Where Collateral Sleeps*

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Abstract

Banks can use the discount window to fend off a run by pre-positioning their assets with the Fed and borrowing against them. While pre-positioning to the Fed can be costly, it allows banks to buy insurance against a bank run. But most banks don't pre-position. We use a novel dataset to study the forces that drive the largest banks' pre-positioning behavior. The quantity and composition of collateral placed at the Fed tell us about the relative value of that insurance. We show that banks pre-position more in bad times but pre-position less when collateral is desirable elsewhere and when stigma is higher. Even though pre-positioning is no panacea—banks still need good assets to borrow against—it can help on the margin. Regulators and bankers alike should worry about where collateral sleeps each night.

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It's called "pre-positioning." Remember the word; it's going to be important.

(Izabella Kaminska, Politico, January 19, 2024)

1 Introduction

The discount window is the central banker's classic lender-of-last-resort tool. During a bank run, Bagehot (1873) dictates that the central bank should lend freely (1) against good collateral, (2) at a penalty rate, and (3) to solvent banks. The details matter, though. Each of Bagehot's requirements involves judgment calls and introduces a bevy of hard questions and time consistency issues. We study a much simpler question: where is the collateral?

Banks can voluntarily *pre-position* their assets with the Fed. Pre-positioning allows banks to quickly borrow from the discount window, and pre-positioning is useful for two reasons. First, the Fed lends through the discount window only against collateral it has valued, a process that can be time-consuming. That valuation is done in advance for pre-positioned collateral. Second, pre-positioned collateral is held directly with the Fed, so it does not rely on third-party financial plumbing, like custodial banks or payment systems.

Since the bank runs of March 2023, pre-positioning has become a point of focus for central bankers and market participants. The Federal Reserve noted that Silicon Valley Bank's (SVB) rapid failure was, at least in part, caused by its collateral sleeping in the wrong place:

> [SVB] had limited collateral pledged to the Federal Reserve's discount window, had not conducted test transactions, and was not able to move securities collateral quickly from its custody bank or the [Federal Home Loan Bank] to the discount window. While contingent funding may not have been able to prevent the failure of the bank after the historic run on the bank, the lack of preparedness may have contributed to how quickly it failed. (Barr, 2023)

March 2023 taught markets that a dollar of good collateral in the wrong place is no different from no collateral at all.

Recently, considerable thought has been given to using pre-positioning to improve the discount window's efficacy. For example, the G30 (2024) proposes that banks should be required to pre-position as much collateral as they have runnable liabilities. Barr (2024) discusses a similar approach that would require banks to cover their uninsured deposits with reserves and pre-positioned collateral. Our results show that the largest banks are deliberate in their pre-positioning, responding to market forces; by revealed preference, banks prefer not to pre-position large swathes of their assets. While pre-positioning with the Fed incurs an opportunity cost, it allows the banks to buy insurance in case of a bank run. The quantity and composition of collateral sleeping at the Fed each night tell us how banks value that insurance.

We study pre-positioning using two novel datasets: confidential supervisory pre-positioning data and a comprehensive dataset spanning banks' voluntary public pre-positioning disclosures from SEC filings. We document two motivating facts.

First, the largest, most sophisticated banks routinely pre-position a large share of assets—more than 33 percent of their unencumbered assets—to the Federal Reserve.[1] These pre-positioned assets serve as collateral against which the bank can immediately borrow from the discount window. At face value, it is surprising that banks have quietly pledged so much of their assets to the Fed. But simultaneously, it is surprising that they don't pledge more, or all, of their unencumbered assets to the Fed. The fact indicates that banks find discount window insurance costly; otherwise, they would pre-position everything.

Second, the largest banks often pledge substantial high-quality assets to the Fed. Over 10 percent of the collateral pledged to the Fed are high-quality liquid assets, like Treasuries or agency securities. This is confusing: these high-quality assets are desirable as collateral in secured financing markets—like the repurchase agreement (repo) market—and could ostensibly provide the bank with cheaper financing. Neither of these facts is a feature of crisis times following the pandemic or March 2023 bank stress, they are nearly unchanged if we focus only on normal times.

We use a simple toy model to understand the forces that affect where collateral sleeps. The model shows how three forces help pin down banks' pre-positioning: (1) the bank's expectations about the future and the odds it will face a liquidity shock; (2) the opportunity cost the bank incurs from pre-positioning since pre-positioned assets can't be used as collateral elsewhere; and (3) stigma, both for borrowing from the window and for simply pre-positioning collateral.

Intuitively, banks may be reluctant to pledge collateral to the Fed if it is more valuable in other collateral markets, like the repo market or to back Federal Home Loan Bank (FHLB) advances, another important collateral market.[2] This calculation depends, in part, on the relative financing rates and haircuts for that collateral. The bank's expectations about the future also matter since a bank with an optimistic view may not think it needs the discount window tomorrow. And stigma plays a role, effectively raising the bar that would compel

[1] Unencumbered assets are assets that are free of any constraints (legal, regulatory, contractual) that would prevent a bank from selling it or pledging it to secure a transaction.

[2] The Federal Home Loan Bank system is a government-sponsored enterprise and an important liquidity provider to the U.S. financial system. See Frame (2017) and Gissler and Narajabad (2017) for details on the FHLBs.

a bank to pre-position and use the discount window beyond the standard pecuniary costs stemming from financing rates and haircuts.

We use the toy model to frame our empirical work, evaluating each force individually before comparing them in a kitchen-sink regression. We show that bank pre-positioning varies with the business cycle, for example, with banks pre-positioning more when credit spreads are higher. While the business cycle can pose challenges to banks through higher defaults and fewer lending opportunities, pre-positioning most specifically helps banks manage liquidity shocks. We infer the odds of a bad state using high-frequency deposit flows and show that banks pre-position more when they have more deposits, especially—but not only—uninsured deposits.

Banks pay an opportunity cost when they pre-position. A Treasury left on the Fed's books is a Treasury that a bank cannot use elsewhere. We use the confidential data to confirm that haircuts in several alternative collateral markets—the tri-party repo market, the bilateral repo market, and the FHLBs—are often much lower than haircuts at the discount window. And financing rates in these markets are lower, too. But the outside option value varies over time, sometimes quickly.

Stigma plays an important role. Banks may plan to never use the window if it's sufficiently stigmatized, in which case they would see no need to pre-position collateral. Recently released public data from the Fed confirms this: before the 2023 turmoil, only 50 percent of banks and credit unions had signed up to use the discount window, and only 25 percent had pledged any collateral at all.[3] Stigma plays an important role in such low take-up.

Importantly, though, we separate stigma into two flavors: borrowing stigma and pre-positioning stigma. Discount window stigma, as typically discussed, refers to borrowing stigma: the stigma a bank incurs once it has actually borrowed from the window. We highlight the possible existence of pre-positioning stigma and show both flavors play a role in banks' pre-positioning behavior.

We exploit variation in banks' borrowing stigma exposure that stems from their Federal Reserve district using intuition from Armantier et al. (2015a). Discount window borrowing may be easier to infer in more concentrated districts since the Fed's weekly balance sheet provides borrowing data by district. In our sample of confidential data from large banks, we find that banks located in more concentrated districts pre-position less.

And we find evidence of pre-positioning stigma. First, we find that less than 30 percent of banks disclose their pre-positioning with the Fed in their public 10-Ks, and many banks only disclose their pre-positioning by co-mingling it with other types of pre-positioning, namely

[3]See "Discount Window Readiness" `https://www.federalreserve.gov/monetarypolicy/discount-window-readiness.htm`, which we summarize in Table 3.

with the unstigmatized FHLBs.[4] Second, we show that banks are less likely to disclose Fed pre-positioning in their 10-K when they are in a more concentrated Fed district. We argue that pre-positioning stigma is a main driving force in this relationship, especially since banks in more concentrated Fed districts are more likely to disclose pre-positioning with the unstigmatized FHLBs.

Related Literature Our paper is most closely related to works studying the discount window and the role of stigma (Armantier et al. 2015a, Carlson and Rose 2017, Anbil 2018, Armantier and Holt 2020, Jaremski et al. 2023). In contrast to this literature, our work shines light on pre-positioning rather than actual discount window borrowing. Few papers have studied pre-positioning empirically. De Roure and McLaren (2021) study pre-positioning in the 2010 Bank of England Funding for Lending Scheme. Hanson et al. (2024) study how to modify current regulations to require banks to pre-position collateral to withstand uninsured deposit runs. Much of the work on pre-positioning is from policymakers in the aftermath of the global financial crisis and the March 2023 bank turmoil (Tucker 2009, King 2018, G30 2024).

2 Brief History of the Discount Window

The discount window has long been a main tool in the Federal Reserve's crisis-fighting toolkit, although its operations have changed over the last century. In its early years, the Fed used the discount window as its primary tool to interact with financial markets, and the Fed set its interest rate below market rates. Banks regularly borrowed from the Fed through the window, and the early discount window had no stigma. Banks often arbitraged the difference between the low discount window rate and prevailing market rates (Armantier et al., 2015b).

But the Fed grew concerned that banks were becoming too reliant on the discount window—sometimes borrowing non-stop—so the Fed introduced several rules to reduce its use. Armantier et al. (2015b) summarize several ways the Fed did this. First, the Fed used "direct pressure" on banks to limit discount window borrowing. In the 1950s, the Fed created rules that would not allow banks to fund their routine business using the discount window. In the 1970s, the Fed required banks to exhaust all other sources of private credit before

[4] We say the FHLB is unstigmatized for several reasons. First, many banks routinely borrow from the FHLBs, so a bank reporting that it has borrowed from the FHLBs is not unusual. Second, Ashcraft et al. (2010) show that banks often preferred to borrow from the FHLBs rather than the discount window during the Global Financial Crisis, and that FHLB funding was often cheaper than discount window lending. Hence banks did not view borrowing from FHLBs as a negative signal during the crisis. Third, the FHLBs do not disclose information about their borrowers like the Fed. The Fed discloses information at the aggregate level in weekly snapshots in its H.4.1 disclosure, and it provides transaction disclosures after a two-year lag.

turning to the window. These actions stigmatized the discount window, and banks did not use it in meaningful amounts.

While stigma prevents banks from using the window when they shouldn't, it also prevents banks from using it when they should. The relative ineffectiveness of the window became especially clear in the 1980s when weak banks were reluctant to use the window, and healthy banks avoided the window if at all possible, as described by Clouse (1994). The Fed responded by introducing some changes to help reduce stigma; for example, it introduced the primary credit facility in 2003 (Carlson and Rose 2017, McLaughlin 2024). Among other changes, borrowing from the primary credit facility is available only to generally sound banks and does not require banks to exhaust other funding sources before borrowing from it.

Despite these efforts, stigma persists. In the 2008 global financial crisis, policymakers structured interventions, in part, to minimize stigma. The Term Auction Facility, for example, used an auction design to avoid the appearance that only the weakest banks were using it. Armantier et al. (2015a) find banks were willing to pay 126 basis points after Lehman's bankruptcy to avoid borrowing from the window. Discount window stigma was first-order during the Covid pandemic, evidenced by the largest banks agreeing to jointly borrow from the window to encourage smaller banks to do the same.[5] Stigma does not entirely preclude banks from using the discount window, though. Ennis and Klee (2021) document that some banks borrow from the discount window in "normal" times due to deliberate liquidity management decisions. More recently, the Fed introduced the Standing Repo Facility in 2021 to finance high-quality collateral for banks (and others) without stigma (Afonso et al., 2022b).

The March 2023 bank runs highlighted the importance of discount window know-how. The speed of the runs placed strains on banks' operational and administrative capacities. For example, the Federal Reserve provided a loan to Signature Bank against collateral that the bank held with the FHLBs because Signature couldn't move the collateral to the Fed fast enough.[6]

[5] Hoffman and Benoit. (March 16, 2020). "Shedding 2008 Stigma, Biggest U.S. Banks Borrow Straight From the Fed" *Wall Street Journal*. `https://www.wsj.com/articles/shedding-2008-stigma-biggest-u-s-banks-borrow-straight-from-the-fed-11584412394`

[6] See "New York State Department of Financial Services Internal Review of the Supervision and Closure of Signature Bank." The report states: "The process of pledging that collateral held at the FHLB to FRBNY was significantly challenged because Signature did not have existing arrangements in place to pledge any available collateral directly to the FRBNY. As an accommodation, given the urgency of the situation, FHLB agreed to subordinate its interest in Signature collateral to the FRBNY in light of Signature's critical liquidity needs and its lack of timely viable alternatives."

3 How to Borrow from the Discount Window

The Fed's Operating Circular Number 10 describes how to borrow from the discount window.[7] The process takes four steps: initial setup, pledging collateral, collateral valuation by the Reserve Bank, and, finally, actually borrowing against that collateral. We now summarize the key points in each step.

1. Initial Set-Up First, the bank must accept the conditions and terms outlined in OC-10, which involves completing several forms. This step also requires the firm to complete several related agreements, for example, to provide information on the borrower and which individuals can authorize the firm's pledging and borrowing. Non-U.S. borrowers have somewhat different requirements.

2. Pledging Collateral Since all discount window loans are secured loans, the Federal Reserve requires firms to pledge collateral before it provides any loans, and the Federal Reserve requires sufficient information to calculate a lendable value against which it lends (after a haircut). The process depends on the collateral type—securities or loans—and where the collateral is located before pledging.[8]

Treasuries and most securities issued by U.S. government agencies are held with the Fed in an automated book-entry system, while other securities are typically held at third-party custodians with specific legal arrangements. Firms can send collateral to the Fed using several platforms.[9] The platforms vary based on which securities they can move, what time of day they can pledge and withdraw securities, and how quickly the pledges take. Table 1 describes the operating hours and processing times across platforms. Loans are often held through borrower-in-custody arrangements, but a third party or Reserve bank can also be a custodian.

3. Collateral Valuation Before the Fed can lend against collateral, it calculates a fair value estimate for each asset and then applies a haircut to calculate the asset's lendable value.[10] Processing times are short and occur within minutes for securities, although exceptions exist. The Fed updates its fair value estimate of the security each day, normally without any action from the bank.

[7] Available here: `https://www.frbservices.org/resources/rules-regulations/operating-circulars.html`.

[8] For more details, see `https://www.frbdiscountwindow.org/Pages/Collateral/pledging_collateral`.

