How (in)effective was bank supervision during the 2022 Monetary Tightening?*

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Abstract

This study examines the effectiveness of bank supervision before, during, and after the 2022 monetary tightening. Supervisors identified emerging interest rate risks and started downgrading riskier banks but only after the Federal Reserve began raising interest rates. Excessive reliance on uninsured deposits was not associated with downgrades. Banks with unrealized losses in AFS securities were more likely downgraded than those with losses in HTM securities. Downgrades subsequently led to lower interest rate risk exposure and increased liquidity. Our back-of-the envelope calculations suggest that earlier intervention could have averted \$9.44 billion in losses corresponding to one percent of the Tier 1 capital of banks that otherwise were not downgraded.

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1 Introduction

A simple combination of events led to the collapse of Silicon Valley Bank (SVB) and First Republic Corporation (FRC) in the first half of 2023. These banks funded sizable holdings of long-term securities with uninsured deposits. Their holdings of long-term securities lost significant market value as the Federal Reserve began raising interest rates during 2022. By categorizing a large portion of their securities as held-to-maturity (HTM), SVB and FRC avoided marking them down on their balance sheets, temporarily evading closer scrutiny of their fragile financial situation. But once concerns emerged that the market value of these banks' assets might not be enough to cover deposits, a large number of uninsured depositors banking with SVB and FRC swiftly withdrew their money and precipitated these banks' demise.

In fact, the events that prompted the failure of these banks were so simple that many commentators questioned how regulators allowed them to amass substantial exposures to interest rate and liquidity risks during 2021 and 2022. Were supervisors oblivious of the systemic risks that were so openly and obviously brewing in the banking system? Were they aware of these risks but lacked the resources and discretionary powers to oversee all banks effectively? Did they willingly decide not to intervene hoping that these emerging risks would eventually subside? And is it possible that supervisors did intervene to curb interest rate risk exposures at some banks, but their actions remained secret due to the confidential nature of supervisory examinations?

The combination of interest rate and liquidity risks that brought down SVB and FRC was not unique to these failed banks. Jiang et al. [2023] show that if half of uninsured depositors decided to withdraw their money, almost 190 banks with assets exceeding $300 billion would be at a potential risk of insolvency by the first quarter of 2023. In this paper, we use confidential information on the regulatory CAMELS ratings of U.S. banks to conduct an anatomy of how supervisors assessed these interest rate and liquidity risks before, during, and after the monetary tightening of 2022.[1] In particular, we investigate: (i) if and when supervisors downgraded banks with large exposures to interest rate risks, (ii) if and when supervisors downgraded banks with excessive reliance on unstable sources of funding, and (iii) if supervisors responded differently to unrealized losses on banks' securities portfolios based on the accounting classification of these securities. Finally, we ask if these rating downgrades disciplined banks' interest rate risk management and contributed to risk reduction at downgraded banks.

We begin by showing that bank supervisors incrementally downgraded the liquidity (L) and sensitivity to risk (S) ratings of banks with high exposure to interest rate risks as the Federal Open Market Committee (FOMC) began raising interest rates. We assess banks' interest rate risk exposure by computing the duration of their asset portfolios and find that, after the beginning of the monetary tightening, supervisors downgraded the "S" rating for about 16% of banks in the highest quintile of exposure to interest rate risks, compared to 8% in the lowest quintile. By contrast, prior to that moment, bank supervisors downgraded the "S" rating of 6% of inspected banks across all quintiles of interest rate risk exposure. These findings suggest that bank supervisors understood and responded to the heightened interest rate risks posed by long-duration securities.

When the FOMC began its sharp monetary policy tightening in March 2022, most banks' securities portfolios had already experienced large unrealized losses as investors had

[1] Bank supervisors conduct periodic on-site examinations to assess the financial condition of regulated entities. The CAMELS rating, covering capital adequacy (C), asset quality (A), management (M), earnings (E), liquidity (L), and sensitivity to risk (S), is a key output from these examinations. It serves as the basis for crucial supervisory interventions, including merger approvals, dividend restrictions, and deposit insurance assessment fees.

incorporated expectations of rising interest rates into the prices of fixed-income securities. We examine the timing of the supervisory response to heightened interest rate risks to determine whether supervisors reacted as soon as banks' portfolios began losing value, when the FOMC officially raised interest rates, or if they waited until the failures of SVB and FRC publicly exposed significant risks in the banking system. Our findings indicate that supervisors began downgrading high-interest rate risk banks in the second quarter of 2022. The timing of this response coincided with the start of monetary tightening but came after most banks had already disclosed significant unrealized losses in their portfolios of securities.

If banks employ interest rate swaps or other derivatives to hedge their interest rate risks, our asset duration-based exposure measures may not fully capture their risk exposures. Granja et al. [2024] and McPhail et al. [2023] find that, on average, banks' swap positions mostly offset each other and do not hedge an economically large amount of interest rate risks. We nevertheless examine whether banks reporting greater use of derivative contracts for non-trading purposes were less likely to be downgraded during the 2022 monetary tightening. Our findings suggest that, after the second quarter of 2022, supervisors were indeed less likely to downgrade banks that intensively used derivative contracts for non-trading purposes. This evidence further implies that supervisors understood emerging interest rate risks.

A potential challenge with the interpretation of these results is that the relationship between interest rate risk exposures and downgrades of the "L" and "S" subcomponents could be due to a spurious relation with other bank characteristics that draw the ire of bank supervisors. If this were the case, we would also expect a positive association between interest rate risk exposures and downgrades of other CAMELS subcomponents. We find no evidence that supervisors were more likely to downgrade the capital (C), asset quality (A), management (M), and earnings (E) ratings of banks with high interest rate risk exposures. This result aligns with the idea that supervisors targeted interest rate risk exposures by specifically downgrading the liquidity (L) and sensitivity to risk (S) ratings components. Notably, the composite CAMELS rating, which aggregates the different CAMELS subcomponents, was also not significantly affected by these interest rate risk exposures, even after the second quarter of 2022.

Next, we examine how bank supervisors evaluated banks that relied more heavily on less stable sources of funding, making them more prone to liquidity and run risks. When interest rates rise, the value of a bank's equity may not necessarily decline if banks can earn rents by paying deposit rates below the fed funds rate. Put differently, banks are naturally hedged if the value of their deposit franchise also rises with rising interest rates (e.g., Drechsler et al. [2021]). This natural hedge is, however, only effective if banks rely on a depositor base that does not swiftly move funds elsewhere. A bank that relies heavily on uninsured depositors is more exposed to liquidity risks and to bank-run equilibria as uninsured depositors are more likely to withdraw swiftly in response to declines in the value of banks' assets when interest rates rise (e.g., Egan et al., 2017; Drechsler et al., 2023).

We examine whether bank supervisors downgraded banks more reliant on unstable funding sources during the 2022 monetary tightening. Our findings show that in 2021 and 2022, bank examiners were not statistically more likely to downgrade the "L" and "S" ratings of banks with higher dependence on uninsured deposits. These results hold even when using an alternative measure of deposit franchise strength based on Drechsler et al. [2021] and an instrumental variables approach with proximity to Wells Fargo as an instrument for the share of uninsured deposits at each bank (e.g., Granja et al., 2022; Ruan and Vij, 2024). We caveat, however, that a few of our analyses have confidence intervals that are not precise enough to reject large supervisory responses. Overall, our findings indicate supervisors were not sensitive to the incremental risks posed by fragile sources of funding. While this lack of supervisory action may be surprising, it aligns with statements in Barr [2023] suggesting that existing supervisory models inadequately captured the incremental liquidity risks associated with uninsured deposits.

Next, we turn our attention to examining the role that the accounting rules governing the valuation of marketable securities in banks' balance sheets played in shaping the supervisory assessments of risks. Banks can classify securities as Available-for-Sale (AFS) or as Held-to-Maturity (HTM) if they declare that they have both the intention and the ability to hold them until maturity.[2] The main difference between these accounting classifications is that unrealized gains and losses on securities classified as AFS are more salient because banks must mark-to-market these securities in their balance sheets with the unrealized gains and losses impacting their statements of comprehensive income. By contrast, the HTM classification enables banks to avoid marking these securities to their market values in their balance sheets and only requires disclosure of unrealized losses in the notes to the financial statements.

We examine how supervisors evaluated unrealized losses in banks' AFS and HTM portfolios. If supervisors find banks' intentions to hold securities until maturity credible, they may consider that unrealized losses in HTM securities pose smaller risks than those in AFS securities, as such losses will revert to zero as these securities mature. However, if the enforcement of the HTM classification rules is weak and fragile banks abuse this classification to hide large unrealized losses, as suggested by Granja et al. [2024] and Kim et al. [2023], supervisors might consider these commitments non-credible. In this case, supervisors might treat unrealized losses in HTM and AFS securities similarly. Our findings reveal that supervisors incrementally downgraded banks with larger unrealized losses in AFS securities

[2] Banks can also classify securities in the trading category. Laux and Leuz [2010] show that only a few of the largest banks in the economy use this classification to a significant extent.

starting in the second quarter of 2022. But it was only during the first quarter of 2023 that supervisors significantly downgraded banks with substantial unrealized losses in their HTM portfolios. These patterns suggest that supervisors initially prioritized AFS unrealized losses over HTM losses, with a shift in attitude coinciding with the failure of SVB. It is possible that SVB's demise served as a wake-up call for supervisors that some fragile banks might have had the intent but did not have the ability to hold HTM securities until their maturity and that the unrealized losses in these portfolios should be evaluated similarly to those in the AFS portfolios.

We examine past episodes of monetary tightening to ascertain if the empirical association between banks' exposure to interest rate risks and supervisory downgrades is a broader phenomenon permeating multiple tightening episodes or is specific to the 2022 monetary tightening. We find that the empirical association between a measure of interest rate risk and the supervisory decisions to downgrade the "L" rating is also evident during the tightening periods of 1988:q2–1989:q2 and 1994:q1–1995:q2.[3] Interestingly, banks' exposures to uninsured deposits are linked to a higher likelihood of "L" rating downgrades in certain periods, though these periods do not generally align with rising interest rates.

We next explore the factors shaping the timing of supervisory downgrades of the "S" and "L" components during the recent monetary tightening cycle. Recent studies such as Agarwal et al. [2014], Ioannidou [2005], Granja and Leuz [2022], Hirtle et al. [2020], or Kandrac and Schlusche [2021] show significant heterogeneity in how different U.S. banking regulators enforce rules. Most notably, Agarwal et al. [2014] suggests Federal Regulators were stricter than state regulators in assigning CAMELS ratings during the 1990s and early 2000s and Ioannidou [2005] finds that monetary policy indicators affect the Federal Reserve's supervisory

[3] The "S" rating was only adopted in 1995 and therefore cannot be analyzed during this sample period.

actions but not those of other regulatory agencies.

In our study, we extend this literature by analyzing whether Federal banking regulators were quicker during the 2022 monetary tightening to recognize emerging risks in the banking system. Unlike prior studies, our findings indicate that state regulatory agencies were just as strict as federal regulators. Both types of agencies were more likely to downgrade banks with large interest rate risk exposures but this occurred only after the first quarter of 2022. These findings suggest that differences in regulatory attitudes or supervisory resources are unlikely to explain differences in the intensity and timing of supervisory downgrades.

In our final analyses, we assess whether downgrades of the "S" and "L" ratings are associated with declining exposure to interest rate risks at the downgraded banks. We find that a supervisory downgrade of the "L" or "S" components of a bank's CAMELS rating is associated with a subsequent decline in the share of a bank's securities with long maturities. Additionally, downgraded banks appear to shift a portion of their assets from securities to cash. There is no evidence indicating that banks intensified their hedging efforts following a supervisory downgrade, suggesting they did not adopt interest rate hedges in response to supervisory concerns about liquidity or interest rate risks. Overall, these results indicate that supervisory downgrades had some effect in mitigating the interest rate and liquidity risks at these banks.

We caution, however, that this final set of empirical analyses has certain limitations. First, the period following the initiation of monetary tightening is not yet sufficiently long to fully assess the effects of supervisory interventions. Many downgrading decisions occurred in the last quarter of 2022 and the first quarter of 2023, which coincides with the end of our sample period. Our results, therefore, may undergo substantial changes in the future if downgrades during this period were less effective in prompting banks to reduce the duration of their asset portfolios. Second, our findings may not exclusively reflect direct supervisory intervention but could also be influenced by mean reversion. In this scenario, banks most exposed to risks were more likely to be downgraded, but they might have taken actions to contain those risks even without supervisory intervention.

How do our findings generalize and what can we learn from them? Most developed economies allocate substantial resources to ensure the stability of their banking systems. The FDIC and OCC collectively employ approximately 6,000 bank examiners and spend approximately $2 billion every year in their supervision and consumer protection programs. If this extensive supervisory apparatus struggles to identify basic bank risks, such as those associated with the maturity mismatch between a bank's assets and liabilities, it raises question about the cost-effectiveness of investing in bank regulation and supervision (e.g., Cochrane [2023]). Our findings suggest that U.S. bank supervisors downgraded banks most exposed to interest rate risks in the banking system starting in the second quarter of 2022, possibly averting certain bank failures. These supervisory interventions, however, might go unnoticed given the confidential nature of bank supervision. On the other hand, our estimates indicate that downgrades of the "S" and "L" components were insufficient to compel a meaningful reduction in these banks' exposures to interest rate risks. It is possible that these supervisory downgrades need to be complemented with other actions from the supervisory toolkit to effectively curb banks' exposures to these risks.

Our paper also relates to the influential work by Peek et al. [1999] suggesting that the bank supervisory function should not be autonomous from central banking because supervisory information improves the conduct of monetary policy. Our findings indicate that this relation was not a two-way street in the recent episode we study. Bank supervisors began downgrading banks that were most exposed to interest rate risks only after the FOMC effectively started raising interest rates. Thus, our paper suggests that bank supervision did not receive insights or private information from monetary policymakers, hindering their ability to proactively manage risks earlier in the monetary tightening cycle. Consequently, our study suggests that policies promoting coordination between central banks and supervisory agencies may enhance the efficiency of bank supervision.

We perform a simple "back-of-the-envelope" computation to assess the potential reduction in unrealized losses if supervisors had increased the frequency of downgrades earlier. Assuming that counterfactually-downgraded banks would have reallocated their portfolios similarly to downgraded banks in our sample, we estimate that unrealized losses in marketable securities at U.S. banks would have been $9.44 billion lower by the end of 2022 if supervisors had started downgrading banks in the last quarter of 2021 and the first quarter of 2022, using the same model criteria implemented in the second quarter of 2022. However, these projected averted unrealized losses, on average, accounted for only one percent of these banks' Tier 1 capital. These findings suggest that even with earlier downgrades, supervisors would have needed to compel banks to take more drastic actions to significantly reduce their exposure to interest rate risks.

2 Institutional Background and Descriptive Statistics

2.1 Bank Supervision in the United States

Regulation in the commercial banking industry involves the coordination and rule-making set by three federal bank regulators: The Office of the Comptroller of the Currency (OCC), the Federal Reserve Board of Governors (FRB), and the Federal Deposit Insurance Corporation (FDIC). These agencies produce standardized procedures of how banks should operate in a safe and sound manner and then use a dispersed system of field offices to closely monitor and track bank performance.

Within each field office (or reserve bank), teams of examiners supervise bank performance through two types of monitoring: off-site surveillance and on-site examinations. When monitoring banks offsite, examiners use quarterly financial reporting to track trends in bank conditions. Regardless of bank size or publicly-traded status, all commercial banks must submit quarterly financial reports to their primary federal regulator. These reports contain extensive balance sheet and income statement information and prior research has shown that the market finds these regulatory reports informative [Badertscher et al., 2018]. As conditions worsen, examiners can follow up with bank management to understand changes in underlying conditions.

Examiners complement off-site monitoring with periodic on-site examinations. Banks with satisfactory performance that are below certain size thresholds receive an on-site examinations every 18 months.[4] Hence, these periodic on-site examinations follow, for the most part, a predetermined schedule and the characteristics of banks that are examined in a given quarter are plausibly orthogonal to current events or shocks affecting the banking system during each period. We illustrate this point by reporting summary statistics of key variables for the banks undergoing examinations before and after the Federal Reserve began raising interest rates in 2022:Q2. Our results in Table 1 suggest that bank supervisors did not systematically target banks with greater exposure to interest rate risks after the beginning of the monetary tightening and that selective examination of banks most exposed to interest rate risks after the second quarter of 2022 is unlikely to be the driving force behind our results.

During the examination process, teams of examiners travel from field offices to the

[4] For state-chartered banks that meet this criteria, on-site examinations alternate between state regulatory agencies and either the FRB or FDIC. Please refer to Agarwal et al. [2014] for more details.

headquarters of the commercial bank. They analyze loan files, screening methodology, risk management processes, and other sources of granular information about the bank. Furthermore, examiners often conduct informal discussions with bank personnel who may be in charge of loan origination, asset-liability management, or risk management more broadly. These examinations are labor intensive and can last weeks.[5]

Through their on-site evaluations and discussions, supervisors assess performance and assign ratings based on the soft and hard information that they glean through their inspections. This rating system grades bank performance across several observable dimensions of bank performance: capital adequacy (C), asset quality (A), management (M), earnings (E), liquidity (L), and sensitivity to market risk (S). These ratings are known by their collective acronym, CAMELS, and represent the primary quantitative output from on-site bank examinations. CAMELS ratings are rated from 1 to 5, with 1-rated bank showing the least amount of risk in a particular dimension, while 5-rated banks showing the most amount of risk. For instance, a bank that was assigned a 5 rating for liquidity or interest rate risk would be deemed by examiners as having severe exposure to potential liquidity or interest rate risk management problems. Prior research has uncovered several features of this rating system. For instance, they are highly subjective and include substantial qualitative information from examination staff. As a result, ratings may be inconsistently applied from one exam, or from one agency, to another [Agarwal et al., 2014, Gopalan et al., 2021]. Furthermore, CAMELS ratings can be used to facilitate governance within the banking organization, by allowing boards of directors to directly monitor management and by also allowing boards to incentivize management to limit excessive risk-taking [Arif et al., 2023, Gopalan, 2022].

