	0.14	0.08	0.33***	0.27**
	(0.14)	(0.16)	(0.09)	(0.11)
Mkt-RF	1.02***	1.05***	0.95***	0.96***
	(0.14)	(0.15)	(0.13)	(0.14)
SMB	0.57***	0.57***	0.42**	0.53***
	(0.19)	(0.19)	(0.17)	(0.17)
HML	0.63**	0.69**	0.59**	0.68***
	(0.26)	(0.27)	(0.23)	(0.25)
RMW	0.24	0.27	0.08	0.29
	(0.28)	(0.27)	(0.26)	(0.26)
CMA	-0.33	-0.42	-0.23	-0.49
	(0.37)	(0.39)	(0.32)	(0.36)
Log(Bank MVE)$_{t-1}$	-5.43***	-5.42***	-5.86***	-5.01***
	(1.77)	(1.79)	(1.65)	(1.62)
Obs	2,769	2,769	2,769	2,769
Adj R2	0.42	0.42	0.44	0.43
Bank FE	YES	YES	YES	YES

Note: This table shows results from estimating regression (5), without the bank group interactions, for the period January 3 to February 28, 2023. The factors are constructed from long-short portfolios based on 2022Q4 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. Standard errors (in parentheses) are robust and clustered by date. Stars represent statistical significance: *$p < 0.1$; **$p < 0.05$; ***$p < 0.01$. SVB, SBNY and Silvergate are not included in the regression.

Table 5: **Bank Balance Sheet Factor Beta: March 1 to May 5, 2023**

	Factor=%UID	Factor=% Losses	Factor=% Cash	Factor = CET1
Factor	0.45***	0.45***	0.42***	0.38***
	(0.13)	(0.13)	(0.10)	(0.11)
Mkt-RF	0.94***	1.07***	1.01***	1.09***
	(0.22)	(0.21)	(0.20)	(0.21)
SMB	0.38	0.38	0.27	0.43
	(0.32)	(0.32)	(0.28)	(0.32)
HML	2.11***	2.07***	2.10***	2.02***
	(0.31)	(0.26)	(0.25)	(0.29)
RMW	-0.45	-0.22	-0.35	-0.20
	(0.46)	(0.35)	(0.35)	(0.37)
CMA	-2.03***	-1.96***	-1.87***	-1.79***
	(0.46)	(0.41)	(0.44)	(0.45)
Log(MVE)_{t-1}	-3.52	-3.48	-3.69	-3.54
	(2.32)	(2.30)	(2.31)	(2.30)
Obs	3,332	3,332	3,332	3,332
Adj R2	0.39	0.39	0.40	0.39
Bank FE	YES	YES	YES	YES

Note: This table shows results from estimating regression (5), without the bank group interactions, for the period March 1 to May 5, 2023. The factors are constructed from long-short portfolios based on 2022Q4 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 regression. FRC is dropped from the sample on and after its failure (May 1). Standard errors (in parentheses) are robust and clustered by date. Stars represent statistical significance: *$p < 0.1$; **$p < 0.05$; ***$p < 0.01$.

Table 6: **Bank-By-Bank Dynamics of Factor Betas in 2023**

Panel A: Including Mar. 9 – 13

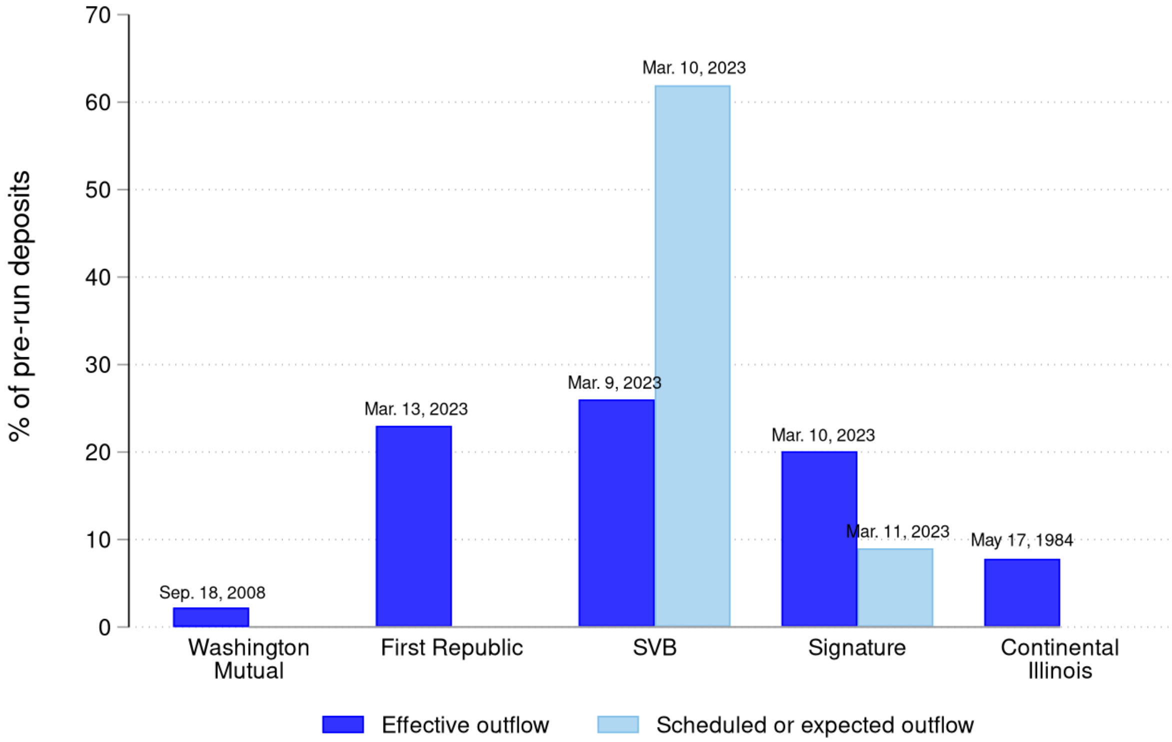
		Factor × Mar. 1 – 13		Factor × Mar. 14 – 24		Factor × Mar. 27 – Apr. 13		Factor × DG – 9 days	
	N Banks	Change in β p50	% positive and $p < 0.05$	Change in β p50	% positive and $p < 0.05$	Change in β p50	% positive and $p < 0.05$	Change in β p50	% positive and $p < 0.05$
Factor = % UID									
March DG Watch Banks	5	0.60	100.00	0.26	40.00	0.18	0.00	0.49	60.00
April Only DG Banks	7	0.48	71.43	0.39	28.57	0.22	28.57	0.47	71.43
Other Regional Banks	38	0.13	26.32	0.29	42.11	0.25	15.79	0.37	39.47
Other Stress-Tested Banks	21	0.45	80.95	0.23	23.81	0.13	14.29	0.30	33.33
Factor = % Losses									
March DG Watch Banks	5	0.76	80.00	0.33	60.00	0.24	20.00	0.56	60.00
April Only DG Banks	7	0.40	57.14	0.07	14.29	-0.08	14.29	0.31	0.00
Other Regional Banks	38	0.17	31.58	0.26	31.58	-0.02	0.00	0.25	26.32
Other Stress-Tested Banks	21	0.33	38.10	-0.06	0.00	0.13	4.76	0.11	9.52
Factor = % Cash									
March DG Watch Banks	5	0.88	100.00	0.30	20.00	0.15	0.00	0.30	60.00
April Only DG Banks	7	0.45	57.14	0.11	0.00	0.16	0.00	0.25	0.00
Other Regional Banks	38	0.08	28.95	0.13	18.42	0.17	23.68	0.07	18.42
Other Stress-Tested Banks	21	0.52	61.90	0.10	14.29	-0.01	9.52	0.15	14.29
Factor = CET1									
March DG Watch Banks	5	0.52	80.00	0.23	40.00	0.21	20.00	0.20	40.00
April Only DG Banks	7	0.38	71.43	0.12	14.29	0.38	14.29	0.33	28.57
Other Regional Banks	38	0.03	13.16	0.44	52.63	0.16	23.68	0.27	34.21
Other Stress-Tested Banks	21	0.23	33.33	-0.08	9.52	0.21	23.81	0.06	14.29

Panel B: Excluding Mar. 9 – 13

		Factor × Mar. 1 – 8		Factor × Mar. 14 – 24		Factor × Mar. 27 – Apr. 13		Factor × DG – 9 days	
	N Banks	Change in β p50	% positive and $p < 0.05$	Change in β p50	% positive and $p < 0.05$	Change in β p50	% positive and $p < 0.05$	Change in β p50	% positive and $p < 0.05$
Factor = % UID									
March DG Watch Banks	5	0.49	80.00	0.27	40.00	0.15	0.00	0.56	60.00
April Only DG Banks	7	0.65	42.86	0.41	28.57	0.18	28.57	0.47	71.43
Other Regional Banks	38	0.33	39.47	0.26	44.74	0.19	15.79	0.32	42.11
Other Stress-Tested Banks	21	0.72	57.14	0.18	28.57	0.12	14.29	0.24	38.10
Factor = % Losses									
March DG Watch Banks	5	0.47	20.00	0.33	60.00	0.25	20.00	0.58	60.00
April Only DG Banks	7	0.77	57.14	0.06	14.29	-0.02	14.29	0.32	0.00
Other Regional Banks	38	0.47	44.74	0.23	34.21	-0.02	0.00	0.21	31.58
Other Stress-Tested Banks	21	0.99	71.43	-0.05	4.76	0.16	4.76	0.09	14.29
Factor = % Cash									
March DG Watch Banks	5	0.34	40.00	0.30	20.00	0.15	0.00	0.33	60.00
April Only DG Banks	7	0.42	14.29	0.12	0.00	0.16	0.00	0.25	14.29
Other Regional Banks	38	-0.08	10.53	0.14	21.05	0.17	26.32	0.08	18.42
Other Stress-Tested Banks	21	0.13	14.29	0.13	14.29	-0.02	9.52	0.17	14.29
Factor = CET1									
March DG Watch Banks	5	0.32	60.00	0.28	40.00	0.22	20.00	0.23	60.00
April Only DG Banks	7	0.61	57.14	0.12	14.29	0.34	28.57	0.36	28.57
Other Regional Banks	38	0.38	44.74	0.40	55.26	0.16	23.68	0.25	39.47
Other Stress-Tested Banks	21	0.51	66.67	-0.03	9.52	0.21	19.05	0.07	28.57

Note: This table summarizes the results of estimating balance sheet factor betas for each bank, as specified in equation 6, from January 1 to May 5, 2023. We show the median of the *change* in the β, for each of four periods (as reported in the column headings) relative to January-February 2023. Also shown is the percentage of banks with a positive and significant β in each period by bank group.

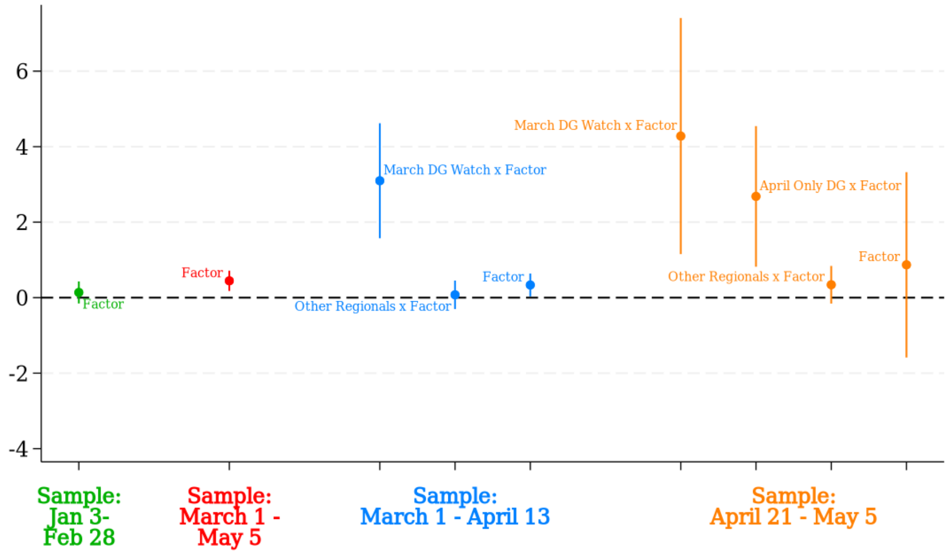
Figure 1: **Peak 1-Day Deposit Withdrawal Rates**