[9] Specifically, they can use Fedwire Securities, DTCC (if the firm is a member, otherwise the firm can pledge through a DTCC member), Clearstream (with a tri-party pledging agreement between Clearstream, the Reserve Bank, and the bank), and Euroclear (through a similar tri-party agreement).

[10] For more details, see `https://www.frbdiscountwindow.org/Pages/Collateral/collateral_valuation`.

Loan processing times are longer than securities. When the local Reserve Bank has already approved the arrangement, the processing time is one business day when the bank provides sufficient details on the loans (e.g., a collateral schedule that provides several loan characteristics). However, the process can take longer, sometimes up to several weeks. The Fed typically requires banks to provide monthly updates on pre-positioned loans so the Reserve Banks can update its fair market value estimates.

Once the Reserve Bank estimates its fair market value, it applies the relevant haircut. Haircuts reflect the riskiness of the underlying collateral. Treasury bills, for example, have a 1 percent haircut, while BBB-rated nonfinancial corporate bonds with more than 10-year maturity have a 10 percent haircut, and raw land loans have haircuts up to 92 percent.[11]

4. Borrowing A firm requests a discount window loan by calling its Reserve Bank or using an online portal. Proceeds are typically posted after Fedwire closes for the day. Banks may prepay without penalty at any time; otherwise, they must repay in full at maturity.

Discussion The process takes time, even if everything runs smoothly. Each step can introduce delays. First, it takes time to complete the initial set-up of step (1). The Fed encourages banks to complete it as soon as possible if they have not:[12]

> Depository institutions that do not envision using the Discount Window in the ordinary course of events are encouraged to execute the necessary documents because a need for Discount Window credit could arise suddenly and unexpectedly.

Second, while the time it takes to pre-position securities is generally short, they may be slowed if the security had been previously pledged to a different counterparty. Such encumbrances must be unwound before the bank can pre-position it with the Fed, which may depend on the speed of the previous counterparty's administrative operations. This administrative work also must be completed before the relevant platform closes for the day, like the DTCC's 5 pm cutoff.

Third, the Reserve Banks may need considerable time to calculate fair market values. The calculation requires several loan characteristics and, given the wide variety of loans banks can pledge, often requires nontrivial staff work.

Fourth, even with enough collateral pre-positioned with market values, administrative hiccups can still make borrowing difficult, especially amid the stress of a bank run. Knowing who to call and what information to provide, or how to use the online self-service discount

[11] For the full set of haircuts, see `https://www.frbdiscountwindow.org/Pages/Collateral/collateral_valuation`.

[12] https://www.frbdiscountwindow.org/Pages/General-Information/The-Discount-Window

window portal, are seemingly simple tasks, but they may be non-trivial for a bank with an overwhelmed back office working under a binding deadline and unfamiliar with the process. For this reason, the Fed also encourages banks to conduct occasional test operations:[13]

> The Federal Reserve Bank's primary credit program, available through our Discount Window, may be a part of your institution's liquidity management or contingency plan. Institutions are encouraged to periodically test their ability to borrow at the Discount Window to ensure that there are no unexpected impediments or complications.

4 Model

We write a simple, two-period endowment model to understand the tradeoffs of pre-positioning collateral at the Fed. The model provides a set of predictions related to the amount of collateral pledged to the Fed which we test in the data.

4.1 Set-Up

There is a representative household that owns a bank. The household has an endowment e each period, and agents discount the second period by β, where $1 > \beta > 0$. In period 1, the household chooses whether to consume its endowment or invest in assets that it can use as collateral to borrow against in period 2.

The model depends on three features to generate its predictions. First, there are two types of assets: one that is pre-positioned with the Federal Reserve, and another that is pre-positioned with private collateral markets. For example, the private market could be the tri-party repo market or the FHLBs. Denote the amount of the assets the bank chooses to put at the Fed with x^F and denote the amount of the assets put in the alternative market with x^M. Assume both assets are claims on the same issuer, so the only difference in their returns stems from where they are pre-positioned. In period 2, the household can borrow from the Fed's discount window using x^F as collateral or borrow from the private collateral market using x^M as collateral. Borrowing against pre-positioned assets at the discount window costs r^F and incurs a stigma cost. There is a haircut h^F to borrow against assets pre-positioned at the discount window. Similarly, the household can use its assets pre-positioned in the alternative collateral market x^M to borrow at r^M with haircut h^M. The alternative collateral market incurs no stigma costs. For simplicity, we assume that in the household can only

[13] https://www.kansascityfed.org/banking/financial-services/test-access-discount-window-contingency-and-liquidity/.

borrow against its pre-positioned assets in period 2, it cannot sell the asset.[14] Denote the total amount of assets as $X = x^F + x^M$.

We treat the two assets as separate for tractability; in practice, a bank could pledge the same asset to the Fed or lend it into collateral markets, but not at the same time. The key friction is that the same asset cannot be pre-positioned in both markets simultaneously. In this framing, the difference between these two does not stem credit risk—both assets are from the same issuer—but instead, their ability to serve as collateral to raise financing in different markets. This delineation implies there are non-trivial frictions to moving collateral from the Fed to private collateral markets or vice versa. We discuss these frictions in practice in section 2.

Second, the model includes two different stigma costs: borrowing stigma and pre-positioning stigma. Borrowing stigma σ occurs in the second period upon realization of a bad state and when the household actually borrows against the collateral it pre-positioned with the Fed. Meanwhile, pre-positioning stigma σ_p is incurred whenever it pre-positions to the Fed, regardless of whether the household borrows against the discount window. The household pays the pre-positioning stigma cost in period 1 before the realization of the good or bad state. The alternative market has no stigma of either kind.

The third feature of the model is that a bad state occurs at $t + 1$ with probability $\pi \in [0, 1]$. In good states, the bank does not borrow from the discount window ($x^F = 0$).[15] The household can borrow against assets in the alternative market at r^M in good states. We make the simplifying assumption that in bad states the household cannot borrow from the private collateral market ($h^M = 1$), consistent with the literature on repo market dislocations in bad states (Gorton and Metrick, 2012). Since borrowing from the Fed or alternative collateral markets requires the household to pay positive interest, we can think of r^F and r^M as negative.

[14] Adding an additional terminal period in which the household sells the asset would not change our results because we assume that the two assets are identical except for where they are pre-positioned. However, if we introduce counterparty risk—the risk that an asset pre-positioned in the alternative market might not be returned by the counterparty—then the expected return on pre-positioning in the alternative market would be lower.

[15] This is clear because the stigma costs are absent in the private collateral market, so the household will prefer to borrow only from the private collateral market. Moreover, in good states, financing rates and haircuts at the discount window are, in practice, higher compared to the private collateral market.

The household solves:

$$\begin{aligned}
&\max_{c_1,c_2,x^F,x^M} u(c_1)+\beta\mathbb{E}[u(c_2)] \quad \text{subject to}\\
&c_1 \le e_1 - x^F - x^M - \sigma_p x^F\\
&c_2^{bad} = e_2 + (1+r^F-\sigma)(1-h^F)x^F\\
&c_2^{good} = e_2 + (1+r^M)(1-h^M)x^M.
\end{aligned}$$

The Lagrangian is

$$\mathcal{L} = u(c_1) + \beta\pi u(c_2^{bad}) + \beta(1-\pi)u(c_2^{good}) - \lambda(e_1 - x^F - x^M - \sigma_p x^F - c_1)$$

The Euler equations with respect to the two assets with respect to x^F are:

$$\begin{aligned}
x^F:&\quad \beta\frac{u'(c_2^{\text{bad}})}{u'(c_1)} = \frac{1+\sigma_p}{\pi(1+r^F-\sigma)(1-h^F)},\\
x^M:&\quad \beta\frac{u'(c_2^{\text{good}})}{u'(c_1)} = \frac{1}{(1-\pi)(1+r^M)(1-h^M)}.
\end{aligned}$$

If we assume log utility, we can see the equilibrium relationship between the returns by equating the two:

$$\pi(1+r^F-\sigma)(1-h^F)c_2^{\text{good}} = (1-\pi)(1+r^M)(1-h^M)(1+\sigma_p)c_2^{\text{bad}}. \tag{1}$$

Equation 1 shows a tradeoff of pre-positioning collateral at the Fed. Collateral at the Fed acts as insurance against bad states, and the expected return of discount window borrowing is $\pi(1+r^F-\sigma)(1-h^F)$, which is the unconditional value of insurance. The bank pays for the Fed insurance by foregoing the ability to borrow in the alternative collateral markets because it cannot pre-position that asset in both markets simultaneously.

Intuitively, the household will prefer to not pre-position at the Fed because bad states are unlikely. For example, Metrick and Schmelzing (2021) estimate the unconditional probability of bank stress from 1665 to 2019 is 3.4 basis points per year.

While the model does not include any details on the asset's characteristics, the model can easily be extended to specific types of assets. The household chooses where to pre-position each asset class separately, and the alternative collateral market differs depending on the asset class. If the assets are Treasuries, the alternative collateral market could be the bilateral repo market. Often, banks can borrow against specific Treasury CUSIPs at lower interest rates, in which case the Treasury is said to be trading *special*. A Treasury CUSIP that trades special means that its repo rate is lower than the general collateral repo rate and hence can provide cheap funding to a bank that borrows against it. This can happen when the Treasury CUSIP is unusually desirable, for example, if they are on the run or the cheapest to deliver.[16]

If the assets are agency MBS, the alternative collateral market could be the tri-party repo market, and the bond would be able to provide financing to the bank at the general collateral repo rate. For many assets, particularly real estate-related assets like mortgages, the alternative market would be pledging to the FHLBs to get an FHLB advance, which is typically viewed as free of stigma (Ashcraft et al., 2010). Borrowing from the FHLBs would incur no stigma but would cost a fee, and the model could be easily extended to incorporate this fee incurred in the alternative market.

4.2 Model Predictions

Setting the first-order conditions with respect to c_1 and x^F equal, we can solve for the amount of collateral pledged to the Fed x^F:

$$x^F = \frac{\beta\pi\gamma(e_1 - X) - (1+\sigma_p)e_2}{\gamma(1+\sigma_p+\beta\pi\sigma_p)}, \tag{2}$$

where $\gamma = (1 + r^F - \sigma)(1 - h^F)$. We normalize x^F by X to get the asset share $\hat{x}^F$. We take partials of $\hat{x}^F$ to generate predictions about banks' pre-positioning behavior, which we use to organize our empirical results.

Proposition 1. *The share of collateral posted at the Fed is increasing in the probability of a bad state π. $\partial\hat{x}^F/\partial\pi > 0$.*

Pre-positioning acts as a form of insurance since the bank can use pre-positioned securities as collateral and borrow against them. All else equal, if a bank thinks there's a higher probability of a bad state, then they will pre-position more collateral as a form of insurance.

Proposition 2. *The share of collateral posted at the Fed is increasing in the alternative collateral market's haircut. $\partial\hat{x}^F/\partial h^M > 0$.*

Higher haircuts in the alternative market make it less attractive and will lead to more prepositioning of collateral at the discount window. This prediction can help us understand the choice of which assets are held with the Fed. For example, Treasuries typically have

[16] Specifically, speculators conduct Treasury basis trades using specific Treasury CUSIPs; in order to locate those CUSIPs, they can use a bilateral repo in which they deliver cash against the specific Treasury CUSIP they want.

low haircuts in repo markets, while unsecuritized whole mortgage loans have high effective haircuts since they are largely not used in repo markets. The proposition predicts that households would pre-position unsecuritized whole mortgage loans at the discount window more often than Treasuries because of the difference in their haircuts.

Proposition 3. *The share of collateral posted at the Fed is decreasing in the discount window's haircut* h^F*.* $\partial \hat{x}^F / \partial h^F < 0$*.*

Haircuts at the Fed also contribute to the share of a collateral class pre-positioned at the Fed. Higher haircuts decrease the amount a bank can borrow from the discount window per unit of collateral. The discount window haircuts vary greatly across asset classes. While Treasury haircuts are often small—currently in the range of 1 to 5 percent depending on tenor—other securities face steeper haircuts. Loans generally face the steepest discount window haircuts, up to 34 percent for mortgages and 74 percent for construction loans, and the large haircuts might help explain why banks do not put all of their loans at the Fed when there isn't a clear alternative market to post loans.

Proposition 4. *The share of collateral posted at the Fed is decreasing in borrowing stigma* σ*.* $\partial \hat{x}^F / \partial \sigma < 0$*.*

If the stigma from using the discount window is too large, a bank will pre-position less because it may believe that it wouldn't use the discount window even in a bad state.

Proposition 5. *The share of collateral posted at the Fed is decreasing in pre-positioning stigma* σ_p*.* $\partial \hat{x}^F / \partial \sigma_p < 0$*.*

The household incurs pre-positioning σ_p even without discount window borrowing. In practice, the proposition implies that banks will try to obscure whether they pre-position and how much they pre-position.

5 Data

Our primary data source is confidential supervisory balance sheet data from the Federal Reserve FR2052a *Complex Institution Liquidity Monitoring Report*. The Fed collects the data as a part of its supervisory requirements under the Dodd-Frank Act. The data includes quantities across the largest banks' balance sheets by asset class, maturity, and other characteristics that vary by line item, but it does not include rates, prices, or CUSIPs. The data is confidential and not published publicly. Our sample runs from 2016 to 2024.[17]

[17] For additional details, see `https://www.federalreserve.gov/apps/reportingforms/Report/Index/FR_2052a`.

Large U.S. and foreign banks must submit the data either daily or monthly. We focus on the bank holding companies (BHCs) that file daily data throughout our sample, namely global systemically important bank holding companies and other banks with more than $700 billion in assets.[18] We principally use data for the bank subsidiaries of each BHC, but we also use data from the consolidated global BHC. The online appendix A.1.1 provides additional details on cleaning the data.

Our focus is unencumbered collateral that banks pre-position with a central bank against which they could borrow. This pre-positioned collateral stands ready to create *capacity*, jargon for the financing a bank can raise from the central bank against its pre-positioned collateral after haircuts, typically with very short notice. Capacity is defined narrowly and must meet two requirements:

1. it does not reflect credit already extended by the central bank to the bank
2. it cannot include pledged assets that must be pledged to support access to the central bank's payment services

The first point means a bank's capacity excludes collateral pledged to the central bank to back existing borrowing, emergency or otherwise. If a bank borrows $1 against its pre-positioned collateral, its capacity falls by $1 unless it pre-positions more. The second point excludes collateral that banks must hold with a central bank to use the central bank payment rails, for example, or to use daylight overdrafts.[19] Afonso et al. (2022a) show that high-frequency liquidity constraints stemming from payment activities are material. However, they also note that the largest banks are extremely conservative in their liquidity to the point that they view daylight drafts as stigmatizing.