Figure 1 provides trends of how the number of supervisory examinations and frequency of

[5] Gopalan et al. [2024] find that the average length of bank exams is roughly 35 days. This duration is measured as the time between the date that the exam opens to the report disposition date.

CAMELS downgrades evolved during our sample period. Out of any given quarter, examiners engage in approximately 750 on-site supervisory examinations or about 15% of all commercial banks. Thus, only a small fraction of banks are examined at any given quarter. While the number of exams have remained relatively constant, the frequency of CAMELS composite rating downgrades slightly increased over the sample period. During the last quarter of 2020 and first and second quarters of 2021, supervisors downgraded about four percent of banks. The rate of downgrade increased to approximately six percent throughout 2022. When the problems at SVB and FRC unraveled during the first quarter of 2023, supervisors raised this rate up a notch and downgraded approximately ten percent of the banks that they inspected in that quarter.

Figure 2 provides a detailed breakdown of changes in the components of the CAMELS rating over our sample period. Two striking patterns emerge: the rate of downgrade of the capital adequacy (C) rating declines over time whereas the rates of downgrade of the Liquidity (L) and Sensitivity to Risk (S) components increase substantially starting in 2022. These patterns likely reflect both a softening of supervisory concerns about the potential impact of the Covid-19 Pandemic on bank capital and the emergence of supervisory apprehension about the effects that the cycle of monetary tightening might have on the liquidity positions of banks that were less prepared to deal with interest rate risks.

2.2 Timing of Monetary Tightening and Declines in the Value of Securities

To combat inflation, the FOMC sharply raised interest rates beginning in March 2022. Between March 17th, 2022 and July 26th. 2023, the effective Fed Funds Rate surged from 0.08% to 5.33%. This increase in interest rates had been partly anticipated and incorporated in security prices by financial markets. Between November 30th, 2021 and the end of 2021, the iShares 20+ Year Treasury Bond ETF declined approximately 5% and when the FOMC announced its initial interest rate hike in March 17th, 2023, it had already declined 12% relative to its value at the end of November of 2021.

As a result of these declines in the prices of securities, most banks experienced sizable unrealized losses in their portfolios of marketable securities already in the first quarter of 2022. Figure 3 plots the evolution of the distribution of total unrealized losses in AFS and HTM securities as a percentage of banks' total assets at the end of each quarter. The median bank had unrealized losses of approximately one percent of its total assets in the first quarter of 2022 and one in each 20 banks disclosed unrealized losses that already exceeded three percent of their total assets at the end of the same period. These unrealized losses increased over the following quarters as the prices of long-term fixed income securities continued to declined. Banks below the fifth percentile of the distribution of unrealized losses experienced losses that exceed 7.5% of their total assets during the sample period.

In section 4.2 we examine whether supervisors began downgrading banks most exposed to interest rate risk only after the FOMC began raising rates or whether they had already begun downgrading these banks in response to declining prices of fixed-income debt securities and rising unrealized losses in banks' portfolios.

3 Data

We construct a dataset that contains the universe of commercial banks CAMELS ratings from the fourth quarter of 2020 to the first quarter of 2023 using confidential regulatory information from the National Information Center (NIC) database. The NIC is a confidential data repository maintained by federal banking regulators and contains granular information on examiners' interactions with commercial banks. From this database, we collect the specific dates of each commercial bank's on-site examinations as well as the confidential CAMELS ratings assigned bank bank supervisors following the completion of their on-site examinations. For every examination observation, we match the latest Call Report information. Call Report filings contain quarterly public information about bank financial condition and are more informative and granular than financial information contained in banks' 10-K filings [Badertscher et al., 2018]. We use Call Reports to compute our quarterly measures of interest rate risk exposure, exposure to uninsured deposits, as well as broader measures of bank size, bank capitalization and asset quality. We complement our measures of exposure to uninsured deposits with deposit beta data obtained from Drechsler et al. [2021].

4 What did Bank Supervisors know?

4.1 Interest rate Risk Exposure and "S" and "L" CAMELS downgrades

In this section, we conduct an empirical examination of how supervisors assessed interest rate risks before, during, and after the Federal Reserve began tightening monetary policy in early 2022. The main premise of our analysis is that supervisors would have needed to identify and understand the risks inherent in these duration mismatches to downgrade banks whose asset portfolios were most vulnerable to such risks. Thus, we interpret a positive association between asset duration and supervisory downgrades as consistent with the idea that supervisors understood the emerging risks in the banking system.

To examine whether the likelihood of a supervisory downgrade is related to a bank's exposure to these interest rate risks, we compute two measures that capture the maturity composition of banks' securities portfolios. These measures of maturity composition capture interest rate risks because the value of longer-term securities is more sensitive to fluctuations in interest rates than the value of short-term securities. Our first measure is the weighted average maturity of all government securities and MBSs held by each bank.[6] Second, we simply take the share of government securities and mortgage backed securities (MBS) that have a remaining maturity or next repricing date of over 15 years.

We begin by examining the relation between banks' interest rate risk exposures and supervisory downgrades of the liquidity strength (L) and sensitivity to market risk (S) ratings of each examined bank, as these components specifically capture supervisory assessments of banks' ability to meet short-term funding obligations (L) and of the quality of their risk management (S). In Figure 4, we partition all examined banks in five bins according to our measures of interest rate risk exposure and we plot the frequency of downgrades in each bin before and after the Federal Reserve began raising interest rates in the second quarter of 2022. The plots of Figure 4 paint a consistent picture. There is no relation between the frequency of downgrade of both the "S" and "L" rating and banks' interest rate risk exposures prior to the second quarter of 2022. But, after the second quarter of 2022, the relation between the frequency of downgrade of both the "S" and "L" rating and banks' interest rate risk exposures turns strongly and monotonically positive. Bank supervisors downgraded five percent of banks in the quintile that was least exposed to interest rate risks but downgraded more than fifteen percent of banks in the quintile that was most exposed to such risks. This pattern offers initial evidence that supervisors understood the interest rate risks that some banks had accumulated and acted upon this knowledge by downgrading these banks more often

[6] We compute the duration using the mid-point of the interval for each maturity category in the Call Reports.

after the Federal Reserve started raising interest rates.

To further probe the association between interest rate risk exposure and "L" and "S" component downgrades, we employ the following differences-in-differences framework:

$$Downgrade_{it} = \alpha_i + \gamma_t + \beta_0 Int.\ Rate\ Risk_{it} + \beta_1 Int.\ Rate\ Risk_{it} \times Post_t + \Gamma X_{it} + \epsilon_{it} \quad (1)$$

in which *Downgrade* is an indicator variable that takes the value of one if the outcome of the on-site examination was a downgrade of the "L" or "S" rating. The main variable of interest, *Int. Rate Risk* is either the average duration of banks' securities portfolio or the share of long-term securities in their securities portfolio. *Post* is an indicator variable that takes the value of one after the second quarter of 2022. X is a vector of characteristics that includes controls for size, asset quality, and capitalization. Finally, we include quarter fixed effects, γ_t, and in some specifications we include bank fixed effects, α_i. Standard errors are clustered at the level of the state where a bank is headquartered.

In the specifications that do not include bank fixed effects, the regression coefficients capture whether supervisors are more likely to downgrade banks with higher levels of exposure to interest rate risk either before and after the Federal Reserve began raising rates. When we include bank fixed effects, our identifying variation comes from changes in the outcomes of banks that received at least two supervisory on-site examinations during the sample period. These specifications exploit only within-bank variation, which means that our coefficients capture whether supervisors were incrementally more likely to downgrade a bank that experienced a deterioration in their measures of interest rate risk exposure in the period spanning two consecutive on-site examinations. The inclusion of bank fixed effects could, therefore, throw the proverbial baby with the bathwater especially if the economic mechanism at play is that supervisors became less comfortable with the *level* of interest rate risk after the start of the monetary tightening.

We present our regression estimates in Table 2. The results of column (1) and (2) suggests that the likelihood of a "L" downgrade increases with interest rate risk exposure. In particular, the coefficient reported in column (1) suggests that when a bank goes from having no long-term securities to a securities portfolio that is entirely composed of long-term securities, supervisors are approximately nine percentage points more likely to downgrade.[7] In columns (3) and (4), our regression coefficients indicate that increasing the duration of the securities portfolio by one year is associated with an increase in the likelihood of downgrade of the "L" rating between 0.4% and 0.6%. In columns (5)–(8), we examine the relation between our interest rate risk measures and the likelihood of downgrade of the "S" rating and we find economically and statistically similar results.

The specifications that include bank fixed effects produce slightly attenuated regression coefficients relative to the specifications without bank fixed effects. These results suggest that supervisors are more likely to downgrade banks after the second quarter of 2022 when a bank's interest rate risk exposure increased compared to the previous examination. However, the regression coefficients in columns (2), (6), and (8) are not statistically significant at conventional levels, although the specification reported in column (4) remains statistically significant at the 5% level. Part of this attenuation and loss of statistical significance could be due to a smaller number of observations resulting from the requirement that each bank undergo two on-site examinations during the sample period. But, as mentioned earlier, it

[7]The coefficient in column (1) of Table 2 indicates that a standard deviation increase in the share of long term securities increases the likelihood of downgrade by approximately 0.022. Given that the standard deviation of the share of long-term securities is .23 (Table 1), then going from no long-term securities to only long-term securities implies an expected increase in the probability of downgrade of $\frac{(1-0)}{0.23} \times 0.02 = 0.09$

could also reflect that as interest rates rise, supervisors become more sensitive to high levels of interest rate risk exposure and not so much to changes in these levels.

We also consider whether supervisors incrementally downgrade banks that are not only exposed to a large share of long-term securities but also have a large portfolio of fixed-income securities as a proportion of their total assets. In Figure 5, we examine whether the relationship between the frequency of downgrades and our measures of interest rate risk exposure is stronger in the subset of banks with above-median holdings of fixed-income securities as a percentage of their total assets. The plots support the idea that the frequency of downgrades for banks with high interest rate risk exposures is even more pronounced for banks with large holdings of securities. For instance, the frequency of an "S" rating downgrade following the second quarter of 2022 was more than 20% for the group of banks most exposed to interest rate risks but only 12% for the group of banks least exposed to these risks.

In Table 3, we further probe whether the response of bank supervisors to our interest rate risk exposure measures is more pronounced for banks holding a larger amount of securities as a fraction of their total assets. We expand the model of equation (1) by interacting the model with a variable representing the amount of securities held by the bank as a fraction of their total assets. The results confirm that the relation between the frequency of rating downgrade and the share of long-term securities after the second quarter of 2022 is more pronounced for banks with more holdings of securities.[8]

[8] In Table A.1, we report a similar analysis showing that the relation between the frequency of rating downgrade and our duration measure after the second quarter of 2022 is more pronounced for banks with more holdings of securities.

4.2 When did bank supervisors start downgrading?

The analyses presented in the previous section show that bank supervisors were more likely to downgrade banks with high interest rate risk exposures after the Federal Reserve began raising interest rates in March 2022. However, these analyses do not clearly discern *when* bank supervisors began downgrading the "S" and "L" ratings of banks in response to rising interest rates. Did supervisors begin downgrading prior to the second quarter of 2022 in response to large unrealized losses in banks' portfolios that were already evident during the first quarter of 2022 (Figure 3)? Did bank supervisors wait for high-level monetary decisions as a signal from the top brass that it was time to act? Or did they only begin downgrading banks once the SVB and FRC failures publicly exposed significant interest rate risk exposures in the banking system?

We plot coefficients and standard errors of quarter-by-quarter regressions of rating downgrades on bank exposure to interest rate risk in Figure 6. The coefficients show that the association between the likelihood of rating downgrade and measures of exposure to interest rate risk becomes positive and statistically significant in the second quarter of 2022, peaking in the fourth quarter of 2022. Thus, the evidence suggests that supervisors increased the rate of downgrades for vulnerable banks only after the Federal Reserve started tightening interest rates. The plots do not indicate that bank supervisors responded to declining prices of long-term securities or unrealized losses in banks' portfolios evident before the second quarter of 2022. This evidence is consistent with the possibility that supervisors wait for announcements from monetary authorities to act more aggressively on interest rate risks. This raises the question of whether closer coordination between the bank supervisory function and the monetary authorities of the Federal Reserve might have allowed supervisors to address interest rate risk exposures in the banking system earlier.

4.3 Interest Rate Hedging and Supervisory Downgrades

Our measures of duration of a bank's portfolio of assets might not fully reflect its exposure to interest rate risk if losses in the value of its assets from rising interest rates are offset by gains from interest rate derivative positions. Thus, it is possible that some banks with longer-duration securities portfolios hedge some of their exposure to interest rate risks and that supervisors take these positions into account in their downgrading decisions. While this is an interesting possibility, Granja et al. [2024] show that the scale of banks' use of derivative contracts for purposes other than trading is, at best, limited. Moreover, McPhail et al. [2023] show that banks' swap positions offset each other and are not economically significant in hedging interest rate risk of banks. Thus, whether the intensity of a bank's use of interest rate derivatives matters for supervisory downgrade decisions is an empirical question.

We compute a measure of the scale of a bank's hedging activities following the work of Granja et al. [2024]. We then examine if supervisors' decisions to downgrade a bank around the monetary tightening cycle of 2022 is associated with a bank's hedging intensity. An association between the rating downgrades and hedging activities would again suggest that supervisors were aware of the interest rate risks emerging in the system and that they understood the role that banks' hedging activities would play in shaping these risks.

In Panels A and B of Figure 7, we partition the sample into six bins. The first bucket is comprised of banks that do not use interest rate derivatives. The remaining bins split the subsample of banks that use interest rate derivatives for purposes other than trading according to how intensively they use those derivatives. Our descriptive findings in panel A of Figure 7 do not indicate a strong association between the intensity of hedging and the frequency of a "L" rating downgrade after the second quarter of 2022. By contrast, the empirical evidence in Panel B suggests a stronger association between the intensity of hedging and the frequency of a "S" rating downgrade in the period after the FOMC began raising interest rates. For instance, the plot shows that bank supervisors downgrade only 5% of the banks in the quintile of banks that most use interest rate derivatives but downgrade approximately 12% of all banks that use no interest rate derivatives.

In Table 4, we provide further evidence supporting the negative relation between use of interest rate hedging and the frequency of downgrades of the "L" and "S" sub-components. The coefficients in columns (1) and (3) suggest that there is a strong negative relation between a bank's hedging intensity *level* and the likelihood of a CAMELS downgrade after the second quarter of 2022. This relation is still negative but not statistically significant at conventional levels as we include bank fixed effects in columns (2) and (4). This lack of statistical significance suggests that regulators are not significantly more likely to downgrade a bank that *reduced* their hedging intensity after the second quarter of 2022 relative to the level that they were using in that bank's prior on-site examination. In Panels C and D of Figure 7, we further investigate the dynamic aspect of the relation between hedging intensity and the likelihood of a downgrade. The results suggest that the negative relation between the "L" rating downgrade and hedging intensity is only negative and pronounced in the first quarter of 2023, whereas the negative relation between the "S" rating downgrade and hedging intensity emerges in the second quarter of 2022.

Overall, these findings provide further evidence that supervisors understood the interest rate risks that were emerging as the Federal Reserve began its monetary tightening and that they were less likely to downgrade banks that had some protection against these risks in the form of derivative contracts for purposes other than trading.

4.4 Interest rate Risk Exposure, Other CAMELS components, and Composite CAMELS rating

Our measures of exposure to interest rate risks might be correlated with broader changes in the financial health of banks or with other bank characteristics and risks that prompt supervisors to downgrade banks. Thus, the high frequency of downgrades of the "L" and "S" ratings that we documented for banks that are more exposed to interest rate risks might reflect supervisory concerns about a broader deterioration of these banks' financial health rather than the targeted efforts of bank supervisors to curb excessive interest rate risk exposures at these banks.

The CAMELS rating consists of four other components. The capital (C) rating measures the adequacy of the capital position of a bank, the asset quality (A) rating measures the overall performance of banks' assets and the quality of their credit administration policies, the management (M) rating broadly measures the quality of managerial input in the business, and the earnings component (E) measures the adequacy of current and expected earnings of the bank. If the interest rate risk exposure measures were correlated with banks' weak financial health during 2022, then we might also expect a strong positive association between the frequency of downgrade of these other components and the interest rate risk exposure measures that we use in our empirical analysis. If, on the other hand, our findings of the previous sections reflect bank supervisors' direct attempts to contain the interest rate and liquidity risks that were emerging in the banking system, then it is not clear that these interest rate risk exposure measures and the likelihood of downgrade of these other components should be related. After all, these interest rate risk exposures play an indirect role in supervisors' qualitative evaluation of the (C), (A), (M), and (E) sub-components of the CAMELS rating.

In Figure 8, we plot coefficients and standard errors of quarter-by-quarter regressions of downgrades of the (C), (A), (M), and (E) components of the CAMELS rating on measures of interest rate risk exposure. The results indicate that our main measures of exposure to interest rate risk do not bear any statistically significant positive relation with the likelihood of downgrade of these ratings throughout the entire sample period. We consider that these results support our assertion that the positive relation between (L) and (S) downgrades and our interest rate risk measures are not confounded by other correlated omitted factors and that they represent bank supervisors' targeted efforts to rein in the overexposure of some banks to interest rate and liquidity risks.[9]

Finally, we also investigate the relation between interest rate risk exposure and the aggregate composite CAMELS rating. Up until now, we have shown that our measures of interest rate risk exposure have a positive relation with the "L" and "S" rating and a weak or insignificant relation with all other components of the CAMELS rating. The aggregate CAMELS rating, however, is more than the average of its parts and also depends on the examiners' subjective assessment of the examined bank's overall condition (e.g., Agarwal et al. [2024]). Moreover, the composite rating is also a key input to many important regulatory and supervisory decisions such as merger approvals and dividend restrictions, which are often based on the aggregate CAMELS rating rather than on the individual components themselves.

