

Mitigating deregulation: The role of supervision

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Abstract

We study how regulation and supervision interact. Exploiting the 2018-2019 relaxation of liquidity requirements for US mid-sized banks, we show that affected banks experienced a deterioration in liquidity. At the same time, using confidential data from the Federal Reserve on supervisory hours, we document that these banks were subject to an increase in supervisory examination activity. The increase in supervisory intensity mitigates the deterioration in liquidity. These effects are stronger in districts where supervisors oversee fewer banks and have longer tenure. Preliminary evidence also suggests that deregulated banks expand lending, without a corresponding increase in other measures of risk. These findings suggest that supervision can partially substitute for regulatory discipline and highlight the importance of supervisory capacity for financial stability.

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“The whole point of supervision is to fill in the many blanks that are left by quantitative metrics,” he said. “If your regulations on capital are less restrictive, then you should be more focused on making sure that any shift in bank activities is not creating problems.”

Daniel K. Tarullo, former Governor of the Federal Reserve Board, quoted in “The Fed is Cutting Bank Oversight. Critics See Risks” *New York Times*, 17 November 2025

1 Introduction

Regulation and supervision are the two principal tools through which policymakers seek to safeguard the stability of the banking system. Regulation establishes formal requirements governing banks’ activities, while supervision assesses individual institutions and intervenes when concerns arise. Yet the relation between these two forms of oversight remains imperfectly understood. In particular, a fundamental question is whether supervision can compensate for regulatory relief. If so, policymakers may be able to achieve prudential objectives through supervisory scrutiny even when regulatory requirements are eased. At the same time, supervision influences banks’ behavior, making it important to understand how banks respond when supervision substitutes for regulation. Recent events, including the role of supervision in the failure of Silicon Valley Bank (Barr 2023) and reductions in supervisory staff at U.S. banking agencies,¹ have renewed attention on these issues, yet there is limited evidence on how regulation and supervision interact in practice.

We study these questions around the relaxation of liquidity regulation for U.S. bank holding companies (BHCs) following the 2018 Economic Growth, Regulatory Relief, and Consumer Protection Act (EGRRCPA) and the subsequent 2019 “tailoring rule,” combining an analysis of BHCs’ liquidity, lending, and risk with confidential data on supervisory hours. BHCs whose liquidity requirements were relaxed exhibit declining liquidity coverage ratios (LCR, Figure 1). Exploiting quasi-random variation in supervisory attention based on banks’ size ranking within Federal Reserve districts (Hirtle, Kovner, and Plosser 2020), we find that the decline in LCR is attenuated when these BHCs receive more supervisory hours. At the same time, we find no evidence of a

¹Federal Reserve Will Cut Staff by 10%,” *Forbes*, 16 May 2025; Federal Reserve to Reduce Bank Supervision Staff by 30%,” *Wall Street Journal*, 30 October 2025; “FDIC Hunts Extra 20% Staff Cut as DOGE Descends on Agency,” *Bloomberg*, 11 April 2025.

deterioration of other measures of risk, and Category IV and “other” BHCs also display increasing lending.

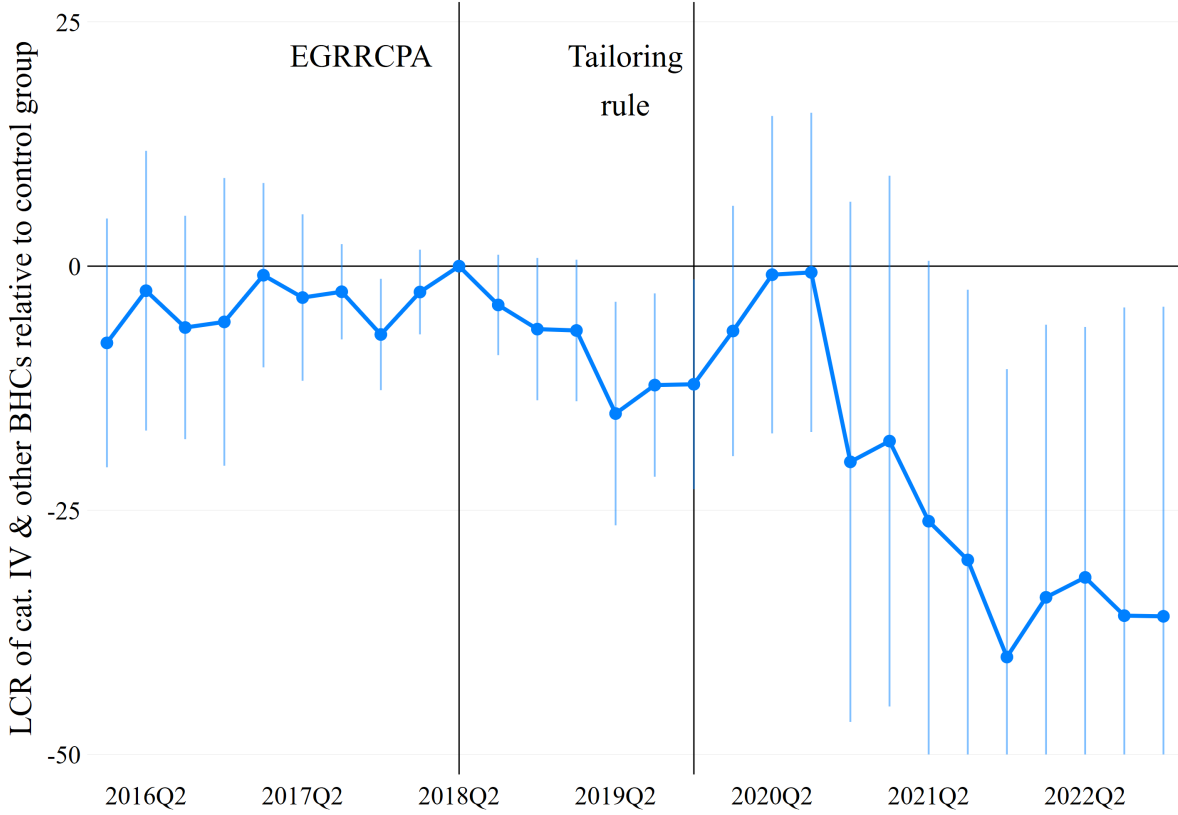


Figure 1. Liquidity deterioration at the “Category IV” and “other” banks

The figure illustrates the estimates of $LCR_{it} = \sum_t \gamma_t CatIV\&Other_i \times \mathbb{1}_t + \ln(1 + Fiscal\ Stimulus_{it}) + \varepsilon_{it}$, where $CatIV\&Other_i$ denotes an indicator equal to 1 for bank holding companies placed in the “Category IV” and “other banks” group in the 2019 tailoring rule, $\mathbb{1}_t$ denotes indicators for each calendar quarter over the period from 2016Q1 to 2022Q4 (the omitted indicator is 2018Q2, corresponding to the passage of the EGRRCPA), and $Fiscal\ Stimulus$ denotes deposits flowing into the bank holding company attributable to the COVID-19 stimulus (defined in detail in Appendix E). It shows that, relative to other top-100 U.S. bank holding companies, liquidity deteriorates for the “Category IV” and “other banks”.

Studying the relation between regulation and supervision, as well as how banks respond to stronger supervision, confronts us with three empirical challenges. First, regulation and supervision are jointly determined: banks subject to stricter regulation are typically larger and more systemic, and therefore also receive more intensive supervision, making it difficult to disentangle their respective effects. Second, supervisory intensity is endogenous, as riskier banks attract

more attention from supervisors, creating a form of assortative matching that can bias estimates of the relationship between supervision and risk. Third, supervision itself is difficult to measure, as researchers typically do not observe supervisory activities directly or the effort devoted to them.

We address these challenges using our setting and data. First, we exploit a regulatory shock that relaxes liquidity requirements for a well-defined set of U.S. bank holding companies: the EGRRCPA of May 2018 and the Federal Reserve’s 2019 “tailoring rule,” which applies less stringent Liquidity Coverage Ratio (LCR) requirements to banks with total assets between \$100 billion and \$250 billion.² This setting allows us to isolate the effects of regulatory relaxation from those of supervision. Second, we address the potential endogeneity of supervision and assortative matching between supervisory attention and bank risk with an identification approach based on the unique institutional features of the Federal Reserve’s supervisory environment (Hirtle, Kovner, and Plosser 2020): because supervision is organized at the level of Federal Reserve districts – whose boundaries were set in the early 1900s and are plausibly unrelated to current bank risk – the within-district size ranking of banks generates variation in supervisory intensity that is orthogonal to underlying risk, which we use as an instrument for supervisory hours. Third, we address measurement challenges by using confidential administrative data from the Federal Reserve Board that report the hours spent by supervisory staff on each bank, providing a direct and granular measure of supervisory attention.

We structure our analysis around the liquidity position of mid-sized U.S. bank holding companies whose requirements are relaxed following the EGRRCPA and the tailoring rule, namely “Category IV” banks (total assets between \$100 billion and \$250 billion) and “other firms” (total assets between \$50 billion and \$100 billion), over the period 2016Q1-2022Q4. We find that these banks exhibit a substantial decline in their LCR following the regulatory change. This pattern is immediately visible in Figure 1, where their LCR falls by more than 30 percentage points relative to the other top 100 largest U.S. bank holding companies.³ The visual evidence is confirmed by formal statistical tests, is robust to the inclusion of control variables, and is not driven by the

²We discuss the details of the EGRRCPA and the tailoring rule in Section 2.A.

³Appendix Figure B.1 plots the average LCR over time for the two groups separately.

COVID-19 recovery stimulus enacted under the Trump and Biden administrations. These results are consistent with a relaxation of the effective liquidity constraint faced by these banks following the EGRRCPA and the tailoring rule.

Next, we turn to the role of supervision. First, we examine how supervisory resources are re-allocated following the EGRRCPA for the banks most directly affected by the regulatory change. The composition of supervision for Category IV and “other” banks shifts markedly, as examination activities account for a larger share of total supervisory effort. This pattern suggests that, following the relaxation of regulatory requirements, supervisors rebalance their attention toward more discrete, exam-based oversight rather than substantially expanding overall supervisory resources.

Second, we relate supervisory hours to the evolution of liquidity at Category IV and other banks. Because supervisory intensity may respond endogenously to bank conditions, simple correlations may reflect assortative matching, with banks facing weaker liquidity positions receiving more supervisory attention. To address this concern, we follow Hirtle, Kovner, and Plosser (2020) and instrument supervisory hours using the Top-5-plus indicator, which identifies the largest banks in each Federal Reserve district and nearby-in-size peers that tend to receive disproportionately high supervisory attention. We find that, among Category IV and other banks, higher supervisory intensity is associated with a more muted LCR deterioration. Banks exposed to lower supervisory intensity experience a substantially larger reduction in LCR, with economically meaningful differences by the end of the sample period. These results suggest that, in an environment of laxer regulation, supervision tightens the effective liquidity constraint faced by banks.

We next shed light on the mechanisms through which supervision affects banks’ liquidity positions, by exploiting heterogeneity in supervisory capacity and experience. First, we find that the attenuating effect of supervisory hours on the post-reform decline in LCR is concentrated in Federal Reserve districts with greater supervisory capacity, measured by the number of supervisory staff relative to the number of bank holding companies overseen, whereas it is largely absent in districts where supervisory resources are more constrained. This pattern is consistent with capacity constraints limiting supervisors’ ability to translate oversight into effective constraints on banks’

liquidity choices. Second, we examine the role of supervisory tenure. Supervisory hours associated with longer-tenured supervisors are linked to a stronger attenuation of the decline in LCR, whereas hours associated with shorter-tenured supervisors exhibit weaker and statistically less precise effects. Taken together, these results suggest that both the availability of supervisory resources and the institutional continuity of supervision shape its effectiveness in influencing banks' liquidity management.

Finally, we examine how banks respond to supervisory attention. The evidence so far is consistent with two interpretations. Under the first one, the relaxation of liquidity requirements increases banks' risk-taking, and supervision mitigates this effect by constraining risk. Under the second interpretation, the reform primarily relaxes a binding liquidity constraint, allowing banks to operate with lower LCRs without necessarily increasing underlying risk; in this case, supervision acts by tightening the effective constraint and thereby limiting its real effects. To distinguish between these interpretations, we turn to alternative measures of risk and to lending. First, we find no evidence of an increase in risk measures other than the LCR at the Category IV and "other" banks. This applies both when looking at the Net Stable Funding Ratio, a measure designed to limit the use short-term funding for long-term lending, and when looking at broader, market-based risk measures such as the CAPM beta, stock return volatility, and tail risk. Second, we find that Category IV and "other" banks expand lending following the EGRRCPA, consistent with a relaxation of liquidity constraints, but that this expansion is significantly weaker for banks exposed to greater supervisory intensity. At the same time, we find no evidence of a deterioration in non-performing loans for these banks. Taken together, these findings are more consistent with the binding-constraint interpretation, in which supervision shapes the liquidity-lending tradeoff by affecting how tightly liquidity requirements bind in practice, rather than primarily curbing an increase in risk-taking.

Related literature. Our paper makes three main contributions to the literature. First, it contributes to the literature on banking supervision, which studies how supervisory oversight affects bank behavior, lending, and broader economic outcomes. Prior work has examined how the in-

stitutional design of supervision, such as supervisory intensity, organization, and accountability, influences risk-taking and compliance (Agarwal, Lucca, Seru, and Trebbi 2014, Hirtle, Kovner, and Plosser 2020), as well as the causal effects of supervisory interventions, including on-site inspections and stress tests, on lending and credit allocation (Bonfim, Cerqueiro, Degryse, and Ongena 2022, Correia, Luck, and Verner 2025, Eisenbach, Lucca, and Townsend 2022, Kandrac and Schlusche 2021, Passalacqua, Angelini, Lotti, and Soggia 2020, Granja and Leuz 2024, Gopalan and Granja 2024, Agarwal, Morais, Seru, and Shue 2024, Beyhaghi, Chae, Curti, and Gerlach 2026). We contribute to this literature by showing that supervision plays a central role in shaping how regulatory constraints bind in practice. Using confidential data on supervisory hours and quasi-random variation in supervisory attention across banks, we provide causal evidence that greater supervisory intensity attenuates the decline in liquidity following a deregulatory shock. Moreover, we show that this effect is stronger in environments with greater supervisory capacity and among more experienced supervisors, highlighting how institutional features of supervision influence its effectiveness. Taken together, our results suggest that supervision is not only a tool for enforcing regulation, but also a key margin through which the real effects of regulatory changes are determined.