We define our key motivating variable as the *capacity ratio*:

$$\text{Capacity Ratio}_t^p = \left(\frac{\text{Pre-positioned Collateral at } p}{\text{Unencumbered Assets} + \text{All Pre-Positioned Collateral}} \right)_t \tag{3}$$

where both the numerator and denominator are measured using the GAAP fair value at the close of business, and loans that are held on an accrual basis are reported at the most recently available fair value. p reflects the capacity provider (e.g., the Fed, FHLBs, or other central banks). The numerator reflects the prepositioned collateral with a specific central bank or GSE, and the denominator is the sum of all unencumbered assets and all

[18] Specifically, three types of banks must submit the data daily: global systemically important bank holding companies, category II banks, and category III banks with more than $75 billion of short-term wholesale funding.

[19] See `https://www.federalreserve.gov/paymentsystems/psr_data.htm`.

pre-positioned collateral across capacity providers. The denominator captures the pool of all possible collateral that could be pre-positioned because it excludes encumbered assets.

We also calculate two more granular versions of the capacity ratio: one that includes the collateral type, which we call Capacity $\text{Ratio}_t^{p,k}$ (e.g., k is Treasury, agency MBS, loans, equities, etc.) and another termed Capacity $\text{Ratio}_{t,t+n}^{p,k}$ that adds the maturity of the collateral n. Capacity $\text{Ratio}_t^{p,Treasuries}$ would compare the pre-positioned Treasuries with the sum of unencumbered Treasuries and all pre-positioned Treasuries. Since the collateral types have a wider maturity range that varies by asset class, we bucket collateral maturities into several buckets: less than 3 months, 6 months, 1 year, 2 years, 3 years, 4 years, and greater than 4 years. Many of our main results aggregate across asset types based on whether it counts as "level 1 high quality liquid assets" (HQLA L1). HQLA level 1 assets include cash, Treasuries, some agency debt, and some foreign sovereign bonds. HQLA level 1 assets can reasonably be considered safe assets, and non-HQLA level 1 assets—defined as any assets that are not HQLA level 1—can reasonably be considered risky assets.[20]

5.1 Capacity Facts

We document two key facts from the data.

First, banks pre-position nearly $1.1 trillion, 34 percent of their eligible assets, to the Fed and 10 percent to the FHLBs, on average. Figure 1 plots the capacity ratio aggregated across all assets and maturities. There is a clear downtrend through the sample, but there is some evidence of a business cyclical component, with a clear spike during the initial stages of the COVID panic and a level shift up during the 2023 bank turmoil. Over the sample, there is considerable range, with the Fed capacity ratio ranging from 26 to 42 percent. The number is surprising in contradictory ways: it's surprising that banks pre-position such a large share of their assets, but simultaneously it's surprising they don't pre-position all or nearly all of their unencumbered assets. Moreover, there is considerable disagreement across banks in their pre-positioning. Figure 2 plots the cross-sectional standard deviation across individual banks' capacity ratios and shows a steady increase. Over time, the banks' behavior has increasingly diverged from one another.

We focus on the capacity ratio measure using unencumbered assets since unencumbered assets can be pre-positioned without restrictions. We can alternatively calculate the capacity ratio including both unencumbered and encumbered assets, which we show in the online

[20] Page 98 of the FR 2052a reporting form provides more details https://www.federalreserve.gov/apps/reportingforms/Download/DownloadAttachment?guid=854f53be-8215-4ce4-958e-5231f4975bc2.

appendix Figure A1.[21] Since encumbered assets are strictly positive, the capacity ratio with encumbered assets in the denominator is always less than the main capacity ratio. The average capacity ratio is 27 percent with encumbered assets in the denominator, compared to 33 percent in the main measure. Table A1 regresses the main capacity ratio on the capacity ratio with encumbered assets and finds the two are highly correlated, with an R^2 of 0.99 for Fed capacity ratios.

How does pre-positioned capacity compare to total bank assets? We plot the ratio of capacity relative to total bank assets for the banks in our sample, using their quarterly call report assets in the denominator, in the online appendix Figure A2. By this measure, the banks pre-positioned 12 percent of their assets at the Fed and 3.6 percent at the FHLBs. But such a comparison is a low estimate: capacity is measured at market value, while banks book nearly all loans at amortized cost. Since the fair value of banks' loans will be less than the amortized cost—because of time discounting and risk premia—the apples-to-apples comparison is capacity relative to the total fair value of bank assets, which is difficult to estimate precisely.

The confidential data does not cover the aggregate banking system since it covers only the largest banks. As a point of comparison, we present aggregated pre-positioning statistics from the Fed in 2024 in Table 3. The table shows that the aggregated banking system has posted collateral with an aggregate lendable value of $2.8 trillion, mostly from loan collateral ($1.8 trillion). The public data only provides yearly snapshots since 2021, but there is a clear upward trend pre-positioning, increasing from 8.2 percent in 2021 to 12.1 percent in 2023.

Our second key fact is that banks pledge a large share of their safe assets to the Fed. Figure 3 shows that banks pre-position about 25 percent of their Treasuries. The figure plots average capacity ratios by asset class and confirms our prior that assets with lower outside options—those with lower collateral value in private collateral markets—are pledged more intensively to the Fed. Asset classes on the top of the chart are those with the least collateral value, while those toward the bottom have the largest collateral value—at least as revealed by bank behavior.

Banks pre-position more than 80 percent of residential and non-residential loans, with the former largely going to the FHLBs. This is unsurprising: whole mortgage loans are not useful as repo collateral, for example. Investment grade debt has the next highest capacity ratio, just under 40 percent.[22] Then Treasuries (24 percent), non-IG debt (16 percent), agency (15 percent, including both agency debt and agency MBS), and other (6 percent). Sovereign

[21] Data on encumbered assets are available beginning only in May 2022.

[22] Investment grade debt includes IG corporate debt, municipal debt, ABS, and covered bonds, and private label CMBS/RMBS.

bonds and equities both have capacity ratios of less than 1 percent.

At face value, it is surprising that banks choose to pre-position such a seemingly large share of their safe assets—Treasuries and agency debt—since pre-positioning requires the bank to forgo using the security as collateral in other markets. Both are safe assets, and both should have higher collateral values in private collateral markets. The paper aims to understand this dynamic.

Table 2 shows the summary statistics for capacity ratios across several groups of asset classes. It shows that Fed capacity ratios are generally more volatile for Treasuries and assets that are not level 1 high-quality liquid assets (HQLA), and all Fed capacity ratios are more volatile than FHLB capacity ratios. In the online appendix, we plot the capacity ratio time series for several asset classes (Figure A3).

6 Empirical Strategy and Results

We use the model to frame our results. First, we test each proposition in isolation. We then combine the propositions into a kitchen-sink regression to fully describe banks' pre-positioning behavior.

6.1 Pre-positioning and the Business Cycle

All else equal, pre-positioning collateral provides a form of insurance in bad states: it minimizes the frictions the bank faces to borrow from the discount window. It allows the bank to respond quickly to a bank run. Proposition 1 shows that banks will position more with the central bank when the probability of the bad states increases. A simple test of this proposition is whether capacity ratios covary with the business cycle. If the frictions involved in borrowing from the window are so high that banks never expect to use it, then there should be no correlation between capacity ratios and the business cycle.

We reject that hypothesis and affirm Proposition 1 in Table 4, which shows the correlation of changes in the Fed capacity ratios across several slices of asset types: all assets, Treasuries, HQLA level 1 assets, and Non-HQLA level 1 assets. The first line shows that capacity ratios, aggregated across all collateral types, increase in bad states. We measure bad states using several standard measures: the VIX, the Baa-Aaa spread, the return on the KBW bank stock index, and an index of bank CDS spreads.[23] A higher VIX, higher spreads, or lower bank stock returns are strongly associated with an increased capacity ratio.

[23]The index of bank CDS spreads is CDX.NA.IG.FIN, which includes 125 of the most liquid North American financial entities with investment-grade credit ratings.

The table is instructive for three reasons. First, the table shows that banks respond quickly to bad states since the correlation uses high-frequency daily data—they are not simply putting collateral with the Fed and leaving it there; instead, they appear to actively manage it. Second, the remaining rows of the table show that banks tend to increase their capacity ratio by pledging more non-HQLA level 1 assets rather than pledging more Treasuries. The bottom row shows this clearly: the capacity ratio for non-HQLA level 1 assets covaries strongly with every measure of the business cycle. This is consistent with Treasuries better retaining their collateral value in bad states. Banks keep Treasuries deployed in private collateral markets while pre-positioning the securities that take the largest hit to their collateral value in bad states. In the online appendix Table A2, we show that the need for intraday liquidity from collateralized daylight overdrafts does not drive capacity ratios.

Since we derive capacity ratios from market values without knowing the price or quantity of the securities, one concern is that capacity ratios mechanically increase in bad states. If the security price increases in bad states, the capacity ratio will increase even with no action from the bank. However, such dynamics would be limited to safe assets since other, riskier asset classes likely lose value in bad states. The effect is also likely limited in agency MBS since they also lose value in flights to safety, as was the case during Covid and the SVB turmoil.

Do banks simply top off their pre-positioning with existing loans in bad states? Or, when they make a new loan, do they pre-position the loan immediately, regardless of the bad state? Of course, a combination of the two may be possible as well. We can exploit a unique feature of the data: banks report forward asset purchases with granular settlement dates. If a bank bought a Treasury or originated a loan today that settles tomorrow, they will report it today. With this information, we can estimate the aggregate banking system's standard pre-positioning risk management by comparing what we know will settle on a date t with the increased capacity on date t.

To test this intuition, we regress the change in the market value of pre-positioned collateral on date t on the market value of forward asset purchases that will settle on date t as reported on the previous business day:

$$\Delta\text{Capacity (Level)}_{t,t+n}^{b,k} = \alpha + \beta\text{Settling Forward Purchases}_{t,t+n}^{b,k} + \gamma\prime X_t + \varepsilon_{t,t+n}^{b,k} \qquad (4)$$

where t is the date, $t+n$ is the maturity bucket, b is the bank, and k is the asset class. X_t is a vector of controls, including date, bank, and asset class fixed effects.

If $\beta = 1$, then all changes in pre-positioning are simply explained by banks pre-positioning all their settling forward purchases with the Fed. A priori, this is implausible since the change in the market value of pre-positioned securities should depend on the pre-positioned securities on date $t-1$, the change in the market value of those securities from $t-1$ to t, and the new securities pre-positioned on t. For this reason, we should expect that $\beta < 1$. Moreover, banks report forward asset purchases for some asset classes more frequently than others; for example, forward purchases of Treasuries are much more common than forward purchases of loans. Hence, the regression likely understates the amount of new assets arriving each day that banks can pre-position.

Table 5 shows the regression results. The main result is in column (1), which shows that roughly 1.7 cents of every dollar of newly settled purchases are pre-positioned with the Fed. Column (2) limits the sample to asset classes that are HQLA level 1 and finds a somewhat higher pass-through of 2.4 cents. One concern is that banks are unable to quickly pre-position their settled purchases. This is not the case, though, since running the regression on lags of the independent variables yields no result, and the coefficients round to 0.00.

Is 1.7 cents large or small? We think it's small for two reasons. One possibility is that banks pre-position so little of their new assets because they immediately encumber them. This is not the case, though, since the last three columns repeat the regression but change the dependent variable to the change in the level of unencumbered assets. These coefficients are much larger—ranging between 36 and 55 cents. Second, 1.7 cents is also small considering that banks pre-position 34 cents for every dollar of their eligible assets. The table shows that banks are largely not simply pre-positioning their new assets as a rote matter of their standard operations, suggesting that instead, they pre-position more when their expectations for the future grow dimmer.

6.2 Alternative Collateral Market

Pre-positioning depends on the alternative collateral market. Is it better to place the collateral with the Fed to hedge against a shock or to use it in secured financing markets, like repo? Conditions in alternative collateral markets change quickly in response to market shocks. Combined with the slow adjustment in lending terms from the Fed, the relative benefit of pre-positioning can change quickly as alternative collateral markets digest shocks and haircuts or financing rates adjust.

Banks publicly note that this channel is important for pre-positioning behavior. In its 2023 10-K, Bank of New York said (emphasis added):[24]

> If there has been no borrowing at the Federal Reserve Discount Window, the

[24] See `https://www.sec.gov/ix?doc=/Archives/edgar/data/1390777/000139077724000051/bk-20231231_d2.htm`.

Federal Reserve generally allows banks to freely move assets in and out of their pledged assets account to sell or repledge the assets for other purposes. *BNY Mellon regularly moves assets in and out of its pledged assets account at the Federal Reserve.*

The model provides little structure on the alternative collateral market since the alternative varies by asset class. For Treasuries, the alternative market could be the bilateral repo market, where levered basis traders want to short specific Treasury CUSIPs. It could also be the tri-party repo market, where money funds provide financing against general high-quality collateral. The alternative market for agencies could similarly be the tri-party repo market. The only alternative market for less liquid assets, like held-to-maturity mortgages, is the Federal Home Loan Banks. There may simply be no collateral market for less liquid assets that fall outside the FHLBs' scope.

The model shows the alternative collateral market will draw more or less collateral depending on its relative costs, namely its haircut (proposition 2). The proposition is a partial derivative, meaning it is a partial equilibrium outcome, assuming the Fed does not change the discount window's financing rate or haircuts. This is a reasonable assumption since both are generally slow-moving. The Fed's haircuts are public knowledge and fixed in advance. Unlike other collateral markets, the Fed does not increase haircuts in bad states as a matter of policy. But since the Fed lends at a haircut to market values, falling market values imply smaller borrowing capacity. Since 2014, the Fed has often changed haircuts once a year each summer.[25]

We can infer haircuts using the data in three ways: for repurchases, banks report both the collateral amount and the loan amount; the difference between the two is the haircut.[26] For capacity, banks report the amount of collateral they pre-positioned and the amount of borrowing it can raise after haircuts. For unencumbered assets, banks report both the market and lendable value, and we estimate the haircut as the difference between the two.[27]

Figure 4 plots the average haircuts for collateral in the 1-month maturity bucket by broad asset class. Within each asset class, the figure shows the Fed haircut and the average haircut for the alternative collateral markets. Bilateral repo markets have the lowest haircuts, followed by tri-party repo. FHLB and Federal Reserve haircuts are always the largest, although the difference between them varies across assets. Treasuries, for example, have an average of a

[25] For historical collateral margins, see `https://www.frbdiscountwindow.org/GeneralPages/historical_margins/margin_tables`.