This begs the question of whether the positive relation between the banks' interest rate risk exposures and the "L" and "S" rating after the second quarter of 2022 carried through to the composite CAMELS rating. In Panel E of Figure 8, we use the downgrade of the composite CAMELS rating as the main outcome variable. We find that the frequency of downgrade of the composite CAMELS rating is not significantly associated with our measures

[9] In the Internet Appendix, we further provide these results using our other measure of interest rate risk exposure.

of interest rate risk exposure throughout the entire sample period. This weak relationship between the composite CAMELS downgrade and interest rate risks might hurt the efficacy of the (L) and (S) downgrades. A downgrade of the composite CAMELS ratings carry greater restrictions to banks' actions, which might be the supervisory "stick" that banks need to put greater effort into resolving existing deficiencies and unwinding specific risks.

4.5 Deposit Funding Fragility and Downgrades

The second key ingredient to the ill-advised recipe that resulted in the recent episode of bank fragility of the 2023 regional banking crisis was the excessive reliance of some banks on uninsured depositors (e.g., Jiang et al. [2023]) or, more broadly, on a deposit base that is unstable and that quickly walks away from the bank if offered better interest rates elsewhere (e.g., Koont et al. [2023]). When their deposit base is unstable, banks are more exposed to interest rate risks during periods of monetary tightening. Their assets lose value as interest rates rise and so does their equity because they cannot count on depositors to naturally hedge the bank by continuing to provide funding at low deposit rates (e.g., Drechsler et al. [2021], Drechsler et al. [2023], Egan et al. [2017], Jiang et al. [2023]). If the deposit outflows are too strong, banks might be forced to sell securities at a loss thus exposing frailties in their capital positions that could further exacerbate their woes. In this section, we investigate if bank supervisors understood these risks and incrementally downgraded banks that over relied on unstable sources of funding.

Our main measure of instability of a bank's deposit funding is the share of uninsured deposits, which we compute as the fraction of deposit and retirement deposit accounts with balances above the deposit insurance limit. We also use an alternative deposit beta measure of deposit fragility that captures the strength of a bank's deposit franchise. This measure is derived from the work of Drechsler et al. [2021] and indicates how much a bank raises its deposit rate for a given increase in the Fed funds rate. A bank with a high beta has a deposit base that is less likely to tolerate low rates in rising interest rate environments. This measure is purely cross-sectional, which means that we cannot employ bank fixed effect in this analysis.

A potential limitation of the share of uninsured deposits as a measure of the stability of deposit funding is that, in equilibrium, banks with systematically different risk exposures could assortatively match with different deposit clienteles (e.g., Drechsler et al. [2023]). We attempt to address this concern by using variation in the share of uninsured deposits of a bank that is plausibly exogenous to its characteristics. In the wake of the 2016 fake accounts scandal, bank supervisors imposed an asset-size cap on Wells Fargo. Granja et al. [2022] and Ruan and Vij [2024] show that Wells Fargo turned down business to stay below the asset-cap threshold and that geographically proximate banks filled the gap. In particular, Ruan and Vij [2024] show that banks operating branches close to Wells Fargo experienced an influx of uninsured deposits that was unrelated to their characteristics and local demand condition. We exploit variation in the proximity of each bank to Wells Fargo branches as a shock to the share of uninsured deposits of each bank in the period immediately leading up to the monetary tightening.

We examine the association between banks' reliance on unstable sources of funding and the likelihood of downgrade of the "L" and "S" ratings using a differences-in-differences similar to that of equation (1). We report the results in Table 5. In columns (1) and (5) we find that a one-standard deviation increase in the share of uninsured deposits, corresponding to approximately fifteen percentage points (p.p.), is associated with a non-statistically significant increase of 0.8 p.p. in the likelihood of downgrade of the "L" rating and with a decline of

0.2 p.p. in the likelihood of downgrade in the "S" rating after the start of the monetary tightening. These results are similar when including bank fixed effects in columns (2) and (6).

In columns (3) and (7), we employ the instrumented share of uninsured deposits at each bank. For each bank in our sample, we compute the average share of deposits held at Wells Fargo branches in zip codes where the bank operated branches in 2019. We also include bank characteristics and asset decile fixed effects in the first stage analysis. The local exposure to Wells Fargo branches is statistically and economically significantly associated with a higher share of uninsured deposits. An increase in our measure of local exposure to Wells Fargo branches from zero to ten percent of local deposits at Wells Fargo is associated with an increase of 0.320 standard deviations in the share of uninsured deposits at the bank (approximately five p.p.) with a t-stat of 20.58. When we use the predicted values from this first-stage regression in the second-stage, we continue not to find a statistically significant association between the uninsured share of deposits and the likelihood of downgrade.

Finally, in columns (4) and (8), we examine if we obtain similar results using the deposit beta measure from the work of Drechsler et al. [2021]. We also do not find a statistically or economically significant relationship between these measures of deposit instability and the likelihood of a downgrade of the "L" and "S" ratings both before and after the Federal Reserve began raising rates in March 2022. In Table A.2 of the Internet Appendix, we examine if supervisors were more likely to downgrade banks with unstable sources of funding when banks were also largely exposed to interest rate risks. We do not find statistically significant evidence that supervisors incrementally downgraded the "S" or "L" ratings of banks with unstable sources of funding even when banks had larger exposures to interest rate risks.

We also provide graphical evidence of the relation between banks' reliance on unstable sources of funding and the likelihood of downgrade of the "L" and "S" rating in Figure

9. The figure repeats the quarter-by-quarter regression analysis of Figure 6, replacing the measures of interest rate risk with our measures of deposit instability. Despite a noticeable increase in the point estimates measuring the relation between the share of uninsured deposits and "L" downgrades after the second quarter of 2022, the regression coefficients are not statistically significant across most analyses. The exception is the statistically positive coefficient associated with the regression of the likelihood of "L" downgrade on the deposit beta measure in the last quarter of 2022. This result could indicate that supervisors started to react to the potential liquidity issues of banks with more flighty deposit funding sources in the last quarter of 2022.

Overall these results suggest that supervisors mostly failed to downgrade banks that were reliant on unstable sources of funding that in turn left them exposed to bank runs. While we caveat that in some analysis our confidence intervals do not allow us to reject large supervisory response, our results generally suggest that supervisors did not account for fragility in the sources of deposit funding in their downgrading decisions. Our conclusions are aligned with the findings of the Silicon Valley Bank failure report (Barr [2023]) which stated that: "Liquidity requirements and models used by both banks and supervisors should better capture the liquidity risk of a firm's uninsured deposit base. For instance, we should re-evaluate the stability of uninsured deposits and the treatment of held to maturity securities in our standardized liquidity rules and in a firm's internal liquidity stress tests."

4.6 Unrealized Losses in AFS and HTM portfolios and Downgrades

Unrealized losses in marketable securities classified as HTM are not recognized in the balance sheets and statements of comprehensive income and are only disclosed in the notes to the consolidated financial statements. Banks are allowed to use the HTM classification if they declare that they have both the intent and the ability to hold the securities until they mature such that the bank does not have to close the position at a significant accounting loss. Otherwise, banks must value their securities using available for sale (AFS) accounting, which forces them to mark the securities in their balance sheets using current market prices and to recognize unrealized losses on those securities in their statements of comprehensive income.[10]

In this section, we examine whether supervisors treated unrealized gains and losses in AFS and HTM securities similarly or placed greater weight on unrealized losses in AFS when making rating decisions. Supervisors might prioritize unrealized losses in AFS because these losses are more salient and could more easily trigger deposit and investor instability (e.g., Choi et al. [2023]). Moreover, if supervisors accept banks' promises to hold securities until maturity, they might consider the unrealized losses in HTM securities as "temporary" and expected to revert. However, as discussed in Bischof et al. [2021], banks' ability to hold securities until maturity depend on difficult-to-evaluate characteristics such as their funding stability. Granja et al. [2024] and Kim et al. [2023] have further shown that banks' declarations of ability to hold securities to maturity are not strongly enforced and that many fragile banks have reclassified securities to HTM to "hide" unrealized losses and avoid scrutiny during the recent tightening episode. Consequently, supervisors might be skeptical of banks' commitments to hold securities until maturity and view unrealized losses in HTM similarly to those in AFS.

Figure 10 plots the coefficients of separate quarter-by-quarter regressions of the indicator

[10]Another key distinction is the treatment of unrealized gains and losses in the determination of regulatory capital. Unrealized gains and losses in HTM securities are not included in regulatory capital whereas unrealized gains and losses in AFS securities can count to regulatory capital depending on whether banks are advanced approach banks and on their AOCI filter election. Our sample is comprised of non-advanced approach banks that can elect to adopt an AOCI filter excluding unrealized gains and losses in AFS securities from the computation of regulatory capital. Over 99% of non-advanced approach banks in the U.S. have adopted the AOCI filter. Thus, our analysis does not reflect differences in the regulatory capital treatment of AFS and HTM unrealized losses.

variables for "S" and "L" downgrades on the unrealized losses in the AFS and HTM portfolios. We find that unrealized losses in AFS securities were associated with statistically significant increases in the probability of ratings downgrade beginning with the second quarter of 2022. By contrast, unrealized losses in the HTM portfolio were not significantly associated with higher probabilities of rating downgrades during 2022. It was only during the first quarter of 2023, that supervisors significantly downgraded the ratings of banks with greater unrealized losses in their HTM portfolios.

These empirical findings are consistent with the idea that supervisors did not initially consider AFS and HTM unrealized losses on equal standing and that they paid greater attention to losses in their AFS portfolios. The failure of SVB brought the spotlight onto the significant losses that some fragile banks had on their HTM portfolios. The positive association between rating downgrades and HTM unrealized losses in the first quarter of 2023 could indicate that SVB's demise served as a wake-up call for supervisors that some fragile banks might have had the intent but did not have the ability to hold HTM securities until their maturity and that the unrealized losses in HTM and AFS should be evaluated similarly.

4.7 Supervisory Downgrading in Past Monetary Cycles

In this section, we examine how the empirical association between supervisory downgrades and banks' risk exposures in the recent tightening episode compares with the historical experience from past tightening cycles. In particular, we examine if the link between interest rate risk exposures and supervisory downgrades is a broader phenomenon across multiple cycles or unique to the recent period, which saw a sharp increase in Fed Funds rates from 0.08% to 4.57% in less than a year. Analyzing historical data can also clarify if the lack of a relationship between banks' exposure to unstable funding sources and supervisory downgrades in the recent period is typical of past cycles or indicative of a loss of institutional memory, given that the Global Financial Crisis did not prominently feature runs on uninsured deposits (e.g., Acharya and Mora [2015]).

The sample period for this historical analysis comprises two past monetary tightening cycles spanning the period between February 1988 and March 1989, in which the Fed Funds rate rose from 6.58% to 9.81% and the period between December 1993 and April 1995 that saw the Fed Funds rate rise again from 2.96% to 6.05%. Similar to the recent tightening episode, these periods were also characterized by banking instability that in large part resulted from the exposure of many Savings & Loans (S&L) banks to interest rate risks.

The regulatory framework and supervisory toolkit have changed substantially since past tightening episodes, partly in response to problems from the S&L crisis of the late '80s and early '90s. Effective January 1, 1997, bank regulatory agencies added the "S" subcomponent to the CAMELS framework to evaluate institutions' preparedness against shifts in interest rates and fluctuations in portfolio values. Thus, we cannot evaluate the relationship between the "S" component of the CAMELS framework and interest rate risks in these past monetary cycles. Moreover, the HTM and AFS classifications were only introduced in 1993 in response to issues with amortized cost accounting during the S&L crisis (Kim et al. [2023]). Finally, we note that historical versions of the Call Reports differ significantly from recent ones. To measure interest rate risk exposure, we must rely on the amortized costs of fixed-rate debt securities with a remaining maturity of five years or more and to measure reliance on uninsured deposits, we use the share of outstanding time deposits of $100,000 or more in a bank's total deposits.

Figure 11 plots coefficients and standard errors of quarter-by-quarter regressions of "L" downgrades on measures of interest rate risk exposure and deposit instability. Panel A shows that the relationship between interest rate risk exposure and supervisory downgrades of the "L" rating is evident during the monetary tightening periods of the late '80s and early '90s. We find that the coefficients of quarterly regressions of the likelihood of downgrade of the "L" rating on the percentage of long-term securities in banks' portfolios increase and become statistically significant during monetary tightening periods and decline during subsequent periods of looser monetary policy. Similar to the recent tightening episode, Panel B indicates that the relationship between banks' interest rate risk exposure and the composite CAMEL rating is less pronounced than with the "L" subcomponent. These findings reinforce the idea that during periods of monetary tightening, supervisors become more sensitive to banks' interest rate risk exposures and primarily respond by downgrading the 'L' rating of the most exposed banks.

In Panel C, we analyze the relation between the share of uninsured time deposits and supervisory downgrades during past monetary cycles. Unlike the most recent cycle, we find that the relation between the share of uninsured time deposits and downgrades of the "L" subcomponent is statistically significant in many quarters during the sample period. However, this relation does not follow a cyclical pattern. It is statistically significant between 1988:q2 and 1989:q1, coinciding with a tightening period, and again between 1990:q3 and 1993:q1, coinciding with a period of declining interest rates. Similar findings arise when examining the relation between the share of uninsured deposits and the CAMEL composite rating in Panel D. Overall, these findings do not suggest a clear relation between exposure to uninsured depositors and supervisory concerns for bank-run equilibria during past monetary tightening cycles.

4.8 Heterogeneity across Regulatory Agencies

A number of studies such as Ioannidou [2005], Agarwal et al. [2014], Costello et al. [2018] Granja et al. [2024], Hirtle et al. [2020], Granja and Leuz [2022], or Kandrac and Schlusche [2021] have shown that there is significant heterogeneity in how different banking regulators in the United States enforce banking rules and respond to changes in monetary policy. Most notably, Agarwal et al. [2014] suggested that Federal Regulators were stricter than state regulators in assigning CAMELS ratings to banks during the '90s and early 2000s. Thus, it is possible that the results that we presented in prior sections conceal significant heterogeneity across banking regulators in how they assessed interest rate risks at banks around the monetary tightening of 2022. For instance, it is possible that Federal Regulators had more and better supervisory resources to identify the risks that were brewing in the banking system and acted earlier to curb those risks. These organizational differences across regulatory agencies might have shaped the timing of the supervisory downgrades of the "S" and "L" components during the recent monetary tightening cycle. Another possibility is that Federal Regulators such as the FDIC, OCC, and especially the Federal Reserve might have had closer access to policymakers involved in monetary policy decisions and were more aware of the interest rate risks that would emerge during 2022.

We examine this possibility in Figure 12. We repeat the analysis of figures 6, 9, and 10 by ploting coefficients of regressions that are estimated separately for bank examinations conducted by state regulatory agencies and federal regulatory agencies (FDIC, OCC, and FRS). Overall, we do not find substantial differences in how Federal and State banking regulatory agencies downgraded banks depending on their exposures to interest rate risks and unstable sources of funding. Panel A of figure 12 shows that both types of agencies downgraded the "S" rating of banks that were more exposed to interest rate risks at a greater rate than other banks but only after the first quarter of 2022. The state banking agencies significantly downgraded the "S" ratings of banks with greater exposures to uninsured depositors but only in the first quarter of 2023 and they were also more likely to downgrade banks with unrealized losses in HTM securities in the last quarter of 2022 but not on the first quarter of 2023.[11] These cross-sectional findings suggest that differences in supervisory attitudes or resources are unlikely to explain differences in the intensity and timing of supervisory downgrades.

5 Did Supervisory Downgrades rein in risks?

In the last section of our paper, we ask if these supervisory downgrades induced banks to limit their interest rate risk exposures. Put differently, in prior sections we showed that supervisors downgraded banks with large interest rate risk exposures and, in this section, we investigate if these actions contained the exposures of downgraded banks to interest rate risks.

To examine this question, we implement a differences-in-differences specification that compares the evolution of key variables and ratios of banks that received a downgrade of their "L" or "S" rating during 2021 and 2022 with the evolution of banks with similar characteristics that did not receive a downgrade of these rating components during the sample period. Specifically, we use the Callaway and Sant'Anna [2021] estimator assuming that when a bank is downgraded during a period it remains treated until the end of our sample. Our empirical specification is:

[11] In figure A.2, we repeat the analysis of figure 12 using the downgrade of "L" ratings as the outcome variable. The only noteworthy different is that Federal agencies seem slightly more adept at downgrading the "L" rating of banks with greater exposure to unstable sources of funding. These coefficients are nevertheless not statistically significant.

$$Y_{it} = \alpha_i + \gamma_t + \sum_{t=-4}^{t=4} (\beta_t Downgrade_i \times \gamma_t) + \Gamma X_{it} + \epsilon_{it} \tag{2}$$

in which Y_{it} represents the outcome variables in our analysis, namely our asset-based duration measures, a measure of hedging intensity, the ratio of securities to assets, and the ratio of cash to assets. $Downgrade_i \times Post_t$ is a dummy variable that takes the value of one for all quarters following a downgrade of the "L" and "S" components of the bank and X_{it} is a vector of bank characteristics that includes measures of bank size, profitability, asset quality, and capitalization. α_i and γ_t are bank and quarter fixed effects and ensure that we exploit variation within a bank around the time of the downgrade after controlling for common shocks that affected banks' balance sheets in each quarter. We cluster standard errors at the level of a bank's state headquarters.