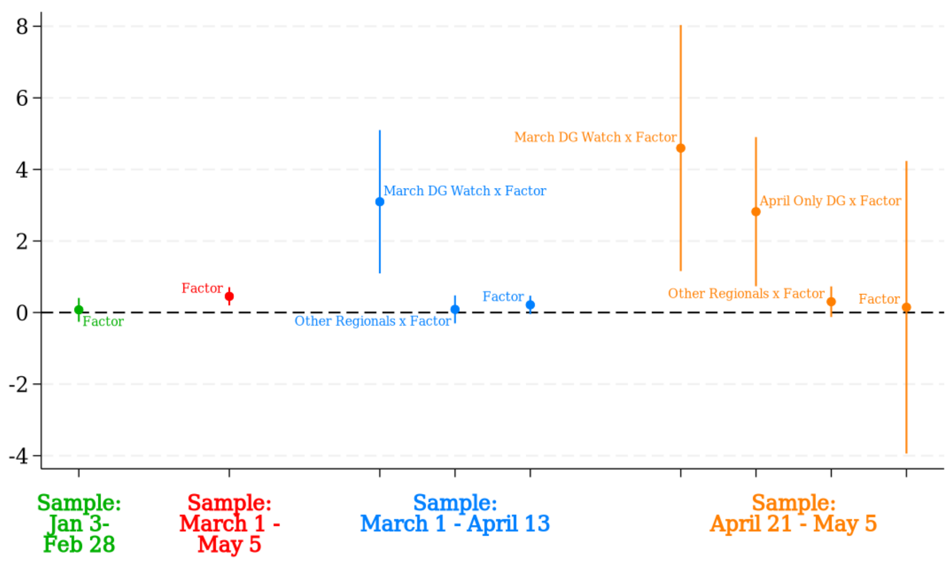
Note: The figure shows the 1-day peak deposit withdrawals as a percent of pre-run deposits, and the associated dates, for select banks during the March 2023 bank run, and for Continental Illinois and Washington Mutual. Banks are sorted by inflation adjusted assets from left (highest) to right (lowest).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

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

(a) Estimated Betas for Factor = UID

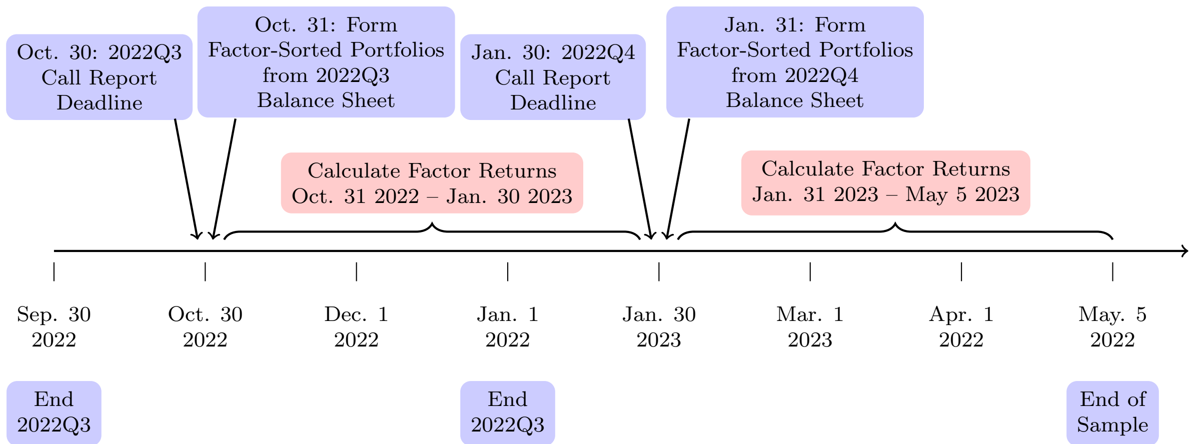


(b) Estimated Betas for Factor = $Losses$



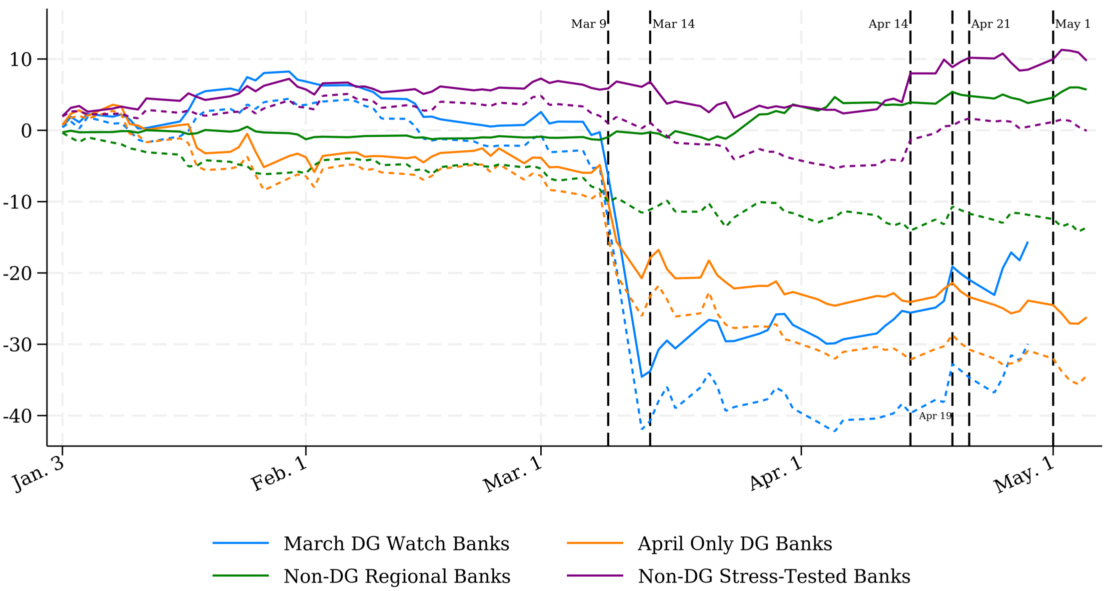
Note: This figure plots point estimates and 95% confidence intervals for the factor and factor times bank group interactions obtained from estimating equation (5). The factors are constructed from long-short portfolios based on 2022Q4 asset shares of uninsured deposits (UID) in Panel (a), and unrealized losses on AFS and HTM securities ($Losses$) in Panel (b). Each panel shows estimates from regressions using 4 sample dates in 2023. January 3-February 28 (green) and March 1-May 5 (red) are the pre- and post-run samples. The estimates from March 1-April 13 (blue) include interactions of the factor with 2 bank groups: those placed on downgrade watch on March 14 (*March DG Watch*) and regionals not in the March group (*Other Regionals*). The estimates from April 21 - May 5 (orange) include interactions of the factor with the *March DG Watch* banks (that were all downgraded in April), banks that were downgraded in April but not previously on downgrade watch (*April Only DG*) and non-downgraded regional banks (*Non-DG Regionals*). In all regressions, the omitted group consists of the non-downgraded stress-tested US banks.

Figure 3: **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.

Figure 4: **Cumulated Abnormal Stock Returns in 2023, By Bank Group**

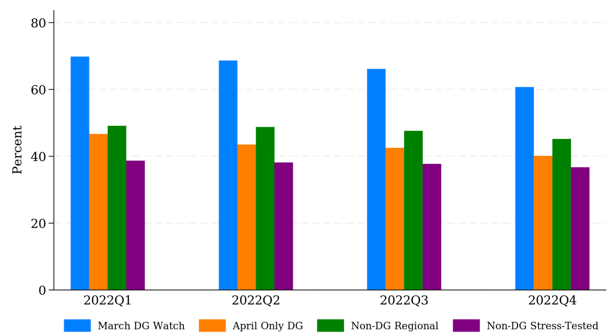


Solid (dashed) lines include (exclude) KBWR-RF in equations (1) and (2).

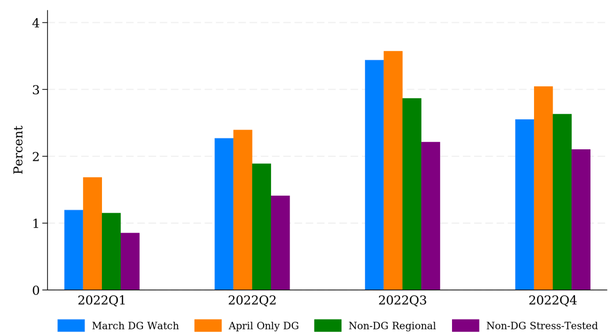
Note: The figure shows value-weighted cumulated bank stock returns (in %) from January 3,2023 to May 5, 2023 for different banks groups. Abnormal returns for each bank are calculated according to equations (1) and (2). Cumulated abnormal returns are calculates as $CAR_{i,t} = \prod_{s=3\text{jan}2023}^{t} AR_{i,s}$. The solid (dashed) lined include (exclude) the KBWR−RF in equations (1) and (2). Lastly, we take the market capitalization-weighted average (using the market cap from the beginning of the year) of $CAR_{i,t}$ for all banks in a given group. The $March\, DG\, Watch$ group includes banks put on downgrade (DG) watch in March. The $April\, Only\, DG\, Banks$ group includes banks downgraded between April 14 and 28. The $Non-DG\, Regional\, (Stress-Tested)\, Banks$ group consists of non-downgraded regional (US stress-tested) banks. Banks in the various groups are listed in appendix A. The drop lines indicate the downgrade watch (March 14, 2023), downgrade events (April 14, 19, and 21 of 2023), and the failure of FRC (May 1, 2023). Observations for SVB, SBNY, and Silvergate stock prices are dropped for the entire period.

Figure 5: **Bank Balance Sheet Characteristics in 2022, by Bank Group**

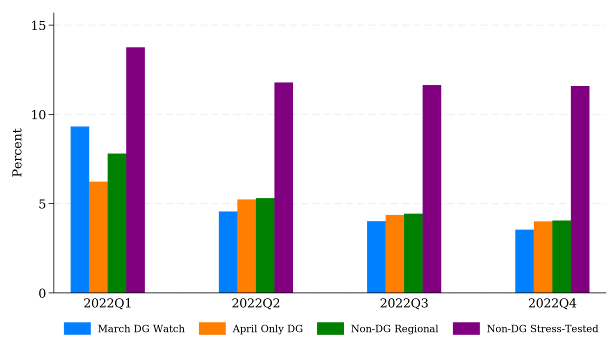
(a) UID



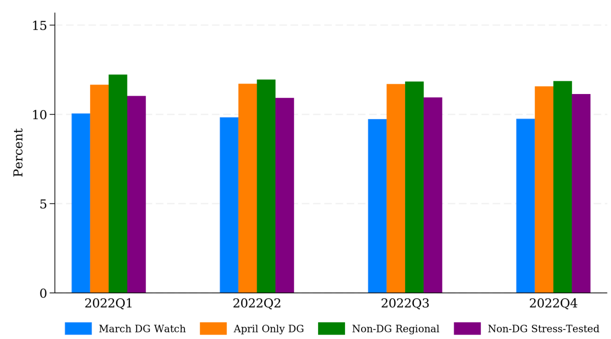
(b) $Losses$



(c) $\frac{Cash}{Assets}$

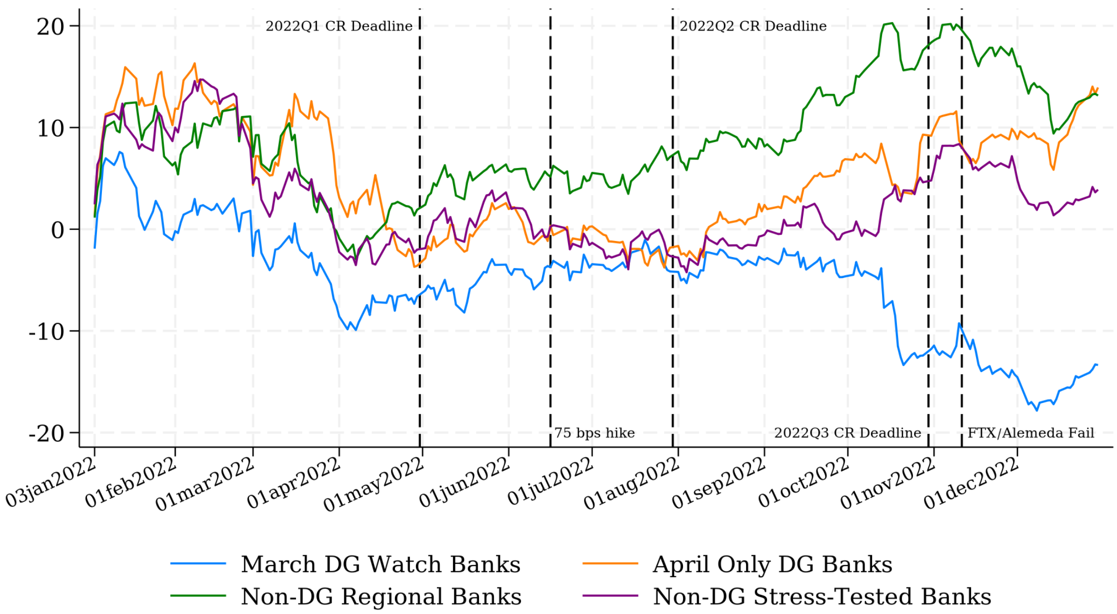


(d) CET1 Ratio



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 $March\, DG\, Watch$ group includes banks put on downgrade watch in March. 2023. The $April\, Only\, DG\, Banks$ group includes banks downgraded between April 14 and 21, 2023. 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.