[26] For repurchases, banks give the maturity of the repurchase rather than the maturity of the underlying collateral so our repo haircuts aggregate across all collateral maturities.

[27] The lendable value is defined as the value the bank "could obtain for assets in secured funding markets after adjusting for haircuts due to factors such as liquidity, credit, and market risks."

0.3 percent haircut in the bilateral repo, 1.6 percent in the tri-party repo, and 2.6 percent in Fed capacity (Treasuries are too infrequently pre-positioned with the FHLBs to have a reliable haircut average). Agency debt follows the same rank ordering: bilateral (0.9 percent), tri-party repo (2.2 percent), FHLBs (3.0 percent), and the Fed (4.7 percent).

The figure, however, does not provide an apples-to-apples comparison across collateral markets because banks endogenously choose where to place collateral. We would expect banks to place collateral into markets where it is most desirable—like those markets that offer the lowest haircuts. In this sense, the figure likely overstates the spread of haircuts across collateral markets. But at the same time, many markets do not accept certain collateral types; hence, their haircut is functionally 100 percent. In this sense, the figure might understate the spread of haircuts.

We can better compare haircuts across markets by comparing haircuts on narrow subsets of assets. Table 6 regresses haircuts in private collateral markets against the Fed haircut:

$$\text{Haircut}^{b,i,k}_{t,t+n} = \alpha + \beta \text{Fed Haircut}^{b,i,k}_{t,t+n} + \varepsilon^{b,i,k}_{t,t+n} \tag{5}$$

where t is the date, $t+n$ is the maturity bucket, b is the bank, k is the collateral class, and i is the currency. The regression provides a more direct comparison of haircuts since the unit of observation is bank $\times$ collateral class $\times$ maturity bucket $\times$ currency. Insofar as this level of granularity captures the variation in risk that haircut-setters care about, the regression provides a valid haircut comparison across collateral markets. We include bank fixed effects to capture the possibility that certain banks persistently have lower or higher haircuts across markets. We also exclude observations where the haircut is 100, implying the bank cannot borrow against the asset at all because sometimes banks report a haircut of 100 and sometimes report nothing; hence, the regression is conditional on the asset having a non-missing haircut in both markets.

Our prior is that $\beta < 1$ since a 1 pp higher haircut at the Fed's discount window should, in normal times, correspond to a smaller than 1 pp larger haircut in other collateral markets. If $\beta > 1$, then—stigma aside—banks could borrow at lower haircuts from the discount window compared to other collateral markets. Table 6 confirms this intuition. A 1 pp increase in the Fed is related to an increase of 0.10 pp in the bilateral repo market, 0.16 in FICC repo, 0.15 in tri-party repo, 0.25 against the FHLB, and 1.70 for unencumbered assets.

The last column shows the regression of the bank's expected haircuts of their unencumbered assets on the Fed capacity haircut. The dependent variable is what banks expect the repo haircuts would be on assets they haven't used in the repo market. Why don't banks put these assets into the repo market? Precisely because the repo market would only be willing to lend against it at haircuts more punitive than the Fed would—hence the coefficient is greater than 1. But this presents a puzzle: why don't banks pre-position those securities where the Fed's haircut would be less than the alternative market's haircut? Stigma likely plays a role, as does the bank's expectations for the future.

Borrowing rates are also important. The discount window's financing rate is the *primary credit* rate, which the Fed sets at a fixed spread to the upper bound of the target Federal Funds rate. Before the Covid pandemic, primary credit was 50 bps above the upper target, but the Fed adjusted the spread to 0 during the initial panicked stages of the pandemic.[28]

Figure 5 plots the spread between the primary credit rate and financing rates across several collateral markets: general collateral repo rate, the special overnight repo rate for the on-the-run 2-year Treasury, tri-party repo rates for Treasury and MBS collateral, and the FHLB advance rate from the Des Moines FHLB.[29] The figure gives a sense of the volatility and relative magnitudes of the financing rates—in essence, the rank ordering of the desirability of collateral—but it is not apples-to-apples since these financing rates are available only for specific subsets of collateral. The special Treasury rate, for example, is available only to investors holding the on-the-run 2-year Treasury, of which maybe there is $40 billion outstanding. Even though it is most desirable—shown by the large spread to the primary credit rate—it is the smallest collateral market of the ones we study. The FHLB rate is also relatively large compared to the other financing rates, but it is only available for housing-related assets. The tri-party repo rates are available for a much wider set of collateral, although they are a bit lower. Notice, however, that the financing rates typically have a positive spread to the discount window rate, evidenced by the fact that each line is virtually always above zero.

6.3 Borrowing Stigma and Pre-Positioning Stigma

Stigma enters our consideration in two ways. First, is discount window borrowing stigmatized? Second, is the mere act of pre-positioning collateral stigmatizing? The answer to the former is emphatically yes, and we argue that the answer to the latter is likely also yes.

[28]The Fed offers two other forms of discount window lending: secondary and seasonal credit. Primary credit is limited to banks in "generally sound financial conditions" while secondary credit is available when a bank is not eligible for primary credit, and the Fed provides it on more stringent terms. Seasonal credit is available to smaller banks that face seasonal liquidity needs, like those that arise from seasonal agriculture fluctuations.

[29]The general collateral repo rate is from DTCC, the special overnight repo rate is from JP Morgan Markets, and the tri-party repo rates are from the Bank of New York Mellon. The overnight FHLB advance rate net of dividends uses the Des Moines FHLB dividend rate on activity-based capital stock and a 4.5 percent activity-based capital stock requirement.

Borrowing Stigma Although the financial system's shape has changed over the past century, discount window borrowing remains stigmatized. Its stigma has been documented in several crises, from the Great Depression to recent turmoil, by both policymakers and researchers (Armantier et al. 2015a, Anbil 2018). The logic of borrowing stigma is straightforward. If everybody knows that only weak banks borrow from the discount window, then borrowing from the discount window signals that the bank is weak. If that borrowing became public knowledge, counterparties would run from the bank, and the bank could fail.

If stigma were sufficiently large, banks would never pre-position collateral—regardless of whether pre-positioning itself had stigma. If stigma was so large that banks would never voluntarily borrow from the window, pre-positioning would have no benefit. But borrowing stigma is not so large that it entirely prevents its use. Banks borrowed more than $100 billion during the 2008 financial crisis and more than $152 billion from the discount window in March 2023.

We find that banks that are more exposed to stigma do pre-position less, consistent with our hypothesis. We test this channel using a measure of borrowing stigma exposure motivated by Armantier et al. (2015a): we proxy for an individual bank's borrowing exposures based on how concentrated the banking system is in its Federal Reserve district. The Federal Reserve does not provide high-frequency borrower-specific discount window borrowing but instead provides weekly snapshots of its balance sheet, where discount window loans appear on the asset side of the Fed's balance sheet. The individual Federal Reserve Banks operate the discount window, so a borrowing bank uses the window from the Reserve Bank in its district. The Fed provides individual Reserve Bank balance sheet data weekly—at a somewhat less granular level—and market participants are attentive to individual Reserve Bank balance sheet growth.[30] Banks residing in Federal Reserve districts with more bank assets can better hide their discount window borrowing.

A simple and exaggerated example makes the intuition clear. Suppose there are only two Federal Reserve districts, each with its own Reserve Bank. One district has 100 equal-sized banks, each with $100 assets. The other district has two equal-sized banks, each with $100 in assets. Stress comes to the banking system, and each Federal Reserve Bank reports that its loans have increased by $200. What can the market infer? For the 100-bank district, it's hard to tell—at least two banks borrowed, and at most 100 banks borrowed $2 each. In the

[30]The aggregate Fed system balance sheet separately lists primary credit as a separate line item in Table 1 of the H.4.1, while the district-specific Table 6 of the H.4.1 groups primary credit into a line item covering "Securities, unamortized premiums and discounts, repurchase agreements, and loans," where loans include discount window loans. The Fed changed the weekly reports in 2020 to help mitigate this potential source of stigma by grouping primary credit along with several other Fed assets in a single line item. Before 2020, the weekly snapshot provided primary credit by district, not aggregated with other asset types (Kelly, 2024).

2-bank district, both banks must have borrowed. The market would infer both banks were weak.

This example is exaggerated and simplified. In practice, each district has a thick cross-section of banks, and discount window borrowing is never such a large share of total bank assets. Still, a more subtle version of these dynamics is likely at play, and market participants say as much. The CEO of PNC, Bill Demchak, noted: "The day you hit [the discount window] for anything other than a test, you effectively have told the world you've failed. And investors look at that number; it's disclosed because it's by district" (Kelly, 2024).[31]

We test the relationship between borrowing stigma and pre-positioning using a proxy for an individual bank's exposure to borrowing stigma, the Herfindahl-Hirschman Index (HHI) of bank assets in a given district. The HHI is a common measure for market concentration calculated using a firm's market share s_i (in percent):

$$HHI = \sum_{i=1}^{N} s_i^2.$$

An HHI of 0 implies that the market has many equally sized firms, while a large HHI implies that fewer firms constitute a large share of the market. The maximum HHI is 10,000 if the firm has the entire market share (HHI $= 100^2 = 10,000$). [32]

We create the data for this test in three steps. First, we use call report data to measure the concentration of bank assets within each Fed district for each quarter:

$$HHI_t^{dist} = \sum_{i \in \text{dist banks}} \left(\text{Market Share}_t^i\right)^2$$

where

$$\text{Market Share}_t^i = \frac{\text{Bank } i \text{ Assets}_t}{\text{Total Bank Assets in Same District}_t}.$$

The process yields a district-by-quarter panel of HHI measures.

Second, we merge the HHIs to individual banks in our sample based on which district the bank is based in. In doing this, each bank in the same district will have the same HHI variable merged to it. If a bank has multiple depository subsidiaries that span different Federal Reserve districts, we calculate a value-weighted HHI with the weights taken from the relative share of its assets in each Fed district.

Third, we calculate quarter-end values for capacity ratios from the daily data since call

[31] See also, WSJ (2023, March 18). "Fed Data: Most Emergency Lending Was in the West."
[32] See https://www.justice.gov/atr/herfindahl-hirschman-index.

report data are available quarterly. We also lag the HHI measures by 1 quarter in the regression since markets would not know contemporaneous district HHIs since the data is released with a lag.

We show that banks pre-position less when they are more exposed to borrowing stigma. Table 7 shows the regression of capacity ratios on the HHI measure using the quarter-by-bank panel. The first two columns use the capacity ratios, as previously defined, as the dependent variable. The independent variables are the HHI measures, which we standardize into z-scores to make the coefficients easy to interpret.[33] The first column is the main result: a one standard deviation increase in the Fed district HHI for a bank decreases its Fed capacity ratio by 24pp—an economically meaningful effect given the aggregate banking system averages a capacity ratio of roughly 34 percent. The regression includes bank fixed effects because banks with different business models and risks may have persistently higher or lower capacity ratios compared to others, even if they agree on the cost of borrowing stigma.

The remaining columns run several robustness tests. Since FHLB borrowing via advances is not stigmatized, we should not see FHLB pre-positioning fall in more concentrated Fed districts. Column (2) confirms that with an insignificant coefficient, the coefficient is an order of magnitude closer to 0. As additional robustness, the last two columns repeat the regression but swap the denominator of the capacity ratio from eligible assets (as used in the first two columns) with total deposits instead. The results show a similar picture: banks in more concentrated districts—and hence with larger exposure to borrowing stigma—pre-position less at the Fed, and the effect is absent for FHLB pre-positioning.

Pre-Positioning Stigma We find evidence that banks may view pre-positioning collateral as stigmatizing, not only because it indicates a potential willingness to borrow from the window in bad states but also because increased pre-positioning could signal that the bank has grown riskier or weaker. We show this in three ways. First, we manually collect data from public SEC filings and find the largest banks virtually never disclose how much they pre-position with the Fed. Second, we use the full sample of 10-Ks from public banks and find only a small share of banks disclose their pre-positioning. Third, we show that banks with higher stigma exposure are also less likely to disclose Fed pre-positioning even though they are more likely to disclose FHLB pre-positioning.

Nearly all of the largest banks publicly disclose no information on their pre-positioning. We manually collate data from eight U.S. GSIBs 10-K reports and categorize the banks into three groups: limited, bucketed, or full details. There is considerable variation in how

[33] The z-scores normalizes each variable using $\hat{x} = (x - \mu)/\sigma$ where μ and σ are the mean and standard deviation of variable x.

firms report their pre-positioning in their public annual reports, although these categories reasonably capture that variation. We define "full details" if the bank provides a specific amount of total pre-positioning with the Federal Reserve for liquidity purposes. We define "bucketed details" if the bank reports a specific pre-positioning amount specific to the Federal Reserve and the FHLBs (or foreign central banks), but not a breakdown between the two. Finally, we define "limited details" as anything between no mention of pre-positioning and mentions that the firm may or does pre-position with the Federal Reserve without more details. Some examples are helpful.

- Limited Details. From Citi's 2022 annual report (emphasis added):

  > As of December 31, 2022, Citigroup had approximately $1,045 billion of available liquidity resources to support client and business needs, including end-of-period HQLA assets; additional unencumbered securities, including excess liquidity held at bank entities that is non-transferable to other entities within Citigroup; *available assets not already accounted for within Citi's HQLA to support the Federal Home Loan Bank (FHLB); and Federal Reserve Bank discount window borrowing capacity.*

  While some firms simply never mention the discount window, many firms explicitly or implicitly describe pre-positioning when they discuss their liquidity sources.

- Bucketed Details. From Bank of America's 2022 annual report (emphasis added):

  > Our bank subsidiaries' liquidity is primarily driven by deposit and lending activity, as well as securities valuation and net debt activity. *Bank subsidiaries can also generate incremental liquidity by pledging a range of unencumbered loans and securities to certain FHLBs and the Federal Reserve Discount Window. The cash we could have obtained by borrowing against this pool of specifically-identified eligible assets was $312 billion and $348 billion at December 31, 2023 and 2022.* We have established operational procedures to enable us to borrow against these assets, including regularly monitoring our total pool of eligible loans and securities collateral. Eligibility is defined in guidelines from the FHLBs and the Federal Reserve and is subject to change at their discretion. Due to regulatory restrictions, liquidity generated by the bank subsidiaries can generally be used only to fund obligations within the bank subsidiaries, and transfers to the Parent or non-bank subsidiaries may be subject to prior regulatory approval.