Second, our paper contributes to the literature on bank liquidity regulation and its real effects. Prior work shows that liquidity requirements such as the LCR increase liquid asset holdings, but may also affect banks' lending capacity, cost of funding and risk-taking incentives (Hong, Huang, and Wu 2014, Bosshardt, Kakhbod, and Saidi 2024, Chavaz, Patozi, and Wazzi 2025, ?, Sundaresan and Xiao 2024, Aldasoro, Doerr, and Zhou 2026). We contribute by providing direct evidence on the liquidity-lending tradeoff and by showing how supervision shapes this tradeoff. We show that relaxing liquidity requirements leads to a meaningful expansion in bank lending, but that this effect is significantly attenuated by supervisory intensity. At the same time, we find no evidence of a deterioration in non-performing loans, and preliminary evidence suggests no increase in broader measures of risk. These findings point to a binding-constraint channel, in which liquidity regulation affects credit supply by limiting balance sheet capacity, and supervision governs how strongly

this constraint operates in practice.

Third, our paper speaks to recent policy debates on bank liquidity risk and the role of supervision in ensuring financial stability. The 2023 U.S. banking turmoil has highlighted the fragility of banks with insufficient liquidity buffers and renewed attention to the design of liquidity regulation (Jiang, Matvos, Piskorski, and Seru 2024, Dursun-de Neef, Ongena, and Schandlbauer 2023, DeMarzo, Jiang, Krishnamurthy, Matvos, Piskorski, and Seru 2023, Giannetti, Jasova, Mendicino, and Supera 2026), as well as to mechanisms such as interest rate risk (Granja, Jiang, Matvos, Piskorski, and Seru 2024, Greenwald, Krainer, and Paul 2024, Cipriani, Eisenbach, and Kovner 2024, Fuster, Paligorova, and Vickery 2024), capital fragility (Flannery and Sorescu 2023), and the amplification of run risk through digital communication (Cookson, Fox, Gil-Bazo, Imbet, and Schiller 2026). Our findings complement this literature by showing that supervision plays a key role in shaping banks' liquidity positions and credit supply ex ante, even when formal regulatory requirements are relaxed. This perspective is particularly relevant in light of recent reductions in supervisory staff at U.S. banking agencies, which may affect the ability of supervision to sustain effective liquidity discipline.

2 Institutional background

A The EGRRCPA and the tailoring rule

During his 2016 presidential campaign, Donald Trump emphasized the objective of reducing regulatory burdens, particularly those imposed by the Dodd-Frank Act (2010), originally enacted in response to the global financial crisis of 2008. Trump frequently criticized the Dodd-Frank Act for being overly burdensome, particularly on smaller banks, and argued that it limited credit and economic growth. As a result, rolling back parts of the Dodd-Frank Act was a key component of Trump's 2016 platform, focusing on relaxing the application of Dodd-Frank's measures based on banks' size and risk profile.⁴

⁴Trump argued that the Dodd-Frank Act made it "impossible for bankers to function" and that its provisions made it "very hard for bankers to loan money for people to create jobs, for people with businesses to create jobs" ("Trump preparing to dismantle Obama's Wall Street reform law." *Reuters*, 18 May 2016). In the aftermath of the 2016

The Economic Growth, Regulatory Relief, and Consumer Protection Act (EGRRCPA) was signed into law on May 24, 2018 with broad support.⁵ The EGRRCPA amended the Dodd-Frank Act in several parts, making targeted changes to the regulatory framework, specifically around the thresholds and tailoring. We focus specifically on the changes made to Section 165 of Dodd-Frank, which raised the total assets threshold for automatic application of enhanced prudential standards (EPS). Pre-EGRRCPA, banks with total assets above \$50bn were subject to enhanced prudential standards including LCR, stress tests, and risk management requirements; post-EGRRCPA, the threshold was raised to \$250bn, although the Federal Reserve retained discretion to apply stricter standards to banks with total assets in the \$100-\$250bn range.

To implement the EGRRCPA, the Federal Reserve, together with the Federal Deposit Insurance Corporation (FDIC) and the Office of the Comptroller of the Currency (OCC), adopted a “tailoring rule” in October 2019. Prior to the EGRRCPA and the tailoring rule, LCR requirements in the U.S. were primarily based on the 2014 LCR rule issued by U.S. banking regulators, which implemented the Basel III liquidity standards. The 2014 rule divided banks into three tiers: (i) Full (100% daily) LCR requirement applying to banks with at least \$250bn in total assets or \$10bn in on-balance-sheet foreign exposure; and (ii) Modified (70% monthly) LCR requirement for banks with between \$50bn and \$250bn total assets and less than \$10bn in foreign exposure; and (iii) No LCR requirement for banks under \$50bn total assets.

The tailoring rule introduces a risk-based tiering of enhanced prudential standards for large and mid-sized BHCs, distinguishing four categories. Category I (U.S. GSIBs) are subject to the full set of enhanced prudential standards. Category II (with at least \$700bn in total assets or \$75bn in cross-jurisdictional activity) and Category III (with at least \$250bn in total assets or at least \$75bn in weighted short-term wholesale funding, non-bank assets, or off-balance-sheet exposure) are

election, Trump’s transition team reiterated this stance, stating that the new administration would replace Dodd-Frank with policies aimed at encouraging economic growth (“Trump’s transition team pledges to dismantle Dodd-Frank Act.” *Bloomberg*, 10 November 2016). Reflecting Trump’s position, the 2016 Republican Party platform explicitly called for the repeal of Dodd-Frank (“8 questions about the future of banking regulation under Trump.” *Washington Post*, 23 November 2016).

⁵The EGRRCPA passed in the Senate on 14 March 2018 by a vote of 67 to 31 (all Republican senators and 17 out of 47 Democrat senators voted in favor); it passed in the House of Representatives on 22 May 2018 by a vote of 258 to 159 (all but one Republican representatives and 33 out of 193 Democrat representatives voted in favor).

subject to progressively reduced standards. Category IV , with \$100-\$250bn in total assets that do not meet the Category III risk thresholds, are subject to the lightest enhanced prudential standards, including biennial stress tests and tailored liquidity requirements. Specifically, for Category IV the application of the LCR depends on their reliance on short-term wholesale funding: BHCs with sufficiently high short-term wholesale funding remain subject to a modified (70%, monthly) LCR requirement, while firms below the threshold are not subject to a standardized LCR. BHCs with total assets between \$50bn and \$100bn (“other” banks) are not subject to the LCR under the tailoring framework.

We therefore focus our analysis on Category IV and other banks, and in particular on their liquidity, as this is the dimension of regulation that changed most sharply following the EGRRCPA and the 2019 tailoring rule. For these institutions, the tailoring framework relaxed quantitative liquidity requirements relative to the pre-EGRRCPA regime by making the application of the LCR conditional on banks’ reliance on short-term wholesale funding, and by eliminating standardized LCR requirements altogether for other banks with \$50-\$100bn in assets. At the same time, both Category IV and other banks remain subject to risk-based capital requirements, and Category IV banks continue to face supervisory stress tests, albeit on a biennial cycle. This institutional setting isolates liquidity regulation as the primary margin of regulatory adjustment for mid-sized banks, making it a natural focus for studying the interaction between deregulation and supervisory oversight. Moreover, as discussed below, liquidity risk played a central role in the 2023 U.S. banking crisis, underscoring the relevance of this dimension for financial stability and bank supervision.

B Federal Reserve supervision

The Federal Reserve supervises bank holding companies and state member banks in the United States with the objective of promoting the safety and soundness of supervised institutions and, more broadly, the stability of the financial system. Supervision is distinct from regulation. While regulation specifies the rules and quantitative requirements under which banks operate, supervision involves the ongoing monitoring and assessment of banks’ risk profiles, governance, and

risk-management practices, as well as the imposition of institution-specific remedial actions when deficiencies are identified (Federal Reserve Board 2023c, Hirtle and Kovner 2022).

Federal Reserve supervision relies on two broad categories of activities: formal supervisory examinations and continuous monitoring. Formal examinations are structured, in-depth reviews of a bank's activities and financial condition. These examinations typically involve on-site or targeted reviews of capital adequacy, asset quality, earnings, liquidity, and risk-management practices, and result in written supervisory assessments communicated to bank management (Federal Reserve Board 2023b). A central role of examinations is the acquisition of quantitative and qualitative supervisory information needed to evaluate a bank's safety and soundness and to determine whether corrective actions are warranted (Hirtle and Kovner 2022).

Supervisory examinations can be conducted at either the consolidated bank holding company level or the individual bank level. At the holding company level, the Federal Reserve's supervisory rating frameworks have evolved over time. From 1979 through 2004, holding companies were evaluated using the BOPEC rating system. In 2005, BOPEC was replaced by the RFI/C(D) framework, which emphasizes risk management (R), financial condition (F), and the potential impact (I) of nonbank activities on depository institutions, along with a composite rating. In 2018, the Federal Reserve introduced the Large Financial Institution (LFI) rating system for the largest and most complex firms, focusing on firm-wide capital, liquidity, and governance and controls (Hirtle and Kovner 2022). At the individual bank level, supervisors assign CAMELS ratings, which summarize examiners' assessments of a bank's Capital adequacy, Asset quality, Management, Earnings, Liquidity, and Sensitivity to market risk. These ratings reflect informed supervisory judgment rather than a mechanical aggregation of component measures (Hirtle and Kovner 2022).

In addition to formal examinations, supervisors engage in continuous monitoring of supervised institutions. Continuous monitoring encompasses supervisory activities conducted outside of scheduled examinations, including regular meetings with bank management, review of internal bank data, audit reports, and regulatory filings, and coordination with other regulatory agencies (Federal Reserve Board 2023a). The purpose of continuous monitoring is to maintain an up-to-

date understanding of a bank’s activities, organizational structure, and risk profile, and to identify emerging risks in a timely manner. Information obtained through continuous monitoring informs supervisory judgments, including decisions about the timing, scope, and focus of future examinations (Federal Reserve Board 2023a, Hirtle and Kovner 2022).

Supervision by the Federal Reserve is risk-focused and tailored to the size, complexity, and activities of supervised institutions. Supervisory resources are allocated based on assessments of risk and systemic importance rather than according to a fixed supervisory schedule. As a result, larger and more complex institutions are subject to more intensive supervisory engagement, both in terms of examination activity and ongoing monitoring, while smaller and less complex institutions typically receive less frequent supervisory attention (Federal Reserve Board 2023a). The intensity and composition of supervision therefore vary systematically across banks and over time.

When supervisors identify material deficiencies through examinations or continuous monitoring, they may require banks to undertake corrective actions. These actions range from informal supervisory guidance to formal enforcement actions, depending on the severity and persistence of the issues identified (Federal Reserve Board 2023c). Through this combination of examinations, continuous monitoring, and follow-up actions, Federal Reserve supervision seeks to mitigate risks at individual institutions and to support the stability of the U.S. banking system as a whole (Hirtle and Kovner 2022).

3 Data

Our data set comprises information on all the bank holding companies (BHCs) active in the U.S. and with available data in the quarterly regulatory FR Y-9C over the period from 2016Q1 to 2022Q4. We supplement these data with bank-level information from the regulatory Call Reports and confidential administrative information on supervisory hours from the Federal Reserve.

A *Liquidity Coverage Ratio*

Our main outcome variable is the Liquidity Coverage Ratio (LCR), a regulatory standard introduced under the Basel III framework designed to ensure that banks maintain a sufficient stock of liquid assets to survive acute short-term funding stress. It reflects the principle that banks should hold enough high-quality liquid assets (HQLA) to cover net cash outflows expected during a standardized 30-day stress scenario. The LCR is defined as:

$$LCR = \frac{\text{High-quality liquid assets}}{\text{Expected 30-day net outflows}} \quad (1)$$

The LCR constrains banks' maturity transformation by linking the composition of liabilities to the required liquidity buffer, thus internalizing the liquidity risk posed by unstable short-term funding. Its aim is to strengthen individual institutions' resilience and, by reducing the risk of fire sales and funding runs, promote overall financial stability.

To operationalize equation (1), we use Call Reports data following Hong, Huang, and Wu (2014) and Sundaresan and Xiao (2024). The Call Reports are quarterly regulatory filings submitted by U.S. commercial banks to their federal regulators (the FDIC, the Federal Reserve, and the OCC), providing detailed balance sheet and income statement data. High-quality liquid assets (numerator) are obtained combining cash and balances from depository institutions, Treasury and agency securities, and other liquid securities, weighted to reflect relative liquidity. Expected 30-day net outflows (denominator) are estimated using a liability-weighted formula, assigning regulatory-style run-off weights to different categories of liabilities, such as demand deposits (with lower weights for stable retail insured deposits), time deposits and wholesale funding (with higher run-off rates), and off-balance-sheet items like unused commitments (estimated using proxies). Both numerator and denominator components are summed using the appropriate regulatory-inspired weights, aiming to reflect the liquidity value (for assets) or risk of net outflows (for liabilities).⁶

The LCR is computed for individual banks in the Call Reports data. We aggregate this infor-

⁶We provide additional details about the calculation of the LCR in Appendix C.

mation to the bank holding company level by forming a weighted average of the individual banks' LCRs, with weights proportional to their total assets. Table 1 shows that, on average, the LCR in our data is 0.754, close to the value of 0.822 reported by Sundaresan and Xiao (2024) for LCR banks using pre-EGRRCPA data.

B Supervisory hours

As our main measure of the intensity of supervision to which a given bank holding company is subject, we use supervisory hours from a proprietary, confidential dataset compiled by the Federal Reserve System, also used by Hirtle, Kovner, and Plosser (2020). The data track the amount of supervisory attention each bank receives over time, measured in examiner hours. These data are drawn from the Federal Reserve's internal systems used to plan and record supervisory activities; they include both on-site examinations and off-site monitoring, and capture the total number of supervisory staff hours allocated to a given bank in each quarter, offering a granular, time-varying proxy for the intensity of supervision.

The dataset covers all institutions under Federal Reserve supervision, including both state member banks and bank holding companies. Because it originates from operational planning and staffing tools used by supervisors, our measure reflects actual resource deployment rather than ex post assessments or outcomes. This makes it a uniquely detailed and direct measure of supervisory effort.