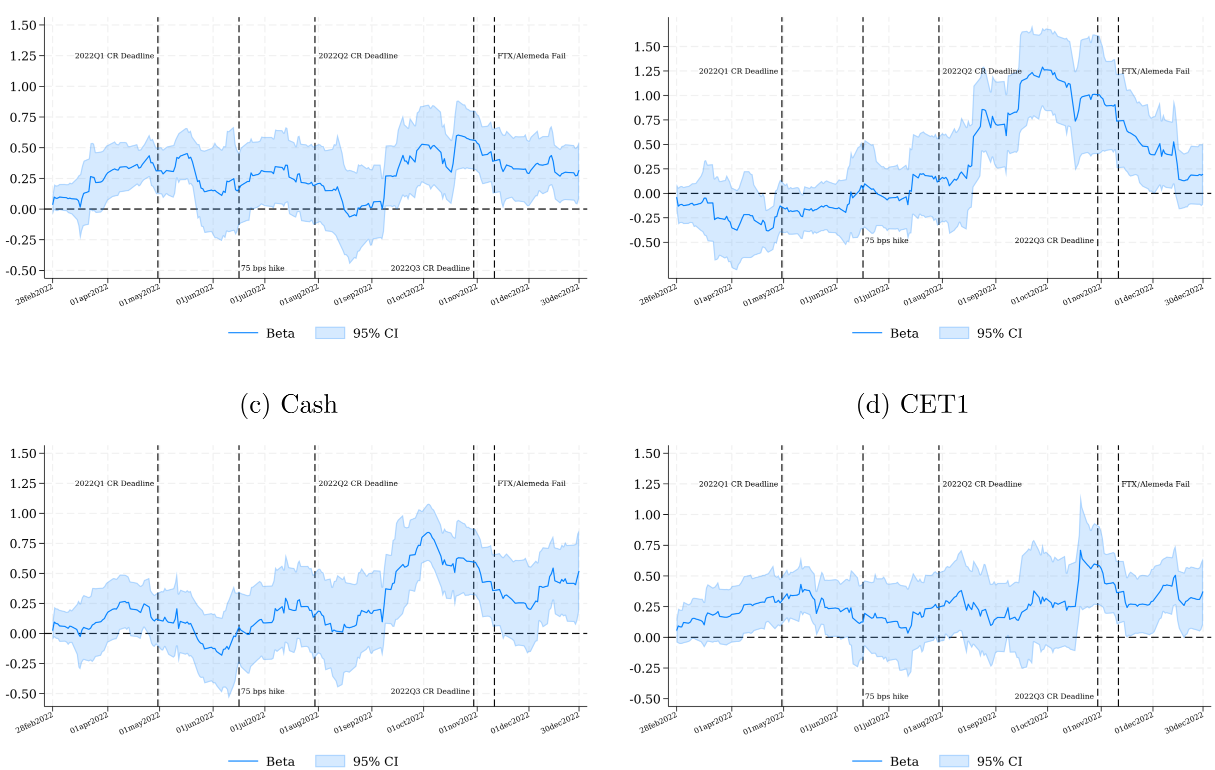
Figure 6: **Cumulated Abnormal Stock Returns in 2022, By Bank Group**



Note: The figure shows value-weighted cumulated bank stock returns relative to Wilshire 500 returns (in %) from January 3,2022 to December 29, 2023 for different banks groups. The $March\,DG\,Watch$ group includes banks put on downgrade (DG) watch in March. The $April\,Only\,DG\,Banks$ group includes banks downgraded between April 14 and 28. The $Non-DG\,Regional\,(Stress-Tested)\,Banks$ group consists of non-downgraded regional (US stress-tested) banks. Banks in the various groups are listed in appendix A. The vertical drop lines in panel indicate the the submission deadlines for the 2022 Q1, Q2 and Q3 Call Reports (April 30, 2022, July 30, 2022 and October 30, 2020, respectively), the first 75bps rate increase of the Federal Reserve's hiking cycle (June 16, 2022), and the failure of FTX (November 11, 2022). Observations for SVB, SBNY, and Silvergate stock prices are dropped for the entire period.

Figure 7: **Bank Balance Sheet Factor Betas in 2022**

(a) Uninsured Deposits (b) Unrealized Losses (c) Cash (d) CET1



Note: This figure plots the factor beta coefficients and 95% confidence intervals from estimating regression 5 for a rolling window of 39 trading days. The dates on the x-axis represent the end date of the rolling regression period. The first regression sample in 2022 is from January 3 to February 28, and the last from November 3 to December 30. The factors are constructed from long-short portfolios based on values 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 using balance sheets from the quarter before the start of the rolling window and after the Call Report filing deadline. 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. The vertical drop lines indicate the submission deadlines for the 2022 Q1, Q2 and Q3 Call Reports (April 30, 2022, July 30, 2022 and October 30, 2020, respectively), the first 75bps rate increase of the Federal Reserve's hiking cycle (June 16, 2022), and the failure of FTX (November 11, 2022). Observations for SVB, SBNY, and Silvergate stock prices are dropped for the entire period. Standard errors (used to compute the 95% confidence interval) are robust and clustered by date.

A Appendix A: Data

A.1 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).[16]. This crosswalk matches with 71 of the 74 banks.[17] 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.[18] 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.2 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 3.

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

A.3 Bank Group Members

A.3.1 March Downgrade Watch and April Downgrade Banks

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.

[16] Available here: `https://www.newyorkfed.org/research/banking_research/crsp-frb`

[17] The three unmatched banks are Cadence Bank, Eastern Bankshares Inc, and Bank OZK,

[18] Available here: `https://www.ffiec.gov/NPW`

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.3.2 April Only Downgrades

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.3.3 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.3.4 Non-Downgraded Stress-Tested Banks

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.[19]

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)
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] For the full list of stress-tested banks see Table 2 of "2022 Federal Reserve Stress Test Results," available at 2022 stress test results.

19. State Street Corporation (STT)

20. Truist Financial Corporation (TFC)

21. Wells Fargo & Company (WFC)

A.4 Overlap of Banks in Long/Short Factor Portfolio Groups

Table A.2 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 A.2: **Overlap of Banks in Factor Groups**

2021Q3

	Losses	UID	Cash	CET1
Losses	.	.	.	.
UID	12	.	.	.
Cash	12	15	.	.
CET1	14	14	14	.

2021Q4

	Losses	UID	Cash	CET1
Losses	.	.	.	.
UID	10	.	.	.
Cash	15	16	.	.
CET1	13	14	16	.

2022Q1

	Losses	UID	Cash	CET1
Losses	.	.	.	.
UID	16	.	.	.
Cash	22	17	.	.
CET1	14	11	13	.

2022Q2

	Losses	UID	Cash	CET1
Losses	.	.	.	.
UID	16	.	.	.
Cash	22	15	.	.
CET1	15	13	18	.

2022Q3

	Losses	UID	Cash	CET1
Losses	.	.	.	.
UID	17	.	.	.
Cash	22	18	.	.
CET1	13	14	15	.

2022Q4

	Losses	UID	Cash	CET1
Losses	.	.	.	.
UID	15	.	.	.
Cash	22	16	.	.
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 if the lowest tercile.

B Appendix B: Robustness Checks

B.1 Abnormal Returns

Table B.1: **Daily Means of Median Abnormal Stock Returns, by Bank Group**

Panel A: Relative to FF 5-Factor Model

	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	Moodys' DGs 4/21	4/24 – 5/5
SVB	0.43	-0.78	-54.13	-57.86	.	.	.	.	.	.	.	.	.	.
SBNY	-0.06	-1.22	-5.88	-17.97	.	.	.	.	.	.	.	.	.	.
Silvergate	0.21	-12.06	-35.07	-3.91	-5.59	-10.68	1.11	-1.64	-1.65	-1.00	6.09	2.32	-6.66	-0.41
March DG Watch Banks	-0.08	-0.86	-7.46	-11.58	-22.60	2.24	-0.70	-0.12	-2.34	0.85	6.91	-1.05	-3.48	-0.81
March DG Watch Banks Ex-FRC	0.13	-0.63	-6.51	-2.45	-22.60	1.80	0.24	0.03	-2.34	1.37	6.91	-1.05	-3.48	-0.96
April Only DG Banks	-0.35	-0.36	-9.29	-9.96	-8.85	7.20	-0.44	-0.92	-1.44	2.89	2.57	-1.19	0.15	-0.59
Non-DG Regional Banks	-0.14	-0.60	-2.02	0.62	-1.96	-0.49	-0.37	-0.40	-1.53	0.20	2.89	-0.75	0.08	-0.24
Non-DG Stress-Tested Banks	0.12	-0.44	-1.64	0.87	-1.17	0.81	-0.38	-0.07	1.64	0.74	0.39	1.04	0.52	-0.22

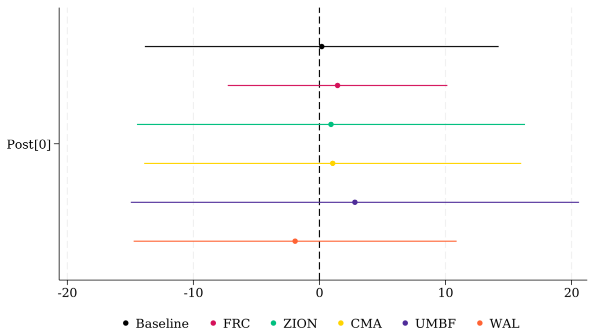
Panel B: Relative to FF 5-Factors and Regional Bank Index

	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	Moodys' DGs 4/21	4/24 – 5/5
SVB	0.55	-0.18	-51.30	-57.80	.	.	.	.	.	.	.	.	.	.
SBNY	0.06	-0.60	-3.00	-17.91	.	.	.	.	.	.	.	.	.	.
Silvergate	0.32	-11.56	-32.71	-3.86	-3.62	-10.97	1.23	-1.27	-0.01	-1.19	3.97	2.49	-6.23	-0.12
March DG Watch Banks	-0.01	-0.56	-5.09	-11.57	-20.47	1.90	-0.54	0.31	-0.57	0.75	4.49	-0.87	-3.01	-0.50
March DG Watch Banks Ex-FRC	0.23	-0.07	-3.82	-2.40	-20.47	1.48	0.39	0.45	-0.57	1.09	4.49	-0.87	-3.01	-0.64
April Only DG Banks	-0.30	-0.09	-8.01	-9.93	-7.79	7.04	-0.37	-0.72	-0.56	2.79	1.42	-1.10	0.38	-0.43
Non-DG Regional Banks	-0.02	-0.07	0.40	0.68	0.27	-0.80	-0.19	0.02	0.26	0.02	0.55	-0.56	0.54	-0.02
Non-DG Stress-Tested Banks	0.18	-0.27	-0.16	0.90	-0.67	0.69	-0.33	0.10	2.33	0.97	-1.24	1.10	0.70	-0.13

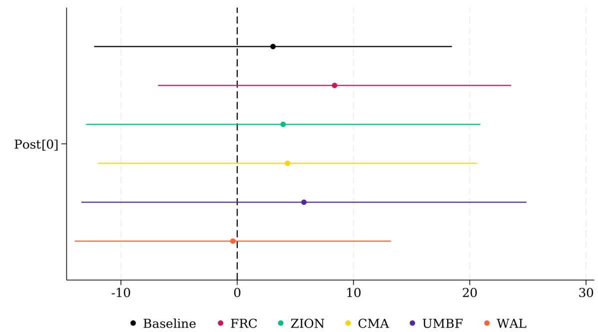
Note: The table shows value-weighted median abnormal bank stock returns (in %) from January 3,2023 to May 5, 2023 for different banks groups and sample periods. Abnormal returns for each bank are calculated according to equations (1) and (2). The values are calculate by first taking the median return across the banks in a given group on each day. Then, we take the average of these medians over the days listed in the column headers. Observations for SVB and SBNY stock prices are dropped after they went into receivership on March 10 and March 12, respectively. The *March DG Watch* group includes banks put on downgrade (DG) watch in March. We include and additional row for the *March DG Watch* group excluding FRC. The *April Only DG Banks* group includes banks downgraded between April 14 and 28. 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.

Figure B.1: **Leave One Out: Abnormal Returns**

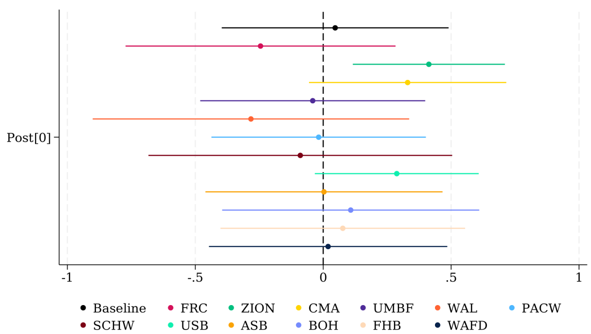
(a) March; Relative to Jan. – Feb.