We present the results of this analysis in Figure 13. Panel A shows that following a downgrade of the "L" or "S" rating, the share of securities with a remaining maturity or next repricing date of over 15 years immediately begins to decline and three quarters following the downgrade it is, on average, one percentage point lower.[12] In Panel B, we find qualitatively similar results using our measure of portfolio duration, albeit the results are not statistically significant at conventional levels. In Panel C, we find that a downgrade does not have a statistically significant impact on banks' hedging intensity. Following the downgrade the confidence intervals on our estimates widen considerably but, if anything, banks seem to lower their hedging intensity following a downgrade. This result likely suggest that while regulators seem to consider a bank's hedging intensity as an important factor in their downgrading decisions of the "S" rating, banks themselves do not turn to hedging to lower their interest

[12]The share of long-term securities variable is standardized such that a β coefficient of -0.05 implies a decline of $0.05 \times 0.23 \approx 0.01$

rate risk exposures following a downgrade.

In Panels D and E of Figure 13, we examine the allocation of a bank's portfolio between securities and cash following a downgrade of the "S" and "L" components of the CAMELS rating. There seems to be a reallocation of a downgraded bank's portfolio from securities to cash with total securities declining by approximately .5% of a bank's total assets and cash increasing by a similar magnitude. Yet, this reallocation begins one quarter prior to the downgrade itself.

There are two possibilities to explain these significant effects prior to the downgrade. First, it is possible that in the course of their off-site preparation for an on-site inspection occurring during the following quarter, supervisors forewarn banks if certain ratios and risks are too high and request that such deficiencies are addressed prior to the exam. Such communications between supervisors and banks occur frequently and may explain why we empirically find that banks began containing these risks during the quarter prior to the exam. Moreover, we find that the reallocation accelerates following the exam quarter, which may suggest that the supervisors were not content with the measures that had been taken, and nevertheless downgrade the bank. Another possibility, however, is that these results reflect mean reversion. The downgraded banks understand that their portfolio allocation is unbalanced and would have taken measures to reallocate between securities and cash even in the absence of a downgrade. In this alternative explanation, the downgrades are a symptom of high exposure to liquidity and interest rate risks but were not the direct cause of the subsequent reduction in these exposures at downgraded banks.

We caution that our last set of empirical analyses comes with an important caveat. We do not yet observe a sufficiently long period following the beginning of the monetary tightening to evaluate the full effects of these supervisory decisions. As seen in Figure 2 most downgrades of the “S” and “L” components came in the last quarter of 2022 and first quarter of 2023, which is when our sample ends at the moment. Thus, our results may change substantially in the future as we extend our sample especially if the downgrade decisions made in the last quarter of 2022 and first quarter of 2023 were less effective in prompting banks to lower the duration of their asset portfolio.

6 Discussion of Results and Policy Implications

In this section, we provide an overall discussion of the results in the paper and evaluate their policy implications. The demise of SVB prompted many economists (e.g., Cochrane [2023]) to ask: “Where were the regulators?...How can this massive [regulatory] architecture fail to spot basic duration mismatch and a massive run-prone deposit base?”. We document a clear inflection in how supervisors downgrade banks with high-duration portfolios of securities when the Federal Reserve began raising interest rates. This finding indicates that banking regulators did understand the nature of the risks that were brewing in the banking system.

That regulators were aware of these risks and even downgraded banks that were more exposed to them, begs the question of why were they unable to prevent the regional banking crisis of 2023? One possible answer to this question might lie in regulators’ lack of discretionary powers to force downgraded banks to follow their recommendations. In the previous section, we find that banks, on average, reallocate securities to cash in the amount of 0.5% of their total assets following a downgrade. While statistically significant, this reallocation between securities and cash after a downgrade was unlikely to make a large difference in these banks’ financial health. After all, in the fourth quarter of 2022, banks held, on average, approximately 27% of their assets in AFS and HTM securities and the unrealized losses on these securities amounted, on average, to 2.5% of their total assets and 28% of their Tier 1 Capital. These findings indicate that regulators might lack the discretionary powers to force banks to meaningfully lower the exposure of their portfolios to risks.

Another interesting line of inquiry lies in understanding if regulators could have stopped the accumulation of interest rate risks if they had acted in a more timely manner. Figure 1 shows that supervisors cover only approximately 15% of all banks with their on-site inspections each quarter. It is, therefore, important that supervisors foresee emerging risks and induce banks to take corrective actions as promptly as possible. We find that bank supervisors downgraded banks with greater exposure to interest rate risks more often but only beginning with the second quarter of 2022. This timing coincided with the beginning of the monetary tightening by the Federal Reserve but came after financial markets were already incorporating expectations of rising interest rates into the price of securities. Could better policy coordination between bank supervisors and monetary authorities (e.g., Peek et al. [1999]) and earlier intervention by bank supervisors have curbed a substantial amount of losses and avoided the regional banking crisis?

We employ a simple "back-of-the-envelope" computation to evaluate how much lower might unrealized losses have been if supervisors had begun downgrading banks at a greater frequency two quarters earlier than they did. Specifically, we repeat the empirical specification of Table 3 using as outcome variable a dummy variable that takes the value of one if a bank received a downgrade of either their "L" or "S" ratings. Using the estimated coefficients from this regression, we then compute the expected probability of downgrade for each examination as if the "post" variable had turned on in the fourth quarter of 2021 and first quarter of 2022. Put differently, we compute the estimated probability of downgrade if the regulators had used theit downgrade criteria for the post-monetary tightening period already in the prior two quarters.

We conduct 1,000 simulations to determine which banks would have been downgraded in the fourth quarter of 2021 and first quarter of 2022 in this counterfactual scenario and we estimate what would have been the averted unrealized losses in securities for each group of downgraded banks in each simulation. To do this, we make the admittedly strong assumption that counterfactually-downgraded banks would have reallocated 0.5% of their asset portfolio from securities to cash at the end of the quarter in which they were downgraded. This amount of reallocation is in line with our estimated impact of a downgrade on reallocation of securities in figure 13. Next, we estimate the losses that counterfactually-downgraded banks would have averted by reallocating 0.5% of their total assets from securities to cash. To do so, we also assume that the maturity composition of the securities (Treasuries or MBS) reallocated to cash mimics that of the securities portfolio of the bank and we use traded indexes in mortgage backed securities (MBS) and treasuries to compute the value of these reallocated securities.[13]

In Figure 14, we present a histogram representing the aggregate amount of averted losses in each simulation (Panel A) and the average averted loss as a fraction of the Tier 1 Capital of each downgraded bank (Panel B). Panel A shows that, according to our "back-of-the-envelope" computations, regulators might have averted, on average, approximately $9.44 billion in losses borne by the U.S. banking system had they begun downgrading banks at their post-monetary tightening frequency two quarters earlier than they did. For comparison, we estimate the banks that were effectively downgraded during these two quarters would have averted approximately $.6 billion if they similarly had reallocated 0.5% of their total assets from securities to cash. Panel B of Figure 14 shows, nevertheless, that these estimated

[13]We refer to Jiang et al. [2023] for additional details on the computation of these values.

averted losses would, on average, account for only .9% of these banks' Tier 1 Capital. Thus, while we find that the aggregate amount of averted unrealized losses in this counterfactual scenario exceeds the combined budgets of the FDIC and OCC by a factor of four, it is also true that under the assumptions and parameters of our "back-of-the-envelope" exercise, these counterfactual downgrades would not have had a large impact on these banks' capital positions. Our computations imply that regulators would have to induce a much larger reallocation of assets from securities to cash if they were to meaningfully improve these banks' capital positions and avoid the externalities associated with bank failures and near-failures.

7 Conclusion

Many commentators were quick to point fingers at bank regulators for failing to prevent the failures of Silicon Valley Bank and First Republic Corporation. However, a complete assessment of the merits and failures of bank regulators and bank regulation is made difficult by the secrecy that shrouds the supervisory process. The CAMELS ratings that bank examiners assign to banks have long been kept confidential due to concerns that their disclosure might precipitate panic-based bank runs (e.g., Goldstein and Sapra [2013]). But this secrecy also means that it is difficult to evaluate the performance of bank supervisors. In some cases, supervisors may receive blame for some very public failures but no glory for the bank failures that they prevented from happening. In other cases, this secrecy may mean that regulators are left unaccountable for failing to properly regulate and supervise banks.

In this paper, we use confidential information from banks' supervisory reports to examine the (in)effectiveness of bank regulation during the 2022 monetary tightening. In doing so, we contribute to a long literature that attempts to examine the role that bank regulation and supervision plays in shaping bank performance and banking crises (e.g., Agarwal et al., 2014; Hirtle et al., 2020; Kandrac and Schlusche, 2021; Bonfim et al., 2023; Eisenbach et al. [2022]; Granja and Leuz [2022]).

There are two main differences between our empirical setting and those of other papers in this literature. Most past studies do not directly observe supervisory actions and rely on indirect sources of variation in supervisory resources or supervisory effort in their analysis. Instead, we directly observe supervisors' confidential assessments of their regulated entities and use this information to evaluate how promptly bank supervisors responded to a well-identified change in interest rate environment that suddenly originated important imbalances in the banking system.

The other notable and related difference between our study and other studies in this literature is that, most often, past studies have examined how bank supervisors manage significant credit risks and losses in the economy. Yet, the emergence of such credit risks is often insidious and difficult to identify in real time. In our setting, a well-defined event, the Federal Reserve's decision to raise interest rates, triggered a shock to the value of equity of banks with significant maturity mismatches and unstable deposits. We exploit this setting to evaluate the preparedness and timeliness of the supervisory responses to this challenge. This aspect is something that is often hard to do as it is difficult to pinpoint the moment in which credit or other risks are formed in the banking system.

This setting also offers an opportunity to better understand the coordination and collaboration between central bankers and bank supervisors in the US economy. Given the crucial role that banks play in the pass-through of monetary policy, close collaboration between central bankers and supervisors could be important in guaranteeing that the fight against inflation does not result in substantial convulsions in the banking system. We provide evidence that during the recent crisis, bank supervisors did not anticipate the cycle of monetary tightening that began in the second quarter of 2022.

Finally, we contribute to an emerging literature that examines the 2023 U.S. regional banks' crisis. Drechsler et al. [2023] and Jiang et al. [2023] characterize the sources of banking instability during the recent period of monetary tightening. McPhail et al. [2023] and Granja et al. [2024] look at banks' use (or lack thereof) of hedging to limit interest rate risks. Cookson et al. [2023], Choi et al. [2023], and Caglio et al. [2023] analyze the dynamics of depositor runs around the Silicon Valley Bank run. Granja et al. [2024] and Kim et al. [2023] examine how fragile banks used accounting to make their financial position more opaque. Our unique contribution is to provide initial evidence about the role that bank supervisors played in the events that led to the demise of SVB and FRC.

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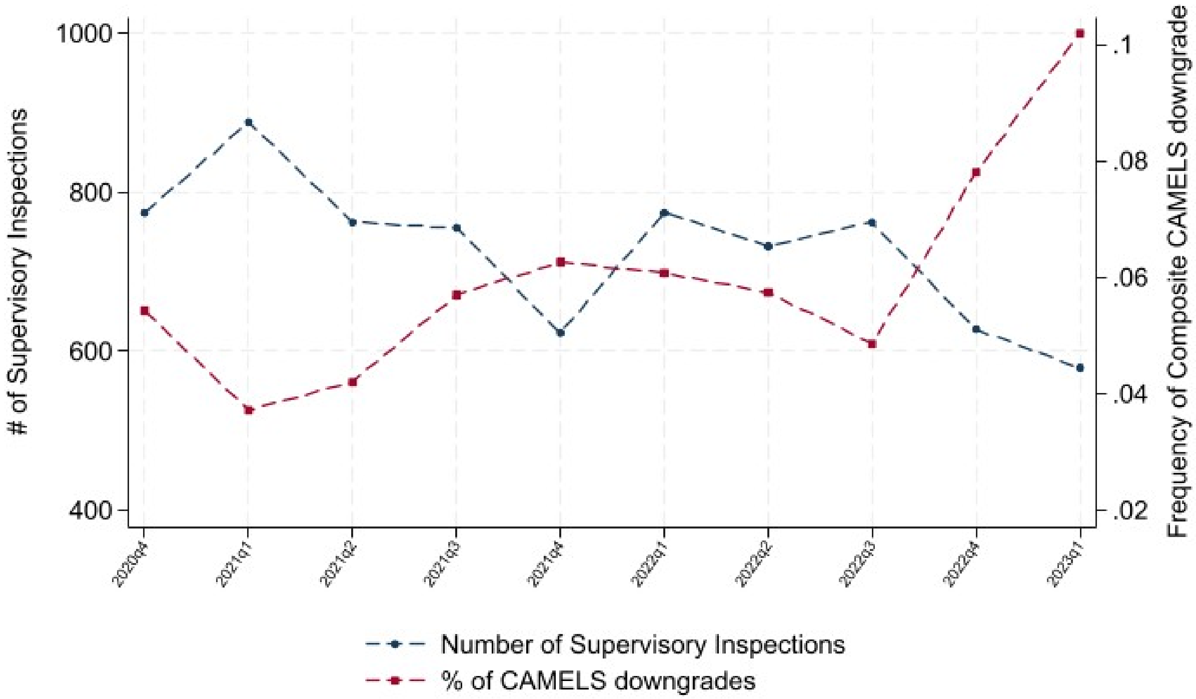


Figure 1: **Number of Exams and Downgrade Rate of the Composite CAMELS rating by Quarter.** This figure shows the total number of supervisory inspections on the left axis and the frequency of composite CAMELS downgrade on the right axis. This figure is computed using the CAMELS rating data from National Information Center (NIC) and the sample period runs from the fourth quarter of 2020 to the first quarter of 2023.

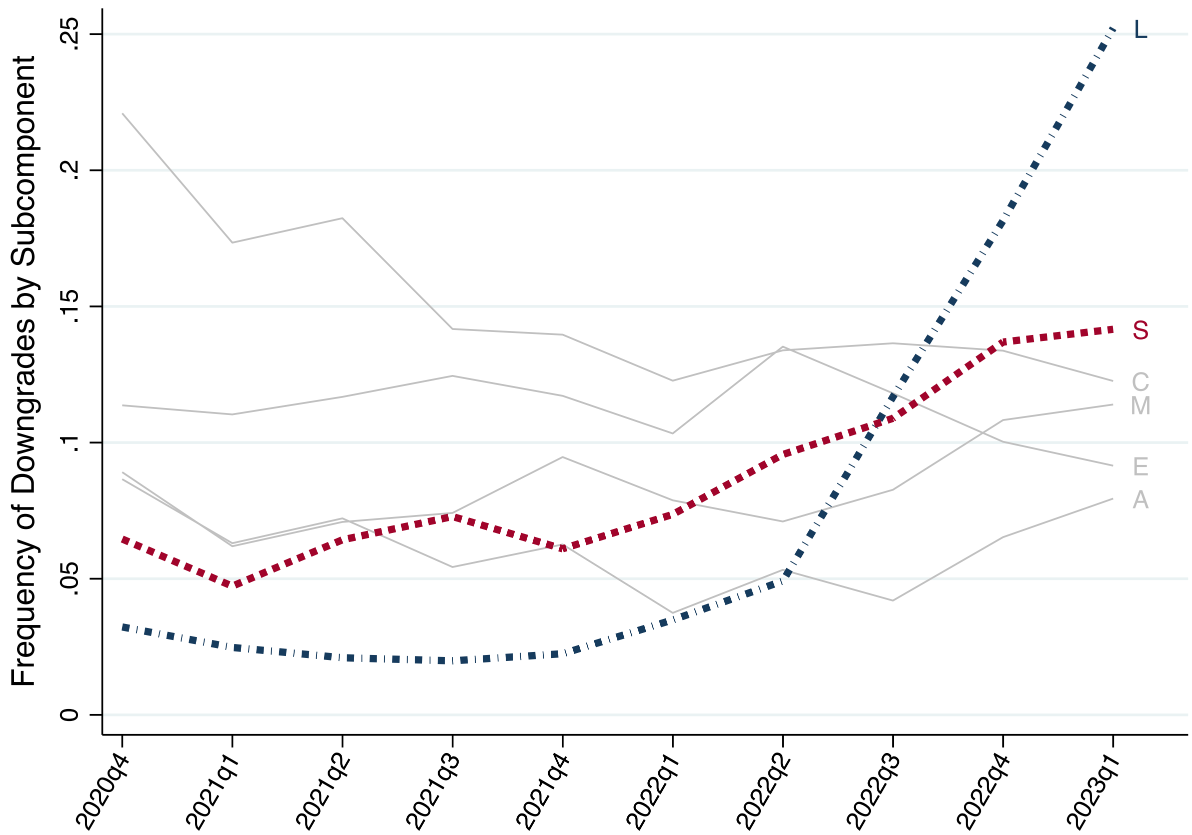


Figure 2: **Downgrade Rate Across CAMELS Components**. This figure shows the frequency of downgrades by the six components of CAMELS – capital adequacy (C), asset quality (A), management (M), earnings (E), liquidity (L), and sensitivity to risk (S) from the fourth quarter of 2020 to the first quarter of 2023. This figure is computed using CAMELS rating data from National Information Center (NIC).