C Other control variables

We use the FR Y-9C Consolidated Financial Statements for Holding Companies, a regulatory report filed quarterly by U.S. bank holding companies with total consolidated assets above a specified threshold. The FR Y-9C provides detailed balance sheet and income statement data, including information on loan portfolios, securities holdings, capital ratios, and off-balance-sheet exposures. These data are collected by the Federal Reserve and are widely used to analyze the financial condition and risk profile of BHCs. We construct control variables that capture key aspects of bank cha-

racteristics, such as size (log total assets), an indicator for publicly listed BHCs, asset composition and quality (loans/assets, HHI of assets, NPL to assets), deposit market share, performance (ROA, loan growth), capital adequacy (Tier 1 capital ratio), funding structure (deposits/liabilities). These controls allow us to account for heterogeneity across banks in terms of their financial strength and business models. In addition, we use the Call Reports to determine the BHC’s complexity (number of subsidiary banks under the umbrella of the BHC), %SMB above \$10bn and below \$10bn assets, and % national bank assets. These variables are defined in Appendix A. Finally, we use data from the Committee for a Responsible Federal Budget/COVID Money Tracker to construct *Fiscal Stimulus*, a measure of the deposits flowing into each BHC associated with the COVID-19 stimulus; we describe this variable in greater detail in Appendix E.

D Descriptives

Throughout the analysis, we focus on the subset of bank holding companies whose liquidity requirements were relaxed by the EGRRCPA and the subsequent tailoring rule, namely BHCs classified as Category IV and other banks under the 2019 tailoring rule.⁷ Our baseline comparison group consists of all other BHCs operating during the sample period whose liquidity requirements were not relaxed at the same time.

Table 1 reports descriptive statistics for all variables used in the analysis, summarizing balance sheet characteristics, performance measures, and supervisory outcomes, as well as the composition of supervisory hours. The sample exhibits substantial heterogeneity in size, organizational complexity, and supervisory intensity, which motivates the inclusion of granular controls in the empirical analysis.

Table 2 compares treated BHCs to other BHCs along key observable dimensions over the period 2016Q1-2018Q2. Treated BHCs are significantly larger, more likely to be publicly listed, and exhibit higher deposit reliance and lower Tier-1 capital ratios than other BHCs. At the same time, the two groups are broadly comparable in terms of profitability, asset composition and quality, loan

⁷Appendix D lists the BHCs belonging to each category of the tailoring rule.

Table 1. Descriptive statistics

The table reports the mean, standard deviation, percentiles 25, 50, and 75, and number of observations of all the variables used in the analysis. The sample comprises all U.S. bank holding companies with available FR Y-9C data, over the period 2016Q1-2022Q4.

	Mean	St. dev.	P25	P50	P75	N
<i>A. Balance sheet characteristics</i>						
LCR	0.754	0.712	0.339	0.556	0.922	9,519
Size	15.606	1.565	14.424	15.294	16.323	9,519
Complexity	0.135	0.399	0.000	0.000	0.000	9,519
% SMB ($>10b$) assets	0.041	0.198	0.000	0.000	0.000	9,519
% SMB ($\leq 10b$) assets	0.001	0.034	0.000	0.000	0.000	9,519
% National bank assets	0.055	0.228	0.000	0.000	0.000	9,519
Public	0.626	0.484	0.000	1.000	1.000	9,519
Loans to assets	67.123	13.933	61.179	69.910	76.753	9,519
HHI of assets	1.168	16.794	0.331	0.419	0.557	9,519
Deposit market share	0.032	0.061	0.005	0.010	0.025	9,452
ROA	0.664	0.456	0.333	0.600	0.916	9,519
Loan growth	1.096	7.237	0.432	0.596	0.889	9,519
T1 capital ratio	0.136	0.063	0.112	0.124	0.144	9,490
NPL to assets	0.003	0.005	0.000	0.001	0.004	9,519
Deposits to liabilities	0.893	0.105	0.868	0.916	0.951	9,519
Fiscal stimulus	5.353	8.107	0.000	0.000	15.446	9,519
<i>B. Supervision</i>						
ln(Total sup. hours)	3.344	3.169	0.000	3.466	6.176	9,519
ln(Exam hours)	2.461	2.786	0.000	0.000	5.069	9,519
ln(Continuous hours)	1.764	2.310	0.000	0.000	3.497	9,519
Exam hours / Total hours	0.205	0.287	0.000	0.000	0.342	9,519
Tenure (qtrs)	30.702	16.061	17.000	30.000	48.000	7,620
FT Employees / BHCs	112.666	100.724	57.680	85.167	126.300	8,826

growth, and loan intensity.

Table 2. Category IV and other firms compared to other BHCs

This table compares BHCs whose liquidity requirements were relaxed by the EGRRCPA and the tailoring rule (Category IV and “other firms”) to all other BHCs in the sample. The table reports sample means for each group and the t-statistic from a test of equality of means. All variables are defined in Appendix A. The standard errors for the t-tests are clustered at the BHC level.

	Category IV and other firms	Other BHCs	t-statistic
	(1)	(2)	(3)
Size	18.492	14.993	24.74
Complexity	0.153	0.124	0.37
% SMB (>10b) assets	0.436	0.017	3.19
% SMB ($\leq$ 10b) assets	0.000	0.002	-1.24
% National bank assets	0.229	0.035	1.88
Public	1.000	0.517	21.55
Loans to assets	67.713	67.866	-0.06
HHI of assets	0.438	1.593	-1.25
Deposit market share	0.072	0.026	3.16
ROA	0.605	0.583	0.36
Loan growth	0.652	1.259	-1.32
T1 capital ratio	0.119	0.138	-4.50
NPL to assets	0.001	0.001	0.75
Deposits to liabilities	0.804	0.894	-2.77

4 Results

A Baseline: LCR after the EGRRCPA

In the first part of the analysis, we examine whether the relaxation of liquidity regulation mandated by the 2018 EGRRCPA and the 2019 tailoring rule is associated with changes in banks’ liquidity positions. We focus on bank holding companies (BHCs) classified as Category IV and other banks under the tailoring framework, whose liquidity requirements were relaxed following the passage of the EGRRCPA and the subsequent implementation of the tailoring rule; our approach is illustrated

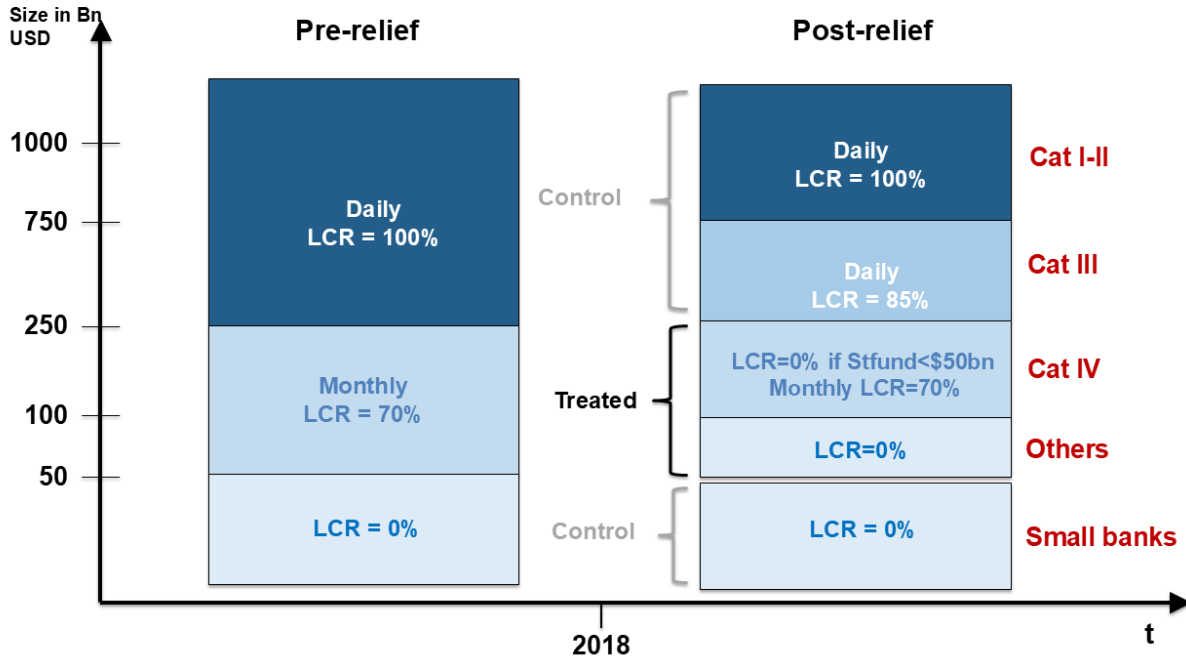


Figure 2. Illustration of the empirical approach

The figure illustrates our empirical approach. Prior to the passage of the EGRRCPA and the tailoring rule, all bank-holding companies with total assets above \$50 bn have an LCR requirement; subsequent to the tailoring rule, “other” banks have no LCR requirement, whereas Category IV banks only have an LCR requirement if they have sufficiently high short-term wholesale funding. We focus on Category IV and “other” banks as the treated group in our analysis, using as the control group the remaining banks, whose LCR requirements do not change (Categories I-II-III retain a 100% requirement, whereas banks below the \$50bn threshold do not have an LCR requirement).

in Figure 2.

We estimate the following specification at the BHC-quarter level:

$$\Delta LCR_{it} = \alpha + \beta_1 CatIV\&Other_i + \beta_2 Post_t + \beta_3 CatIV\&Other_i \times Post_t + \mu' \Delta x_{it} + \varepsilon_{it} \quad (2)$$

where ΔLCR_{it} denotes the quarterly change in the LCR of BHC i in quarter t . $CatIV\&Other_i$ is an indicator equal to one for BHCs in the Category IV and other banks groups and zero otherwise, $Post_t$ is an indicator equal to one for quarters following the passage of the EGRRCPA (2018Q2), and x_{it} are control variables, including the full list of control variables used by Hirtle, Kovner, and Plosser (2020) as well as calendar quarter fixed effects.⁸ The coefficient of interest, β_3 , captures the

⁸A potential challenge is that the implementation of the tailoring rule closely preceded the onset of the COVID-19

differential change in LCR for Category IV and “other” BHCs relative to the remaining U.S. BHCs after the regulatory relaxation.

Table 3 reports the estimates of equation (2). Across both specifications, we find that the LCR of treated BHCs declines significantly relative to that of other BHCs following the tailoring rule. The estimated coefficient on the interaction term $\text{CatIV\&Other} \times \text{Post}$ implies a relative decline in LCR of approximately 2 percentage points per quarter for treated institutions. Given that our post-period spans 18 quarters, this corresponds to a cumulative decline of about 36 percentage points relative to other BHCs.

Table 3. Tailoring rule and liquidity

The table reports the estimates of a regression of the quarterly change in LCR on an indicator equal to 1 for Category IV and other banks, and indicator equal to 1 for the period following the passage of the EGRRCPA in May 2018, and their interaction, along with control variables and calendar quarter fixed effects. The control variables, omitted from the table, are: size (natural logarithm of total assets), Tier 1-capital ratio, NPL/Assets, Deposits/Liabilities, Complexity (number of banks under the umbrella of the BHC), % SMB (>10b) assets, % SMB (≤ 10 b) assets, % National bank assets, Public indicator, Loans/Assets, Assets HHI, Deposit market share, ROA, Loan growth, indicators for CAMELS ratings of the BHC's subsidiary banks (all defined in Appendix A), and the *Fiscal Stimulus* control for COVID stimulus-driven deposits (defined in Appendix E). The sample comprises all BHCs with available FR Y-9C data during the period 2016Q1-2022Q4. In both specifications the standard errors are clustered around individual BHCs.

	(1)	(2)
Category IV and other banks	-0.001	-0.012
	(0.008)	(0.010)
Category IV and other banks $\times$ Post	-0.019**	-0.019*
	(0.009)	(0.010)
Controls		✓
Calendar quarter f.e.	✓	✓
N	11,051	9,519
R ²	0.039	0.046

These magnitudes are economically meaningful and consistent with the visual evidence in Figure 1. To control for the effects of the COVID-19 pandemic and the associated fiscal and monetary interventions, the CARES Act, enacted in March 2020, injected an unprecedented amount of liquidity into the U.S. economy and was accompanied by a sharp increase in bank deposits system-wide. As shown in Appendix E, this episode is associated with pronounced spikes in deposits, personal savings, and fiscal expenditures. To account for these confounding dynamics, we include in x_{it} *Fiscal Stimulus*, a control that proxies for the inflow of deposits driven by the COVID-19 fiscal stimulus at the BHC level.

figure 1. Importantly, the estimates reflect differential changes in liquidity positions rather than level differences, suggesting that the regulatory relaxation is associated with a persistent adjustment in liquidity dynamics at treated BHCs, rather than a one-time reclassification effect. The combined evidence of Table 3 and Figure 1, moreover, shows that LCR declines at Category IV and “other” BHCs precisely when the regulation is relaxed, consistent with the LCR requirement being binding for these BHCs before that point.⁹

B Supervisory hours and liquidity risk

We next study the role of supervisory attention in shaping banks’ liquidity responses to the relaxation of liquidity regulation. We first document how the level and composition of supervisory hours change for BHCs affected by the tailoring rule, and then examine whether supervisory attention attenuates the decline in liquidity at treated institutions. To address potential endogeneity in supervisory intensity, we complement the baseline estimates with instrumental-variables specifications following Hirtle, Kovner, and Plosser (2020).

Figure 3 shows no evidence of a change in the number of supervisory hours to which U.S. are exposed around the passage of the EGRRCPA, whether they belong to the Category IV and “other” banks group or not. The typical Category IV/“other” BHC receives 4088 supervisory hours per quarter prior to the EGRRCPA and 3743 thereafter.

What appears to change is how supervisory resources are allocated following the EGRRCPA. Table 4 reports the estimates of:

$$Hours_{it} = \alpha + \beta_1 CatIV\&Other_i + \beta_2 Post_t + \beta_3 CatIV\&Other_i \times Post_t + \gamma' \Delta x_{it} + \varepsilon_{it} \quad (3)$$

where $Hours_{it}$ measures supervisory hour composition for BHC i in quarter t , measured as the ratio of supervisory exam hours to total hours. Category IV and “other bank” BHCs experience a significant increase in examination-based supervision: the ratio of supervisory exam hour to

⁹Similarly, Sundaresan and Xiao (2024) find that the first introduction of LCR requirements in 2014 led to a pronounced increase in LCR, also consistent with the LCR being binding.