The bucketed category is limited to firms that report pre-positioning specific to central banks or other government-affiliated agencies, like the FHLBs. If a bank discloses its total pledged assets without specifically stating the amount to central banks, we consider that "limited details" since we cannot tell how those pledged assets are used (e.g., as repo collateral vs. capacity with central banks).

- Full Details. Bank of New York Mellon's 2022 annual report:

  At Dec. 31, 2022, BNY Mellon had pledged assets of $138 billion, including $106 billion pledged as collateral for potential borrowings at the Federal Reserve Discount Window and $8 billion pledged as collateral for borrowing at the Federal Home Loan Bank.

Figure 6 plots the information in the banks' annual reports between 2007 and 2023. More than half of the banks provide limited details. The next largest group is "bucketed," and the smallest is the "full detail" group. The is perhaps a weak trend for banks to provide more information over time, with an uptick of banks reporting bucketed information. The preferred choice to report bucketed information is consistent with pre-positioning itself possibly being stigmatized because FHLB borrowing is not stigmatized.

There is likely pooling by bank type. Based on our small sample of large banks, the money-center banks (Bank of America, Citi, JP Morgan, Wells Fargo) tend to follow a similar bucketed reporting strategy. Both custodial banks (State Street and Bank of New York Mellon) provide full details. Both legacy investment banks—Goldman Sachs and Morgan Stanley—are in the limited details group with one notable exception: the 2010 MS 10-K provided full details, perhaps as a response to turmoil during the fallout of the financial crisis.

How representative is the behavior of the largest banks for the rest of the banking system? We turn to automated textual methods to estimate the total amount of pre-positioning across all publicly traded banks. We begin with the universe of 10-K filings from 1995 to 2023, and we limit the sample to SIC codes that could include banks.[34] We then identify 10-Ks that disclose pre-positioning. We do basic cleaning on the raw SEC filings to remove various formatting elements and tags. We look for excerpts within a filing that include the string "pledg" along with one of "federal reserve," "frb," "discount window," "fhlb," or "federal home loan bank." This process flags roughly about 10,000 10-Ks with 34,000 candidate excerpts about pre-positioning. As robustness, we also checked other phrases, including "capacity," "pre-positioning," and "position," but found that pledging is by far the most common way banks describe their pre-positioning.

[34]Specifically, we use 6021, 6022, 6029, 6035, 6036, 6141, 6172, 6199, 6211. This spans a wider set than depository institutions since many types of financial firms can have bank subsidiaries.

Given the number of filings and the variety in how firms report their pre-positioning data, we turn to a standard large-language mode (LLM), ChatGPT 4o, to help us process the data.[35] The process yields an estimated pre-positioned amount with the Fed, the FHLBs, or a combined Fed and FHLB number.

Our data-cleaning process requires several caveats. First and foremost, the LLM may inaccurately answer the prompt. We randomly select 5 percent (about 2,000 excerpts) of the sample and verify that it is correct more than 96 percent of the time. Second, we manually verify its accuracy for the largest 25 banks since these banks likely dominate aggregate pre-positioning if they disclose. Third, we run the model several times over the same excerpts and check instances when the model reports different values, which happens in less than 1 percent of the excerpts.

There are two cases when the LLM performs poorly: first, in a small number of cases, firms report their pre-positioning in a table rather than in a sentence. We will miss these cases since we focus on excerpts that have "pledging" or a variant of the word. Second, the LLM will record the incorrect level in the relatively infrequent case that the excerpt does not include the units (e.g., thousands, millions, billions).

Figure 7 shows the results. The left-hand side of the figure shows the share of all filers that disclose their pre-positioning with either the Fed, the FHLBs, or the combination of the Fed and the FHLB.[36] The "combined" line reflects banks that report *only* a combined amount.

The figure makes three facts clear: first, less than 30 percent of banks disclose how much they pre-position with the Fed. This is evidence that at least some banks view pre-positioning disclosures as stigmatizing. One challenge is distinguishing disclosure of pre-positioning from whether the bank actually pre-positions. Fed pre-positioning disclosure could be low because banks choose not to disclose it or because they simply do not pre-position. Either case would be consistent with pre-positioning stigma. An alternative would be that all banks that pre-position disclose they do so, implying that only 30 percent of banks pre-position. This is

[35]We provide each excerpt to the LLM with the following prompt (without the JSON formatting): In the following excerpt, identify and extract the amounts of collateral pledged for potential borrowing from the Federal Reserve (also called the Fed or FRB) or the Federal Home Loan Banks (FHLB). If only a combined amount is provided, use the combined field. If no amounts are specified but pledging to one of these institutions is mentioned, use "Not Specified." If the excerpt is irrelevant, use "Not Relevant." For amounts from two different years, use the most recent. Provide your confidence level on a scale of 1 (low) to 10 (high). Respond only with the JSON format: Fed_Specific_Amt: "amount"; FHLB_Specific_Amt: "amount"; Fed_And_FHLB_Combined_Amt: "amount"; Confidence_Level: "confidence.")

[36]The denominator is the total number of filers in the SIC codes of interest for each year, as provided by the 10-K filing summary data from Loughran and McDonald (2016). Since their data ends in early 2023 and therefore does not include the full set of filers that reported annual reports for 2023 after February 2023, we set the denominator in 2023 equal to the number of relevant filers in 2022 from their data.

likely not the case, at least in recent years when public pre-positioning data is available. For example, public Fed data shows that between 1,700 and 2,000 banks have pre-positioned some nonzero collateral amount between 2021 and 2023. But there are about 4,100 commercial banks[37] This implies that about 40 percent of banks have pre-positioned, which is greater than the highest disclosure share in the 10-K data. The comparison is imperfect since our sample is limited to publicly-traded banks.

Second, the figure also suggests the existence of pre-positioning stigma because a larger share of banks disclose that they pre-position with the FHLBs than with the Fed, and a sizable portion of filers only report a combined pre-position amount. As mentioned, FHLB advances are not stigmatized like discount window loans.

Third, the figure also suggests that pre-positioning stigma has fallen, at least insofar as more banks report pre-positioning over time. The number of banks disclosing pre-positioning tends to jump after crisis periods, which is clear from the vertical lines at 2008, 2020, and 2023. We cannot distinguish whether more banks are simply disclosing their pre-positioning amounts or more banks are choosing to pre-position and one-for-one disclosing that. Either case suggests that pre-positioning stigma is falling over time, at least somewhat.

The right panel of Figure 7 goes one step further and calculates the actual level of pre-positioning disclosed by the 10-K filers. This measure is subject to more error since the LLM is better able to identify whether a bank discloses a pre-positioning than it can identify that amount (namely because the LLM inaccurately records the level when the excerpt excludes the units, like billions or millions). Still, the figure is instructive along several dimensions. It shows that the amount of pre-positioning tends to increase over time, with the largest change coming from banks disclosing a combined Fed and FHLB pre-positioning amount, as shown in the red line. Over the last three years, the combined pre-positioning amount has increased by more than $500 billion. The figure also shows that disclosed Fed pre-positioning tends to be smaller than FHLB pre-positioning at all points since 1995.

The online appendix breaks down the pre-positioning 10-K disclosures based on bank size: GSIBs, medium-sized banks, and all other banks.[38] These are shown in figures A4, A5, and A6. Looking at each bank group, we see that there has been a shift toward more banks disclosing their pre-positioning over time, but only 25 percent of the largest and smallest banks disclose Fed pre-positioning. Medium-sized banks are unique because they are more

[37] For public pre-positioning numbers see `https://www.federalreserve.gov/monetarypolicy/discount-window-readiness.htm`. For the total number of commercial banks see `https://banks.data.fdic.go`.

[38] Medium-sized banks are category II to category IV banks, which includes banks with over $100 billion in total assets. This bucketing of banks did not exist in 1995 and thus is subject to backward-looking bias. But other ranking systems, like ranking based on bank assets, are nearly identical for the largest banks, and merging SEC filings with bank call reports is imperfect, especially in the earlier part of the sample.

likely than not to disclose Fed pre-positioning, with about 50 percent disclosing in 2023.

Our final test to show evidence of pre-positioning stigma compares a bank's stigma exposure with its decision to disclose pre-positioning. We find that banks with higher stigma exposure, proxied using the HHI measure, are significantly less likely to disclose any pre-positioning with the Fed.

We calculate each bank's stigma exposure using the concentration of bank assets in its Federal Reserve Bank district in a given quarter, as before. We then merge in the 10-K pre-positioning data.[39] As before, we standardize the HHI measure to a z-score. The regression is

$$\mathbb{I}(\text{Disclose Fed Pre-positioning}_t^b) = \alpha + \beta \text{HHI}_{t-1}^d + \delta_t + \varepsilon_t^b$$

where δ_t are time fixed effects, and HHI_{t-1}^d is the HHI of the bank's district d. The regression is at the bank-by-year level, although banks sometimes report their 10-K for a quarter other than the fourth calendar quarter. We also lag the district HHI by a quarter to reflect the lag in available information.

The first two columns in Table 8 show the main result: the negative coefficient on HHI_t^b means that a one standard deviation increase in stigma exposure decreases the probability the bank discloses its pre-positioning by 0.8pp. The effect is sizable when compared to the unconditional probability a bank discloses of 12 percent. The second column excludes quarter fixed effects, instead using a time trend and a proxy for the business cycle, the Baa-Aaa spread, and finds a nearly identical coefficient.

Since the regression does not control for bank risk or business models, one concern is that banks systematically sort into Fed districts based on their line of business. In that case, the bank's characteristics determine its pre-positioning disclosure rather than its Fed district. To be sure, banks' choices about where to locate are endogenous. Still, we find evidence that this channel is likely not the primary one with a robustness test using FHLB pre-positioning disclosures in columns (3) and (4). In these two columns, we replace the Fed disclosure dummy with a dummy equal to 1 if the bank discloses its FHLB pre-positioning and 0 otherwise. The tests show that banks with more stigma exposure are more likely to disclose FHLB pre-positioning, the opposite of the results in the first two columns. It is unlikely that banks sort into Fed districts in a way that systematically coincides with not disclosing Fed pre-positioning yet disclosing FHLB pre-positioning. It also rules out the

[39] To merge these datasets, we merge the CRSP/Compustat link and the New York Fed's CRSP-FRB link, which links RSSD IDs to CRSP permcos. We then merge with the FFEIC attributes file, and keep the resulting matched dataset, providing the universe of publicly traded banks. We then merge this sample to the 10-K data on CIKs.

possibility that banks in high HHI districts simply prefer not to disclose anything—Fed or FHLB—since they are more likely to disclose FHLB pre-positioning. The regression shows that banks with more stigma exposure are more likely to disclose potential un-stigmatized funding from the FHLBs and less likely to disclose potential stigmatized funding from the Fed.

Table 8 is similar to the regression of capacity ratios on HHIs shown in Table 7, but there are several important differences. First, Table 7 used confidential data on actual pre-positioning for only the largest banks. Second, recall that we have shown the largest banks tend to not publicly disclose their Fed pre-positioning. For these reasons, we argued that the regression in Table 7 focused on *borrowing* stigma, and not pre-positioning stigma. The regression in Table 8 using 10-K disclosures introduces an extra level: it could be that banks with higher stigma exposure prefer to obfuscate their pre-positioning (which would be pre-positioning stigma) or it could be that they are actually pre-positioning less with the Fed, presumably because they are concerned about borrowing stigma. In this case, the reason they are more likely to disclose FHLB pre-positioning when stigma is higher is because they are indeed more likely to borrow from the FHLBs. We reject this alternative because there is a strong negative relationship between a bank's HHI and its FHLB borrowing as a share of its total assets, using FHLB borrowing data from public call reports. This fact indicates that banks in more stigma exposed districts do not borrow more from the FHLBs generally.

6.4 Comparing the Pre-Positioning Dynamics

We now jointly compare the forces that could drive pre-positioning dynamics using a kitchen sink regression. We show that banks pre-position less when the risk of a bad state is lower, when the alternative market is more attractive, and when stigma is higher.

We proxy for the probability of a bad state (proposition 1) using the Baa-Aaa spread and the bank's FDIC-insured or uninsured deposits. Deposits directly proxy for the bad state probability since the capacity ratio is related to the bank's expectation that it may need to tap the discount window to fund deposit outflows. Deposit levels are not directly comparable across banks since larger banks have more deposits, so we normalize the deposit values by the size of the bank's capacity plus its unencumbered assets, the same denominator we use for the capacity ratio measure.

We capture the alternative collateral market (proposition 2) by calculating the bank's average Treasury haircut across all repo markets with data (tri-party, bilateral, FICC, and other). We trim the haircuts at the 5th and 95th percentiles to reduce the influence of unrealistic outliers. Ideally, we would directly compare haircuts across more than just

Treasuries, but the data are not sufficiently granular to tell if differences in haircuts are due to collateral differences. However, we assume that a bank facing a larger Treasury haircut would likely also face higher haircuts to finance riskier securities. On a given day, the Treasury repo haircut functionally ranks banks based on how attractive the alternative collateral market is for that bank. A bank might have a higher haircut than other banks because its counterparties view it as riskier or because the bank has a different segment of counterparties, and those counterparties do not value the Treasury collateral as highly as another bank's counterparties do. Such dynamics are first-order given the importance of relationships in secured financing markets, as documented by Senyuz et al. (2023). We also capture the opportunity cost of the alternative collateral market by using the spread between the effective fed funds rate and the general collateral financing rate, which broadly captures the advantage of secured repo financing compared to unsecured financing.

We also capture stigma exposure using the HHI measures that reflect the concentration of a bank's FRS district, following the method described earlier. We compare how the three frictions measured above contribute to the share pre-positioned. We run the following regression:

$$\begin{aligned}\text{Capacity Ratio}_t^{k,b} = \alpha &+ \beta_1(Baa - Aaa)_t \\ &+ \beta_2(\text{Insured Deposits}_t^b) + \beta_3(\text{Uninsured Deposits}_t^b) \\ &+ \beta_4\left(EFFR - GCF\right)_t + \beta_5(\text{Treasury Repo Haircut}_t^b) \\ &+ \beta_6\left(\text{HHI}_t^b\right) \\ &+ \gamma^b + \delta_t + \varepsilon_t^k\end{aligned}$$

where t is the date, b is the bank, and k is the asset class type (aggregated across all collateral types, only Treasuries, or aggregated across all types of non-HQLA level 1 collateral). We also include time fixed effects δ_t and bank fixed effects γ^b in several specifications. We transform each variable into a z-score using its mean and standard deviation, so each coefficient can be read as the effect of increasing the candidate force by one standard deviation, all else equal.