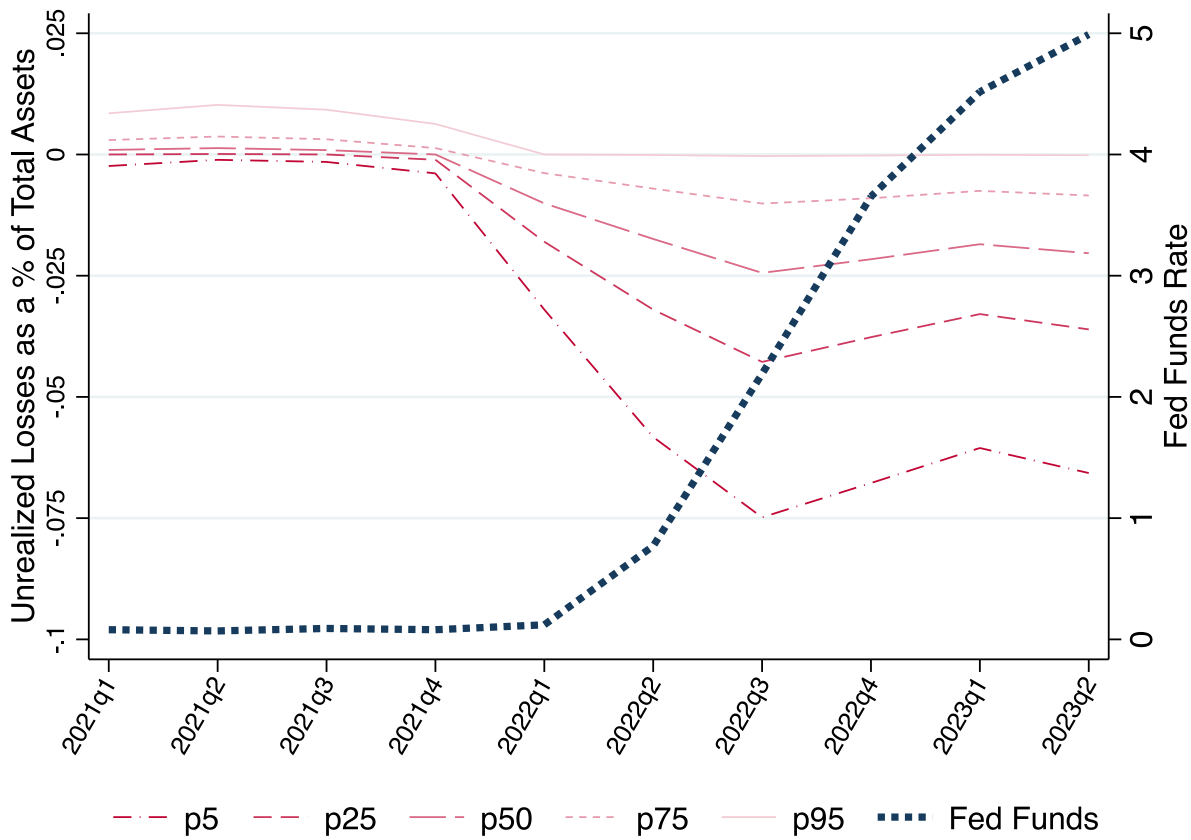
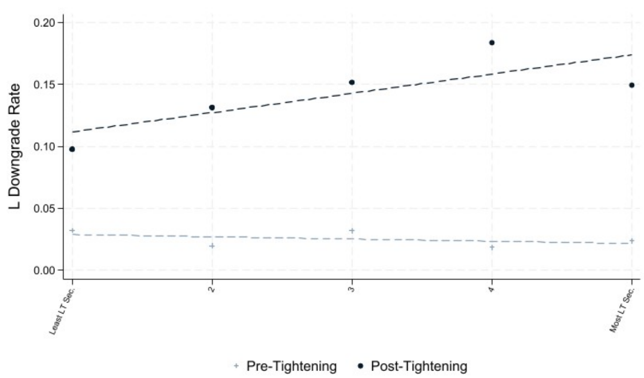


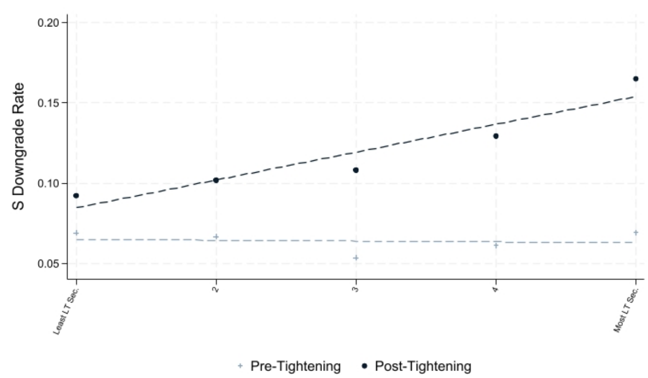
Figure 3: **Timing of Monetary Tightening and Declines in the Value of Securities**. The thin red lines of this figure show the evolution of the 5th, 25th, 50th, 75th, and 95th percentiles of the distribution of unrealized losses as a % of banks' total assets. The thick blue line represents the evolution of the Fed Funds Rate. This figure is computed using data from Call Reports and from FRASER.

Figure 4: **"L" and "S" rating downgrades by Interest Rate Exposure Bin**. This figure examines the relation between "L" and "S" rating downgrades and interest rate exposures for both the pre- and post-tightening periods. We partition all banks into five interest rate exposure bins using the share of banks' long-term securities in Panel A and B and the duration of banks' securities portfolio in Panel C and D. Interest rate exposure bins in Panel A and B range from the lowest share of long-term securities to the highest share of long-term securities, while the bins in Panel C and D range from the shortest securities portfolio duration to the longest duration. We also present best-fit lines to show the relation between "L" and "S" rating downgrades and interest rate exposure more clearly. This figure is computed using CAMELS rating data from National Information Center (NIC) and the Call Reports.

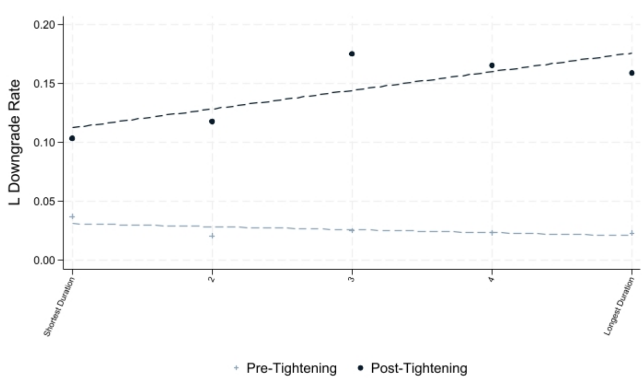
Panel A. "L" Rating and Share of LT Sec.



Panel B. "S" Rating and Share of of LT Sec



Panel C. "L" Rating and Duration



Panel D. "S" Rating and Duration

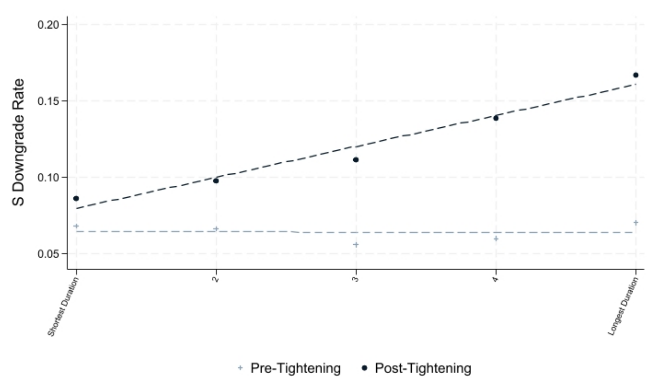
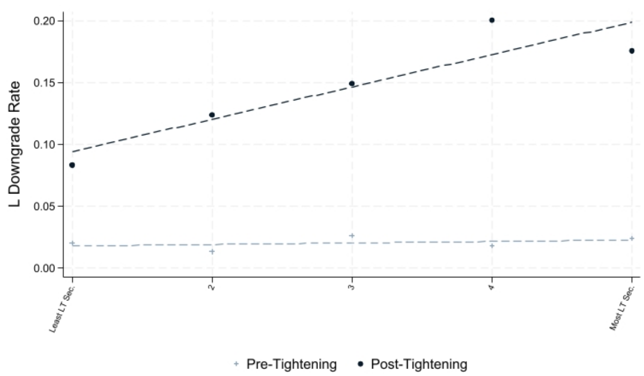
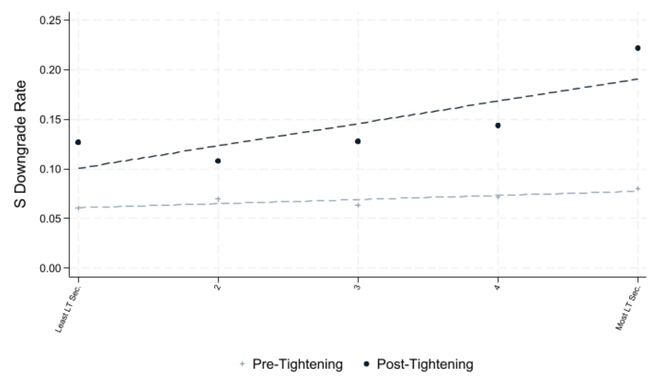


Figure 5: **"L" and "S" rating downgrades by Interest Rate Exposure Bin: Above-median Holdings of Securities**. This figure examines the relation between "L" and "S" rating downgrades and interest rate exposures for the sub-sample of banks with above-median holdings of securities. We partition all banks into five interest rate exposure bins using the share of banks' long-term securities in Panel A and B and the duration of banks' securities portfolio in Panel C and D. Interest rate exposure bins in Panel A and B range from the lowest share of long-term securities to the highest share of long-term securities, while the bins in Panel C and D range from the shortest securities portfolio duration to the longest duration. We also present best-fit lines to show the relation between "L" and "S" rating downgrades and interest rate exposure more clearly. This figure is computed using CAMELS rating data from National Information Center (NIC) and the Call Reports.

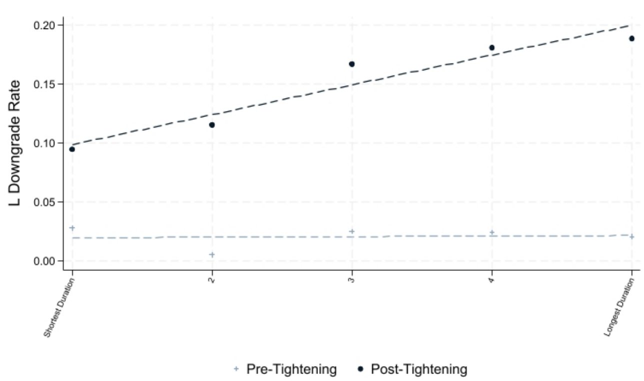
Panel A. "L" Rating and Share of LT Sec.



Panel B. "S" Rating and Share of of LT Sec



Panel C. "L" Rating and Duration



Panel D. "S" Rating and Duration

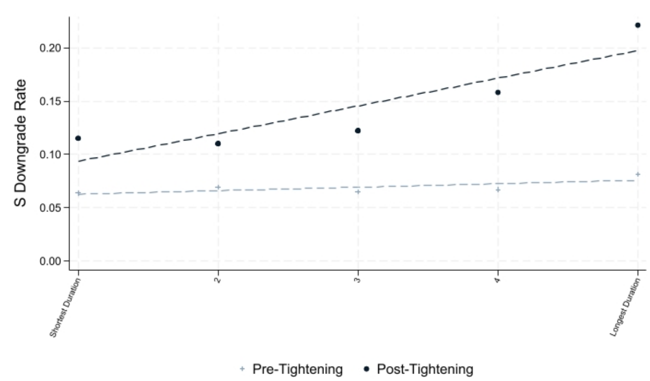
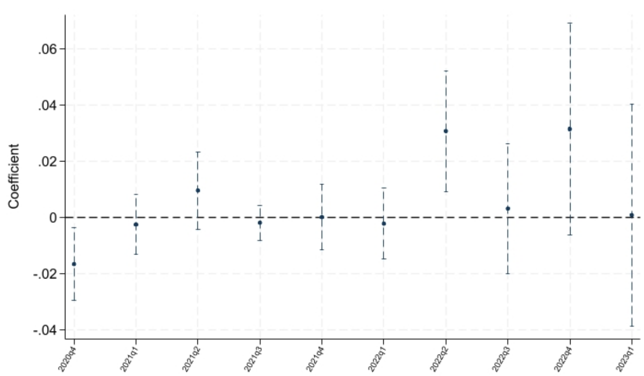
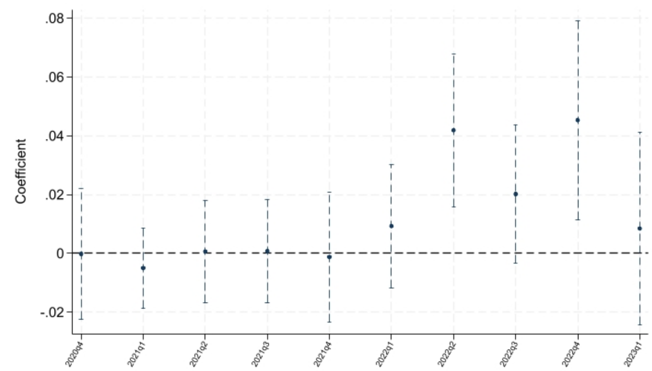


Figure 6: **Interest Rate Risk Exposures and "L" and "S" rating downgrades over time**. This figure plots the coefficients of the regression of "L" and "S" rating downgrades on interest risk exposure for each quarter and presents the results in a time series manner. In each quarterly regression, we include controls for bank size, loan to asset ratio, ROA, loan loss reserve to asset ratio, non-performing loan to asset ratio, equity to asset ratio, and banks' asset decile fixed effects. Bank sizes are defined as the natural logarithm of banks' total assets. In all other control variables, we divide the first term by banks' total assets to obtain the ratio. 95% confidence interval of each coefficient is also presented. In Panel A and B, we use banks' share of long-term securities as the proxy for interest rate exposure; in Panel C and D, banks' securities portfolio duration is used instead. We use CAMELS rating data from National Information Center (NIC) and banks' quarterly Call Reports to compute this figure.

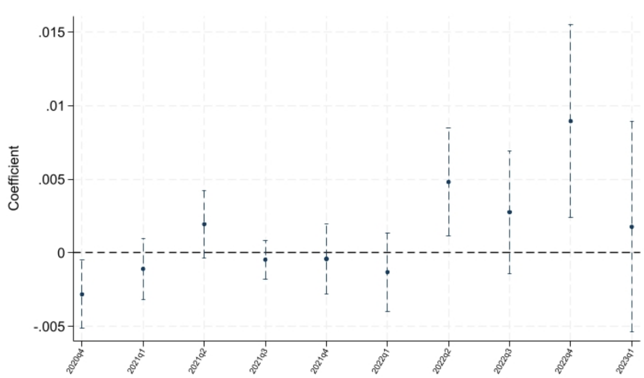
Panel A. "L" Rating and Share of LT Sec.



Panel B. "S" Rating and Share of of LT Sec



Panel C. "L" Rating and Duration



Panel D. "S" Rating and Duration

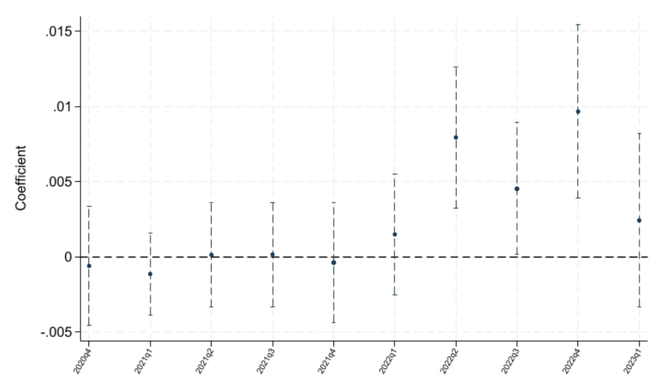
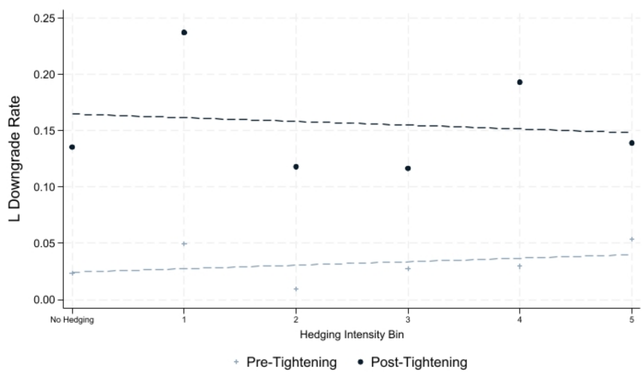
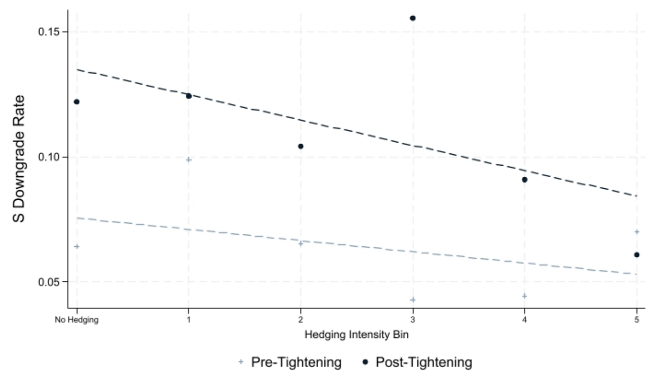


Figure 7: **Hedging Intensity and "L" and "S" rating downgrades over time**. This figure plots the relation between “L” and “S” rating downgrades and a measure of the intensity of hedging of interest rate risks. In Panels A and B, we repeat the exercise of Figure 4 after splitting the sample into bins according to their measure of hedging intensity. In Panels C and D, we repeat the exercise of Figure 6 using the measure of hedging intensity. We use CAMELS rating data from National Information Center (NIC) and banks’ quarterly Call Reports to compute this figure.