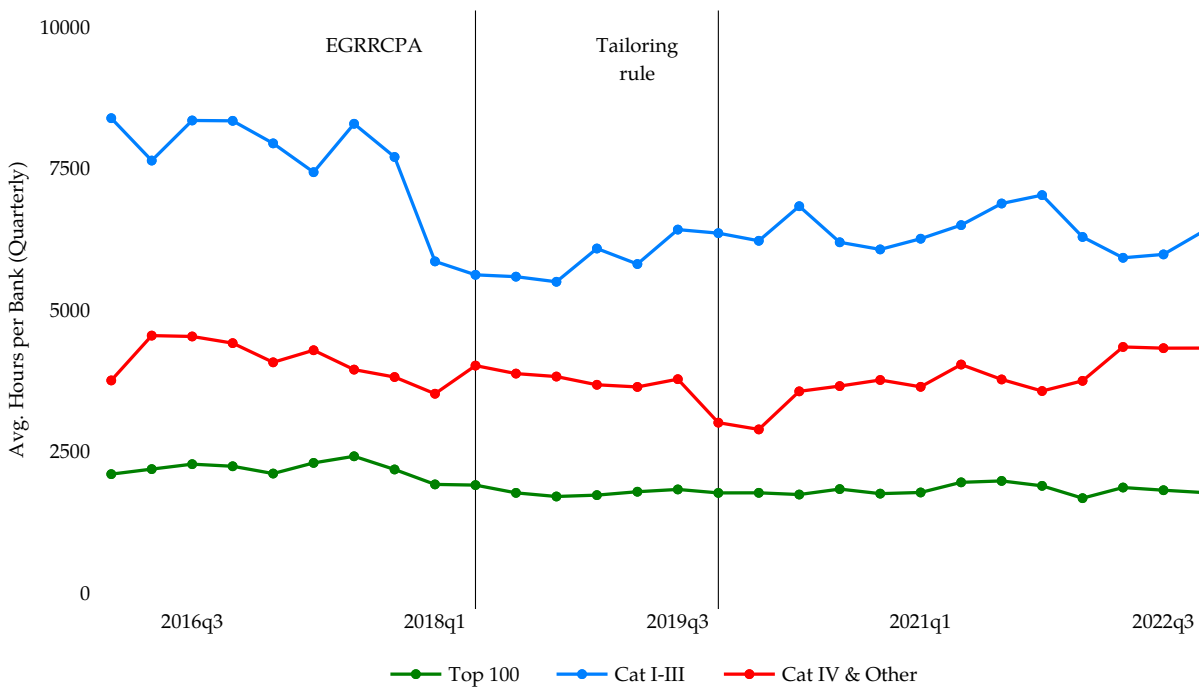


Figure 3. Supervisory hours at Category IV and “other” BHCs and remaining U.S. BHCs
The figure shows the average supervisory hours at the Category IV and “other” BHCs (red line), Category I-III BHCs (blue line), and all the other top-100 U.S. bank holding companies (green line) over the period 2016Q1-2022Q4.

total supervisory hours increases by 8-9 percentage points relative to other BHCs, an economically large increase relative to the average of 20 percentage points (Table 1). This pattern is consistent with supervisory attention shifting along the intensive margin – from ongoing monitoring toward discrete examinations – rather than expanding uniformly following the regulatory relaxation.

The change in supervisory composition raises the possibility that supervisory attention may condition how banks adjust their liquidity positions following the tailoring rule. To test this hypothesis, we extend the baseline liquidity specification (equation 2) to allow the post-EGRRCPA effect for treated BHCs to vary with supervisory intensity, interacting the treatment indicator and post period with the logarithm of supervisory hours:

$$\begin{aligned}
\Delta LCR_{it} = & \alpha + \beta_1 CatIV\&Other_i + \beta_2 Post_t + \beta_3 \log(SupHours_{it}) \\
& + \beta_4 CatIV\&Other_i \times Post_t + \beta_5 CatIV\&Other_i \times \ln(SupHours_{it}) \\
& + \beta_6 Post_t \times \ln(SupHours_{it}) \\
& + \beta_7 CatIV\&Other_i \times Post_t \times \ln(SupHours_{it}) \\
& + \mu' \Delta x_{it} + \varepsilon_{it}.
\end{aligned} \tag{4}$$

One challenge in estimating equation (4) is the potential assortative matching between supervisory hours and (liquidity) risk. It is possible that riskier banks endogenously receive more attention from the supervisor, resulting in a bias in the estimated relation between risk and supervisory hours and leading us to underestimate any beneficial impact of supervision.

To address this empirical challenge, we follow Hirtle, Kovner, and Plosser (2020) and employ an instrument for supervisory hours that builds on unique institutional features of the U.S. supervisory environment. In the U.S., supervisory activities conducted by the Federal Reserve System are organized on the level of the regional Federal Reserve Banks, which are divided into 12 districts. The district boundaries were set in 1913 (Ghizoni 2013) and have little relation to present-day economic or administrative activity.¹⁰ Hirtle, Kovner, and Plosser (2020) argue and show evidence

¹⁰For instance, several districts divide individual U.S. states between them. This is the case of Missouri, divided between the 8th (St. Louis) and the 10th (Kansas City) districts; Kentucky, divided between the 8th (St. Louis) and the 4th (Cleveland) districts; Mississippi, divided between the 8th (St. Louis) and the 6th (Atlanta) districts; Tennessee, also

Table 4. Composition of supervisory hours

The table reports the estimates of regressions that analyze the composition of supervisory hours around the passage of the EGRRCPA (May 2018). The sample includes all BHCs with available FR Y-9C data during the period 2016Q1–2022Q4. The dependent variable is the ratio of supervisory exam hours to total hours. The regressions include an indicator for Category IV and other banks, an indicator for the post-EGRRCPA period, and their interaction. Column 2 includes an indicator for Category I–III BHCs and its interaction with the post-EGRRCPA indicator. Standard errors are clustered at the BHC level.

	(1)	(2)
Category IV and other banks	0.142*** (0.023)	0.145*** (0.023)
Category IV and other banks $\times$ Post	0.084*** (0.022)	0.087*** (0.022)
Category I–III		0.095*** (0.019)
Category I–III $\times$ Post		0.028 (0.019)
Controls	✓	✓
Calendar quarter f.e.	✓	✓
N	9,423	9,423
R ²	0.034	0.039

consistent with the notion that regional Federal Reserve Banks can face a binding constraint when allocating supervisory attention within their district, so that the largest BHCs within each district receive more supervisory hours. This means that similar banks headquartered in different districts may receive very different supervisory hours. As an illustration, M&T Bank, ranked #13 in the 2nd district (New York) in terms of its total assets, may receive fewer supervisory hours than similarly-sized Regions Financial, ranked #2 in the 6th district (Atlanta).¹¹ Following Hirtle, Kovner, and Plosser (2020), we define within each Fed district and calendar quarter an indicator Top equal to 1 for the top five largest BHCs in the district based on assets plus BHCs within 25% of the top five. We use Top and its interactions with Category IV and other banks and the Post indicator as instrumental variables for log-supervisory hours and their interactions with Category IV and other banks and the Post indicator, in a two-stage least squares (2SLS) framework.

Table 5 reports the estimates. In column 1 we report the OLS estimates; columns 2-4 report the IV/2SLS estimates. In the latter specifications, because Top is potentially related to the BHC's size (natural logarithm of total assets), we include as controls second- and third-degree polynomials in size; intuitively, they ensure that the instrument does not capture the effect of size or some other factor that relates to size, but only the effect of the BHC's *relative* size ranking within the district. Across all specifications, greater supervisory attention is associated with a smaller decline in LCR at Category IV and other banks BHCs following the EGRRCPA. The coefficient on the triple interaction between the treatment indicator, the post-EGRRCPA period, and supervisory hours is positive and statistically significant, both in OLS and in the IV specifications. This pattern implies that, among Category IV and other banks, institutions receiving more supervisory hours experience a smaller reduction in their LCR after the regulatory relaxation. The magnitude and significance of this effect are stable across alternative instrumented specifications that flexibly control for bank size, suggesting that supervisory attention plays a mitigating role in the liquidity adjustment of

divided between the 8th (St. Louis) and the 6th (Atlanta) districts; Wisconsin, divided between the 9th (Minneapolis) and the 7th (Chicago) districts; and West Virginia, divided between the 4th (Cleveland) and the 5th (Richmond) districts.

¹¹This example is fictional and exclusively for illustrative purposes, as we are not allowed to single out individual cases in the supervisory hours data.

Table 5. Supervisory hours and liquidity

The table reports the estimates of equation (4). Column 1 reports OLS estimates; columns 2-4 2SLS estimates, where the *Top* indicator for the set of the largest BHCs in each district and its interactions are used as instrumental variables for log-supervisory hours and their interactions with Category IV and other banks and the Post indicator. The sample comprises all BHCs with available FR Y-9C data over the 2016Q1-2022Q4 period. In all specifications the standard errors are clustered around individual BHCs.

	(1)	(2)	(3)	(4)
Category IV and other banks	0.243*** (0.042)	0.420*** (0.119)	0.416*** (0.120)	0.414*** (0.116)
Cat. IV & other $\times$ Post	-0.248*** (0.069)	-0.404*** (0.118)	-0.400*** (0.117)	-0.400*** (0.116)
ln(Sup. hours)	-0.001 (0.001)	0.001 (0.002)	0.001 (0.002)	0.001 (0.002)
Cat. IV & other $\times$ ln(Sup. hours)	-0.027*** (0.005)	-0.050*** (0.014)	-0.050*** (0.015)	-0.049*** (0.014)
Post $\times$ ln(Sup. hours)	0.002 (0.001)	0.001 (0.002)	0.001 (0.002)	0.001 (0.002)
Cat. IV & other $\times$ Post $\times$ ln(Sup. hours)	0.027*** (0.008)	0.047*** (0.015)	0.046*** (0.014)	0.046*** (0.014)
Size polynomial control of degree	1	1	2	3
Controls	✓	✓	✓	✓
Calendar quarter f.e.	✓	✓	✓	✓
N	9,407	9,407	9,407	9,407
R ²	0.332			
Kleibergen-Paap F stat		60.127	58.453	58.503
Sanderson-Windmeijer F stat:				
ln(Sup. hours)		240.257	239.715	241.957
Cat. IV & other $\times$ ln(Sup. hours)		228.631	207.112	211.837
Post $\times$ ln(Sup. hours)		294.467	296.467	293.796
Cat. IV & other $\times$ Post $\times$ ln(Sup. hours)		237.549	240.190	239.871

treated BHCs rather than merely reflecting differences in scale or observable risk characteristics.¹²

The estimates are consistent with the view that exposure to more supervisory hours mitigates the liquidity deterioration for BHCs in the “Category IV” and “Other banks” group. Their magnitudes are also economically meaningful. To fix ideas, BHCs in these categories receive on average around 10,000 supervisory hours per year, or 2,500 hours in a given quarter (Federal Reserve Board 2019). Consider a counterfactual increase to 5,000 per quarter, approximately the level received by Category I, II, and III banks. This implies an increase in log-Supervisory hours by $\ln(1 + 5,000) - \ln(1 + 2,500) = 0.693$. Using the estimates in column (4) of Table 5, the coefficient on the triple interaction implies that such an increase in supervisory attention is associated with an about $0.046 \times 0.693 \approx 3.2$ percentage points higher quarterly change in the LCR of Category IV and “Other banks” BHCs, or 4.1% relative to the average LCR of 78.3 percentage points from Table 1. Over the 18-quarter period between 2018Q3 and 2022Q4, this amounts to over 57 percentage points, close to the size of the gap in LCR between BHCs in the “Category IV” and “Other banks” categories and the benchmark groups illustrated in Figure 1.

In Table 6, we reproduce this analysis decomposing the change in LCR into the change in high quality liquid assets (HQLA), in expected cash outflows, and in expected cash inflows. The results appear entirely driven by changes in HQLA, with small and insignificant effects on expected outflows and inflows. The coefficient on the triple interaction between the treatment indicator, the post-EGRRCPA period, and supervisory hours is positive and statistically significant for HQLA, and quantitatively large: using the estimate in column (1), a counterfactual increase in supervisory hours from 2,500 to 5,000 per quarter is associated with an about $0.085 \times 0.693 \approx 5.9$ percentage point higher quarterly change in HQLA at Category IV and other banks following the regulatory relaxation. By contrast, the corresponding coefficients for expected cash outflows and expected cash inflows are small in magnitude and statistically indistinguishable from zero. This pattern

¹²Since equation (4) involves multiple endogenous regressors and instruments, in Table 5, in addition to the Kleibergen-Paap first-stage F test, we also report the Sanderson-Windmeijer F statistics associated with each endogenous variable. These statistics are uniformly large across specifications, indicating strong first-stage relationships for supervisory hours and their interactions, even in specifications that flexibly control for bank size using higher-order polynomials.

suggests that supervisory attention operates primarily through the asset side of the liquidity buffer, inducing treated BHCs to maintain larger holdings of high-quality liquid assets, rather than through adjustments to their funding structure or cash flow management.

C Channels: Supervisory capacity constraints and tenure

We next explore potential mechanisms through which supervisory attention mitigates the increase in liquidity risk following the relaxation of regulatory requirements. We exploit heterogeneity in the institutional environment in which supervision takes place to shed light on two non-mutually exclusive channels. First, we examine whether the effectiveness of supervisory hours depends on supervisory capacity constraints at the Federal Reserve district level, measured by the availability of supervisory resources relative to the number of institutions overseen. Second, we study whether supervisory continuity matters, by distinguishing supervisory hours supplied by more versus less tenured supervisors. Together, these tests aim to clarify how organizational constraints and human capital shape the transmission of supervisory attention into effective risk mitigation.

We begin by examining whether the effectiveness of supervisory attention depends on supervisory capacity at the Federal Reserve district level. Intuitively, supervisory hours may translate into less effective oversight when supervisory resources are stretched thin, limiting supervisors' ability to follow up on identified issues, escalate concerns, or impose corrective actions. To capture this dimension, we construct a measure of district-level supervisory capacity based on the number of full-time equivalent (FTE) supervisory employees relative to the number of bank holding companies (BHCs) supervised in a given district and quarter.¹³ Districts with higher values of this ratio have more supervisory resources available per institution. We then classify districts into high-capacity and low-capacity groups based on whether their supervisory capacity lies above or below the median in a given quarter.

We then estimate regressions similar to equation (4), separately for high- and low-capacity districts. In high-capacity districts, supervisory attention is associated with an attenuation of the

¹³The supervisory capacity variable is defined in detail in Appendix A.

Table 6. The table reports the estimates of regressions similar to Table 5, decomposing the change in LCR into the change in high quality liquid assets (HQLA), expected cash outflows, and expected cash inflows. The sample comprises all BHCs with available FR Y-9C data over the 2016Q1-2022Q4 period. In all specifications the standard errors are clustered around individual BHCs.