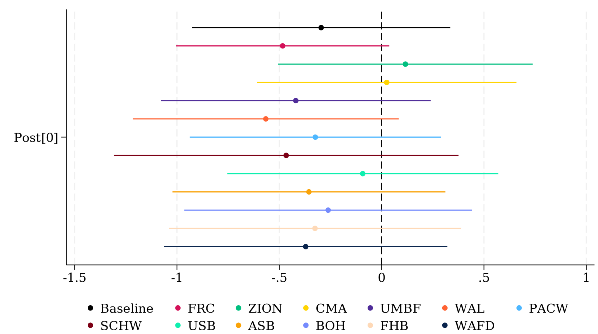
(b) March; Relative to Mar. 1 – 12



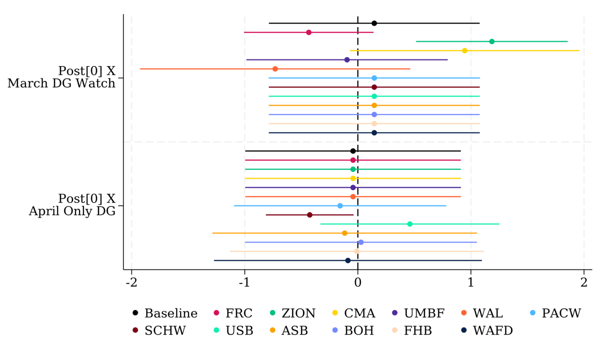
(c) April; Relative to Jan. – Feb.



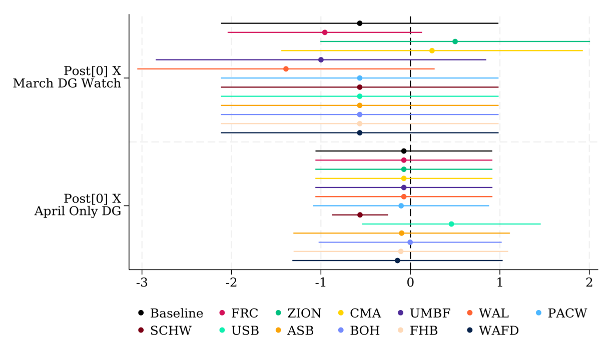
(d) April; Relative to Mar. 27 – two days before DG



April by Group;
(e) Relative to Jan. – Feb.



April by Group;
(f) Relative to Mar. 1 – two days before DG



Note: This figure shows the coefficient estimates on Post[0] from estimating equations (3) and (4) excluding one event bank at a time. Panels (a) and (b) focus on the March 14 downgrade watch announcement, and panels (c) – (f) focus on the April downgrade announcement.

B.2 Excluding First Republic Bank (FRC)

Table B.2: **Bank Balance Sheet Factor Beta: March 1 to May 5, 2023, Excluding FRC**

	Factor=%UID	Factor=% Losses	Factor=% Cash	Factor = CET1
Factor	0.45***	0.46***	0.43***	0.42***
	(0.13)	(0.13)	(0.10)	(0.11)
Mkt-RF	0.95***	1.08***	1.02***	1.11***
	(0.23)	(0.22)	(0.21)	(0.22)
SMB	0.34	0.34	0.22	0.36
	(0.36)	(0.35)	(0.32)	(0.35)
HML	1.93***	1.88***	1.90***	1.79***
	(0.31)	(0.27)	(0.24)	(0.29)
RMW	-0.43	-0.20	-0.35	-0.21
	(0.49)	(0.38)	(0.37)	(0.39)
CMA	-1.72***	-1.65***	-1.54***	-1.42***
	(0.45)	(0.43)	(0.44)	(0.44)
Log(MVE)$_{t-1}$	-5.18	-5.13	-5.42*	-5.20*
	(3.10)	(3.06)	(3.04)	(3.03)
Obs	3,290	3,290	3,290	3,290
Adj R2	0.44	0.44	0.45	0.44
Bank FE	YES	YES	YES	YES

Note: This table shows that the estimates in Table 5 are robust to the exclusion of First Republic Bank (FRC). This table presents the results from estimating regression (5), without the bank group interactions, for the period March 1 to May 5, 2023. The factors are constructed from long-short portfolios based on 2022Q4 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. FRC, SVB, SBNY and Silvergate are not included in the regression. FRC is dropped from the sample on and after its failure (May 1). Standard errors (in parentheses) are robust and clustered by date. Stars represent statistical significance: $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

C Appendix C: Additional Results for Beta Estimations

C.1 Panel Results

Table C.1: **Bank Balance Sheet Factor Beta, Interacted with Bank Groups, March 1 to April 13**

	Factor=%UID	Factor=% Losses	Factor=% Cash	Factor = CET1
Factor	0.34**	0.22*	0.18	0.20
	(0.15)	(0.13)	(0.16)	(0.15)
March DG Watch × Factor	3.10***	3.10***	2.45**	2.73***
	(0.75)	(0.98)	(0.96)	(0.80)
Other Regionals × Factor	0.08	0.09	0.28	0.03
	(0.18)	(0.19)	(0.19)	(0.16)
Mkt-RF	0.88***	1.21***	0.88***	1.09***
	(0.22)	(0.21)	(0.18)	(0.23)
SMB	0.14	0.13	0.02	0.14
	(0.26)	(0.28)	(0.23)	(0.28)
HML	1.92***	1.96***	2.12***	2.05***
	(0.30)	(0.18)	(0.25)	(0.29)
RMW	-0.66	-0.12	-0.87**	-0.39
	(0.44)	(0.43)	(0.41)	(0.55)
CMA	-1.83***	-1.85***	-1.90***	-1.83***
	(0.43)	(0.36)	(0.46)	(0.46)
Log(MVE)_{t-1}	-2.91**	-2.73*	-3.66**	-2.96**
	(1.40)	(1.41)	(1.56)	(1.44)
Obs	2,201	2,201	2,201	2,201
Adj R2	0.52	0.51	0.51	0.51
Bank FE	YES	YES	YES	YES

Note: This table shows results from estimating regression 5 for the period March 1 to April 13. The *March DG Watch* group includes banks put on downgrade (DG) watch in March. The *Other Regional Banks* group consists of the regionals that were not on downgrade watch. Stress-tested US banks are the omitted group. Banks in the various groups are listed in appendix A. The factors are constructed from long-short portfolios based on 2022Q4 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 excluded from the regression sample. Standard errors (in parentheses) are robust and clustered by date. Stars represent statistical significance: $*p < 0.1$; $**p < 0.05$; $***p < 0.01$.

Table C.2: **Bank Balance Sheet Factor Beta, Interacted with Bank Groups, After Downgrade Announcements**

Panel A

	Factor=%UID	Factor=% Losses	Factor=% Cash	Factor = CET1
Factor	0.87	0.14	0.55	0.42
	(1.11)	(1.84)	(0.48)	(0.55)
DG Banks × Factor	3.25**	3.46**	1.68**	1.96**
	(1.03)	(1.15)	(0.55)	(0.73)
Non-DG Regional Banks × Factor	0.34	0.30	0.26*	0.19
	(0.22)	(0.19)	(0.12)	(0.14)
Obs	770	770	770	770
Adj R2	0.48	0.48	0.48	0.48
Bank FE	YES	YES	YES	YES
Controls Included?	YES	YES	YES	YES

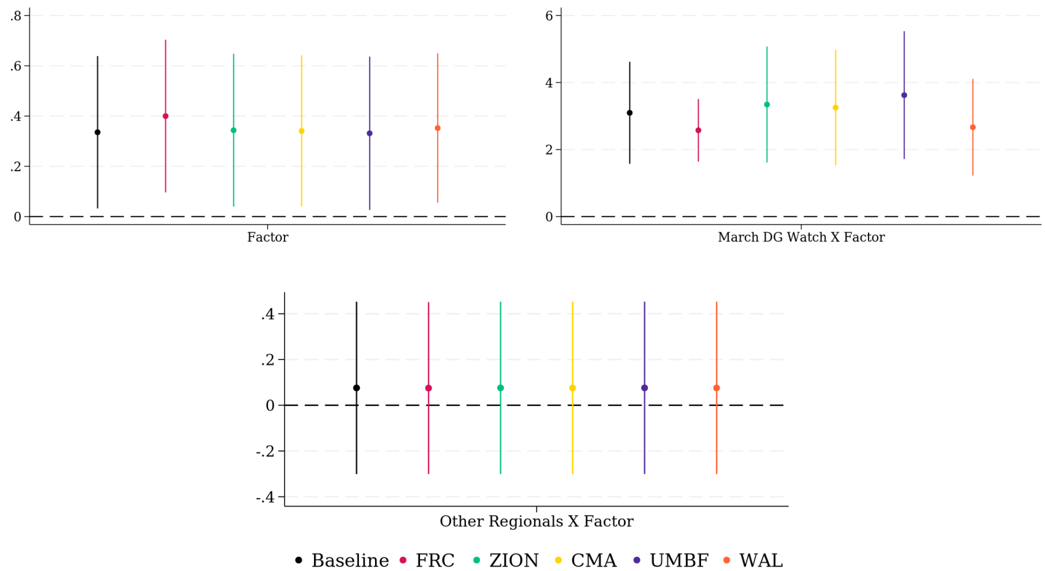
Panel B

	Factor=%UID	Factor=% Losses	Factor=% Cash	Factor = CET1
Factor	0.87	0.15	0.55	0.42
	(1.10)	(1.83)	(0.47)	(0.54)
DG Watch Banks × Factor (α)	4.28**	4.60**	2.16**	2.56**
	(1.40)	(1.54)	(0.77)	(1.02)
April Only DG Banks × Factor (β)	2.68***	2.82**	1.41***	1.63**
	(0.84)	(0.94)	(0.44)	(0.57)
Non-DG Regional Banks × Factor	0.34	0.30	0.26*	0.19
	(0.22)	(0.19)	(0.12)	(0.14)
Obs	770	770	770	770
Adj R2	0.48	0.48	0.48	0.48
Bank FE	YES	YES	YES	YES
Controls Included?	YES	YES	YES	YES
p-value from test of $\alpha = \beta$	0.03	0.03	0.07	0.09

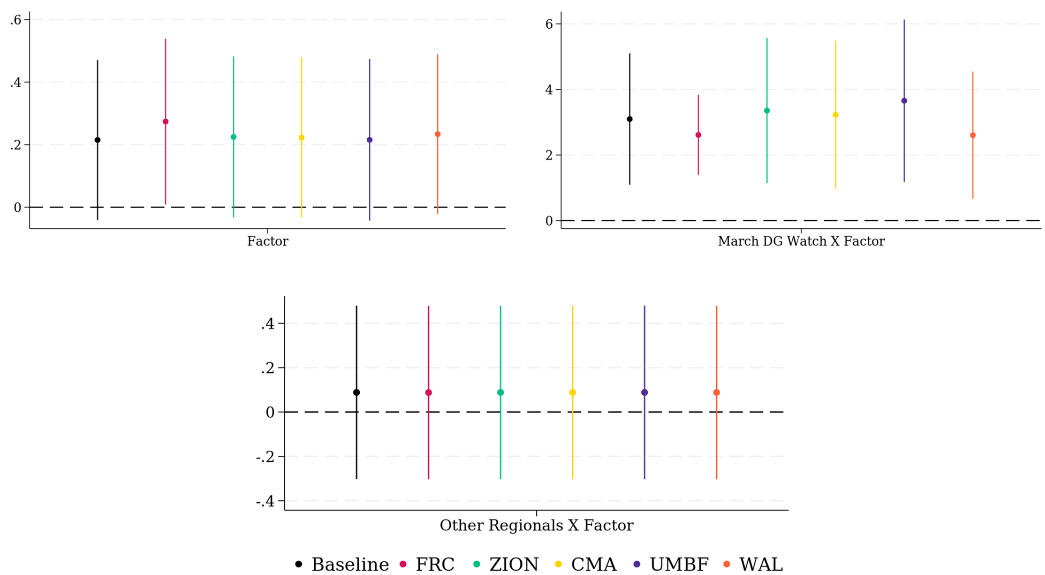
Note: This table shows results from estimating regression 5 for April 21-May 5, 2023. In Panel A, *DG Banks* is a dummy variable equal to one for banks that were downgraded in April. In Panel B, *March DG Watch Banks* equals 1 for banks put on downgrade watch in March and subsequently downgraded in April while *April Only DG Banks* is 1 for downgraded banks not placed on watch previously. All banks on downgrade watch were also downgraded. In both panels, the *Non-DG Regional Banks* group consists of the regionals that were not downgraded. Non-downgraded stress-tested US banks are the omitted group. We exclude FRC, SVB, SBNY, and Silvergate from the regression sample. All regressions control for the five Fama-French factors and the (lagged) log of the bank's market value of equity, but we do report their estimates for brevity. The final row of Panel B reports the p-value for the null hypothesis that the *DG Watch Banks* × Factor coefficient (α) is equal to the *April Only DG Banks* × Factor coefficient (β). The factors are constructed from long-short portfolios based on 2022Q4 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. 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: **Leave-One-Out Analysis: Balance Sheet Factor Betas with Bank Group Interactions, March 1 to April 13, 2023**