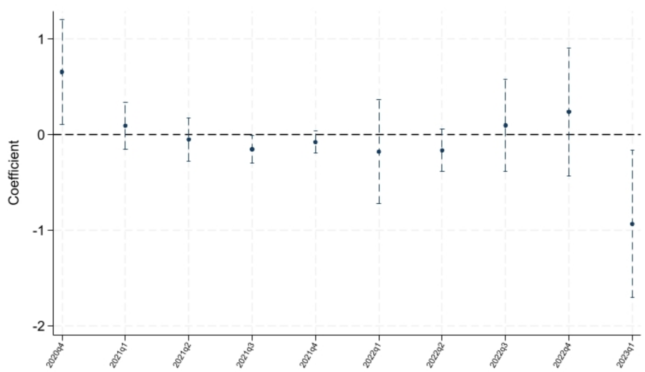
Panel A. “L” Rating and Hedging Intensity



Panel B. “S” Rating and Hedging Intensity



Panel C. “L” Rating and Hedge Intensity (Coef)



Panel D. “S” Rating and Hedge Intensity (Coef.)

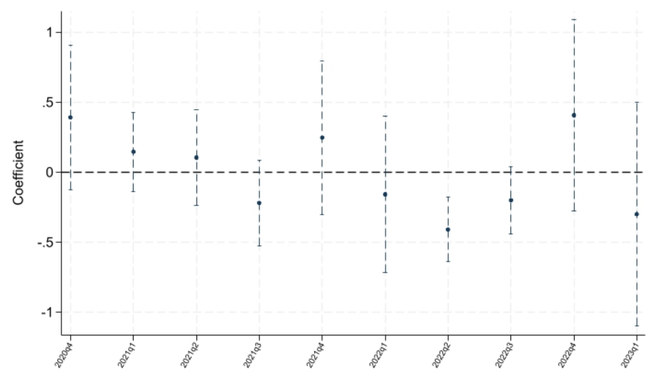


Figure 8: **Interest Rate Risk Exposures and Downgrades of other CAMELS Components over time**. This figure plots the coefficients of the regression of "C", "A", "M", "E", and Composite CAMELS rating downgrades on interest risk exposure for each quarter and presents the results in a time series manner. All variables are defined as in Figure 6. We use CAMELS rating data from National Information Center (NIC) and banks' quarterly Call Reports to compute this figure.

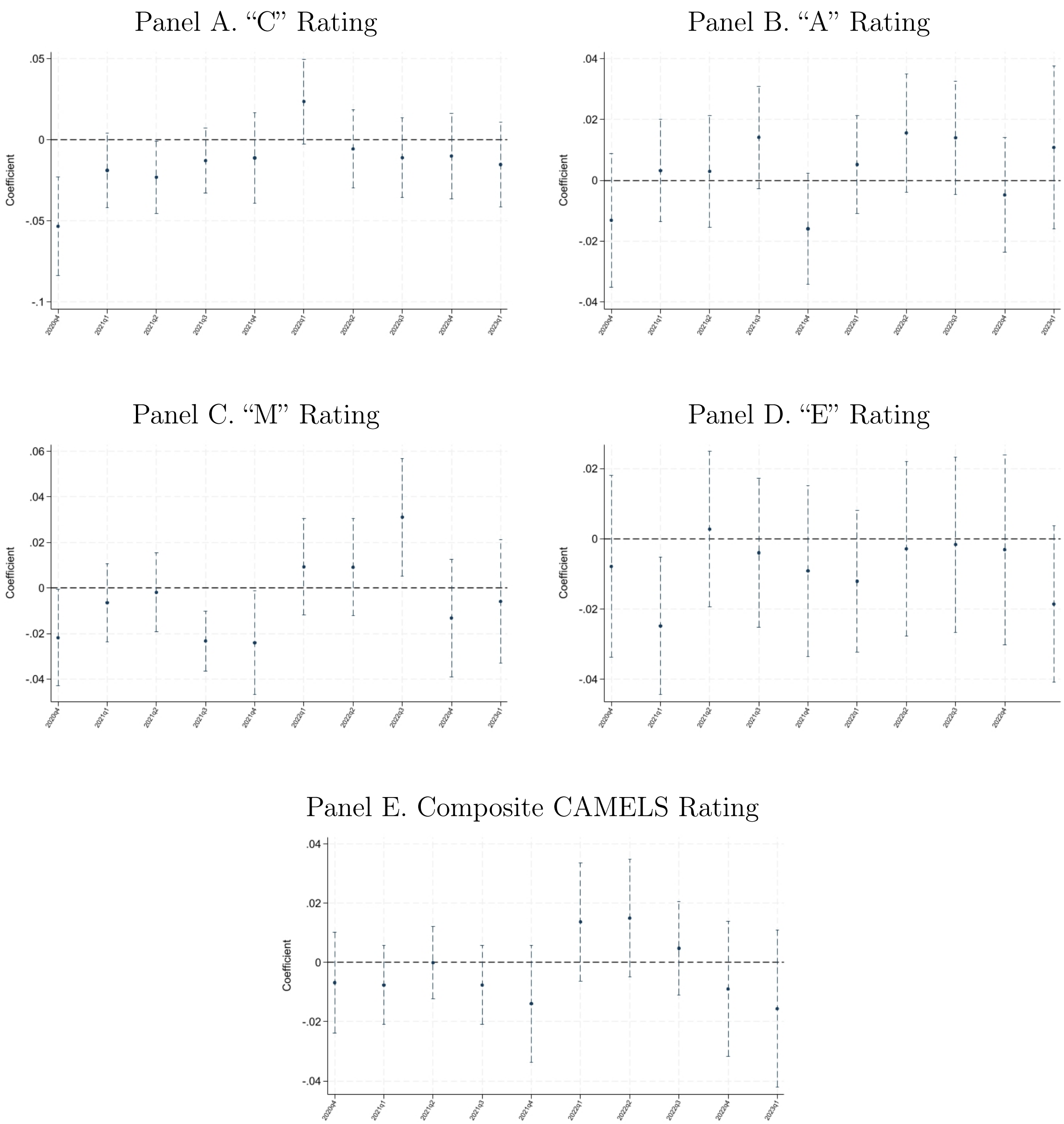


Figure 9: **Unstable Sources of Funding and "L" and "S" rating downgrades over time**. This figure plots the coefficients of the regression of "L" and "S" rating downgrades on measures of deposit instability for each quarter and presents the results in a time series manner. In each quarterly regression, we include controls for bank size, loan to asset ratio, ROA, loan loss reserve to asset ratio, non-performing loan to asset ratio, equity to asset ratio, and banks' asset decile fixed effects. Bank sizes are defined as the natural logarithm of banks' total assets. In all other control variables, we divide the first term by banks' total assets to obtain the ratio. We also provide the 95% confidence interval. In Panel A and B, we use banks' total share of uninsured deposits as the proxy for deposit instability; in Panel C and D, banks' deposit beta is used instead. We utilize CAMELS rating data from National Information Center (NIC) and banks' quarterly Call Reports to compute this figure.

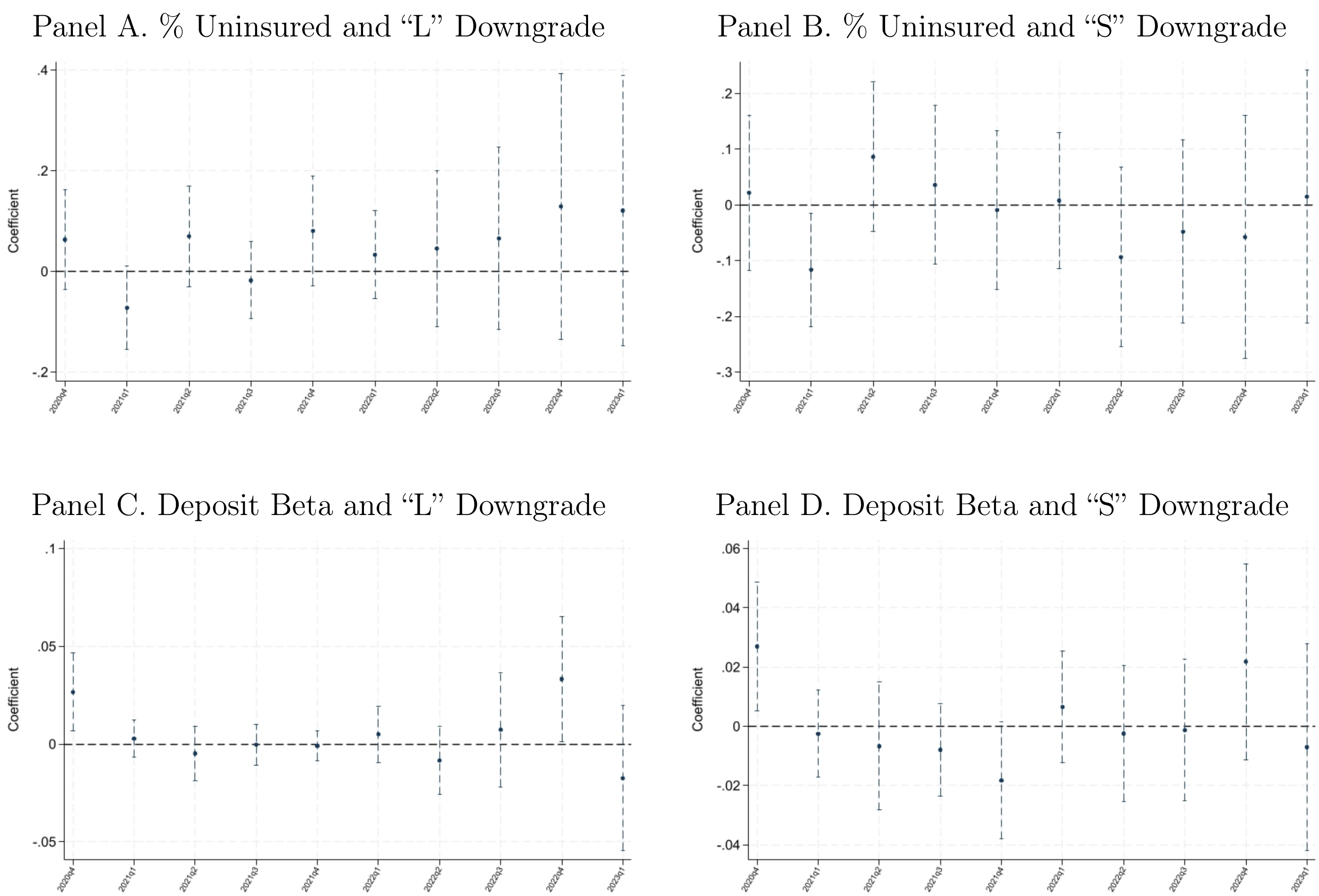
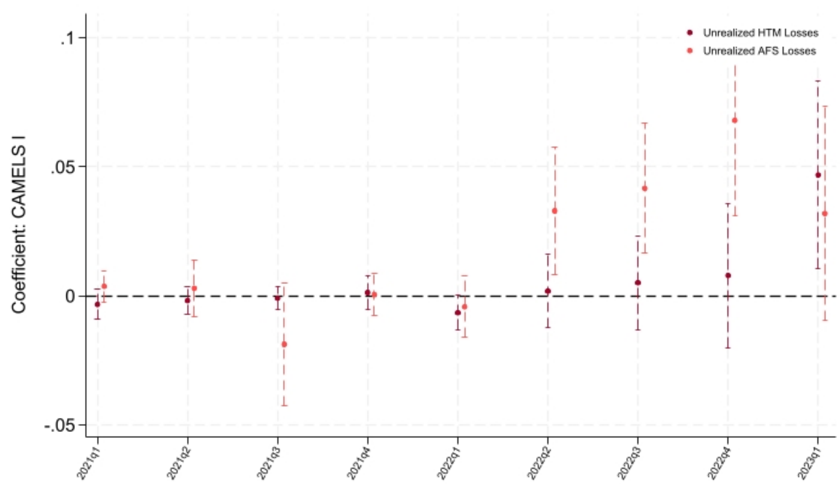


Figure 10: **Accounting Classification of Securities and "L" and "S" rating downgrades over time**. This figure plots the coefficients of the regression of "L" and "S" rating downgrades on measures of unrealized losses on securities classified as AFS and HTM. We estimate quarter-by-quarter regressions using an indicator variable that assumes the value of one if an inspected bank is downgraded and zero otherwise. In Panel A, we plot regression coefficients and respective confidence intervals of the downgrade of the "L" subcomponent on AFS unrealized losses as a percentage of assets (pink bars) and HTM unrealized losses as a percentage of assets (red bars). In Panel B, we repeat the exercise with the downgrade of the "S" subcomponent as the outcome variable. In each quarterly regression, we include controls for bank size, loan to asset ratio, ROA, loan loss reserve to asset ratio, non-performing loan to asset ratio, equity to asset ratio, and banks' asset decile fixed effects. Bank sizes are defined as the natural logarithm of banks' total assets. In all other control variables, we divide the first term by banks' total assets to obtain the ratio. We utilize CAMELS rating data from National Information Center (NIC) and banks' quarterly Call Reports to compute this figure.

Panel A. AFS and HTM Losses and "L" Downgrade



Panel B. AFS and HTM Losses and "S" Downgrade

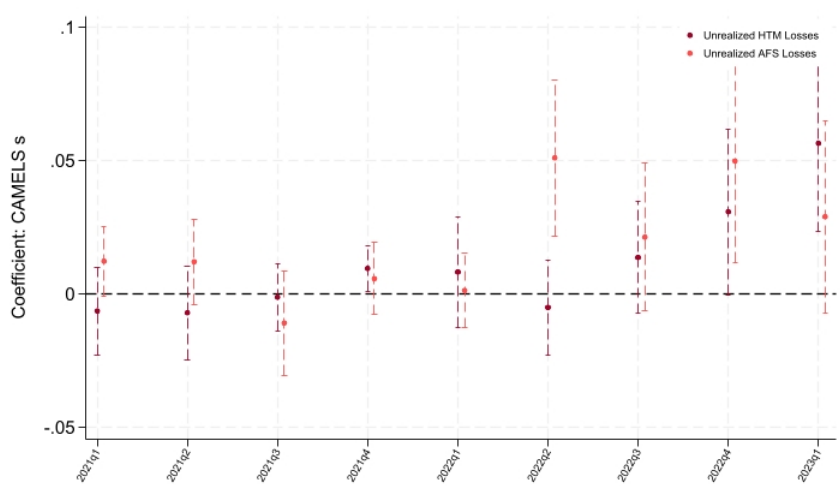
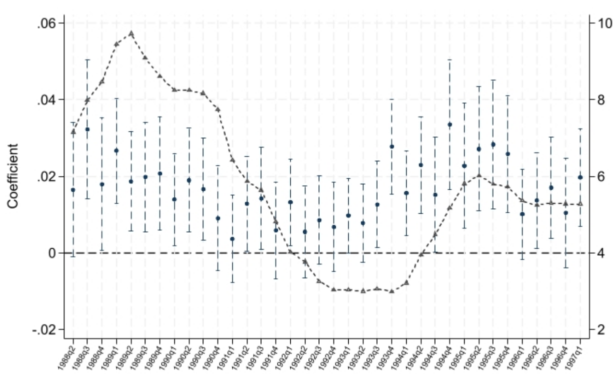
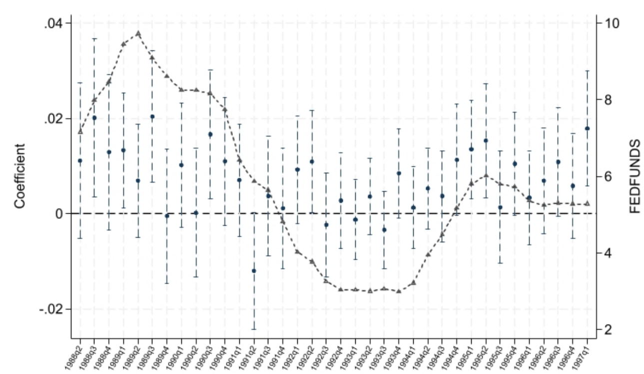


Figure 11: **Supervisory Downgrades during Past Monetary Cycles** This figure plots the coefficients of the regression of the "S" rating downgrades on measures of interest rate risk and stability of funding sources during past monetary cycles. The blue circles represent coefficients associated with regressions of supervisory downgrades on measures of exposure to interest rate risk and stability of deposit funding. We include controls for bank size, loan to asset ratio, ROA, loan loss reserve to asset ratio, non-performing loan to asset ratio, equity to asset ratio, and banks' asset decile fixed effects. Bank sizes are defined as the natural logarithm of banks' total assets. In all other control variables, we divide the first term by banks' total assets to obtain the ratio. 95% confidence interval of each coefficient is also presented. The gray triangles represent the FED FUNDS rate in each quarter of the sample. We utilize CAMELS rating data from National Information Center (NIC), banks' characteristics from quarterly Call Reports, and FED FUNDS rate data obtained from FRASER to compute this figure.