	HQLA	$E(\text{Cash Out})$	$E(\text{Cash In})$
	(1)	(2)	(3)
Cat. IV & other	0.997*** (0.151)	0.039 (0.144)	0.662** (0.280)
Post $\times$ Cat. IV & other	-0.777*** (0.172)	0.146 (0.239)	0.073 (0.719)
ln(Sup. hours)	-0.003** (0.002)	-0.001* (0.001)	0.000 (0.002)
Cat. IV & other $\times$ ln(Sup. hours)	-0.116*** (0.019)	-0.004 (0.017)	-0.088** (0.034)
Post $\times$ ln(Sup. hours)	0.004* (0.002)	0.001 (0.001)	0.002 (0.004)
Post $\times$ Cat. IV & other $\times$ ln(Sup. hours)	0.088*** (0.022)	-0.018 (0.029)	-0.001 (0.088)
Controls	✓	✓	✓
Calendar quarter f.e.	✓	✓	✓
N	9,407	9,407	9,346
R ²	0.386	0.421	0.070
Kleibergen-Paap F stat	60.127	60.127	59.701
Sanderson-Windmeijer F stat:			
ln(Sup. hours)	240.257	240.257	239.616
Cat. IV & other $\times$ ln(Sup. hours)	228.631	228.631	230.252
Post $\times$ ln(Sup. hours)	294.467	294.467	293.954
Cat. IV & other $\times$ Post $\times$ ln(Sup. hours)	237.549	237.549	229.977

Table 7. Effect of Supervision on Bank Liquidity: By District Capacity

The table reports the estimates of regressions similar to Table 5, splitting the sample based on the Fed district's supervisory capacity (above/below the median). Supervisory capacity is proxied by the ratio of full-time supervisory employees in the district to the number of BHCs under the district's supervision.

Capacity:	OLS		IV	
	High (1)	Low (2)	High (3)	Low (4)
Cat. IV & other	0.311*** (0.099)	0.127 (0.165)	0.313 (0.237)	0.250 (0.499)
Cat. IV & other $\times$ Post	-0.292** (0.127)	0.037 (0.188)	-0.688** (0.272)	0.219 (0.616)
ln(Sup. hours)	-0.001 (0.002)	-0.001 (0.001)	0.011 (0.008)	0.001 (0.006)
Cat. IV & other $\times$ ln(Sup. hours)	-0.038*** (0.013)	-0.018 (0.020)	-0.038 (0.030)	-0.034 (0.059)
Post $\times$ ln(Sup. hours)	0.000 (0.003)	0.004* (0.003)	0.002 (0.003)	0.001 (0.003)
Cat. IV & other $\times$ Post $\times$ ln(Sup. hours)	0.034** (0.015)	-0.009 (0.022)	0.081** (0.033)	-0.029 (0.074)
Controls	✓	✓	✓	✓
Calendar quarter f.e.	✓	✓	✓	✓
N	3,551	5,275	3,551	5,275
R ²	0.044	0.058		
Kleibergen-Paap F stat				
Sanderson-Windmeijer F stat:				
ln(Sup. hours)			7.458	15.267
Cat. IV & other $\times$ ln(Sup. hours)			33.631	106.036
Post $\times$ ln(Sup. hours)			52.378	50.412
Cat. IV & other $\times$ Post $\times$ ln(Sup. hours)			195.056	535.988

LCR deterioration experienced by deregulated banks following the EGRRCPA: the coefficient on the triple interaction term $\text{Category IV \& Other banks} \times \text{Post} \times \ln(\text{Supervisory hours})$ is positive, statistically different from zero, and economically large. In contrast, in low-capacity districts, the corresponding interaction term is small in magnitude and statistically indistinguishable from zero. This pattern holds across both the OLS and instrumental variables specifications. These results suggest that supervisory hours are more effective in constraining liquidity risk when they are deployed in an environment with sufficient supervisory resources, consistent with capacity constraints limiting the transmission of supervisory attention into effective oversight.

We next examine whether the effectiveness of supervisory attention varies with supervisory tenure, measured as the length of time a supervisor has been active within the Federal Reserve System. Supervisors with longer tenure may be better positioned to translate supervisory attention into effective oversight, for instance because they have greater familiarity with supervisory procedures, regulatory expectations, and the institutions they oversee, or because they have previously observed episodes of financial stress. This conjecture echoes a broader literature documenting how past exposure to adverse events can shape subsequent decision-making (e.g., Malmendier and Nagel 2011), although our focus remains on tenure as an institutional characteristic rather than on individual beliefs or preferences.

To capture this dimension, we construct a measure of supervisory tenure based on the primary supervisor assigned to each bank holding company, defined as the supervisor who records the largest share of supervisory hours for that institution. We measure tenure as the number of quarters the primary supervisor has been active in the supervisory data as of 2018Q1, prior to the implementation of the EGRRCPA. We then classify banks into long-tenure and short-tenure groups depending on whether their primary supervisor's tenure lies above or below the sample median.

Using this split, we estimate regressions similar to equation (4), separately for banks supervised by long- and short-tenure supervisors. The results are reported in Table 8. For banks whose primary supervisor has longer tenure, supervisory hours are associated with a stronger attenuation of the post-EGRRCPA liquidity deterioration: the coefficient on the triple interaction term Category IV

Table 8. Effect of supervision on bank liquidity: By supervisor tenure

The table reports the estimates of regressions similar to Table 5, splitting the sample based on the length of the tenure of the BHC's primary supervisor, measured as the number of quarters the primary supervisor has been active in the supervisory data as of 2018Q1, prior to the implementation of the EGRRCPA.

Tenure:	OLS		IV	
	Long (1)	Short (2)	Long (3)	Short (4)
Category IV and other banks	0.208* (0.113)	0.144*** (0.031)	0.603 (0.394)	0.175 (0.134)
Cat. IV & other $\times$ Post	-0.703*** (0.165)	-0.036 (0.113)	-1.253*** (0.238)	0.121 (0.172)
ln(Sup. hours)	-0.001 (0.001)	-0.001 (0.001)	0.001 (0.002)	0.003 (0.004)
Cat. IV & other $\times$ ln(Sup. hours)	-0.024* (0.013)	-0.016*** (0.004)	-0.073 (0.047)	-0.022 (0.016)
Post $\times$ ln(Sup. hours)	0.000 (0.002)	0.002 (0.002)	-0.003 (0.003)	0.000 (0.004)
Cat. IV & other $\times$ Post $\times$ ln(Sup. hours)	0.085*** (0.020)	0.001 (0.014)	0.154*** (0.029)	-0.017 (0.021)
Controls	✓	✓	✓	✓
Calendar quarter f.e.	✓	✓	✓	✓
N	3,757	3,801	3,757	3,801
R ²	0.335	0.318		
Kleibergen-Paap F stat			68.694	25.670
Sanderson-Windmeijer F stat:				
ln(Sup. hours)			283.271	103.305
Cat. IV & other $\times$ ln(Sup. hours)			231.302	111.005
Post $\times$ ln(Sup. hours)			285.405	153.022
Cat. IV & other $\times$ Post $\times$ ln(Sup. hours)			247.087	101.660

$\& \text{ Other banks} \times \text{Post} \times \ln(\text{Supervisory hours})$ is positive and statistically significant in the OLS specification. In contrast, for banks supervised by lower-tenure supervisors, the corresponding effect is smaller in magnitude and statistically indistinguishable from zero. The instrumental-variables estimates point in the same direction but are less precisely estimated. Overall, these results provide suggestive evidence that supervisory tenure shapes the effectiveness of supervisory attention, although the estimates are noisier than for the capacity channel.

Our findings also speak to the role of supervisory capacity in shaping outcomes under regulatory relaxation, and raise the question of how these results reconcile with recent reductions in supervisory staffing at U.S. banking agencies. One possibility is that technological change, often referred to as SupTech, may partially offset reductions in headcount by increasing the productivity of supervisors. Recent work shows that digital supervisory tools can strengthen compliance and discipline bank behavior (Degryse, Huylebroek, and Van Doornik 2025), and that their effectiveness depends on organizational readiness and task suitability (Gambacorta, Lauridsen, Kiuhan-Vásquez, and Prenio 2025). These developments suggest that supervisory capacity need not scale one-for-one with staffing if technology meaningfully augments supervisory effectiveness.

A complementary perspective is that supervisory hours capture, in part, time-intensive tasks such as reviewing filings, synthesizing information, and drafting supervisory communications. Evidence from other professional settings indicates that generative AI can increase productivity in similar activities (Noy and Zhang 2023, Peng, Kalliamvakou, Cihon, and Demirer 2023). While such tools are unlikely to substitute for supervisory judgment or on-site examinations, they may enhance effective capacity along the margin captured by our supervisory-hours measure. Interpreted in this light, our results are consistent with a view in which technological advances can help sustain the role of supervision by increasing the effectiveness of existing supervisory resources.

5 Risk and Lending

The evidence so far shows that the LCR declines for Category IV and other banks following the relaxation of liquidity regulation. This pattern is consistent with two distinct interpretations. Under

the first one, the relaxation of regulatory requirements increases banks' risk-taking, leading them to operate with lower liquidity buffers. Under the other interpretation, the reform primarily relaxes a binding liquidity constraint, allowing banks to reduce their LCR without necessarily increasing underlying risk. These two interpretations have different implications for risk and real outcomes, which we examine next.

We begin by studying measures of risk other than LCR. We consider the Net Stable Funding Ratio (NSFR), an alternative measure of liquidity close to the LCR but that was not targeted by the EGRRCPA and the Tailoring Rule, as well as three stock market-based measures of risk: the CAPM beta, stock return volatility, and tail risk, defined as the expected return on a given bank's stock conditional on the banking sector's 5% worst returns. Across all measures, we do not detect any evidence of an increase in risk for BHCs in the Category IV and "other" banks group.¹⁴

Next, we turn to lending. If the LCR represents a binding constraint on banks' balance sheets, its relaxation should allow banks to expand credit. Table 10 provides evidence consistent with this prediction. The coefficient on $\text{Post} \times \text{Treated}$ is positive and statistically significant across specifications, indicating that Category IV and other banks increase lending following the EGRRCPA. At the same time, the triple interaction $\text{Post} \times \text{Treated} \times \ln(\text{Supervisory hours})$ is negative and statistically significant, implying that this expansion is attenuated for banks exposed to greater supervisory intensity. These results mirror the earlier findings on liquidity: supervision tightens the effective constraint faced by banks, limiting the extent to which regulatory relaxation translates into increased lending.

We also examine whether the observed increase in lending is accompanied by a deterioration in credit quality. Columns (3) and (4) of Table 10 report results for non-performing loans (NPLs). In contrast to the lending results, the coefficient on $\text{Post} \times \text{Treated}$ is not statistically significant, indicating no evidence of a deterioration in credit quality for the affected banks. Moreover, we do not find robust evidence that supervisory intensity differentially affects NPL outcomes following the reform. Taken together, these results provide little support for an interpretation based on

¹⁴In a future draft of the paper, we will broaden the range of risk measures we analyze.

Table 9. The table reports the estimates of regressions similar to Table 5, considering the Net Stable Funding Ratio (NSFR), an alternative measure of liquidity close to the LCR but that was not targeted by the EGRRCPA and the Tailoring Rule, as well as three stock market-based measures of risk: the CAPM beta, stock return volatility, and tail risk, defined as the expected return on a given bank's stock conditional on the banking sector's 5% worst returns. The sample comprises all BHCs with available FR Y-9C data over the 2016Q1-2022Q4 period. In all specifications the standard errors are clustered around individual BHCs.

	NSFR (1)	Beta (2)	Volatility (3)	Tail risk (4)
Category IV and other banks	0.141 (0.109)	0.012 (0.140)	-0.035 (0.035)	0.138 (0.964)
Post $\times$ Cat. IV and other	-0.201 (0.186)	0.151 (0.248)	0.074* (0.044)	0.128 (1.676)
ln(Sup. hours)	0.000 (0.000)	-0.002 (0.002)	0.001*** (0.000)	-0.005 (0.009)
Cat. IV and other $\times$ ln(Sup. hours)	-0.017 (0.013)	-0.001 (0.017)	0.004 (0.004)	-0.014 (0.117)
Post $\times$ ln(Sup. hours)	0.000 (0.000)	0.002 (0.002)	-0.000 (0.000)	-0.005 (0.011)
Post $\times$ Cat. IV and other $\times$ ln(Sup. hours)	0.024 (0.022)	-0.018 (0.030)	-0.009* (0.005)	-0.013 (0.205)
N	9,407	5,759	5,882	5,759
R ²	0.198	0.004	0.008	0.003
Sanderson-Windmeijer F stat:				
ln(Sup. hours)	240.257	207.967	211.178	207.967
Cat. IV and other $\times$ ln(Sup. hours)	228.631	186.429	195.157	186.429
Post $\times$ ln(Sup. hours)	294.467	224.292	226.720	224.292
Cat. IV and other $\times$ Post $\times$ ln(Sup. hours)	237.549	190.749	194.175	190.749

Table 10. Loans and NPLs

The table reports the estimates of regressions similar to Table 5, where the dependent variables are the change in log-total loans (columns 1-2), or the change in log-NPLs (columns 3-4). Columns 1 and 3 report OLS estimates; columns 2 and 4 IV/2SLS estimates.

	$\Delta \ln(\mathbf{Loans})$		$\Delta \ln(\mathbf{NPL})$	
	(1)	(2)	(3)	(4)
Category IV & other banks	-0.008*** (0.002)	-0.061 (0.041)	-0.039*** (0.009)	-0.203 (0.183)
Post $\times$ Cat. IV & other	0.005** (0.002)	0.104** (0.046)	0.038* (0.022)	0.977 (0.720)
$\ln(\text{Sup. hours})$		-0.000 (0.000)		-0.008** (0.004)
Cat. IV & other $\times \ln(\text{Sup. hours})$		0.007 (0.005)		0.025 (0.022)
Post $\times \ln(\text{Sup. hours})$		-0.000 (0.000)		0.002 (0.004)
Post $\times$ Cat. IV & other $\times \ln(\text{Sup. hours})$		-0.012** (0.006)		-0.117 (0.087)
Controls	✓	✓	✓	✓
Calendar quarter f.e.	✓	✓	✓	✓
N	9,407	9,407	9,282	9,282
R ²	0.514		0.038	
Kleibergen-Paap F stat		60.118		60.661
Sanderson-Windmeijer F stat:				
$\ln(\text{Sup. hours})$		240.384		284.563
Cat. IV & other $\times \ln(\text{Sup. hours})$		225.797		263.476
Post $\times \ln(\text{Sup. hours})$		294.639		322.992
Cat. IV & other $\times$ Post $\times \ln(\text{Sup. hours})$		238.306		268.353

increased risk-taking.