Table 9 shows the regression result. The first three columns have no fixed effects, the next three have bank fixed effects, and the final three have both time and bank fixed effects. The first column looks at pre-positioning aggregated across all collateral types with no fixed effects. It shows that banks pre-position more when the Baa-Aaa spread is higher, when the bank has more uninsured deposits, or when it faces larger Treasury repo haircuts. Banks pre-position less when the EFFR-GCF spread is larger, meaning borrowing in GCF repo markets is cheaper than in fed funds. Banks pre-position less when they are in more concentrated Federal Reserve districts. Intuitively, each force behaves as expected, but the relative magnitude is important: a one standard deviation increase in uninsured deposits is associated with an 18pp higher capacity ratio, a much larger effect than any other variable. The next largest are HHI (−1.7pp) and the repo haircut (1.4pp). This specification does not exclude the possibility that banks with large uninsured deposits also happen to be banks that prefer to pre-position more for unrelated reasons.

We address this by including bank fixed effects in column (4). A bank fixed effect effectively strips out the average capacity ratio for each bank, so the coefficients tell us about the marginal relationship between the forces and the demeaned capacity ratio for each bank. The uninsured deposits coefficient is still large (6.9pp) but smaller than the HHI, which is now much larger (−19.2pp). Insured deposits have a similar coefficient to uninsured deposits, so banks hedge deposits—either insured or uninsured—by pre-positioning. Finally, the Treasury repo haircut is still significant, but the EFFR-GCF spread is no longer significant, although the coefficient is still weakly negative. The disadvantage of this specification is that it does not control for possible time trends in the sample.

We address this last point by including both time and date fixed effects, shown in column (7). The coefficients tell us about the marginal effect after stripping out a given bank's average pre-positioning and stripping out the average pre-positioning across all banks on a given date. Date fixed effects are perfectly colinear with time-series variables that do not vary in the cross-section, so we can no longer include the interest rate spreads in the regression; in this sense, the date fixed effect will control for the bad-state risk captured by the Baa-Aaa spread and the alternative collateral market EFFR-GCF spread. The specification makes clear that uninsured deposits and insured deposits both increase pre-positioning in roughly equal amounts, while the Treasury haircut relationship is much smaller: a one standard deviation increase in a bank's Treasury haircut increases its pre-positioning by 1.6pp. Stigma is the most important explanatory variable: banks with one standard deviation increase in stigma exposure as captured by the HHI measure pre-position nearly 22pp less. The effect is large, given the average capacity ratio is about 33 percent.

A bank's pre-positioning behavior depends on the type of collateral, though. Looking at the first three columns, total pre-positioning varies with bad state risk mainly because banks move Treasuries in and out rather than other non-HQLA level 1 assets. This is unsurprising since the processing times for Treasuries are faster, and the alternative collateral market for Treasuries can change materially from day to day. Moreover, given the possibility of pre-positioning stigma, it would likely be easier and faster for banks to withdraw pre-positioned Treasuries. Even so, banks appear to pre-position more non-HQLA level 1 assets when the bank has more deposits, likely because deposits are generally highly persistent.

Treasury pre-positioning also strongly responds to the alternative collateral market more than non-HQLA assets, evidenced by the larger haircut coefficient for Treasury pre-positioning (column 2, 5.0) compared to the non-HQLA pre-positioning (column 3, 0.8). Since the alternative collateral market measure for Treasuries is likely highly correlated with conditions in other collateral markets, non-HQLA pre-positioning is still significantly responsive to the EFFR-GCF and haircut measures. Similar dynamics persist when adding bank fixed effects (columns 5 and 6) or bank and time fixed effects (columns 8 and 9).

The table also confirms that pre-positioning stigma may affect a bank's choice of which collateral to pre-position. If banks want to pre-position securities that are both cheapest to pre-position and fastest to withdraw, then we'd expect banks to prefer Treasuries over other less liquid assets, like loans. The coefficient on stigma HHI confirms this intuition in columns (8) and (9): banks with more stigma exposure pre-position fewer loans (non-HQLA level 1) than they do Treasuries. In other words, a bank with high stigma exposure could pull back on pre-positioning loans much faster than pre-positioning Treasuries. This could be because banks can withdraw their pre-positioned Treasuries much faster and because loans require more administrative costs and a longer onboarding process, so impose a larger fixed cost to pre-positioning in the first place. A bank could be reluctant to pay that fixed cost if it wants the option to withdraw it later.

In the online appendix Table A3, we also include several additional controls, including the amount of Treasury debt outstanding, the 10-year Treasury yield, and unrestricted reserves standardized by the bank's capacity and unencumbered assets (the same denominator as for capacity ratios). One concern is that capacity ratios might mechanically increase through the business cycle. We show this is not the case using the 10-year Treasury yield, a standard proxy for fixed income valuations. In columns (1) and (4) of the table, we see that when Treasury yields are higher (equivalent to lower Treasury prices), capacity ratios are also higher. Another concern is that the bank's unrestricted reserves drive the variation in capacity ratios. We find our results are largely unchanged when we include a control for banks' reserves, but the significant and negative coefficient indicates that banks do have lower capacity ratios when they have more reserves.

7 Conclusion

We show that banks' pre-positioning behavior is deliberate and responds to market forces. In bad states, they pre-position more. When they have more deposits, they pre-position more. But stigma weighs on pre-positioning, as does the value of that collateral elsewhere. Banks must balance the benefits and costs of pre-positioning, and we show they do just that.

More pre-positioning is no panacea. The discount window is no fix for a fundamentally insolvent bank: Only solvent banks can borrow against good collateral. A bank with too many bad investments will stop being a going concern, even if those investments are diligently pre-positioned with the Fed. Yet even if pre-positioning is no panacea, it likely helps on the margin. Central bankers—and the real economy that depends on the stability of the financial system—should take every margin they can get.

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8 Figures

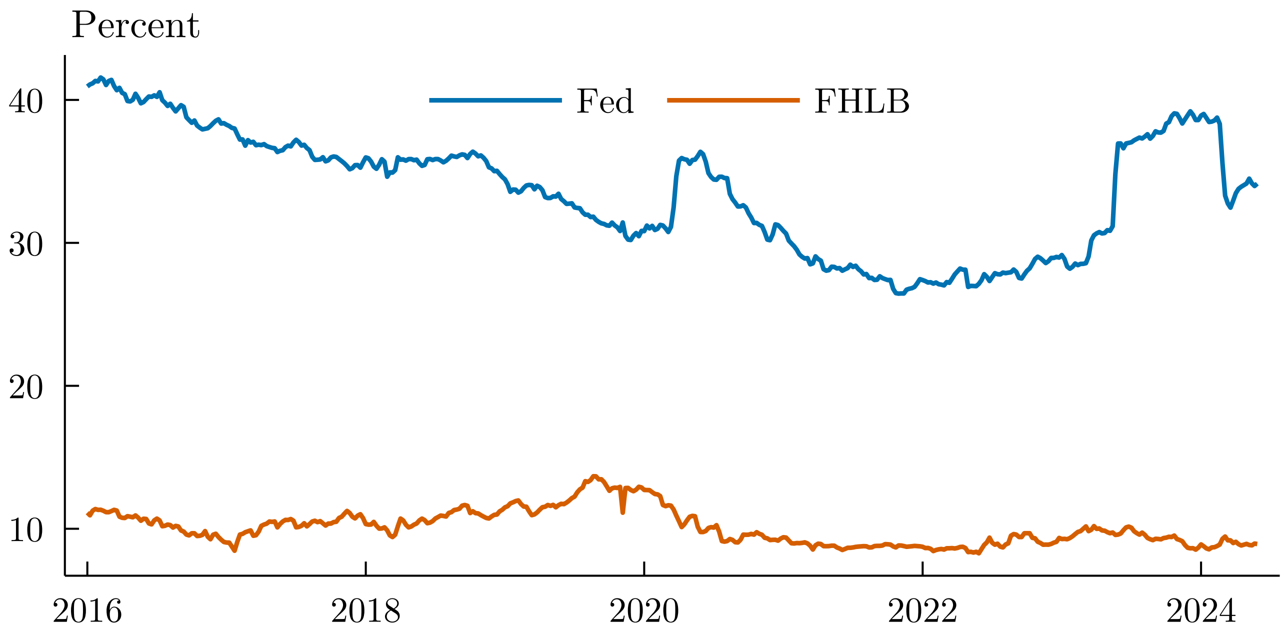

Figure 1: Capacity Ratio. Capacity Ratio$_t^p$ = (Pre-positioned Collateral/(Unencumbered Assets + All Pre-Positioned Collateral))$_t$ where both numerator and denominator are market values of the assets and p reflects the capacity provider (e.g., the Fed or the FHLBs). The numerator reflects the pre-positioned collateral with a specific central bank or GSE, and the denominator is the sum of all unencumbered assets and all pre-positioned collateral across all capacity providers. We calculate Capacity Ratio$_t^p$ separately for the Fed and the FHLBs. Plots are weekly averages of daily data.

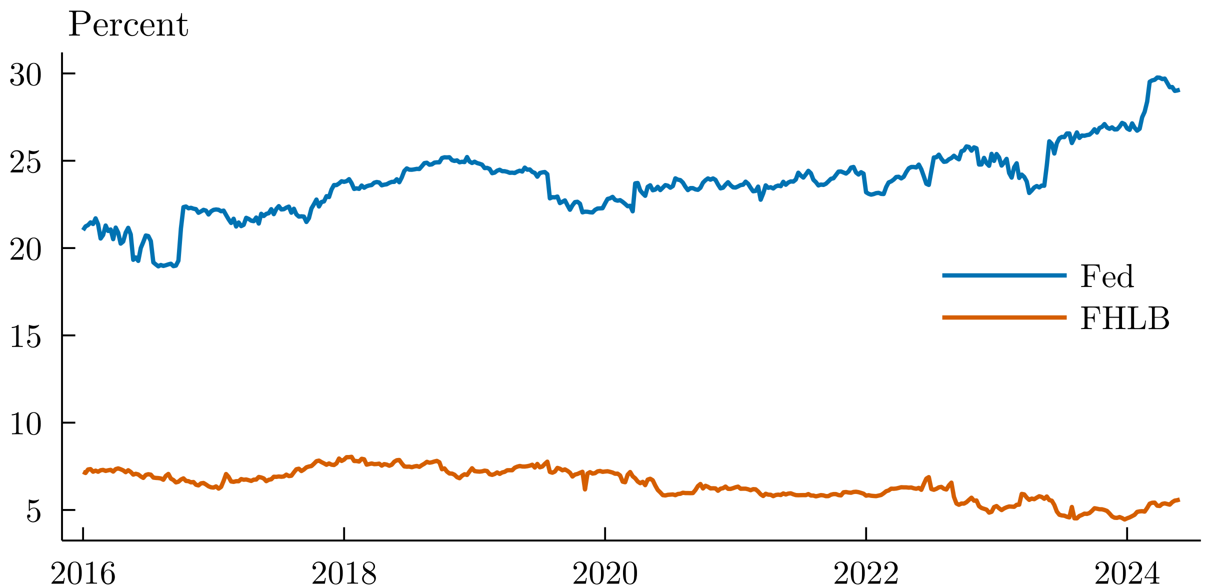

Figure 2: Cross-Section Standard Deviation of Capacity Ratio. Plot shows the standard deviation across individual banks' capacity ratios at a point in time. Capacity Ratio$_t^p$ = (Pre-positioned Collateral/(Unencumbered Assets + All Pre-Positioned Collateral))$_t$ where both numerator and denominator are market values of the assets and p reflects the capacity provider (e.g., the Fed or the FHLBs). The numerator reflects the pre-positioned collateral with a specific central bank or GSE, and the denominator is the sum of all unencumbered assets and all pre-positioned collateral across all capacity providers. We calculate Capacity Ratio$_t^p$ separately for the Fed and the FHLBs. Plots are weekly averages of daily data.

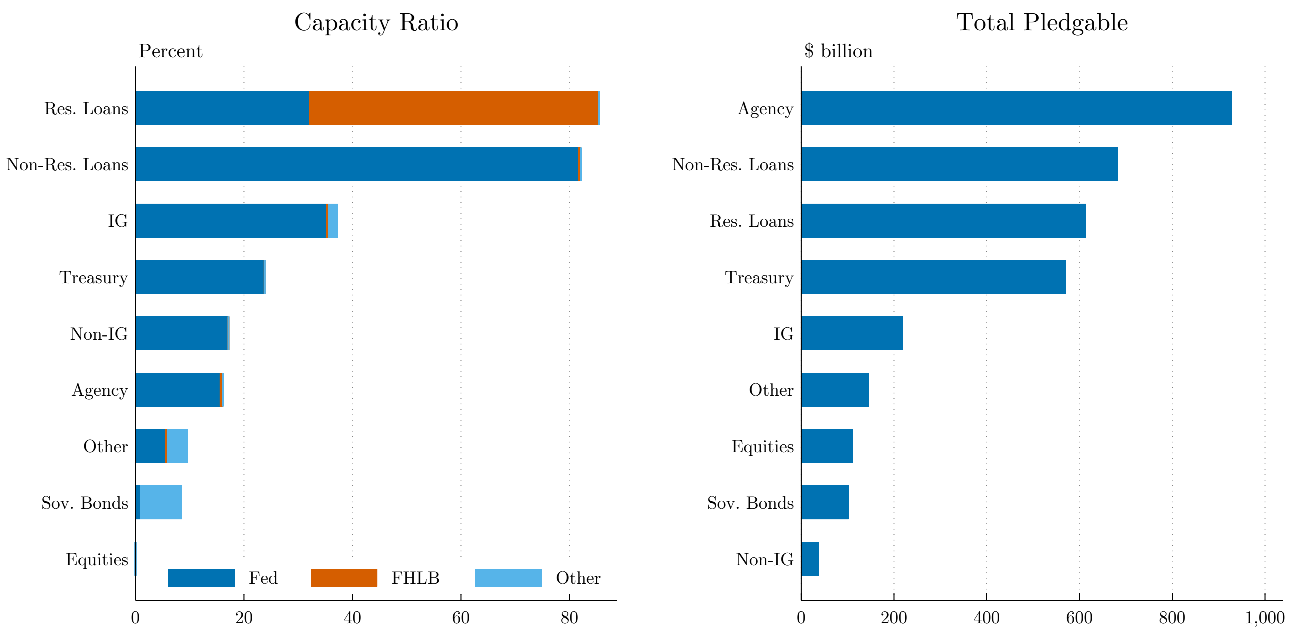

Figure 3: Average Capacity Ratio and Total Pledgeable by Asset Type and Provider. Left panel plots the average capacity ratio by provider and asset class, where capacity ratio is the capacity with that provider divided by the total amount of pledgable assets. Total pledgable assets is the sum of unencumbered assets and pre-positioned assets across all providers. IG is investment grade bonds, ABS, and MBS; Non-IG is non-investment grade bonds, ABS, and MBS; Agency is both agency MBS and agency debt.