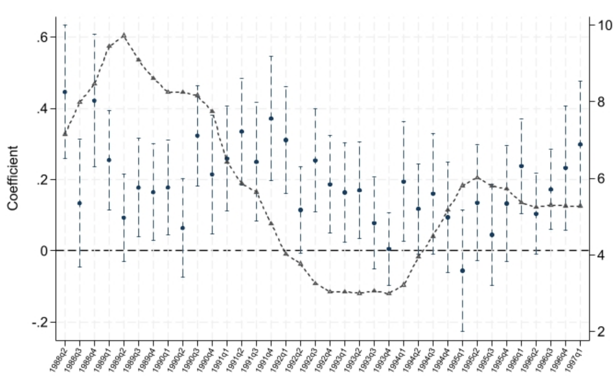
Panel A. % LT Sec and "L" rating



Panel B. % LT Sec and Composite rating



Panel C. % Uninsured and "L" rating



Panel D. % Uninsured and Composite rating

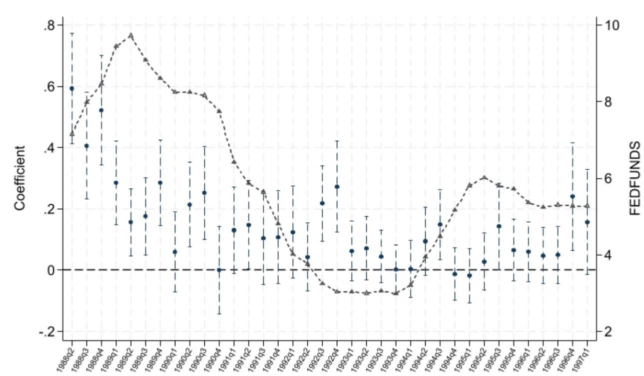
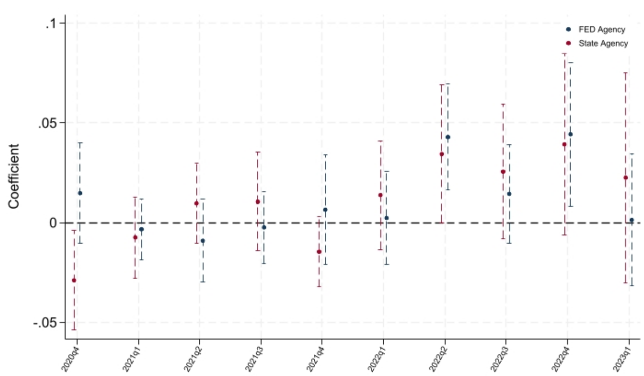
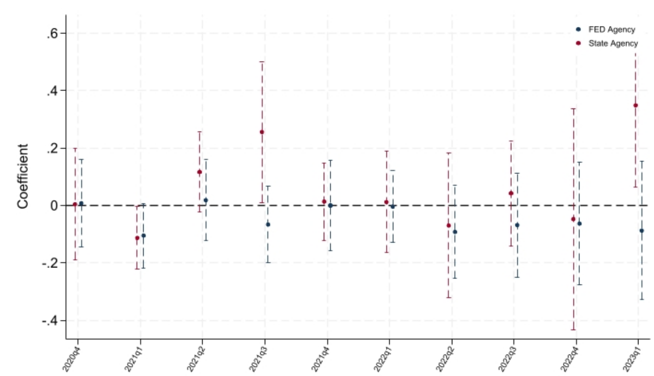


Figure 12: **Heterogeneity in Supervisory Downgrades of "S" and Ratings Across Regulatory Agencies.** This figure plots the coefficients of the regression of the "S" rating downgrades on measures of interest rate risk, stability of funding sources, and unrealized losses in AFS and HTM securities. The red circles represent coefficients associated with regressions on the subset of bank examinations led by state regulatory agencies while the blue circles represent coefficients associated with regressions on the subset of bank examination. We include controls for bank size, loan to asset ratio, ROA, loan loss reserve to asset ratio, non-performing loan to asset ratio, equity to asset ratio, and banks' asset decile fixed effects. Bank sizes are defined as the natural logarithm of banks' total assets. In all other control variables, we divide the first term by banks' total assets to obtain the ratio. 95% confidence interval of each coefficient is also presented. We utilize CAMELS rating data from National Information Center (NIC) and banks' quarterly Call Reports to compute this figure.

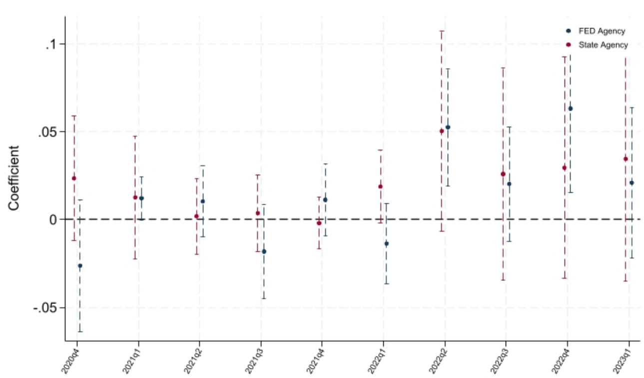
Panel A. % LT Sec



Panel B. % Uninsured



Panel C. Unrealized Losses in AFS Sec.



Panel D. Unrealized Losses in HTM Sec.

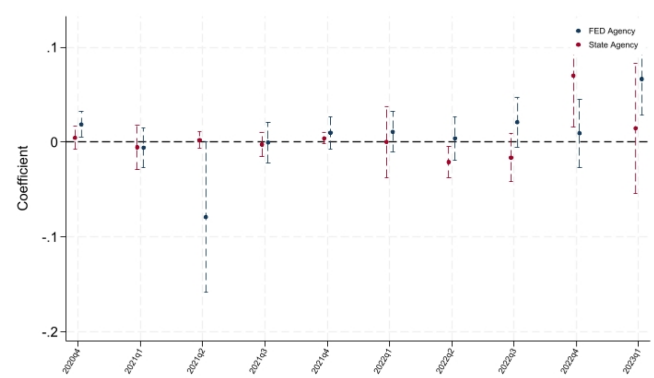
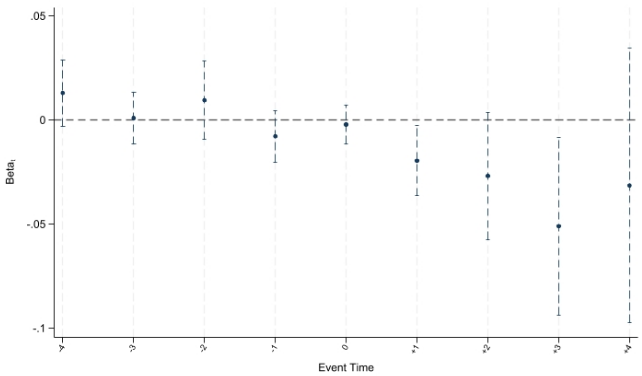
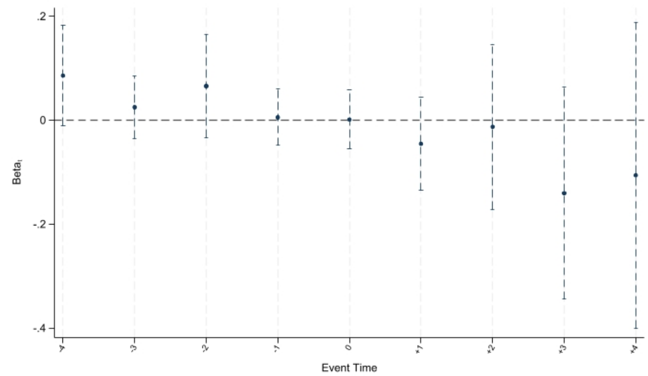


Figure 13: **Evolution of Interest rate risk exposure measures following a "S" or "L" downgrade**. We use CAMELS rating data from National Information Center (NIC) and banks' quarterly Call Reports to compute this figure.

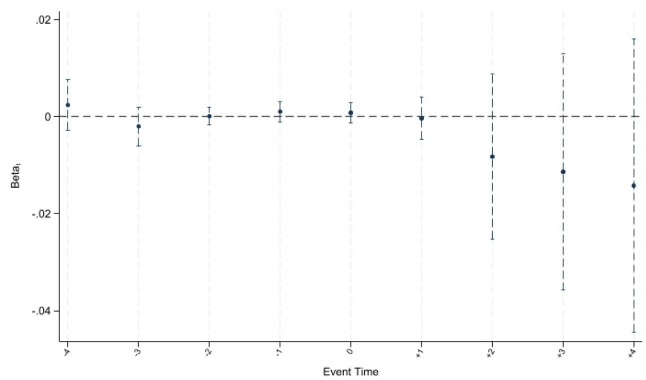
Panel A. Share of LT Sec.



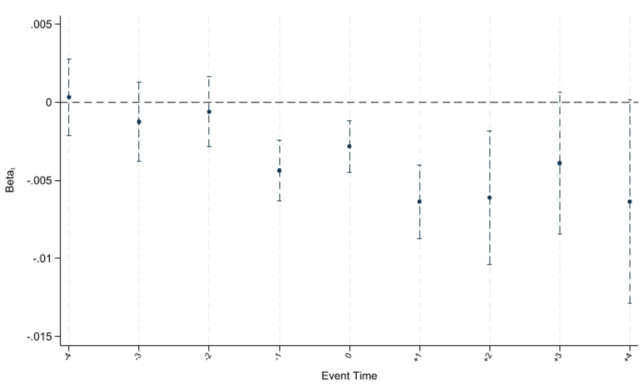
Panel B. Duration



Panel C. Hedging Intensity



Panel D. Total Securities (% Assets)



Panel E. Total Cash (% Assets)

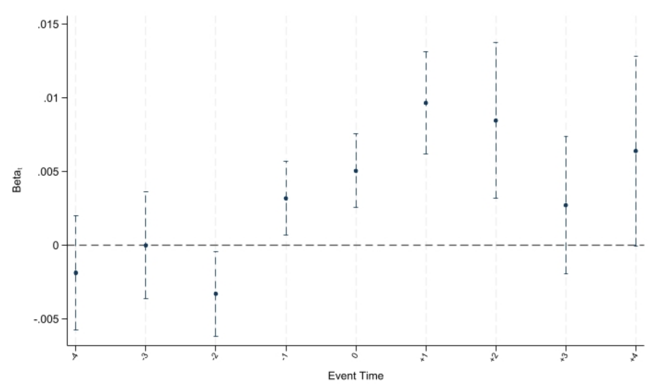
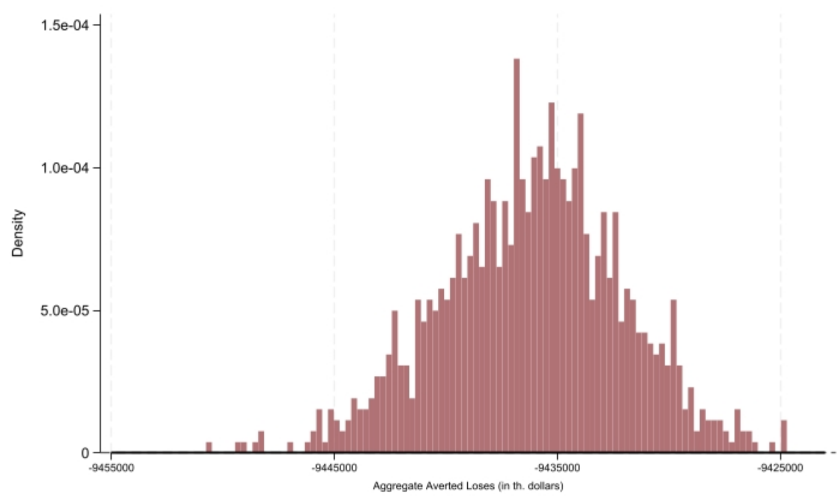


Figure 14: **Counterfactually Averted Unrealized Losses**. This histogram represents the aggregate amount of estimated averted unrealized losses in securities (Panel A) and average estimated averted unrealized losses in securities as a fraction of Tier 1 capital (Panel B) in a counterfactual scenario in which bank supervisors downgrade banks in the fourth quarter of 2021 and second quarter of 2022 according to the model criteria that they used to downgrade banks in the post-monetary tightening period.

Panel A. Aggregate amount of Averted Unrealized Losses



Panel B. Average Averted Unrealized Losses as a fraction of Tier 1 Capital

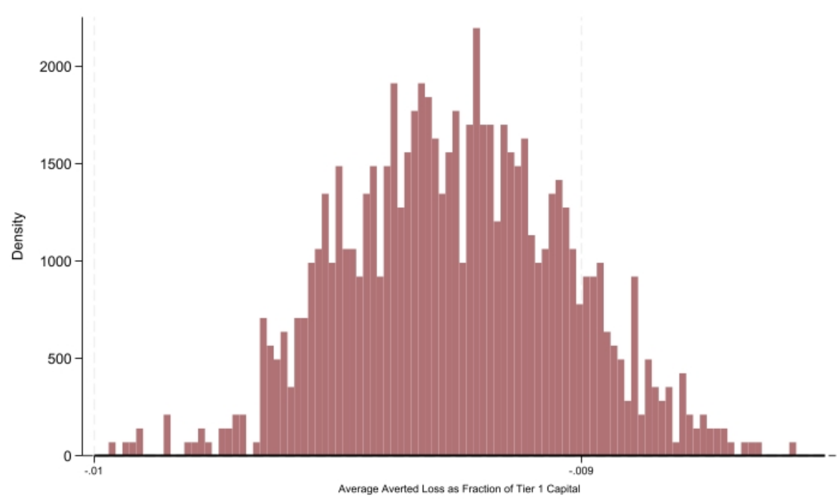


Table 1: Summary Statistics

Table 1 reports the summary statistics for our main sample. The unit of observation is at the examination level. Duration is defined as the sum of 0.25x(RCFDA549 +RCFDA555), 0.75x(RCFDA550+RCFDA556), 2.0x(RCFDA551+RCFDA557), 4.0x(RCFDA552+RCFDA558), 10.0x(RCFDA553+RCFDA559), and 25x(RCFDA554+RCFDA560) divided by the sum of RCFDA549, RCFDA550, RCFDA551, RCFDA552, RCFDA553, RCFDA554, RCFDA555, RCFDA556, RCFDA557, RCFDA558, RCFDA559, and RCFDA560. Share of LT Sec is defined as (RCFDA554+RCFDA560) divided by the sum of RCFDA549, RCFDA550, RCFDA551, RCFDA552, RCFDA553, RCFDA554, RCFDA555, RCFDA556, RCFDA557, RCFDA558, RCFDA559, RCFDA560. Hedging Intensity is defined as RCFD8725 divided by RCFD2170. If RCFD8725 is missing then we set Hedging Intensity to equal zero. Share Uninsured is defined as (RCONF047+RCONF045) divided by (RCONF045+RCONF047+RCONF049+RCONF051). If (RCONF045+RCONF047+RCONF049+RCONF051) is greater than zero, otherwise Share Uninsured is set to missing. Dep. Beta is the deposit expense beta as discussed in Drechsler et al. [2021]; Dep. Beta data are downloaded from Phillip Schnabl's webpage. Ln(Assets) is defined as ln(1+RCFD2170). Loans as % Total Assets is defined as RCFD2122 divided by RCFD2170. ROA is defined as RIAD4340 (annualized) divided by RCFD2170. LLR as a % Total Assets is defined as RCFD3123 divided by RCFD2170. NPL as a % Total Assets is defined as RCFD1403 divided by RCFD2170. Equity as % Total Assets is defined as RCFD3210 divided by RCFD2170.

	Pre-Tightening Exams			Post-Tightening Exams				
	Mean	St. Dev.	N	Mean	St. Dev.	N	Diff	t-stat
Duration	10.26	5.340	4445	9.760	5.360	2657	-0.500	-1.540
Share of LT Sec	0.220	0.230	4445	0.210	0.230	2657	-0.0100	-0.610
Hedging Intensity	0.0200	0.0500	4576	0.0100	0.0500	2701	0	-2.580
Share Uninsured	0.400	0.160	4576	0.430	0.150	2701	0.0300	4.030
Dep. Beta	0.320	0.0900	4576	0.320	0.0900	2701	0	-0.0900
Ln(Assets)	12.77	1.580	4576	12.88	1.570	2701	0.100	1.640
Loans as % Total Assets	59.06	16	4576	57.90	16.97	2701	-1.160	-0.850
ROA	0.0200	0.0200	4576	0.0100	0.0200	2701	-0.0100	-0.500
LLR as % Total Assets	0.850	0.400	4576	0.810	0.380	2701	-0.0400	-4.010
NPL as % Total Assets	0.440	0.650	4576	0.310	0.540	2701	-0.120	-4.850
Equity as % Total Assets	10.98	3.200	4576	9.250	3.730	2701	-1.730	-8.690

Table 2: Rating Downgrade and Interest Rate Risk Exposure

Table 2 reports the coefficients of OLS regressions examining the relation between CAMELS rating downgrade and interest rate risk exposure. *I(S-Downgrade)=1* and *I(L-Downgrade)=1* are indicator variables for whether there is a downgrade for S or L aspect of the CAMELS rating for a given bank. *Post* is the indicator variable that equals to one after the monetary tightening in the first quarter of 2022. We include controls for bank size, loan to asset ratio, ROA, loan loss reserve to asset ratio, non-performing loan to asset ratio, and equity to asset ratio. Bank sizes are defined as the natural logarithm of banks' total assets. In all other control variables, we divide the first term by banks' total assets to obtain the ratio. For each specification, we include quarter and banks' asset decile fixed effects. We also include bank fixed effects in Columns (2), (4), (6), and (8). CAMELS ratings data are from NIC database, share of long-term securities and portfolio duration are computed from banks' Call Reports. Call Report variable definitions can be found in the description of Table 1. Standard errors are presented in parentheses, and are clustered at the state level. ***, **, and *, represent statistical significance at 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	I(L-Downgrade)=1				I(S-Downgrade)=1			
Share of LT Sec	-0.003	-0.009			0.001	0.015		
	(0.002)	(0.018)			(0.004)	(0.013)		
Share of LT Sec × Post	0.022***	0.016			0.028***	0.018		
	(0.008)	(0.013)			(0.010)	(0.014)		
Duration			-0.001*	0.000			-0.000	0.004
			(0.000)	(0.003)			(0.001)	(0.003)
Duration × Post			0.006***	0.004**			0.006***	0.004
			(0.001)	(0.002)			(0.002)	(0.002)
Observations	7102	5620	7102	5620	7102	5620	7102	5620
Adjusted R^2	0.087	0.074	0.090	0.075	0.022	-0.006	0.024	-0.006
Other Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Quarter Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank Fixed Effects	No	Yes	No	Yes	No	Yes	No	Yes