Overall, the evidence is more consistent with a binding-constraint interpretation. The relaxation of liquidity requirements allows banks to expand lending, while supervision attenuates this effect by tightening the effective constraint on banks' balance sheets. Importantly, this adjustment in lending does not appear to be accompanied by a deterioration in credit quality. In the next draft of the paper, we plan to extend this analysis by looking more closely at lending and the performance of loans, exploiting individual loan-level data from the Y-14 database.

6 Conclusion

We study how supervision and regulation interact in the banking system. We exploit the relaxation of liquidity requirements for U.S. mid-sized BHC in 2018-19, and examine whether supervisory oversight can compensate for a reduction in formal regulatory requirements. Using confidential data on supervisory hours from the Federal Reserve, we show that banks whose liquidity requirements were relaxed experienced a deterioration in liquidity, but that this deterioration was significantly attenuated when banks were subject to greater supervisory attention. These effects are stronger in districts with greater supervisory capacity and among more experienced supervisors.

Our findings have important implications for prudential policy. They suggest that the effectiveness of regulation depends not only on the formal requirements imposed on banks, but also on the supervisory resources available to monitor and enforce them. In particular, supervision can partially substitute for regulation by maintaining liquidity discipline even when regulatory requirements are relaxed. At the same time, the effectiveness of supervision depends on supervisory capacity and experience, implying that reductions in supervisory staffing may weaken its ability to compensate for regulatory relief. More broadly, our results suggest that debates about financial regulation should consider supervision and regulation as complementary components of prudential policy rather than as separate instruments.

References

- Agarwal, Sumit, David O. Lucca, Amit Seru, and Francesco Trebbi. 2014. “Inconsistent Regulators: Evidence from Banking.” *Quarterly Journal of Economics* 129 (2):889–938.
- Agarwal, Sumit, Bernardo C. Morais, Amit Seru, and Kelly Shue. 2024. “Noisy Experts? Discretion in Regulation.” NBER Working Paper 32344.
- Aldasoro, Iñaki, Sebastian Doerr, and Haonan Zhou. 2026. “Liquidity Regulation and Bank Funding Costs.” HKU Global Research Institute Paper No. 2026/024.
- Barr, Michael S. 2023. “Review of the Federal Reserve’s Supervision and Regulation of Silicon Valley Bank.” Report, Board of Governors of the Federal Reserve System.
- Beyhaghi, Mehdi, Jiyoung Chae, Filippo Curti, and Jeffrey R. Gerlach. 2026. “Bank Supervision as Information Production: Evidence from U.S. Bank Holding Companies.” Working paper, Federal Reserve Board of Governors.
- Bonfim, Diana, Geraldo Cerqueiro, Hans Degryse, and Steven Ongena. 2022. “On-Site Inspecting Zombie Lending.” *Management Science* 69 (5):2547–2567.
- Bosshardt, Joshua, Ali Kakhbod, and Farzad Saidi. 2024. “Banking on the Edge: Liquidity Constraints and Illiquid Asset Risk.” Working paper, UC Berkeley.
- Chavaz, Matthieu, Alba Patozi, and Mo Wazzi. 2025. “Quantitative Tightening: The Bank Liquidity-Duration Nexus.” Working paper, Bank for International Settlements.
- Cipriani, Marco, Thomas M. Eisenbach, and Anna Kovner. 2024. “Tracing Bank Runs in Real Time.” FRB of New York Staff Report 1104.
- Cookson, J. Anthony, Corbin Fox, Javier Gil-Bazo, Juan F. Imbet, and Christoph Schiller. 2026. “Social Media as a Bank Run Catalyst.” *Journal of Financial Economics* 176:104218.
- Correia, Sergio, Stephan Luck, and Emil Verner. 2025. “Supervising Failing Banks.” Working paper, MIT.
- Degryse, Hans, Cédric Huylebroek, and Bernardus F. Nazar Van Doornik. 2025. “The Disciplining Effect of Bank Supervision: Evidence from SupTech.” BIS Working paper 1256.
- DeMarzo, Peter, Erica X. Jiang, Arvind Krishnamurthy, Gregor Matvos, Tomasz Piskorski, and Amit Seru. 2023. “Resolving the Banking Crisis.” Working paper, Stanford University.
- Dursun-de Neef, H. Özlem, Steven Ongena, and Alexander Schandlbauer. 2023. “Monetary Policy, HTM Securities, and Uninsured Deposit Withdrawals.” Working paper, Goethe University Frankfurt.
- Eisenbach, Thomas M., David O. Lucca, and Robert M. Townsend. 2022. “Resource Allocation in Bank Supervision: Trade-Offs and Outcomes.” *Journal of Finance* 77 (3):1685–1736.
- Federal Reserve Board. 2019. “Supervision and Regulation Report.” Board of Governors of the Federal Reserve System, available at: <https://www.federalreserve.gov/publications/files/201905-supervision-and-regulation-report.pdf>.
- . 2023a. “Approaches to Bank Supervision.” Board of Governors of the Federal Reserve System, available at: <https://www.federalreserve.gov/supervisionreg/approaches-to-bank-supervision.htm>.
- . 2023b. “How Federal Reserve Supervisors Do Their Jobs.” Board of Governors of the Federal Reserve System, available at: <https://www.federalreserve.gov/supervisionreg/how-federal-reserve-supervisors-do-their-jobs.htm>.

- . 2023c. “Understanding Federal Reserve Supervision.” Board of Governors of the Federal Reserve System, available at: <https://www.federalreserve.gov/supervisionreg/understanding-federal-reserve-supervision.htm>.
- Flannery, Mark J. and Sorin M. Sorescu. 2023. “Partial Effects of Fed Tightening on U.S. Banks’ Capital.” Working paper, University of Florida.
- Fuster, Andreas, Teodora Paligorova, and James Vickery. 2024. “Underwater: Strategic Trading and Risk Management in Bank Securities Portfolios.” Working Paper, EPFL.
- Gambacorta, Leonardo, Nico Lauridsen, Samir Kiuhan-Vásquez, and Jermy Prenio. 2025. “Making SupTech Work: Evidence on the Key Drivers of SupTech Adoption.” BIS Working Paper 1309.
- Ghizoni, Sandra Kollen. 2013. “Reserve bank organization committee announces selection of reserve bank cities and district boundaries.” Federal Reserve Bank of Richmond website: https://www.federalreservehistory.org/essays/reserve_bank_organization_committee.
- Giannetti, Mariassunta, Martina Jasova, Caterina Mendicino, and Dominik Supera. 2026. “Securities Losses and the Bank Collateral Channel of Monetary Transmission.” Working paper, Stockholm School of Economics.
- Gopalan, Yadav and João Granja. 2024. “How (In)Effective was Bank Supervision During the 2022 Monetary Tightening?” Working paper, Booth School of Business.
- Granja, João, Erica X. Jiang, Gregor Matvos, Tomasz Piskorski, and Amit Seru. 2024. “Book Value Risk Management of Banks: Limited Hedging, HTM Accounting, and Rising Interest Rates.” NBER Working Paper 32293.
- Granja, João and Christian Leuz. 2024. “The Death of a Regulator: Strict Supervision, Bank Lending, and Business Activity.” NBER Working Paper 24168.
- Greenwald, Daniel L., John Krainer, and Pascal Paul. 2024. “Monetary Transmission Through Bank Securities Portfolios.” Working paper, NYU Stern.
- Hirtle, Beverly and Anna Kovner. 2022. “Bank Supervision.” *Annual Review of Financial Economics* 14:39–56.
- Hirtle, Beverly, Anna Kovner, and Matthew Plosser. 2020. “The Impact of Supervision on Bank Performance.” *Journal of Finance* 75 (5):2765–2808.
- Hong, Han, Jing-Zhi Huang, and Deming Wu. 2014. “The Information Content of Basel III Liquidity Risk Measures.” *Journal of Financial Stability* 15 (1):91–111.
- Ihrig, Jane E., Edward Kim, Cindy M. Vojtech, and Weinbach Gretchen C. 2019. “How Have Banks Been Managing the Composition of High-Quality Liquid Assets?” *Federal Reserve Bank of St. Louis Review* 101:177–202.
- Jiang, Erica X., Gregor Matvos, Tomasz Piskorski, and Amit Seru. 2024. “Monetary Tightening and U.S. Bank Fragility in 2023: Mark-to-Market Losses and Uninsured Depositor Runs?” *Journal of Financial Economics* 159:103899.
- Kandrac, John and Bernd Schlusche. 2021. “The Effect of Bank Supervision and Examination on Risk Taking: Evidence from a Natural Experiment.” *Review of Financial Studies* 34:3181–3212.
- Kovner, Anna, James Vickery, and Lily Zhou. 2014. “Do Big Banks Have Lower Operating Costs?” *FRBNY Economic Policy Review* December 2014:1–27.
- Malmendier, Ulrike and Stefan Nagel. 2011. “Depression Babies: Do Macroeconomic Experiences Affect Risk Taking?” *Quarterly Journal of Economics* 126 (1):373–416.
- Noy, Shakked and Whitney Zhang. 2023. “Experimental Evidence on the Productivity Effects of Generative Artificial Intelligence.” *Science* 381 (6654):187–192.

- Passalacqua, Andrea, Paolo Angelini, Francesca Lotti, and Giovanni Soggia. 2020. “The Real Effects of Bank Supervision: Evidence from On-Site Bank Inspections.” Working paper, Board of Governors of the Federal Reserve System.
- Passmore, Wayne and Judit Temesvary. 2022. “How Investor Demands for Safety Influence Bank Capital and Liquidity Trade-Offs.” *Journal of Financial Stability* 60:100987.
- Patel, Ajay, Nonna Sorokina, and John H. Thornton. 2022. “Liquidity and Bank Capital Structure.” *Journal of Financial Stability* 62:101038.
- Peng, Sida, Eirini Kalliamvakou, Peter Cihon, and Mert Demirer. 2023. “The Impact of AI on Developer Productivity: Evidence from GitHub Pilot.” Working Paper, Microsoft Research.
- Sundaresan, Suresh and Kairong Xiao. 2024. “Liquidity Regulation and Banks: Theory and Evidence.” *Journal of Financial Economics* 151 (4):103747.

Appendix to “Mitigating deregulation: The role of supervision”

by Elena Carletti, Filippo De Marco, Alberto Manconi, and Isabella Wolfskeil

A Variables description

A.1 Variables based on the FR Y-9C and Call Report data

LCR Liquidity Coverage Ratio, computed as described in Appendix C.

Size Natural logarithm of total assets (FR Y-9C data item BHCK2170).

Loans to assets Ratio of loans (FR Y-9C data item BHCK2122) to total assets.

Loan growth Growth rate of loans.

ROA Ratio of income before extraordinary items (FR Y-9C data item BHCK4300) to total assets.

T1 capital ratio Ratio of Tier 1 capital (FR Y-9C data item BHCK8274) to risk-weighted assets (FR Y-9C data item BHCKA223).

NPL to assets Ratio of non-performing loans (sum of FR Y-9C data items BHCKA223 and BHCAA223 to total assets).

Deposits to liabilities Ratio of deposits (sum of FR Y-9C data items BHDM6631, BHDM6636, BHFN6631, and BHFN6636) to total liabilities (FR Y-9C data item BHCK3300).

HHI of assets Defined following Kovner, Vickery, and Zhou (2014), as the sum of the squares of the shares of loans to individuals for household, family, and other personal expenditures, residential real estate loans, commercial real estate loans, C&I loans, investment securities, and trading assets in total BHC assets. Instead of loans to individuals for household, family, and other personal expenditure (FR Y-9C data item BHDM1975), Kovner, Vickery, and Zhou (2014) use credit card loans, defined as FR Y-9C data item BHCKB538, but this item is not available for most of our sample period. Residential real estate loans are defined as the sum of FR Y-9C data items BHDM1797, BHDM5367, and BHDM5368. Commercial real estate loans are defined as total loans (FR Y-9C data item BHCK1410) minus residential real estate loans (BHDM1797 plus BHDM5367 plus BHDM5368) minus FR Y-9C data items BHCKF160 and BHDM1420 (Kovner, Vickery, and Zhou (2014) use data items BHCKf158, BHCKF159, and BHCKF161; but these items are missing for most of our sample). C&I loans are defined as FR Y-9C data item BHDM1766. Investment securities are defined as FR Y-9C data items BHCK1754 plus BHCK1773. Trading assets are defined as FR Y-9C data item BHCK3545.

Complexity Number of banks with data in the Call Reports under the umbrella of the BHC.

% SMB ($\leq \$10\text{bn}$) assets / % SMB ($> \10bn) assets % of SMBs (entity type equal to “SMB”) with total assets below/above \$10bn in the total assets of the BHC.

% National bank assets % of national banks (entity type equal to “NAT”) in the total assets of the BHC.

A.2 Confidential data on supervisory hours

ln(Total Sup. Hours) Natural log of total supervisory hours associated with a bank holding company in a given quarter. Hours are aggregated from the ROAM data.

ln(Exam Hours) Natural log of supervisory hours where the category of work is associated with an examination. This is a subset of total supervisory hours.

ln(Continuous Hours) Natural log of supervisory hours where the category of work is associated with ongoing supervision or continuous monitoring activities. This is a subset of total supervisory hours and captures non-examination supervisory attention.

Exam/Total Ratio of examination hours to total supervisory hours in a given bank-quarter. This measure captures the composition of supervisory attention between periodic examinations and ongoing monitoring. A version that fills in zeros for bank-quarters with no recorded hours is also used.

Rate 1–4 Indicator variables for CAMELS composite ratings of 1, 2, 3/4. Rating of 3 and 4 have been combined into a single group.

Tenure (qtrs) Tenure of the primary supervisor assigned to a bank as of 2018Q1, measured in quarters. The primary supervisor is identified as the employee who recorded the most hours for a given bank in each quarter. Tenure is calculated using the anonymized employee identifier in the ROAM hours data by identifying the first quarter the supervisor appears in the data and computing the number of quarters elapsed between that first appearance and 2018Q1. This fixed-point measure captures supervisory experience at the onset of the EGRRCPA implementation.

High/Low Tenure An indicator for whether a bank's primary supervisor has above-median tenure as of 2018Q1. Banks are classified as high tenure if their primary supervisor's tenure exceeds the sample median, and low tenure otherwise.