(a) Uninsured Deposits (UID) Factor

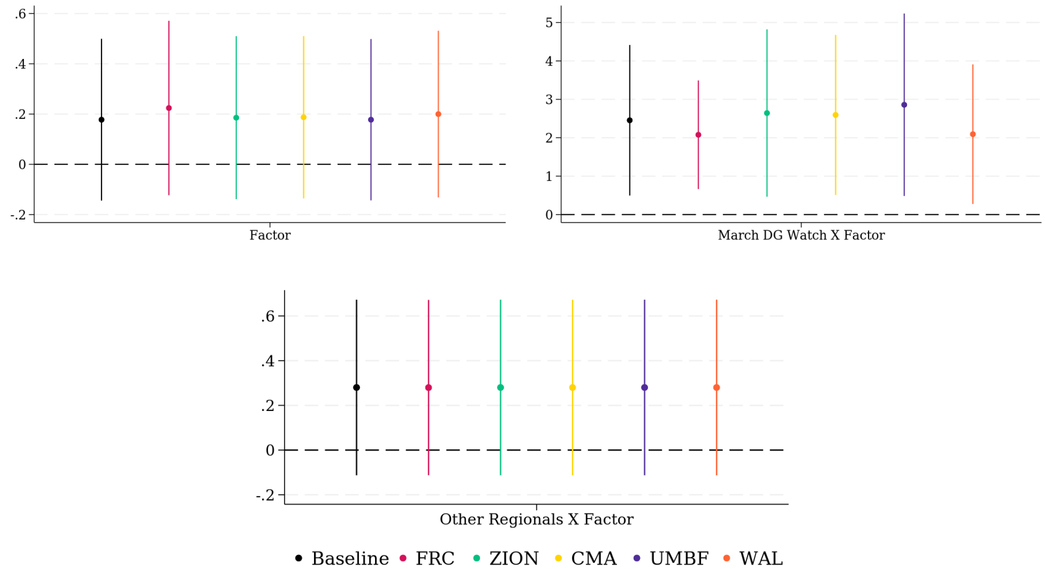


(b) Unrealized Losses ($Losses$) Factor

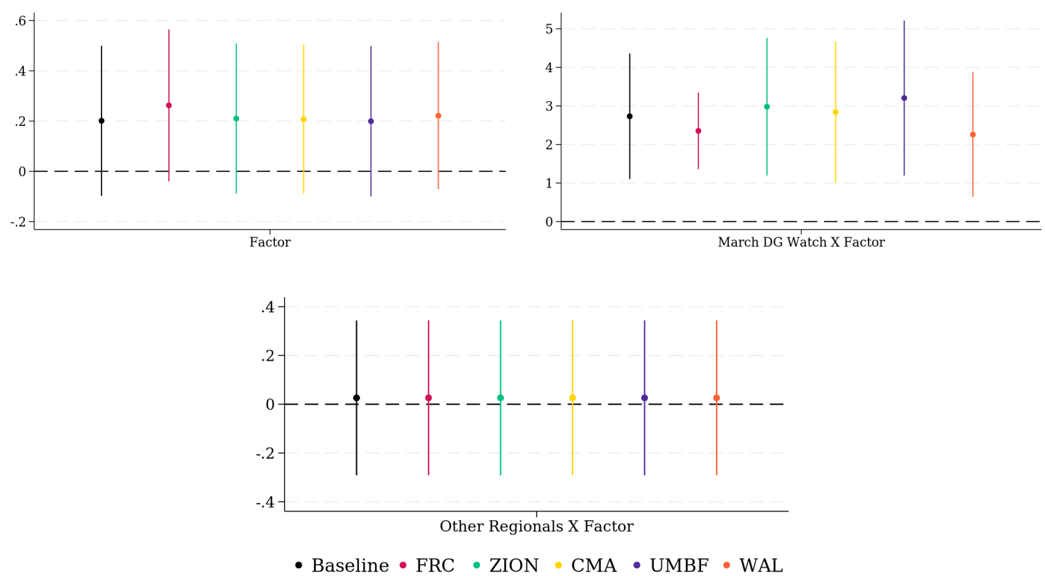


[Figure continues on next page.]

(c) Cash Factor



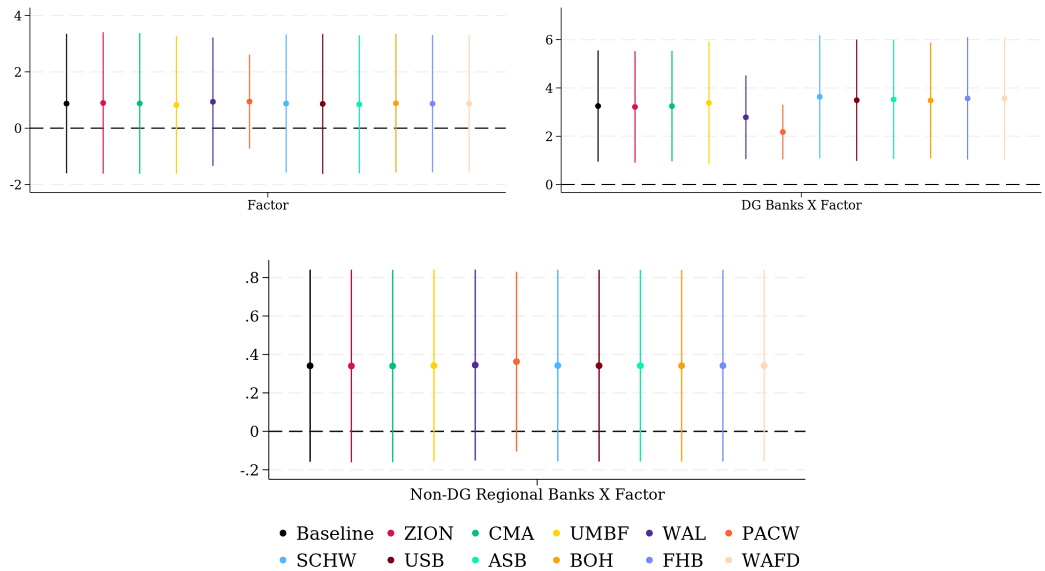
(d) CET1 Factor



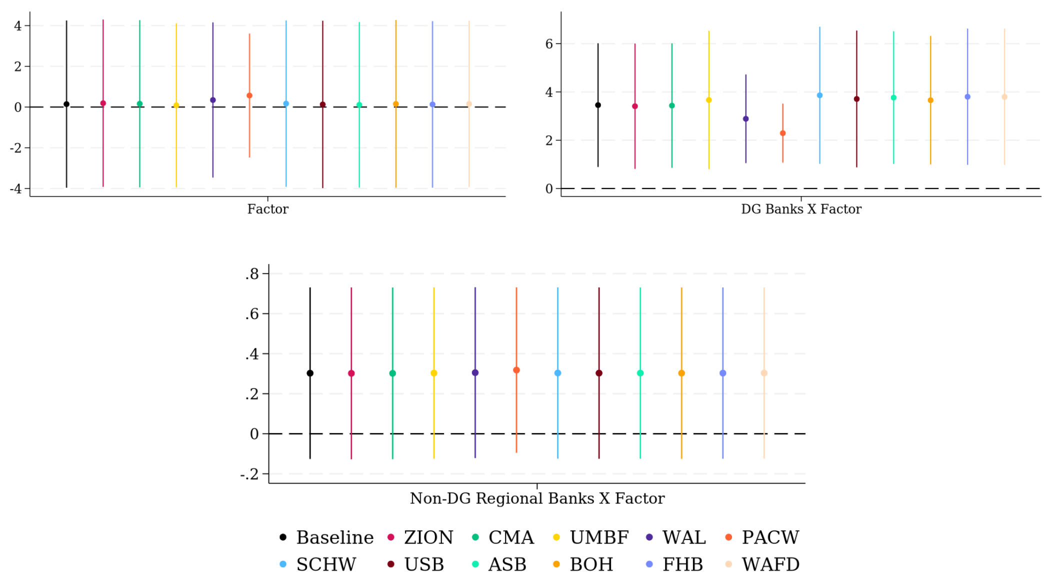
Note: This figure shows the results of leave-one-out robustness checks for the regression estimates in Table C.1 by excluding each bank in the *March DG Watch* group one at a time. The sample period in each regression is March 1 to April 13, 2023. Each panel of the figure plots the point estimate and 95% confidence interval for the coefficient on the factor and the factor times bank group interactions. Within each panel, the different colors represent estimates obtained from excluding the corresponding bank in the legend. The point estimates and confidence intervals in black, labeled "Baseline" in the legend, are the estimates obtained without dropping any banks and are identical to those in Table C.1.

Figure C.2: **Leave-One-Out Analysis: Balance Sheet Factor Betas with Bank Group Interactions, After Downgrade Announcements**

(a) Uninsured Deposits (UID) Factor

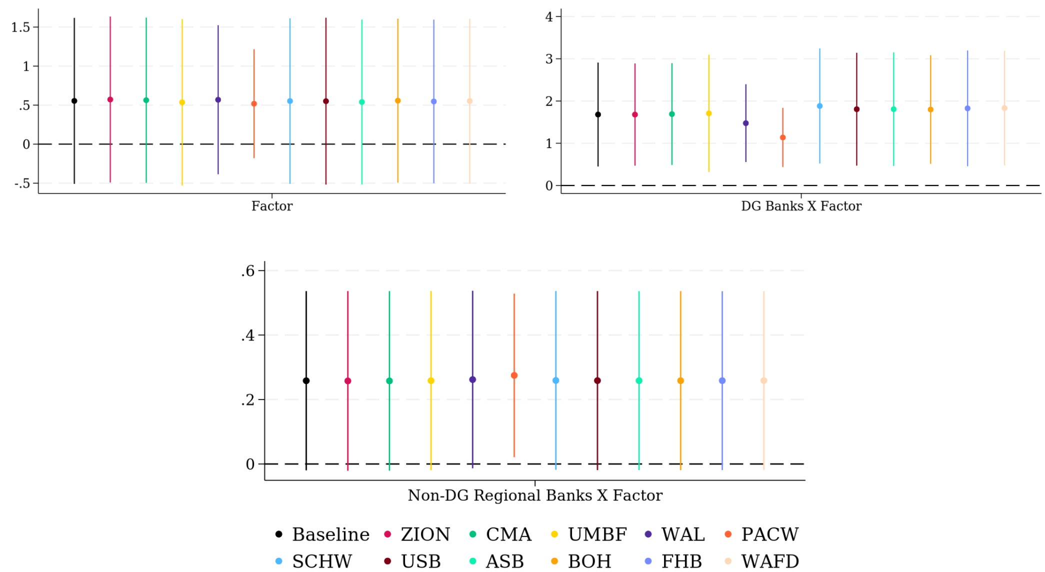


(b) Unrealized Losses ($Losses$) Factor

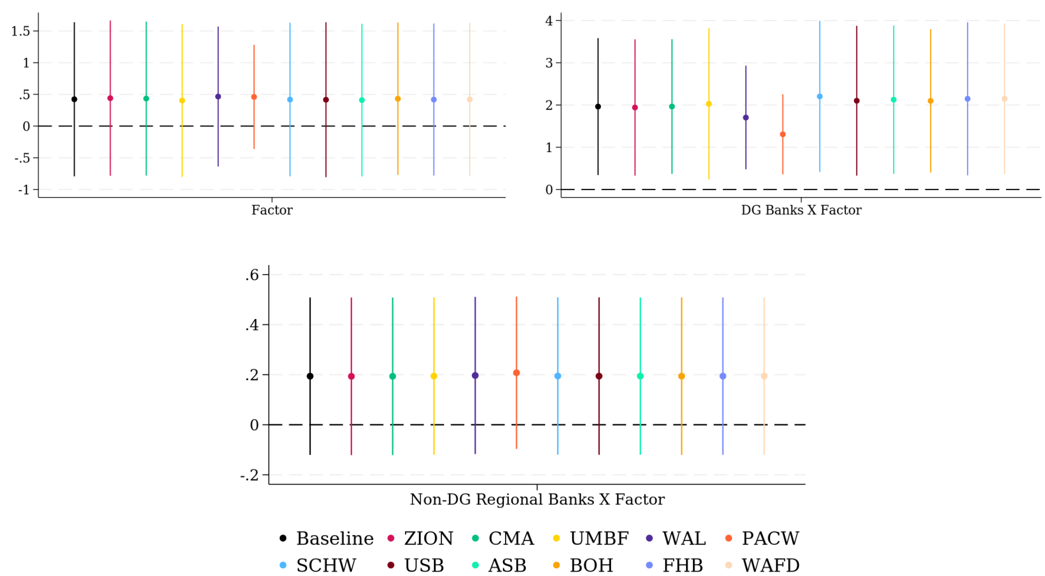


[Figure continues on next page.]