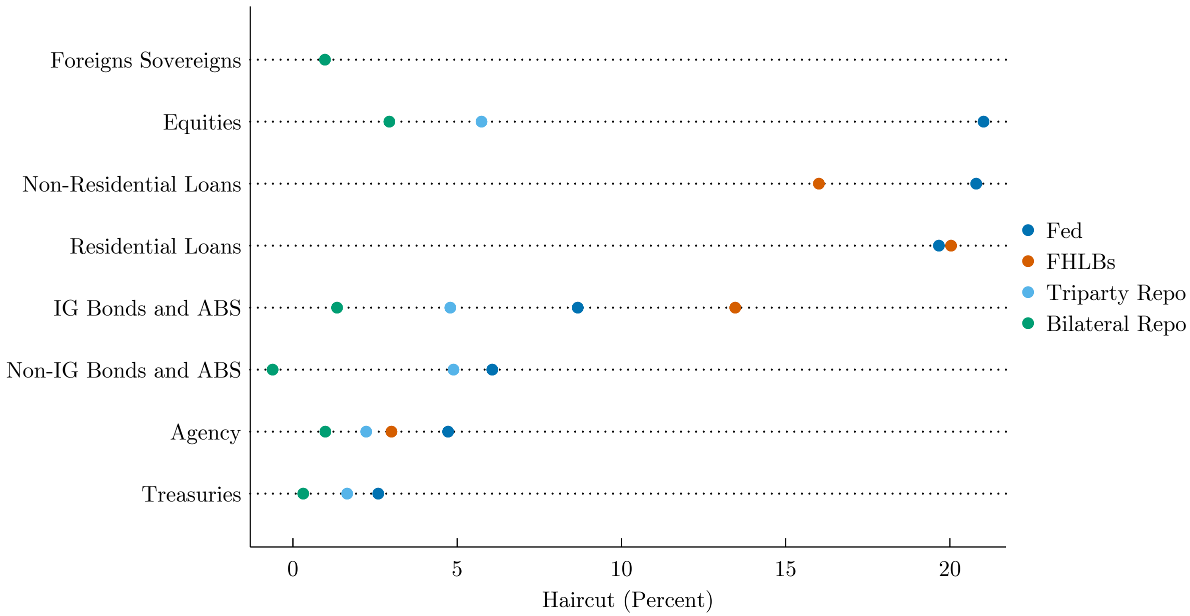

Figure 4: Haircuts Across Collateral Markets. Figure plots the average haircut on 1-month tenor collateral across asset classes and collateral markets. We exclude small markets by adding tri-party repo, bilateral repo, FICC repo, FHLB capacity, and Federal Reserve capacity, and dropping collateral markets that have less than 5 percent of the total on a given day. Excludes "other" collateral types.

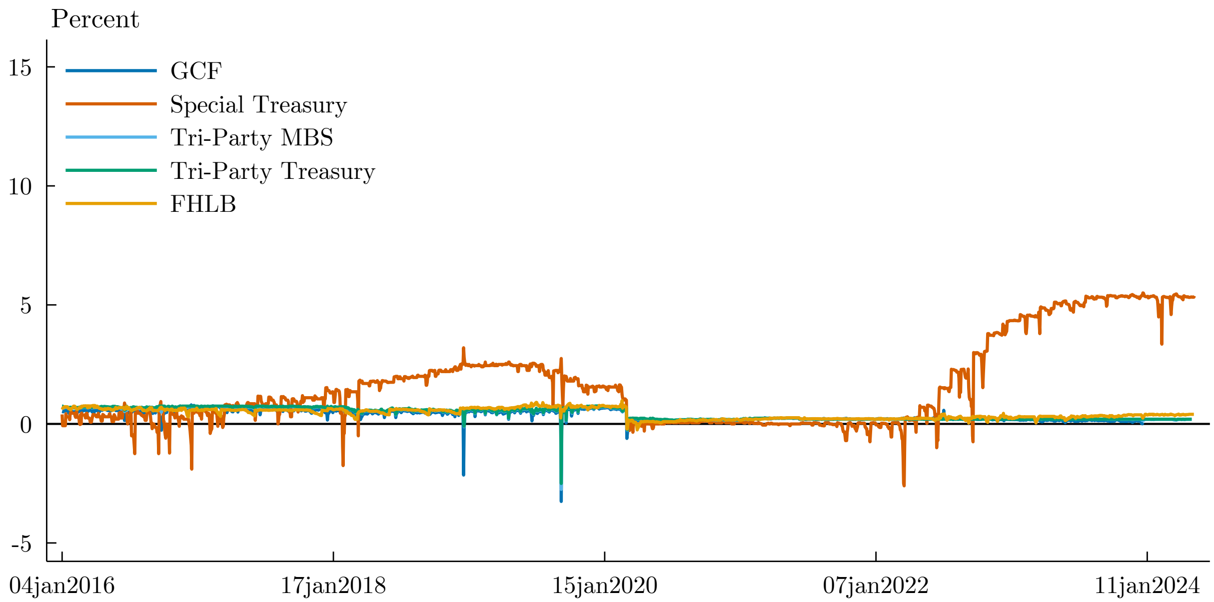

Figure 5: Financing Rates Across Collateral Markets. Figure plots the spread between the primary credit rate and the collateral market financing rate, where the financing rates are (1) general collateral finance (GCF) rate from DTCC, (2) the overnight repo rate for on-the-run 2-year Treasuries from JP Morgan Markets, (3) the tri-party MBS repo rate from BONY, (4) the tri-party Treasury repo rate from BONY, and (5) the overnight FHLB advance rate net of dividends from the Des Moines FHLB. FHLB rate uses the FHLB Des Moines dividend rate on activity-based capital stock and a 4.5 percent activity-based capital stock requirement.

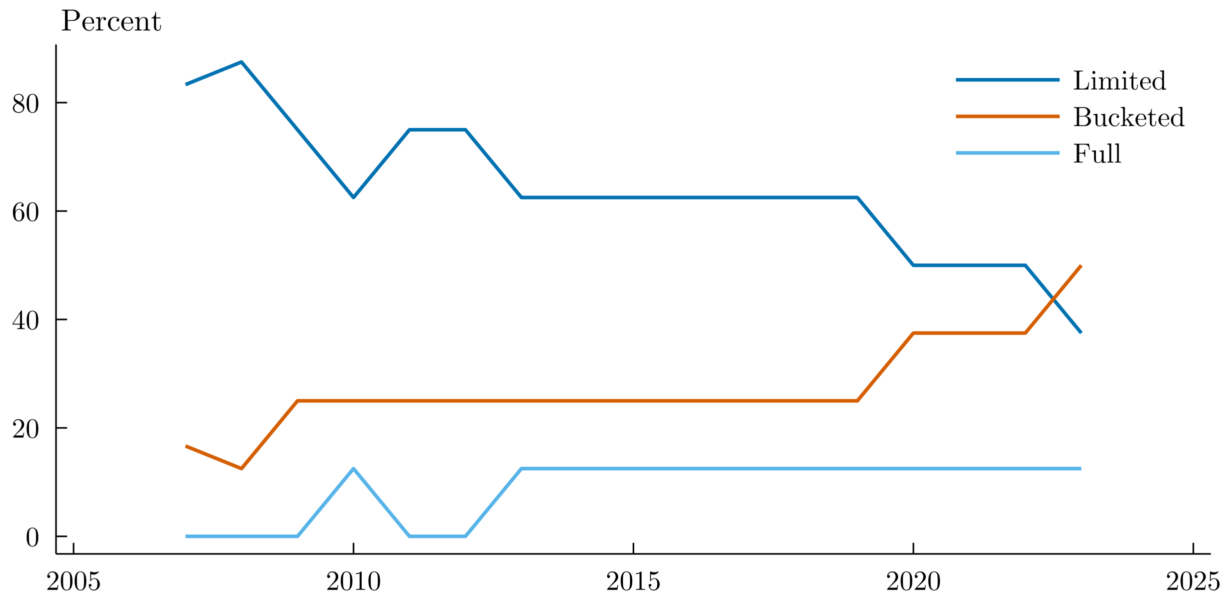

Figure 6: Public 10-K Pre-Positioning Style. Figure plots the share of banks reporting their pre-positioning by type. Figure derived only from public 10-K filings.

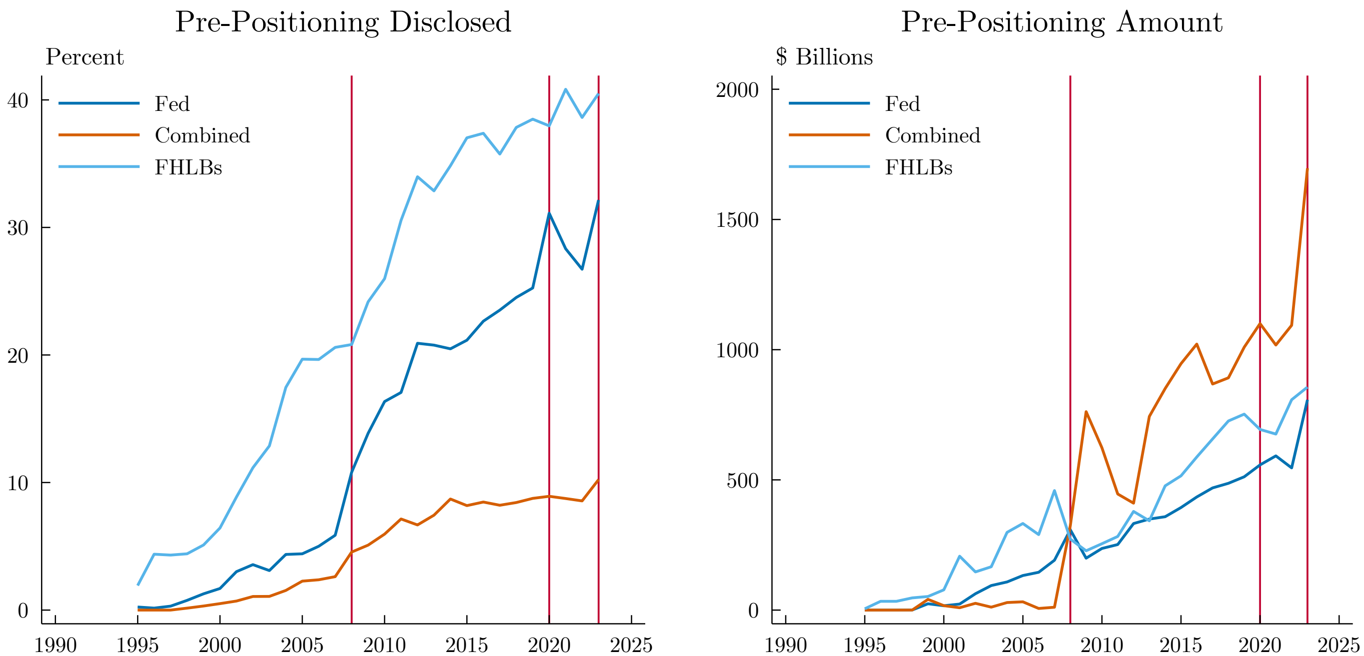

Figure 7: Pre-Positioning Disclosed in Public 10-Ks. Figure plots the share of banks reporting their pre-positioning by type. Figure derived only from public 10-K filings.

9 Tables

		Operating Hours		Processing Time	
	Form	Pledges	Withdrawals	Pledges	Withdrawals
Securities	Fedwire Securities Services	8:30am ET to 7:00 pm ET	8:30am ET to 3:15 ET	minutes	minutes
	Depository Trust Company	8:00 am ET to 5:00 pm ET	8:00 am ET to 5:00 pm ET	minutes*	minutes*
	Clearstream	Before 1:00pm ET**	Before 1:00pm ET†	varies	varies
	Euroclear	Before 12:15pm ET**	Before 10:00am ET†	varies	varies
Loans	Borrower-in-Custody	Local Reserve Bank hours	Local Reserve Bank hours	$\geq$ 1 business day	$\geq$ 1 business day
	Third-party Custody	Local Reserve Bank hours	Local Reserve Bank hours	$\geq$ 1 business day	$\geq$ 1 business day
	Reserve Bank Custody	Local Reserve Bank hours	Local Reserve Bank hours	$\geq$ 1 business day	$\geq$ 1 business day

Table 1: Pledge and Withdrawal Options. Summarized from `https://www.frbdiscountwindow.org/Pages/Collateral/pledging_collateral`. *: Most DTCC securities receive “straight through” processing; if not, it may take 10 minutes to several hours. Withdrawals that require manual intervention will be approved or rejected same day. †: cutoff time for same-day pledges.

			All	Treasuries	Agency	HQLA L1	Non-HQLA L1
(a):	*Pre-Positioned At Fed ($bn)*	Mean	1,126	136	144	161	965
		Std. Dev.	179	55	56	71	118
(b):	*Pre-Positioned At FHLBs ($bn)*	Mean	339	0	6	1	337
		Std. Dev.	51	0	5	1	50
(c):	*Unencumbered*	Mean	1,929	434	779	797	1,133
		Std. Dev.	518	216	178	226	301
$(a)/(a+b+c)^{\dagger}$:	*Capacity Ratio Fed*	Mean	33.6	25.0	15.8	16.1	40.1
		Std. Dev.	4.2	5.0	6.0	3.8	4.9
$(b)/(a+b+c)^{\dagger}$:	*Capacity Ratio FHLB*	Mean	10.1	0.0	0.6	0.1	14.0
		Std. Dev.	1.2	0.0	0.4	0.1	1.4
$(a)/\sum(a)$:	*Share of Total Pre-Positioned at Fed*	Mean		11.7	12.5	13.8	86.2
		Std. Dev.		3.6	2.7	4.3	4.3
$(b)/\sum(b)$:	*Share of Total Pre-Positioned at FHLBs*	Mean		0.0	1.7	0.3	99.7
		Std. Dev.		0.0	1.2	0.3	0.3

Table 2: Pre-Positioning Summary Statistics. Table shows summary statistics for pre-positioned assets and unencumbered assets. Summary statistics are calculated from daily observations between January 2016 and December 2023. HQLA L1 is level 1 high-quality liquid assets. †: the denominator of the capacity ratios also includes pre-positioning at other central banks, which is typically small or zero.