FT Empl/BHCs Full-time equivalent (FTE) supervisory employees per BHC in a Federal Reserve district, measuring district-level supervisory capacity. FTE is calculated from the ROAM hours data by summing total hours worked by all employees in a district-quarter and dividing by 520 (corresponding to a 40-hour work week over a 13-week quarter). This is then divided by the number of unique BHCs supervised in that district-quarter. Districts with higher values have more supervisory resources available per institution.

High/Low Capacity District An indicator for whether a bank's Federal Reserve district has above-median supervisory capacity. Districts are ranked each quarter by FTE per BHC, and banks in districts ranked 7–12 (top half) are classified as high capacity, while banks in districts ranked 1–6 (bottom half) are classified as low capacity.

B Additional tables and figures

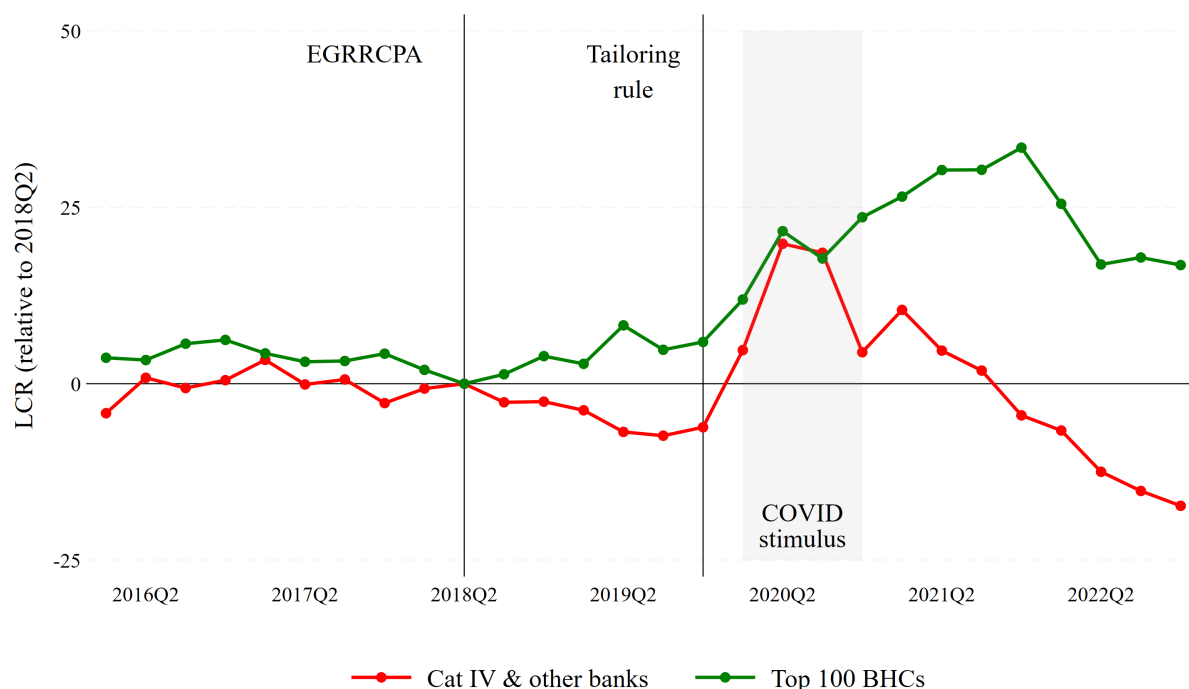


Figure B.1. Liquidity deterioration at the “Category IV” and “other” banks

The figure illustrates the average LCR, relative to the 2018Q2 level, for the “Category IV”/“other” banks group relative to all the other top-100 U.S. bank holding companies. The shaded area in the plot highlights the 2020Q2-2021Q2 period associated with the COVID stimulus.

Table B.1. Distribution of Supervisory Hours Across Federal Reserve Districts The table reports summary statistics on the distribution of supervisory hours across Federal Reserve districts for BHCs in the regression sample. Each statistic is computed at the BHC-year level. Fraction single-district is an indicator equal to one if 100% of supervisory hours originate from a single district. District shares are computed as the fraction of total annual supervisory hours allocated by each district, ranked by size. The Banks column reports the number of unique BHCs with non-missing values for each variable.

	Mean	Std. Dev.	p25	p50	p75	Banks
	(1)	(2)	(3)	(4)	(5)	(6)
Fraction single-district	0.778	0.415	1.000	1.000	1.000	545
Primary district share	0.986	0.049	1.000	1.000	1.000	545
2nd district share	0.044	0.078	0.009	0.018	0.043	158
Number of districts	1.696	1.821	1.000	1.000	1.000	545

C Computing the LCR

This Appendix describes the construction of a regulatory-style Liquidity Coverage Ratio (LCR) for U.S. bank holding companies (BHCs) using publicly available data. Our starting point is the methodology developed by Hong, Huang, and Wu (2014), which maps Basel III liquidity standards into Call Report information and has been adopted in subsequent work, including Passmore and Temesvary (2022), Patel, Sorokina, and Thornton (2022), and Sundaresan and Xiao (2024). A central challenge in implementing the LCR outside the supervisory environment is that publicly available balance-sheet data lack the granularity banks use internally when computing regulatory LCRs, particularly for modeling cash outflows under stress. Consistent with the existing literature, we therefore approximate Basel III definitions using observable balance-sheet items, while introducing additional heterogeneity across BHCs when more detailed regulatory filings allow us to do so. We proceed by first describing the benchmark approach and its underlying assumptions, then detailing our construction of high-quality liquid assets and net cash outflows, and finally validating the resulting LCR against banks' disclosed measures.

Our benchmark for constructing the LCR is the approach of Hong, Huang, and Wu (2014), who compute a Basel III-consistent LCR for U.S. banks using Call Report data. Their methodology is based on the original Basel III liquidity standards issued in 2010 and the subsequent revisions finalized in 2013 and 2014, and it provides a transparent mapping from regulatory definitions to publicly observable balance-sheet items. Because Call Reports do not allow for a fully granular implementation of the regulatory rules, Hong, Huang, and Wu (2014) introduce a set of simplifying assumptions (most notably regarding the composition and stability of funding sources) and assess robustness by considering alternative optimistic and pessimistic scenarios.

We adopt this framework as our point of departure and retain its core structure, while updating several assumptions to better reflect heterogeneity across bank holding companies and changes in available regulatory disclosures over time. In particular, where more detailed regulatory filings permit, we replace fixed or sample-wide assumptions with bank-specific measures, while maintaining consistency with the Basel III definitions and the spirit of the original approach.

High-quality liquid assets (HQLA). The numerator of the Liquidity Coverage Ratio is the stock of high-quality liquid assets (HQLA). We construct HQLA following the Basel III definitions and the implementation in Ihrig, Kim, Vojtech, and Gretchen C (2019), using publicly available Call Report data. Under Basel III, HQLA are classified into three categories, Level 1, Level 2A, and Level 2B, based on their liquidity and credit risk characteristics, with category-specific haircuts and aggregate caps.

Level 1 assets are the most liquid and are not subject to haircuts. They include cash, reserve balances held at the central bank, and securities issued or guaranteed by the U.S. government. Level 2A assets include certain securities issued or guaranteed by U.S. government-sponsored enterprises (GSEs) and are subject to a 15% haircut. Level 2B assets consist primarily of certain corporate debt securities, which are subject to a 50% haircut and, together with Level 2A assets, are subject to an aggregate cap of 40% of total HQLA. Because Level 2B assets account for only a marginal share of HQLA holdings in our sample, we exclude them from our analysis.

Consistent with these definitions, we identify the following assets as Level 1 HQLA: (i) excess reserves, (ii) U.S. Treasury securities, and (iii) Government National Mortgage Association (Ginnie Mae) mortgage-backed securities and other non-GSE agency debt. We classify as Level 2A

HQLA: (i) GSE debt, (ii) GSE mortgage-backed securities, and (iii) GSE commercial mortgage-backed securities. All asset categories are identified using specific line items in the Call Report, and the corresponding regulatory haircuts and caps are applied in constructing total eligible HQLA.

Net cash outflows. The denominator of the Liquidity Coverage Ratio is the total net cash outflows over a 30-day stress period. We construct this component following the framework of Hong, Huang, and Wu (2014), which maps Basel III runoff and inflow assumptions into publicly available balance-sheet data. Under this approach, net cash outflows are computed as expected cash outflows net of expected cash inflows, where outflows depend on the composition and stability of funding sources and inflows are subject to regulatory caps.

As in Hong, Huang, and Wu (2014), the main challenge in implementing this framework with public data is the limited observability of funding stability and counterparty characteristics that enter the Basel III runoff rates. Their baseline implementation therefore relies on simplifying assumptions regarding the composition of wholesale versus retail funding, and explores alternative optimistic and pessimistic scenarios to assess sensitivity. We adopt their baseline structure but introduce several modifications to allow for heterogeneity across bank holding companies and over time, while remaining consistent with the regulatory definitions.

Our first modification concerns the composition of retail and wholesale funding. Rather than assuming a fixed or scenario-dependent share of wholesale funding, we exploit information from the FR Y-15 Systemic Risk Report, which provides a detailed breakdown of funding sources for U.S. bank holding companies with combined U.S. assets of at least \$100 billion. Beginning in 2020, these filings are available at a quarterly frequency and allow us to measure each BHC's share of retail funding directly.¹⁵ For BHCs that do not file the FR Y-15, and for quarters prior to 2020, we impute the retail funding share using the average across banks in our sample, which is approximately 60%.¹⁶

A second modification concerns outstanding lines of credit and other off-balance-sheet commitments. Consistent with the Basel III liquidity coverage framework and the U.S. LCR Final Rule, we assume an average drawdown rate of 20 percent on these commitments when computing expected cash outflows.¹⁷

All other components of net cash outflows follow the baseline implementation of Hong, Huang, and Wu (2014).

Benchmark comparison and validation. Having constructed the numerator and denominator of the LCR, we next compare the resulting measure with the benchmark implementation of Hong, Huang, and Wu (2014) to assess how our refinements affect both the level and the dynamics of the LCR over time. Figure C.2 compares the asset-weighted average LCR implied by our approach with the LCR computed using the baseline methodology of Hong, Huang, and Wu (2014), for bank holding companies in regulatory Categories I-III and Category IV and other banks under the 2019

¹⁵Specifically, Schedule F, variable 2 reports total retail funding. We use this value to compute the share of retail funding in total deposits reported in the FR Y-9C.

¹⁶Hong, Huang, and Wu (2014) assume a wholesale funding share of 50% in their baseline scenario, 20% in their optimistic scenario, and 80% in their pessimistic scenario.

¹⁷Details of the regulatory treatment of cash outflows and inflows are available in the U.S. LCR Final Rule, Federal Register, <https://www.ecfr.gov/current/title-12/chapter-II/subchapter-A/part-249/subpart-D/section-249.30>.

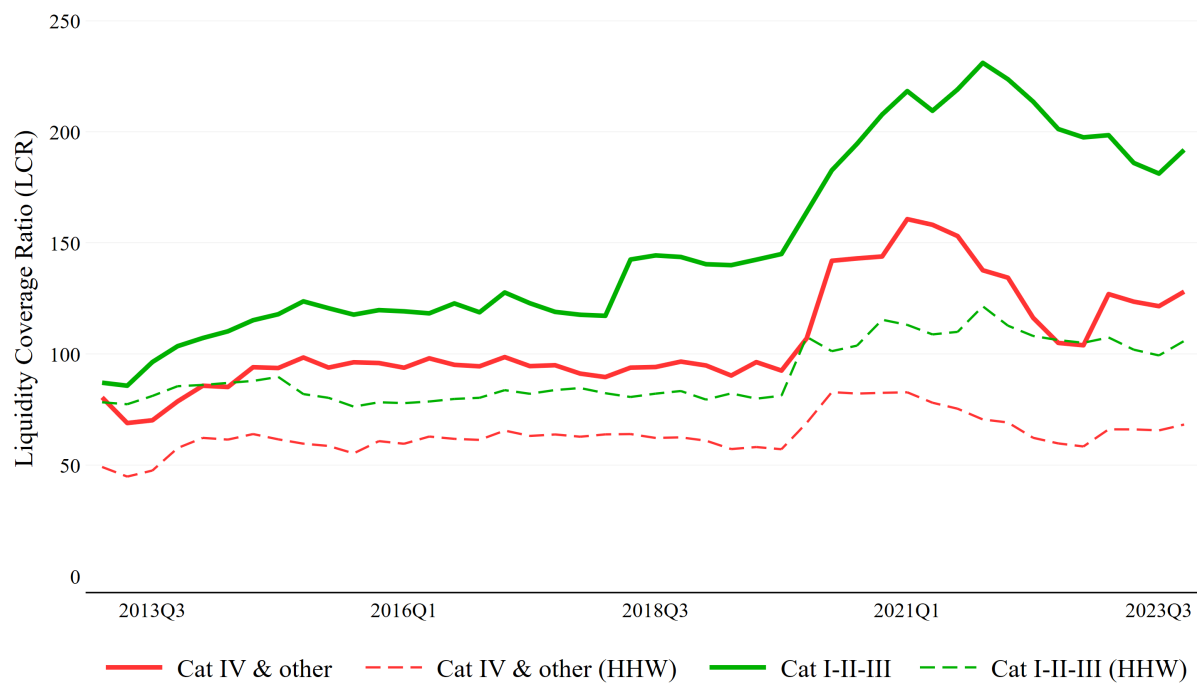


Figure C.2. LCR computation

The figure compares the LCR calculated using the Hong, Huang, and Wu (2014) method and our computation. It shows the total asset weighted averages BHC LCRs for the period 2013Q1-2023Q4, for categories I-II-III and IV-other from the 2019 tailoring rule.

tailoring rule, over the period 2013Q1-2023Q4. Across both groups, the LCR constructed using our approach is generally higher than that obtained under the benchmark method.

The difference in levels primarily reflects our use of more granular information on funding composition, which leads to lower estimated net cash outflows for some institutions relative to the benchmark assumptions. Importantly, despite these level differences, the two series exhibit very similar time-series dynamics, suggesting that our refinements do not materially alter the cyclical behavior of the LCR.

A further and quantitatively important source of divergence between our BHC-level LCR and the benchmark measure relates to the treatment of transferability restrictions under the U.S. LCR Final Rule. When reporting their consolidated LCR, U.S. bank holding companies are subject to restrictions that limit the amount of high-quality liquid assets (HQLA) that can be transferred from their banking subsidiaries to the parent entity.¹⁸ In particular, the amount of eligible HQLA held at the subsidiary level that can be recognized at the parent level is capped by the subsidiaries' net cash outflows. As a result, the consolidated LCR of the parent BHC may be lower than what would be obtained by mechanically aggregating subsidiary balance sheets.