Table 3: Rating Downgrade and Interest Rate Risk Exposure

Table 3 reports the coefficients of OLS regressions examining the relation between CAMELS rating downgrade and interest rate risk exposure. *I(S-Downgrade)=1* and *I(L-Downgrade)=1* are indicator variables for whether there is a downgrade for S or L aspect of the CAMELS rating for a given bank. *Post* is the indicator variable that equals to one after the monetary tightening in the first quarter of 2022. We include controls for bank size, loan to asset ratio, ROA, loan loss reserve to asset ratio, non-performing loan to asset ratio, and equity to asset ratio. Bank sizes are defined as the natural logarithm of banks' total assets. In all other control variables, we divide the first term by banks' total assets to obtain the ratio. For each specification, we include quarter and banks' asset decile fixed effects. We also include bank fixed effects in Columns (2), (4), (6), and (8). CAMELS ratings data are from NIC database, share of long-term securities and portfolio duration are computed from banks' Call Reports. Call Report variable definitions can be found in the description of Table 1. Standard errors are presented in parentheses, and are clustered at the state level. ***, **, and *, represent statistical significance at 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	I(L-Downgrade)=1				I(S-Downgrade)=1			
Share of LT Sec	-0.010*	-0.002	-0.010*	-0.002	-0.010	0.029	-0.010	0.029
	(0.005)	(0.029)	(0.005)	(0.029)	(0.008)	(0.018)	(0.008)	(0.018)
Share of LT Sec × Post	-0.005	-0.019	-0.005	-0.019	-0.007	-0.008	-0.007	-0.008
	(0.013)	(0.019)	(0.013)	(0.019)	(0.008)	(0.015)	(0.008)	(0.015)
Pct Sec	0.132***	-0.073	0.132***	-0.073	0.012	0.038	0.012	0.038
	(0.032)	(0.212)	(0.032)	(0.212)	(0.033)	(0.204)	(0.033)	(0.204)
Share of LT Sec × Pct Sec	0.021	-0.040	0.021	-0.040	0.051	-0.087	0.051	-0.087
	(0.019)	(0.115)	(0.019)	(0.115)	(0.041)	(0.094)	(0.041)	(0.094)
Post × Pct Sec	0.116**	0.192*	0.116**	0.192*	0.200***	0.150	0.200***	0.150
	(0.046)	(0.103)	(0.046)	(0.103)	(0.048)	(0.112)	(0.048)	(0.112)
Share of LT Sec × Post × Pct Sec	0.092**	0.138*	0.092**	0.138*	0.105*	0.114	0.105*	0.114
	(0.041)	(0.072)	(0.041)	(0.072)	(0.055)	(0.080)	(0.055)	(0.080)
Observations	6963	5492	6963	5492	6963	5492	6963	5492
Adjusted R^2	0.098	0.081	0.098	0.081	0.030	-0.005	0.030	-0.005
Other Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Quarter Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank Fixed Effects	No	Yes	No	Yes	No	Yes	No	Yes

Table 4: Rating Downgrade and Hedging

Table 4 reports the coefficients of OLS regressions examining the relation between CAMELS rating downgrade and hedging. *I(S-Downgrade)=1* and *I(L-Downgrade)=1* are indicator variables for whether there is a downgrade for S or L aspect of the CAMELS rating for a given bank. *Post* is the indicator variable that equals to one after the monetary tightening in the first quarter of 2022. *Hedging Intensity* is the ratio between the gross notional amount of interest rate derivatives for purposes other than trading and total assets. In each specification, we include controls for bank size, loan to asset ratio, ROA, loan loss reserve to asset ratio, non-performing loan to asset ratio, and equity to asset ratio. Bank sizes are defined as the natural logarithm of banks' total assets. In all other control variables, we divide the first term by banks' total assets to obtain the ratio. For each specification, we include quarter and banks' asset decile fixed effects. we also include bank fixed effects in Columns (2) and (4). CAMELS ratings data are from NIC database, share of uninsured deposits are from banks' quarterly Call Reports. Call Report variable definitions can be found in the description of Table 1. Standard errors are presented in parentheses, and are clustered at the state level. ***, **, and *, represent statistical significance at 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)
	I(L-Downgrade)=1		I(S-Downgrade)=1	
Hedging Intensity	0.086	0.224	0.102	0.153
	(0.079)	(0.258)	(0.092)	(0.253)
Hedging Intensity × Post	-0.218*	-0.155	-0.209*	-0.059
	(0.128)	(0.174)	(0.120)	(0.175)
Observations	7277	5781	7277	5781
Adjusted R^2	0.084	0.070	0.018	-0.009
Other Controls	Yes	Yes	Yes	Yes
Quarter Fixed Effects	Yes	Yes	Yes	Yes
Bank Fixed Effects	No	Yes	No	Yes

Table 5: Rating Downgrade and Deposit Instability

Table 5 reports the coefficients of OLS regressions examining the relation between CAMELS rating downgrade and measures of stability of deposit funding. *I(S-Downgrade)=1* and *I(L-Downgrade)=1* are indicator variables for whether there is a downgrade for S or L aspect of the CAMELS rating for a given bank. *Post* is the indicator variable that equals to one after the monetary tightening in the first quarter of 2022. *Share Uninsured* is the share of uninsured deposits of a given bank. Share $\widehat{\text{Uninsured}}$ is the instrumented share of uninsured deposits at the bank. *Dep. Beta* is retail deposit beta computed by Drechsler et al. [2021]. In each specification, we include controls for bank size, loan to asset ratio, ROA, loan loss reserve to asset ratio, non-performing loan to asset ratio, and equity to asset ratio. Bank sizes are defined as the natural logarithm of banks' total assets. In all other control variables, we divide the first term by banks' total assets to obtain the ratio. For each specification, we include quarter and banks' asset decile fixed effects. We also include bank fixed effects in Columns (2) and (6). CAMELS ratings data are from NIC database, share of uninsured deposits are from banks' quarterly Call Reports. Call Report variable definitions can be found in the description of Table 1. Standard errors are presented in parentheses, and are clustered at the state level. ***, **, and *, represent statistical significance at 1%, 5%, and 10% levels, respectively.

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	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	I(L-Downgrade)=1				I(S-Downgrade)=1			
Share Uninsured	0.004	-0.010			-0.002	-0.029		
	(0.003)	(0.032)			(0.004)	(0.023)		
Share Uninsured × Post	0.008	0.011			-0.002	0.002		
	(0.007)	(0.012)			(0.006)	(0.009)		
Share $\widehat{\text{Uninsured}}$			-0.004				-0.008	
			(0.012)				(0.012)	
Share $\widehat{\text{Uninsured}}$ × Post			0.002				0.015	
			(0.011)				(0.010)	
Dep. Beta				0.004				0.000
				(0.003)				(0.004)
Dep. Beta × Post				-0.001				-0.001
				(0.007)				(0.007)
Observations	7302	5806	7302	7303	7302	5806	7302	7303
Adjusted R^2	0.084	0.069	0.083	0.083	0.018	-0.009	0.018	0.018
Other Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Quarter Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank Fixed Effects	No	Yes	No	No	Yes	No	No	No

Internet Appendix for "How (in)effective was bank supervision during the 2022 Monetary Tightening?"

Table A.1: Rating Downgrade and Interest Rate Risk Exposure: Duration Measure

Table A.1 reports the coefficients of OLS regressions examining the relation between CAMELS rating downgrade and the interaction between the duration measure of interest rate risk exposure and the share of marketable securities as a fraction of total assets. All variables and specifications are defined as in Table 3. Call Report variable definitions can be found in the description of Table 1. Standard errors are presented in parentheses, and are clustered at the state level. ***, **, and *, represent statistical significance at 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	I(L-Downgrade)=1				I(S-Downgrade)=1			
Duration	-0.003***	0.002	-0.003***	0.002	-0.002	0.006	-0.002	0.006
	(0.001)	(0.004)	(0.001)	(0.004)	(0.001)	(0.004)	(0.001)	(0.004)
Duration × Post	0.001	-0.002	0.001	-0.002	-0.000	-0.001	-0.000	-0.001
	(0.002)	(0.003)	(0.002)	(0.003)	(0.002)	(0.003)	(0.002)	(0.003)
Pct. Sec.	0.074	0.053	0.074	0.053	-0.101	0.221	-0.101	0.221
	(0.046)	(0.229)	(0.046)	(0.229)	(0.074)	(0.256)	(0.074)	(0.256)
Duration × Pct. Sec.	0.006	-0.011	0.006	-0.011	0.011	-0.017	0.011	-0.017
	(0.004)	(0.020)	(0.004)	(0.020)	(0.007)	(0.019)	(0.007)	(0.019)
Post × Pct. Sec.	-0.061	-0.087	-0.061	-0.087	0.010	-0.060	0.010	-0.060
	(0.090)	(0.159)	(0.090)	(0.159)	(0.145)	(0.222)	(0.145)	(0.222)
Duration × Post × Pct. Sec.	0.017**	0.028**	0.017**	0.028**	0.019	0.020	0.019	0.020
	(0.007)	(0.012)	(0.007)	(0.012)	(0.011)	(0.016)	(0.011)	(0.016)
Observations	6963	5492	6963	5492	6963	5492	6963	5492
Adjusted R^2	0.100	0.083	0.100	0.083	0.031	-0.004	0.031	-0.004
Other Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Quarter Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank Fixed Effects	No	Yes	No	Yes	No	Yes	No	Yes

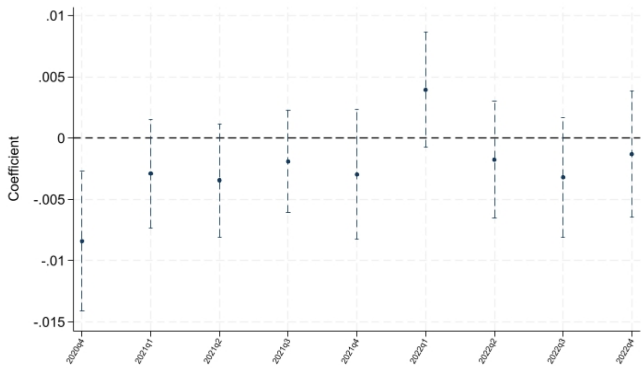
Table A.2: Rating Downgrade and Interaction between Interest Rate Risk and Deposit Instability

Table A.2 reports the coefficients of OLS regressions examining the relation between CAMELS rating downgrade and the interaction between interest rate risk exposure and deposit instability. *I(S-Downgrade)=1* and *I(L-Downgrade)=1* are indicator variables for whether there is a downgrade for S or L aspect of the CAMELS rating for a given bank. *Post* is the indicator variable that equals to one after the monetary tightening in the first quarter of 2022. We include controls for bank size, loan to asset ratio, ROA, loan loss reserve to asset ratio, non-performing loan to asset ratio, and equity to asset ratio. Bank sizes are defined as the natural logarithm of banks' total assets. In all other control variables, we divide the first term by banks' total assets to obtain the ratio. For each specification, we include quarter and banks' asset decile fixed effects. We also include bank fixed effects in Columns (2), (4), (6), and (8). CAMELS ratings data are from NIC database and share of long-term securities, share of uninsured deposits, and other control variables are computed from banks' Call Reports. Call Report variable definitions can be found in the description of Table 1. Standard errors are presented in parentheses, and are clustered at the state level. ***, **, and *, represent statistical significance at 1%, 5%, and 10% levels, respectively.

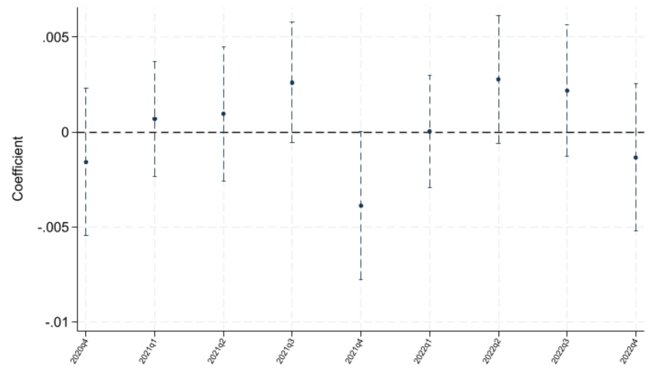
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	I(L-Downgrade)=1				I(S-Downgrade)=1			
Share of LT Sec	-0.011	-0.003	-0.011	-0.003	-0.007	-0.006	-0.007	-0.006
	(0.008)	(0.044)	(0.008)	(0.044)	(0.010)	(0.029)	(0.010)	(0.029)
Share of LT Sec × Post	0.007	-0.011	0.007	-0.011	0.028	0.003	0.028	0.003
	(0.024)	(0.036)	(0.024)	(0.036)	(0.024)	(0.031)	(0.024)	(0.031)
Share Uninsured	0.020	-0.083	0.020	-0.083	-0.013	-0.203	-0.013	-0.203
	(0.016)	(0.207)	(0.016)	(0.207)	(0.027)	(0.160)	(0.027)	(0.160)
Share of LT Sec × Share Uninsured	0.022	-0.011	0.022	-0.011	0.019	0.046	0.019	0.046
	(0.019)	(0.094)	(0.019)	(0.094)	(0.020)	(0.070)	(0.020)	(0.070)
Post × Share Uninsured	0.037	0.067	0.037	0.067	-0.035	0.005	-0.035	0.005
	(0.047)	(0.086)	(0.047)	(0.086)	(0.039)	(0.063)	(0.039)	(0.063)
Share of LT Sec × Share Uninsured× Post	0.029	0.052	0.029	0.052	-0.001	0.027	-0.001	0.027
	(0.055)	(0.085)	(0.055)	(0.085)	(0.048)	(0.076)	(0.048)	(0.076)
Observations	7125	5643	7125	5643	7125	5643	7125	5643
Adjusted R^2	0.087	0.072	0.087	0.072	0.022	-0.007	0.022	-0.007
Other Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Quarter Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank Fixed Effects	No	Yes	No	Yes	No	Yes	No	Yes

Figure A.1: “C”, “A”, “M”, and “E” rating downgrades by Interest Rate Exposure Bin: Duration Measure

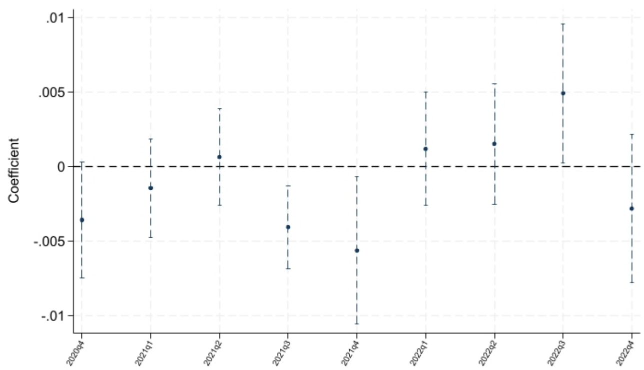
Panel A. “C” Rating



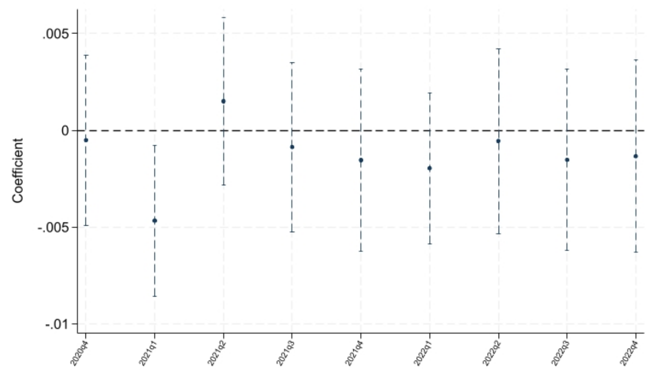
Panel B. “A” Rating



Panel C. “M” Rating



Panel D. “E” Rating



Panel E. Composite CAMELS Rating

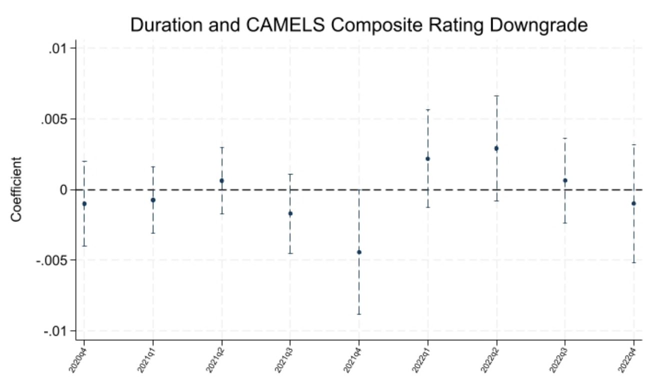


Figure A.2: **Heterogeneity in Supervisory Downgrades of "L" and Ratings Across Regulatory Agencies.** This figure plots the coefficients of the regression of the "L" rating downgrades on measures of interest rate risk, stability of funding sources, and unrealized losses in AFS and HTM securities. The red circles represent coefficients associated with regressions on the subset of bank examinations led by state regulatory agencies while the blue circles represent coefficients associated with regressions on the subset of bank examination. We include controls for bank size, loan to asset ratio, ROA, loan loss reserve to asset ratio, non-performing loan to asset ratio, equity to asset ratio, and banks' asset decile fixed effects. Bank sizes are defined as the natural logarithm of banks' total assets. In all other control variables, we divide the first term by banks' total assets to obtain the ratio. 95% confidence interval of each coefficient is also presented. We utilize CAMELS rating data from National Information Center (NIC) and banks' quarterly Call Reports to compute this figure.