(c) Cash Factor



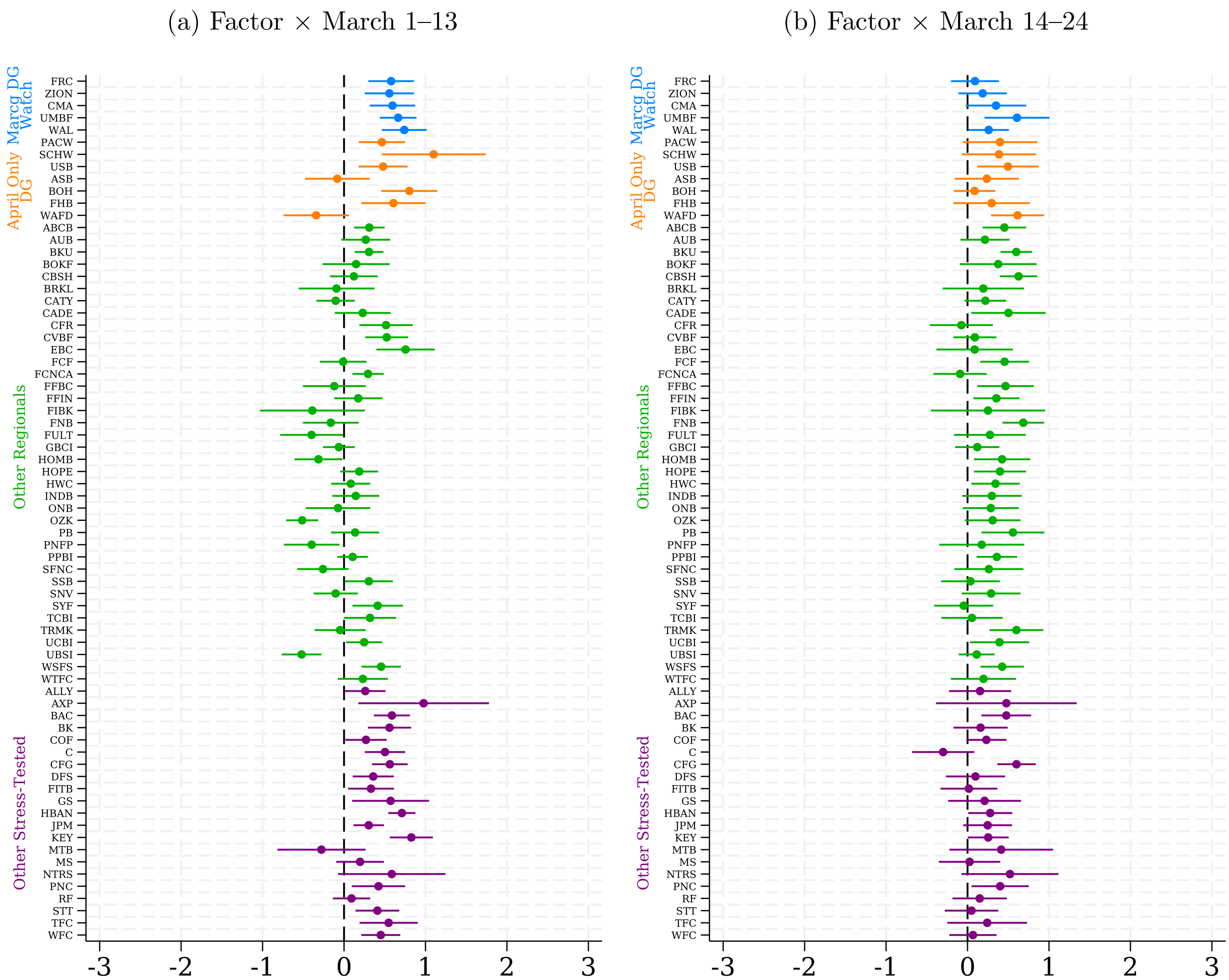
(d) CET1 Factor



Note: This figure shows the results of leave-one-out robustness checks for the regression estimates in Panel A of Table C.2 by excluding each bank in the *DG Banks* group one at a time. The sample period in each regression in April 21 to May 5, 2023. Each panel of the figure plots the point estimate and 95% confidence interval for the coefficient on the factor and the factor times bank group interactions. Within each panel, the different colors represent estimates obtained from excluding the corresponding bank in the legend. The point estimates and confidence intervals in black, labeled "Baseline" in the legend, are the estimates obtained without dropping any banks and are identical to those in Table C.2.

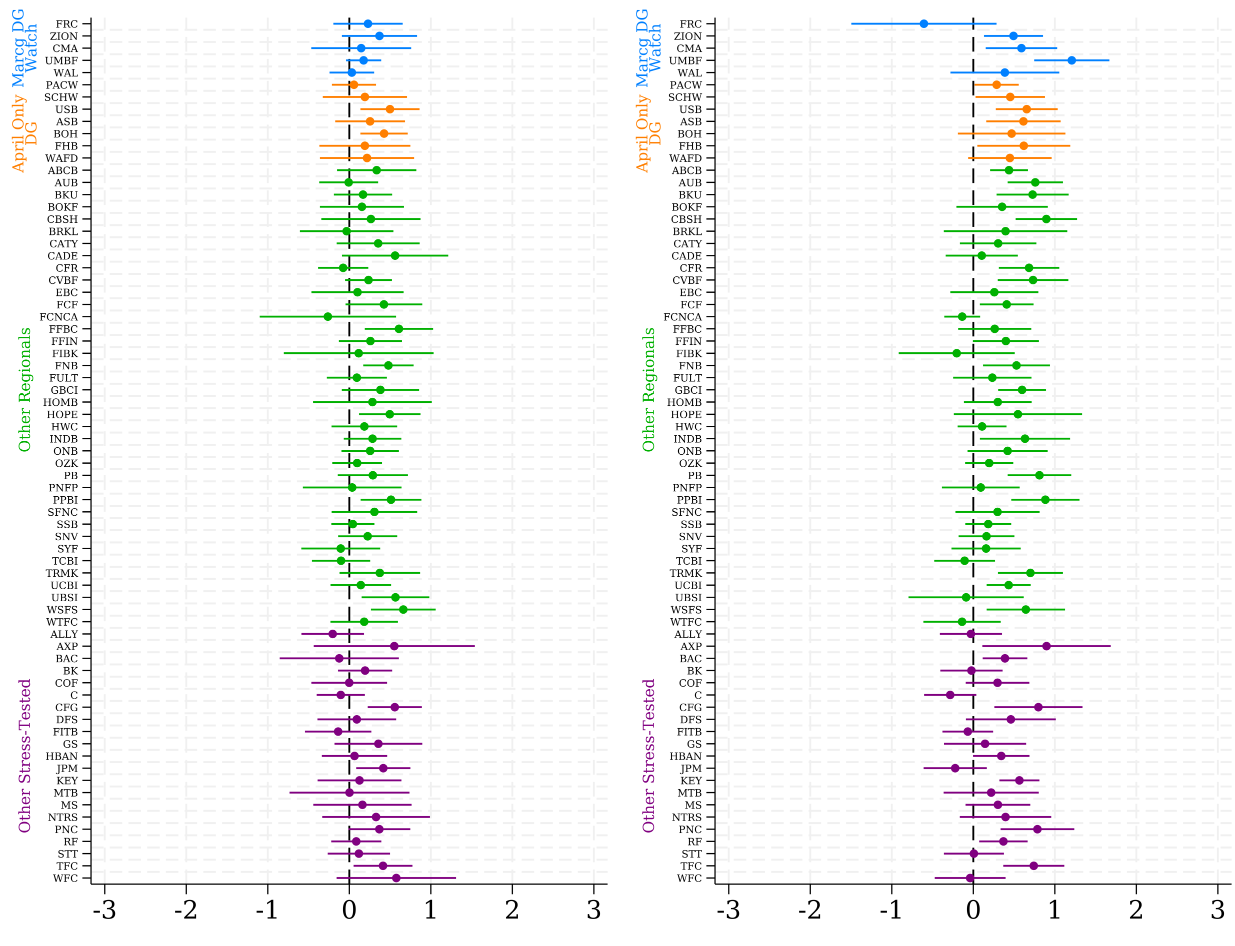
C.2 Dynamic Bank-by-Bank Results

Figure C.3: **Factor = %UID**



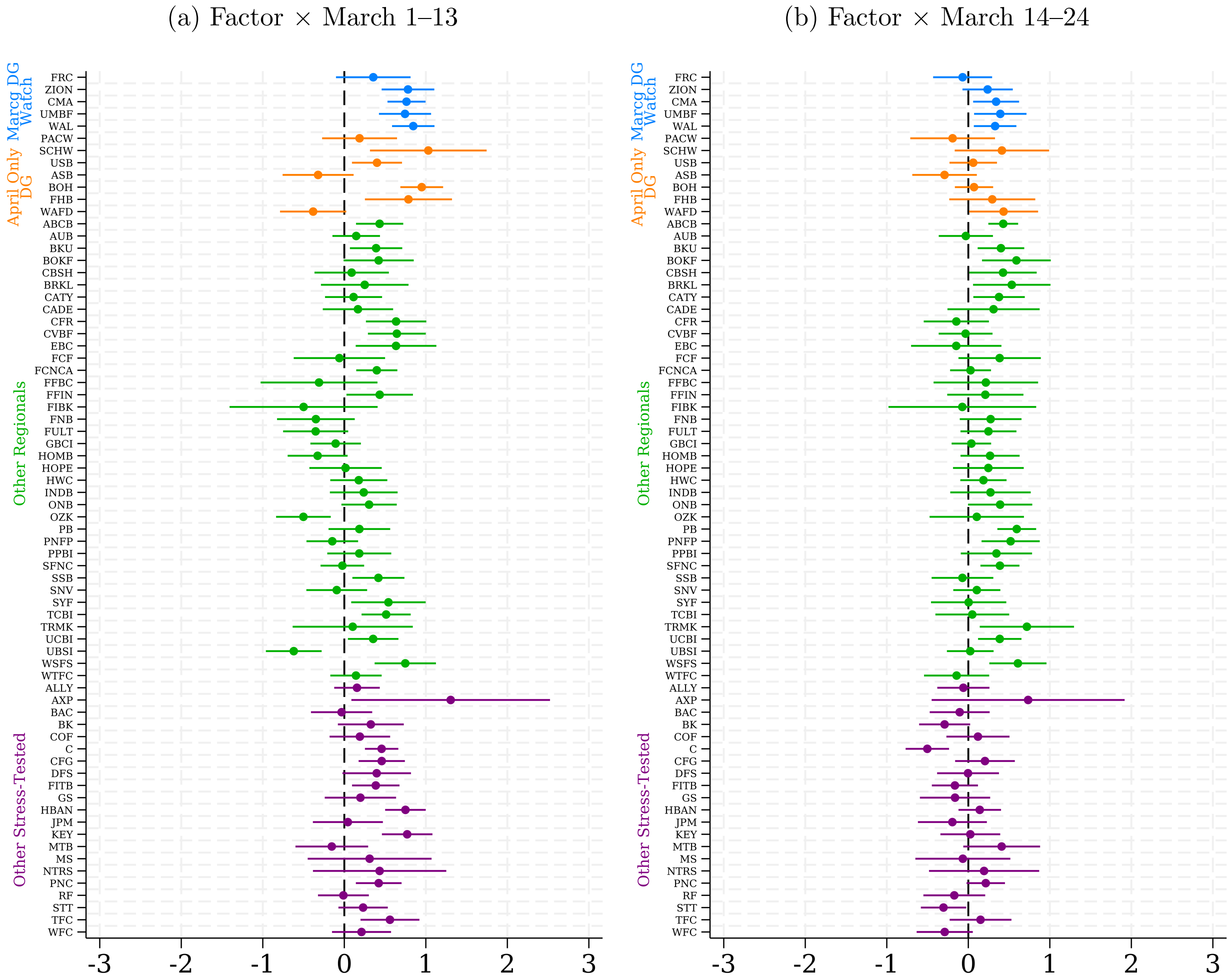
[Figure continues on next page.]