We explicitly account for these transferability restrictions when constructing the BHC-level LCR. Specifically, we cap the contribution of subsidiaries' eligible HQLA at their respective net cash outflows, and add parent-level HQLA holdings that are not subject to such constraints, including Treasury securities and excess reserves held directly by the parent.¹⁹

Figure C.3 shows that, once these transferability restrictions are incorporated, the LCR of Category I-III banks computed under our approach closely tracks both the level and the dynamics of the average LCR disclosed by banks in our sample. By contrast, the benchmark measure of Hong, Huang, and Wu (2014), which is based on a mechanical consolidation of subsidiary balance sheets, frequently yields BHC-level LCRs below 100 percent. In such cases, transferability restrictions are effectively non-binding, making the benchmark measure less comparable to the regulatory LCR reported by large U.S. bank holding companies.

We validate our constructed LCR by comparing it with LCRs publicly disclosed by large U.S. bank holding companies. Figure C.3 shows that, once transferability restrictions are incorporated, our measure closely matches both the level and the time-series dynamics of the disclosed LCR for banks in our sample.

Table C.2 reports the correlation between disclosed LCRs and LCRs computed under alternative approaches. Our preferred specification exhibits the highest correlation with the disclosed data, while implementations that omit eligibility criteria or transferability restrictions display substantially lower correlations.

¹⁸See the U.S. LCR Final Rule, Federal Register, <https://www.federalregister.gov/documents/2014/10/10/2014-22520/liquidity-coverage-ratio-liquidity-risk-measurement-standards>.

¹⁹To the capped sum of subsidiary-level eligible HQLA, we add Treasury securities held by the parent (FR Y-9LP Schedule PC, item 2.a.) and intragroup deposits held by the parent, which we assume to be fully backed by reserve balances. This amount is calculated as the maximum of intragroup deposits reported in FR Y-9LP Schedule PC, item 1.a.

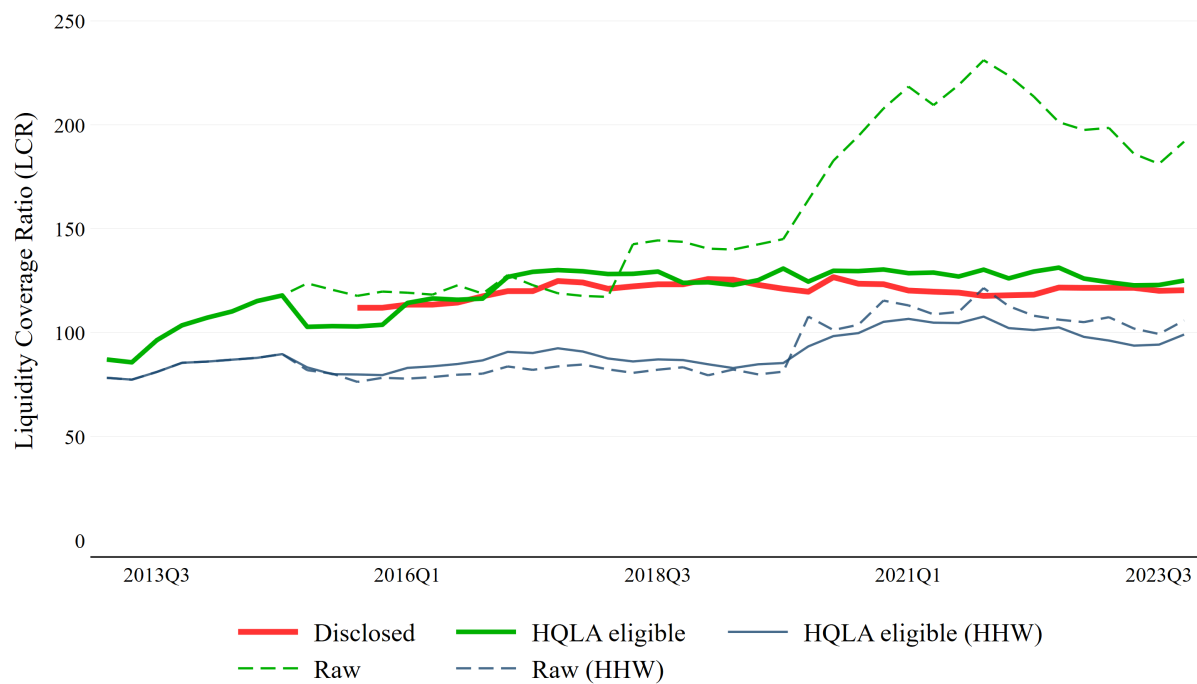


Figure C.3. Computed LCR and disclosed LCR

The figure plots the LCR disclosed by category I-II-III banks, comparing it to the LCR computed based on our approach, raw and accounting for the HQLA eligibility cap, and to the LCR computed based on the Hong, Huang, and Wu (2014) approach, raw and accounting for the HQLA eligibility cap.

Table C.2. Correlation between disclosed and computed LCR.

The table reports the correlation between the LCR disclosed by banks in our sample and the LCR computed under the different approaches described in this Appendix.

Our approach		Hong, Huang, and Wu (2014)	
HQLA eligible	Raw	HQLA eligible	Raw
0.768	0.171	0.226	0.145

D Tailoring rule summary

Table D.3. Tailoring rule visual

The table lists the U.S. bank-holding companies affected by the 2019 tailoring rule and the resulting changes in their liquidity regulation, along with their capital requirements. Panels A, C, and D are retrieved from the “tailoring rule visual” available on the Federal Reserve webpage; panel B is based on the 2014 LCR rule. wSTWF denotes weighted short-term wholesale funding.

I U.S. GSIBs	II ≥\$700bn tot. assets or ≥\$75bn in cross- jurisdictional activity	III ≥\$250bn tot. assets or ≥\$75bn non-bank assets, wSTWF, or off-balance sheet exposure	IV \$100bn–\$250bn tot. assets	Other firms \$50bn–\$100bn tot. assets
<i>A. U.S. bank-holding companies</i>				
Bank of America	Northern Trust	Capital One	Ally Financial	Comerica Inc.
BNY Mellon		Charles Schwab	American Express	CIT Group Inc.
Citigroup		PNC Financial	BB&T Corp.	E*TRADE
Goldman Sachs		U.S. Bancorp	Citizens Financial	Financial
JPMorgan Chase			Discover	NY Community
Morgan Stanley			Fifth Third	Bancorp
State Street			Huntington	Silicon Valley
Wells Fargo			KeyCorp	Bank
			M&T Bank	
			Regions Financial	
			SunTrust Inc.	
			Synchrony	
			Financial	
<i>B. Liquidity requirements pre-EGRRCPA (2014 LCR rule)</i>				
Full daily LCR (100%)	Full daily LCR (100%)	Full daily LCR (100%)	Modified daily LCR (70%)	Modified daily LCR (70%)
<i>C. Liquidity requirements post-Tailoring rule</i>				
Full daily LCR (100%)	Full daily LCR (100%)	wSTWF < \$75Bn: reduced daily LCR and proposed NSFR [†] (85%)	wSTWF < \$50bn: no LCR	No LCR
Proposed full daily NSFR (100%) [†]	Proposed full daily NSFR (100%) [†]	wSTWF ≥ \$75bn: full daily LCR and proposed NSFR [†] (100%)	wSTWF ≥ \$50bn: reduced monthly LCR and proposed NSFR [†] (70%)	

[†]: NSFR is not finalized as a result of the tailoring rule.

Table D.3 continues on the next page

Table D.3 continues from the previous page

I	II	III	IV	Other firms
U.S. GSIBs	≥\$700bn tot. assets or ≥\$75bn in cross- jurisdictional activity	≥\$250bn tot. assets or ≥\$75bn non-bank assets, wSTWF, or off-balance sheet exposure	\$100bn–\$250bn tot. assets	\$50bn–\$100bn tot. assets
<i>D. Capital requirements</i>				
<i>Stress testing:</i> Annual company-run stress testing; Annual supervisory stress testing; Annual capital plan submission	<i>Stress testing:</i> Annual company-run stress testing; Annual supervisory stress testing; Annual capital plan submission	<i>Stress testing:</i> Biennial company-run stress testing; Annual supervisory stress testing; Annual capital plan submission	<i>Stress testing:</i> Supervisory stress testing (two-year cycle); annual capital plan submission	
<i>Risk-based capital:</i> GSIB surcharge; advanced approaches; countercyclical buffer; no opt-out of AOCI capital impact	<i>Risk-based capital:</i> Advanced approaches; countercyclical buffer; no opt-out of AOCI capital impact	<i>Risk-based capital:</i> Countercyclical buffer; allow opt-out of AOCI capital impact	<i>Risk-based capital:</i> Allow opt-out of AOCI capital impact	<i>Risk-based capital:</i> Allow opt-out of AOCI capital impact
<i>Leverage capital:</i> Enhanced supplementary leverage ratio	<i>Leverage capital:</i> Supplementary leverage ratio	<i>Leverage capital:</i> Supplementary leverage ratio	<i>Leverage capital</i>	<i>Leverage capital</i>
<i>TLAC/Long-term debt</i>				

E 2020 CARES Act and *Fiscal Stimulus* control variable

On 27 March 2020 the CARES Act launched the largest stimulus package in U.S. history, worth \$2.5Tr, or about 12% of U.S. GDP. Most of the stimulus materialized over the year 2020 and in early 2021. In comparison, the stimulus launched in the wake of the Great Recession was smaller at \$1.8Tr, and more importantly it was spent more gradually. As illustrated in Figure E.1, we observe a sharp spike in deposits, the personal savings rate, and fiscal expenditures. The result is a pronounced increase in liquidity in the U.S. banking system.

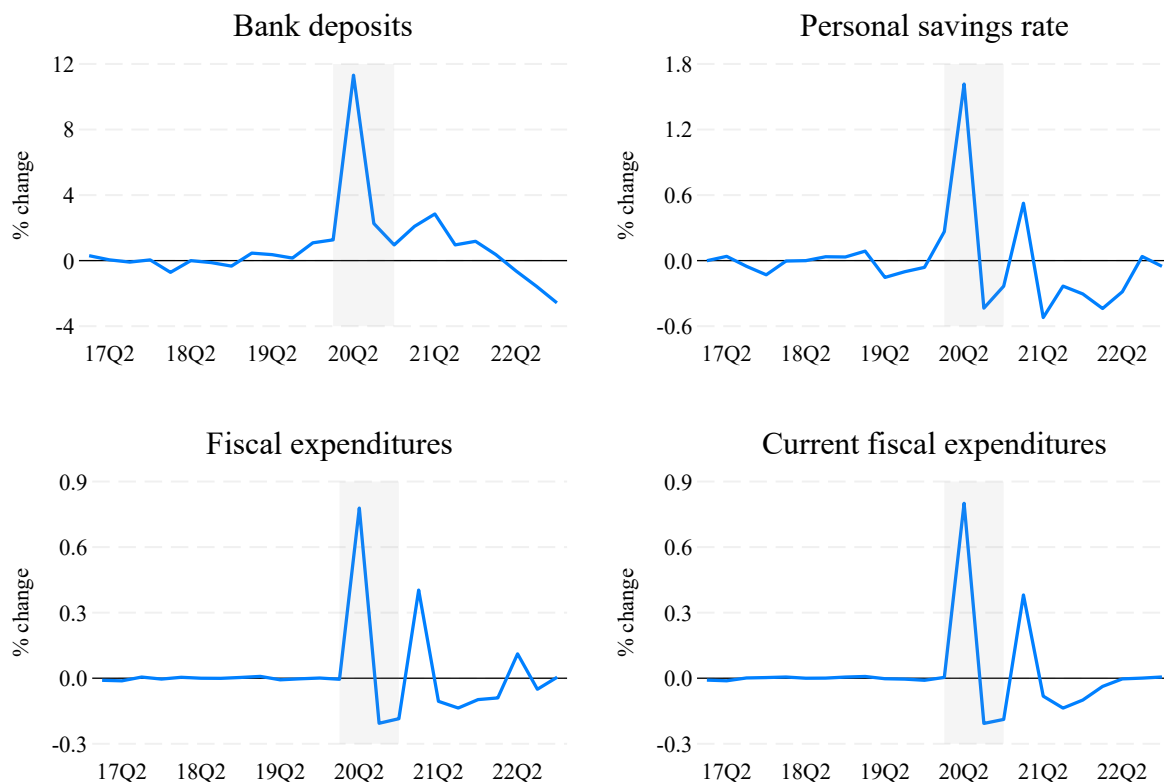


Figure E.1. COVID stimulus package

The figure illustrates the effects of the COVID stimulus package associated with the CARES Act. In all graphs, the area shaded in gray corresponds to the calendar year 2020, during which the stimulus materialized.

To control for the impact of the COVID stimulus package on bank liquidity, we include in our tests a control variable *Fiscal Stimulus*, reflecting the flow of liquidity into bank deposits associated with the COVID stimulus. The variable is constructed from input data from the COVID Money Tracker (CMT, <https://www.covidmoneytracker.org/>), which tracks federal spending, tax cuts, loans, grants, and subsidies authorized and disbursed in response to the pandemic. We remove duplicates using the program hierarchy to avoid double-counting and restrict the attention to non-zero disbursements and a valid single U.S. state or territory as the recipient.

Next, each program (and respective amount) is classified as fiscal or monetary policy based on

the CMT taxonomy (Level 1 aggregation). We label a program as Fiscal if its origin is indicated as “Legislative” or “Administrative”. We further map the result into a small set of economically meaningful categories corresponding to loans and different types of deposits: Consumer (“Direct Payments,” “Income Support,” “Trump Administration,” “Tax Policy,” “Other Spending”), State (“State & Local Funding,” “State & Local”), and Wholesale (“Health programs,” “Health spending”).²⁰ The result is a balanced state, quarter, and spending category panel.

Finally, these state-level spending measures are mapped to bank holding companies using pre-pandemic branch deposit data from the FDIC. For each bank, we compute the deposit shares at the state level based on the distribution of branch deposits. State-level COVID spending is then allocated to banks proportionally to these deposit shares. The *Fiscal Stimulus* variable is defined as the sum of the Consumer, State, and Wholesale components.

²⁰A separate category consists of fiscal stimulus components affecting corporations, reported in the CMT as “Business support” and “Loan programs.”