(c) Factor × March 27–9 Days (d) Factor × Day of DG–End of Sample



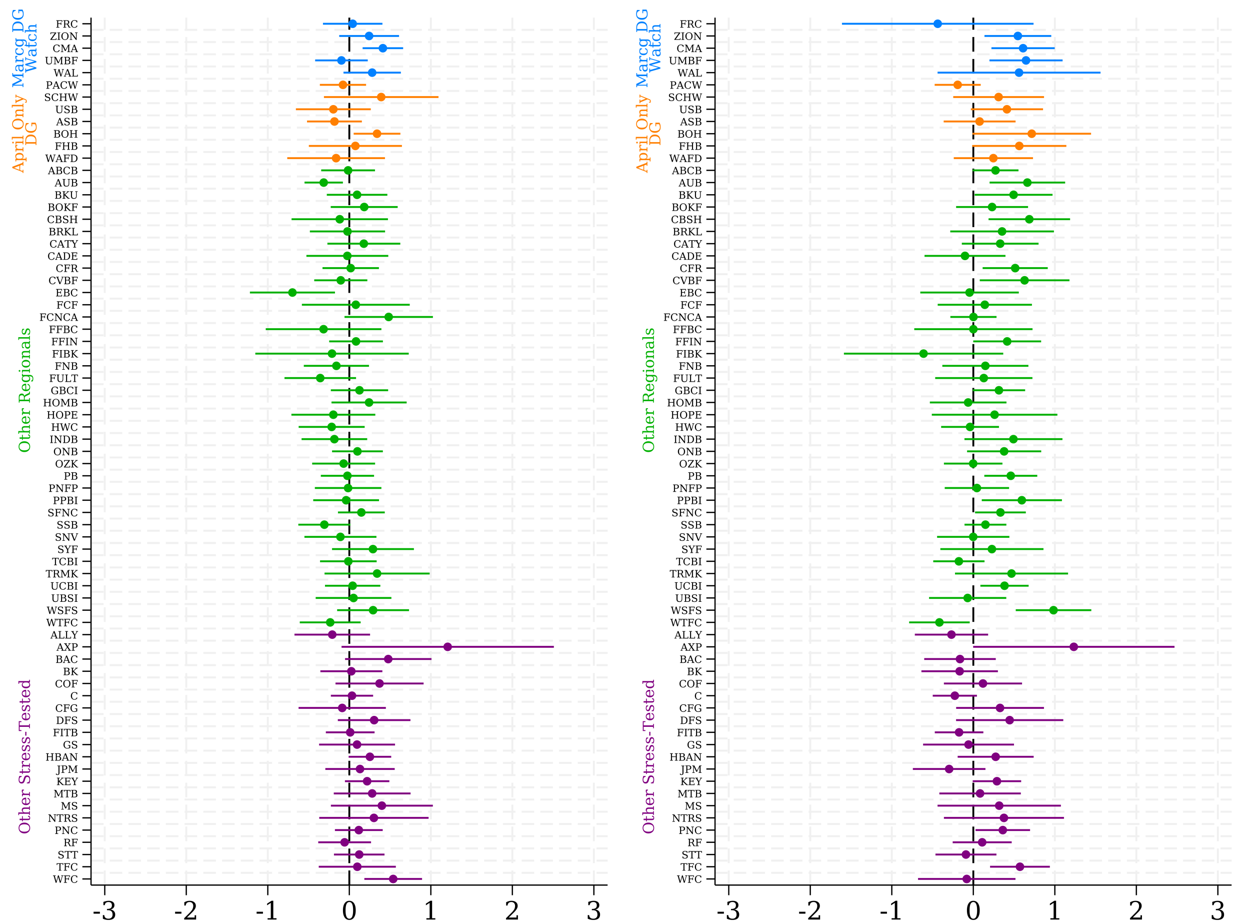
Note: This figure reports the results of estimating equation 6. 95% Confidence intervals are constructed using Newey-West standard errors with a maximum lag of 6. All regressions control for the five Fama-French factors and the lagged natural log of MVE.

Figure C.4: **Factor = %Losses**



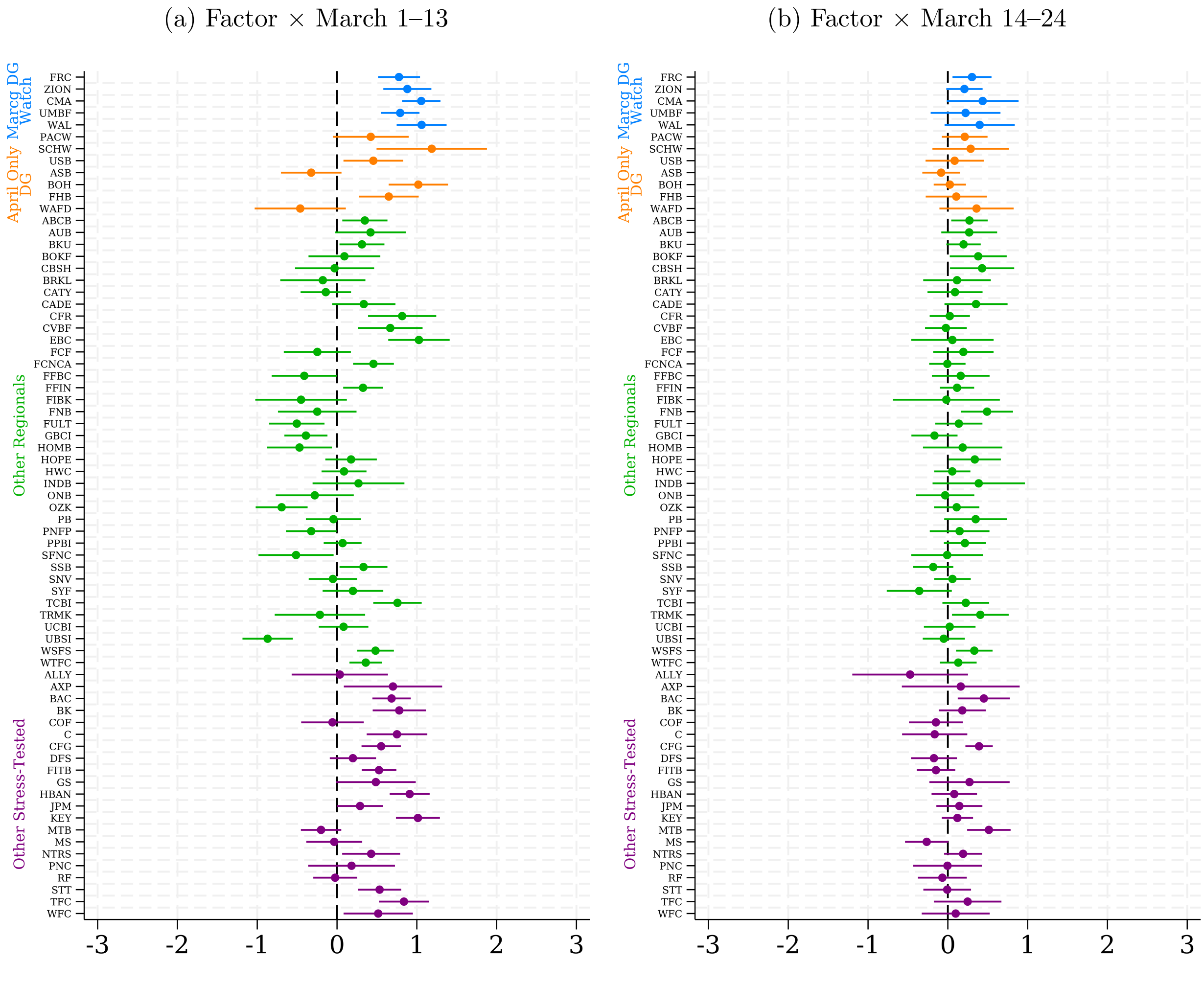
[Figure continues on next page.]

(c) Factor × March 27–April 13 (d) Factor × Day of DG–9 Days

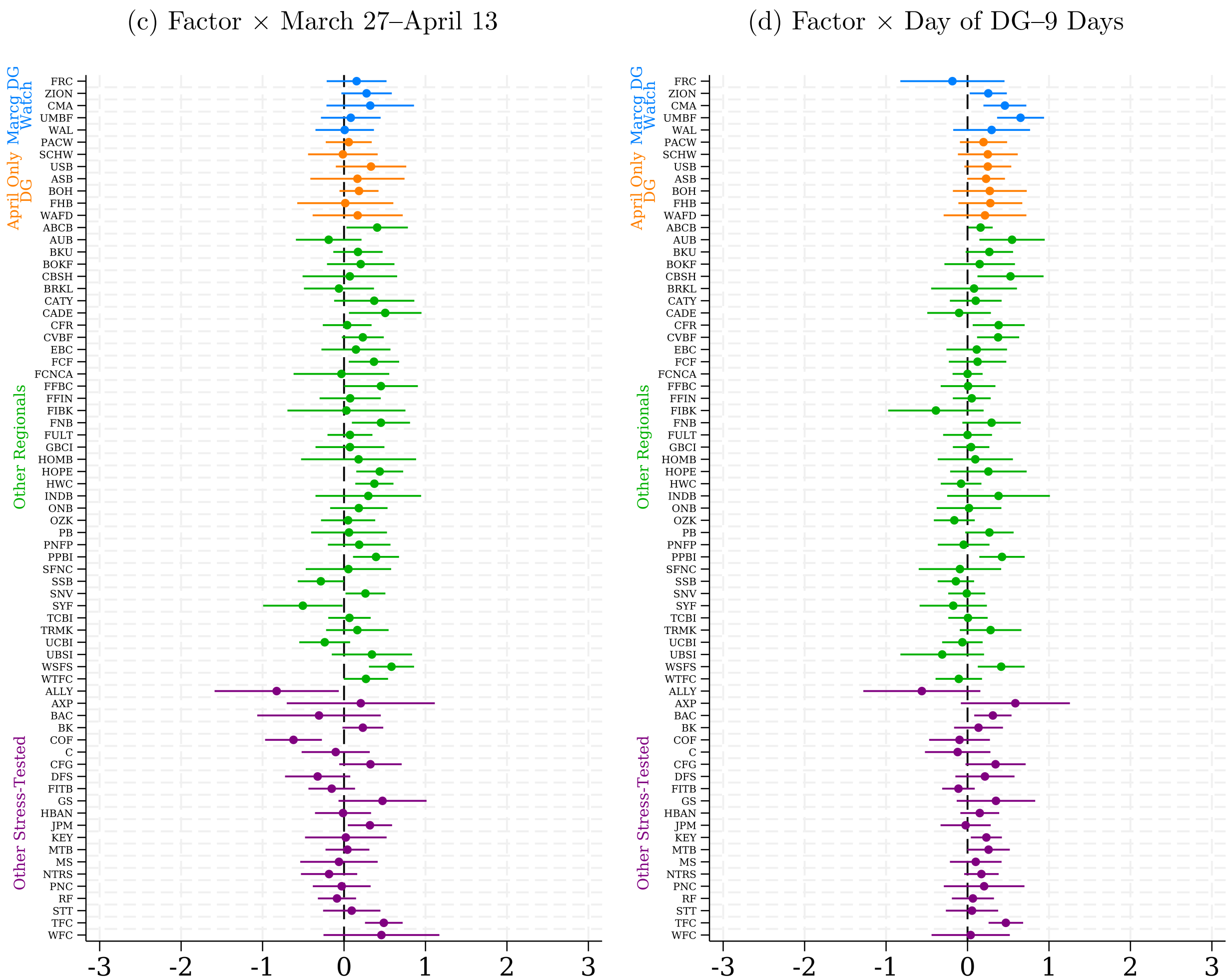


Note: This figure reports the results of estimating equation 6. 95% Confidence intervals are constructed using Newey-West standard errors with a maximum lag of 6. All regressions control for the five Fama-French factors and the lagged natural log of MVE.

Figure C.5: **Factor = %Cash**



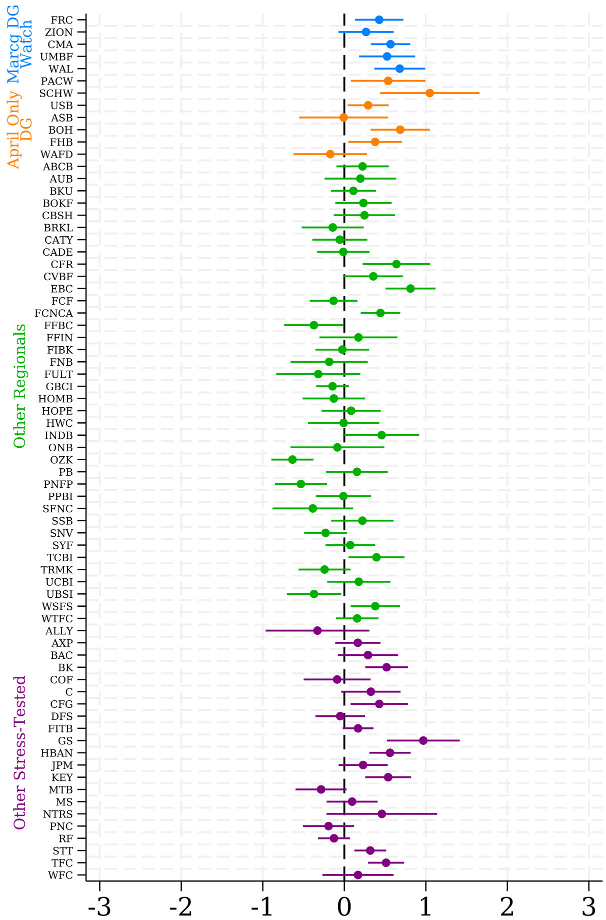
[Figure continues on next page.]



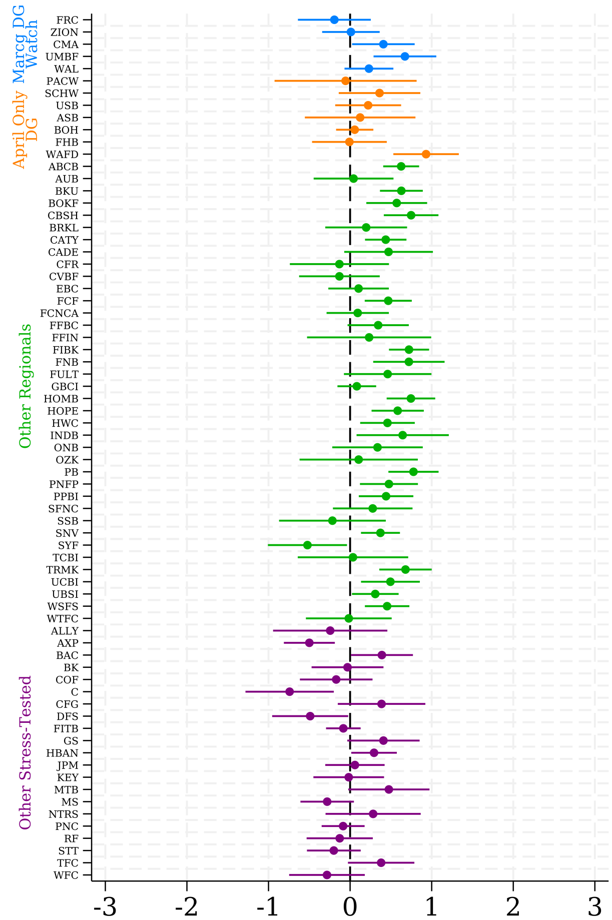
Note: This figure reports the results of estimating equation 6. 95% Confidence intervals are constructed using Newey-West standard errors with a maximum lag of 6. All regressions control for the five Fama-French factors and the lagged natural log of MVE.

Figure C.6: **Factor = CET1**

(a) Factor × March 1–13

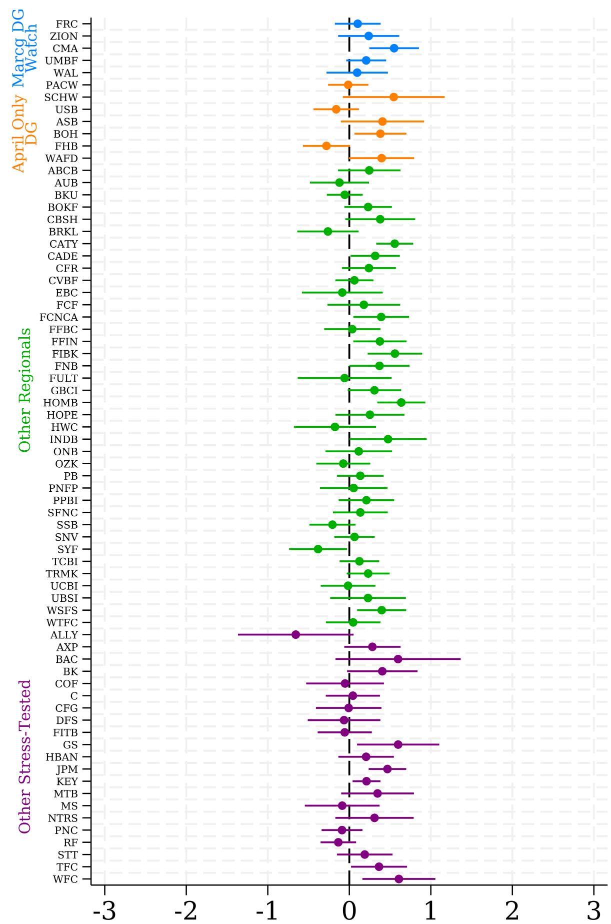


(b) Factor × March 14–24

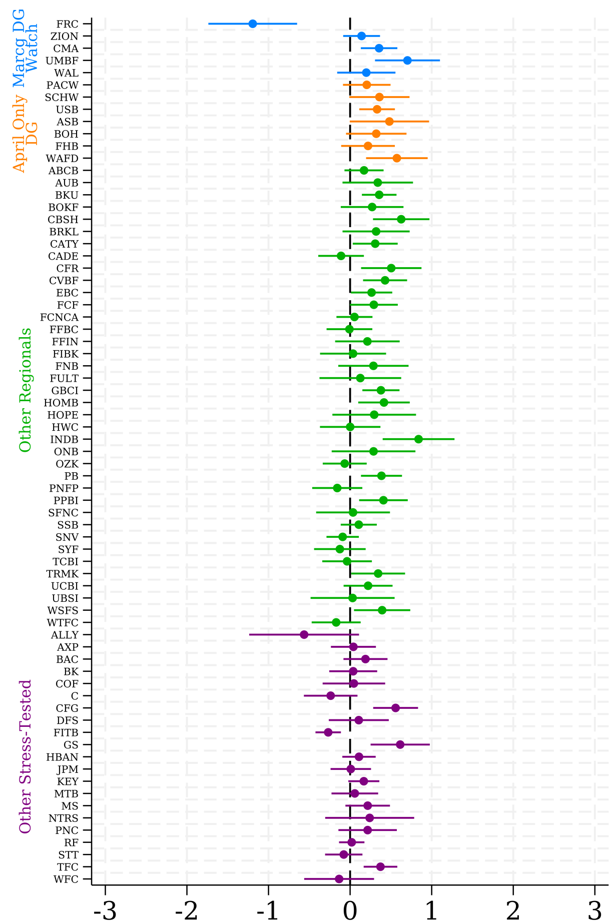


[Figure continues on next page.]

(c) Factor × March 27–April 13



(d) Factor × Day of DG–9 Days



Note: This figure reports the results of estimating equation 6. 95% Confidence intervals are constructed using Newey-West standard errors with a maximum lag of 6. All regressions control for the five Fama-French factors and the lagged natural log of MVE.

D Appendix D: Results for CET1 with Losses Factor

CET1 with losses is defined as the hypothetical CET1 ratio if AFS + HTM losses were realized, as follows:

$$CET1\ With\ Losses_i = \frac{CET1 - Losses \times (1 - 0.21)}{RWA} \tag{D.0}$$

$Losses$=Unrealized losses from AFS and HTM securities; RWA=Risk-weighted assets.

The adjustment of 0.21 reflects and adjustment for capital gains taxes. We assume that, after the unrealized securities losses becomes realized, the loss is recorded on the income statement along with other non-interest income as a pre-tax item. To flow down to net income (where it would hit retained earnings, and thereby capital) it would need be taxed. We assume that this tax rate is 21%.

The factor is constructed similar to the others: we first sort banks into terciles based on the 2022Q4 balance sheet values of *CET1 with losses* and then calculate the (negative of) the return spread between the top and bottom portfolios. Table D.1 shows that the hypothetical CET1 with losses tracks the unrealized loss shares in Table 1: they are highest for the downgraded banks and the non-downgraded regionals.

Table D.1: **Average CET1 with Losses as of 2022Q4, by Bank Group**

	Number of Banks	CET1 with Losses
SVB	1	-0.25
SBNY	1	7.58
Silvergate	1	35.90
March DG Watch Banks	5	7.21
April Only DG Banks	7	6.74
Non-DG Regional Banks	38	9.08
Non-DG Stress-Tested Banks	21	9.79

Note: The table shows the average value of CET1 Ratio with losses for SVB, SBNY, Silvergate and four bank groups, reported as of 2022Q4. The ratios is reported in %.The *April Only DG Banks* group includes banks downgraded between April 14 and 28. 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: **CET1 With Losses Factor Beta: January to February 2023**

	Factor = CET1 with Losses
Factor	0.27^{**}
	(0.13)
Mkt-RF	0.93^{***}
	(0.13)
SMB	0.48^{**}
	(0.19)
HML	0.62^{***}
	(0.22)
RMW	0.25
	(0.25)
CMA	-0.41
	(0.32)
Log(MVE)_{t-1}	-5.18^{***}
	(1.65)
Obs	2,769
Adj R2	0.43
Bank FE	YES

Note: This table shows results from estimating regression (5), without the bank group interactions, for the period January 3 to February 28, 2023. The factor is constructed from a long-short portfolio based on values of the (negative of the) hypothetical CET1 ratio if AFS and HTM losses were realized. Downgraded and failed banks are excluded from the factor construction. Standard errors (in parentheses) are robust and clustered by date. Stars represent statistical significance: $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$. SVB, SBNY and Silvergate are not included in the regression.

Table D.3: **CET1 With Losses Factor Beta: March 1 to May 5, 2023**

	Factor = CET1 with Losses
Factor	0.33***
	(0.12)
Mkt-RF	1.08***
	(0.30)
SMB	0.45
	(0.43)
HML	1.68***
	(0.40)
RMW	-0.12
	(0.47)
CMA	-1.35**
	(0.57)
Log(MVE)_{t-1}	-9.88**
	(4.50)
Obs	2,906
Adj R2	0.42
Bank FE	YES

Note: This table shows results from estimating regression (5), without the bank group interactions, for the period March 1 to May 5, 2023. The factor is constructed from a long-short portfolio based on values of the (negative of the) hypothetical CET1 ratio if AFS and HTM losses were realized from 2022Q4. Downgraded and failed banks are excluded from the factor construction. Standard errors (in parentheses) are robust and clustered by date. Stars represent statistical significance: $^*p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$. SVB, SBNY and Silvergate are not included in the regression.

Table D.4: **CET1 with Losses Factor Beta, Interacted with Bank Groups, March 1 to April 13**

	Factor = CET1
Factor	0.11
	(0.18)
March DG Watch × Factor	1.83**
	(0.68)
Other Regionals × Factor	0.08
	(0.16)
Mkt-RF	0.96**
	(0.40)
SMB	0.08
	(0.41)
HML	1.81***
	(0.43)
RMW	-0.03
	(0.60)
CMA	-1.82***
	(0.62)
Log(MVE)_{t-1}	-12.51***
	(3.17)
Obs	1,775
Adj R2	0.55
Bank FE	YES

Note: This table shows results from estimating regression 5 for the period March 1 to April 13, 2023. The *March DG Watch* group includes banks put on downgrade (DG) watch in March. The *Other Regional Banks* group consists of the regionals that were not on downgrade watch. Stress-tested US banks are the omitted group. Banks in the various groups are listed in appendix A. The factor is constructed from a long-short portfolio based on values of the (negative of the) hypothetical CET1 ratio if AFS and HTM losses were realized. Downgraded and failed banks are excluded from the factor construction. Standard errors (in parentheses) are robust and clustered by date. Stars represent statistical significance: $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$. SVB, SBNY and Silvergate are excluded from the regression sample.

Table D.5: **CET1 with Losses Factor Beta, After Downgrade Announcement**

Panel A

	Factor = CET1 with Losses
Factor	0.48
	(0.45)
DG Banks × Factor	1.48**
	(0.57)
Non-DG Regional Banks × Factor	0.14
	(0.10)
Obs	770
Adj R2	0.48
Bank FE	YES
Controls	YES

Panel B

	Factor = CET1 with Losses
Factor	0.47
	(0.45)
DG Watch Banks × Factor(α)	1.93**
	(0.80)
April Only DG Banks × Factor (β)	1.23**
	(0.45)
Non-DG Regional Banks × Factor	0.14
	(0.10)
Obs	770
Adj R2	0.48
Bank FE	YES
Controls	YES
p-value ($\alpha = \beta$)	0.10

Note: This table shows results from estimating regression 5 for April 21-May 5, 2023. In Panel A, *DG Banks* is a dummy variable equal to one for banks that were downgraded in April. In Panel B, *March DG Watch Banks* equals 1 for banks put on downgrade watch in March and subsequently downgraded in April while *April Only DG Banks* is 1 for downgraded banks not placed on watch previously. All banks on downgrade watch were also downgraded. In both panels, the *Non-DG Regional Banks* group consists of the regionals that were not downgraded. Non-downgraded stress-tested US banks are the omitted group. We exclude FRC, SVB, SBNY, and Silvergate from the regression sample. All regressions control for the five Fama-French factors and the (lagged) log of the bank's market value of equity, but we do report their estimates for brevity. The final row of Panel B reports the p-value for the null hypothesis that the *DG Watch Banks* × Factor coefficient (α) is equal to the *April Only DG Banks* × Factor coefficient (β). The factor is constructed from a long-short portfolio based on values of the (negative of the) hypothetical CET1 ratio if AFS and HTM losses were realized. Downgraded and failed banks are excluded from the factor construction. Standard errors (in parentheses) are robust and clustered by date. Stars represent statistical significance: *$p < 0.1$; **$p < 0.05$; ***$p < 0.01$.