	2021	2022	2023
Number of institutions signed up to use the discount window	5,029	4,952	5,418
Number of institutions with collateral pledged	2,596	2,634	2,917
Total lendable value of collateral ($ billions)	1,904	2,060	2,756
Loan collateral ($ billions)	1,257	1,373	1,806
Securities collateral ($ billions)	647	687	950
Memo: number of institutions	10,134	9,813	9,537
Total Commercial Bank Assets ($ billions)	23,315	23,028	22,852
Lendable value vs. Total Assets (percent)	8.2	8.9	12.1
Share of firms signed up to use discount window	49.6	50.5	56.8
Share of firms with collateral pledged	25.6	26.8	30.6

Table 3: Aggregate Banking System Pre-Positioning Summary Statistics. Table shows the publicly available summary statistics provided by the Federal Reserve for banks and credit unions. Total commercial bank assets are non-seasonally adjusted total assets in the last weekly public H.8 report from the Federal Reserve. See `https://www.federalreserve.gov/monetarypolicy/discount-window-readiness.htm`.

	Correlation of ΔCapacity Ratio$_t^{Fed,k}$ with:				
k	VIX	Baa-Aaa	Bank Index Stock Return	Bank Index CDS	$\Delta\ln$(Unrestricted Reserves)
All	0.08***	0.06**	−0.06**	0.10***	0.09***
Treasuries	0.04	0.01	−0.04	0.03	0.01
HQLA 1	0.05*	0.02	−0.05*	0.04	0.01
Non-HQLA1	0.07***	0.06**	−0.6***	0.09***	0.08***

Table 4: Fed Capacity Ratio Correlations. Table shows correlation of the daily change in the Fed capacity ratio, limited to specific asset classes, with the VIX, Baa−Aaa corporate bond spread, bank index stock return using the KBW bank stock index, an index of bank CDS spreads (CDS NA IG FIN), and aggregated unrestricted reserves. t-statistics are reported in parentheses where * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

	ΔCapacity (Level)$^{b,k}_{t,t+n}$			ΔUnencumbered (Level)$^{b,k}_{t,t+n}$		
	All	HQLA L1	Non-HQLA L1	All	HQLA L1	Non-HQLA L1
Settling Forward Purchase$^{b,k}_{t,t+n}$	0.0174***	0.0238***	0.00997**	0.537***	0.482***	0.367***
	(3.34)	(4.81)	(2.36)	(3.31)	(3.52)	(3.85)
N	3,659,836	910,602	2,749,234	3,659,836	910,602	119,003
R^2	0.00	0.00	0.00	0.01	0.01	0.01

Table 5: Most Forward Purchases Are Not Pre-Positioned. Table shows the regression $\Delta \textit{Capacity (Level)}^{b,k}_{t,t+n} = \alpha + \beta \textit{Settling Forward Purchases}^{b,k}_{t,t+n} + \gamma' X_t + \varepsilon^{k}_{t,t+n}$. Panel is at the date-bank-asset type-maturity bucket level. Fixed includes include date, bank, and asset class. Standard errors clustered at the date and asset class level. Both variables are measured in market values, and the settling forward amount is the market value of forward asset purchases that will settle on date t as reported on the previous business day. Dependent variable for first three columns is the change in capacity with the Fed; last three columns is the change in unencumbered assets. t-statistics are reported in parentheses where * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

	Bilateral Repo	FICC Repo	Triparty Repo	FHLB Capacity	Unencumbered Haircut
	(1)	(2)	(3)	(4)	(5)
Fed Capacity Haircut$_{t,t+n}^{b,i,k}$	0.0972***	0.164***	0.148***	0.246***	1.695***
	(16.72)	(8.47)	(49.76)	(11.87)	(96.91)
N	113,998	16,296	98,467	20,543	196,005
R^2	0.00	0.00	0.09	0.03	0.24

Table 6: Haircuts Across Collateral Markets. Table presents the regression of haircuts in several collateral markets—including bilateral repo, triparty repo, FICC repo, FHLB capacity, and unencumbered haircuts—on Fed capacity haircuts. Regression is at the date by bank by collateral class by maturity bucket by currency level. Includes bank fixed effects. Unencumbered haircuts are estimated from the bank's estimates of the lendable value for its unencumbered assets in secured funding markets. t-statistics are reported in parentheses where * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

	Capacity vs. Eligible Assets		Capacity vs. Deposits	
	Fed	FHLB	Fed	FHLB
HHI^{b}_{t-1}	-24.20^{***}	-1.961	-13.44^{***}	-0.0843
	(-5.46)	(-1.17)	(-6.03)	(-0.12)
N	288	288	288	288
Within R^2	0.06	0.01	0.05	0.00
Bank Fixed Effect	Yes	Yes	Yes	Yes

Table 7: Pre-Positioning Decreases with Stigma Exposure. Table presents the regression of capacity ratios on bank-specific HHI measures. The first column columns use the capacity ratio, as defined in the paper as the ratio of total pre-positioned collateral as a ratio of eligible assets, either the Fed capacity ratio or the FHLB capacity ratio. The last two columns replace the denominator of the capacity ratio from the bank's eligible assets to the bank's total deposits. The HHI measure is calculated using the total assets by Fed district by quarter and is lagged by 1 quarter. The HHI measure is standardized as a z-score for legibility. t-statistics are reported in parentheses using robust standard errors where * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

	$\mathbb{I}$(Disclose Fed Pre-positioning^b_t)		$\mathbb{I}$(Disclose FHLB Pre-positioning^b_t)	
HHI^b_{t-1}	-0.804^{**}	-0.841^{**}	1.125^{***}	1.139^{***}
	(-2.41)	(-2.54)	(3.97)	(3.82)
Baa-Aaa_t		-0.474		0.725
		(-0.89)		(1.36)
Time Trend_t		0.342^{***}		0.432^{***}
		(36.90)		(35.17)
N	14,566	14,568	14,566	14,568
Within R^2	0.00	0.11	0.00	0.13
Time Fixed Effect	Yes	No	Yes	No

Table 8: Pre-Positioning Disclosure Decreases with Stigma Exposure. Table shows the regression of a dummy variable equal to 1 if a bank has disclosed its pre-positioning in that period on the HHI of bank assets in that bank's district. First two columns dependent variable is whether the bank discloses Fed pre-positioning, last two columns is FHLB pre-positioning. t-statistics are reported in parentheses using robust standard errors where * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

	All	Treasuries	Non-HQLA L1	All	Treasuries	Non-HQLA L1	All	Treasuries	Non-HQLA L1
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Bad State Risk									
$\text{Baa} - \text{Aaa}_t$	0.97*	1.80***	0.87	0.94**	2.99***	0.55			
	(1.73)	(2.82)	(1.31)	(2.28)	(4.18)	(1.23)			
$\text{Insured Deposits}_t^b$	−0.88	−7.92***	−1.01	6.94***	4.57***	6.04***	7.08***	8.02***	5.24***
	(−1.11)	(−7.83)	(−1.07)	(4.95)	(3.48)	(4.35)	(4.61)	(5.47)	(3.43)
$\text{Uninsured Deposits}_t^b$	18.09***	15.63***	21.38***	6.90***	4.30*	7.28***	7.54***	1.39	9.14***
	(17.12)	(10.62)	(17.47)	(4.72)	(1.94)	(4.96)	(4.83)	(0.61)	(5.88)
Alternative Collateral Market									
$\text{EFFR}_t - \text{GCF}_t$	−0.96**	−0.78**	−1.03*	−0.11	−0.11	−0.06			
	(−2.01)	(−2.35)	(−1.96)	(−0.53)	(−0.51)	(−0.25)			
$\text{Treasury Repo Haircut}_t^b$	1.42***	4.96***	0.78**	1.30***	1.98***	0.83**	1.61***	2.16***	0.91**
	(3.59)	(6.58)	(2.14)	(4.77)	(6.42)	(2.57)	(4.84)	(6.79)	(2.31)
Stigma									
HHI_t^b	−1.70***	−7.52***	0.18	−19.16***	2.54	−16.68***	−21.89***	−4.70**	−18.05***
	(−3.37)	(−10.26)	(0.32)	(−9.42)	(1.04)	(−6.59)	(−9.52)	(−2.12)	(−6.22)
N	14,008	13,912	14,008	14,008	13,912	14,008	14,510	14,413	14,510
R^2	0.61	0.47	0.68	0.23	0.12	0.17	0.27	0.11	0.21
Time FE	No	No	No	No	No	No	Yes	Yes	Yes
Bank FE	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes

Table 9: Sizing the Pre-positioning Forces. Table shows the regression of Capacity Ratio_t^k on several potential explanatory variables: 1) the probability of a bad state (proposition 1) using the Baa-Aaa spread and the bank's FDIC insured or uninsured deposits, where the deposits are normalized by the size of the bank's capacity plus its unencumbered assets (the same denominator we use for the capacity ratio measure); 2) the alternative collateral market (proposition 3) by calculating bank's average Treasury haircut across all repo markets with data (tri-party, bilateral, FICC, and other), the haircuts at the 5 percentile and 95 percentile to reduce the influence of unrealistic outliers; 3) we also reflect the alternative collateral market using the spread between the effective fed funds rate and the general collateral financing rate; 4) stigma exposure using the HHI measures that captures the concentration of a bank's FRS district. The first three columns have no fixed effects, the next three have bank fixed effects, and the final three have both time and bank fixed effects. R^2 is within-R^2. t-statistics are reported in parentheses using robust standard errors clustered by month where * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

A Online Appendix

A.1 Data Details

A.1.1 FR 2052a Complex Institution Liquidity Monitoring Report

Our sample is the set of banks that file daily through the file sample at the consolidated bank-holding company level. BHCs must file data for each material entity, and we manually identify the bank subsidiaries for each BHC. When a BHC has more than one bank subsidiary, we collapse across bank subsidiaries for a given BHC. We exclude internal transactions. We drop less than 10 dates with outliers and we drop dates with fewer than seven filers' data available.

The data reporting form modestly changed in April 2022; on the handful of dates when a bank reports data for both the previous and the updated version, we keep only the previous version. The updated reporting form included a wider set of collateral classes, including property, which required banks to redefine the collateral types for some of their loans which would better be described as property. In these cases, we aggregate across the collateral classes to form an "other residential real estate loans" and "other commercial real estate loans" category, which provides a consistent definition over time.

The updated reporting instructions also asked banks to report their unencumbered assets by line of business, and by separately reporting their available-for-sale and held-to-maturity assets. We limit ourselves to the business lines and portfolio classifications they initially reported to create a panel that is directly comparable over the sample. Namely, the fair value of some hold-to-maturity portfolios were revised up with the updated instructions. As robustness, we confirm that using the post-2022 collateral categories does not meaningful change our main results, and the capacity ratios calculated under the two methods are highly correlated.

A.2 Figures

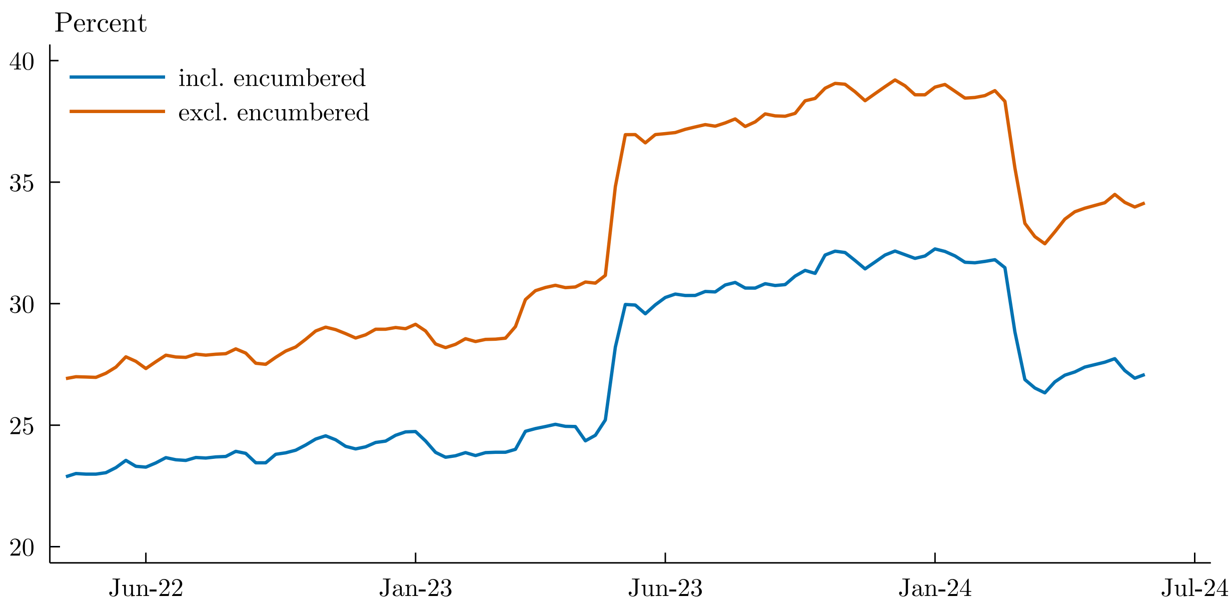

Figure A1: Capacity Ratio including Encumbered Assets. Capacity Ratio$_t^p$ = (Pre-positioned Collateral/(Unencumbered Assets + Encumbered Assets + All Pre-Positioned Collateral))$_t$ where both numerator and denominator are market values of the assets and p reflects the capacity provider (e.g., the Fed or the FHLBs). The numerator reflects the pre-positioned collateral with a specific central bank or GSE, and the denominator is the sum of all unencumbered assets, encumbered assets, and all pre-positioned collateral across all capacity providers. We calculate Capacity Ratio$_t^p$ separately for the Fed and the FHLBs. Plots are weekly averages of daily data.

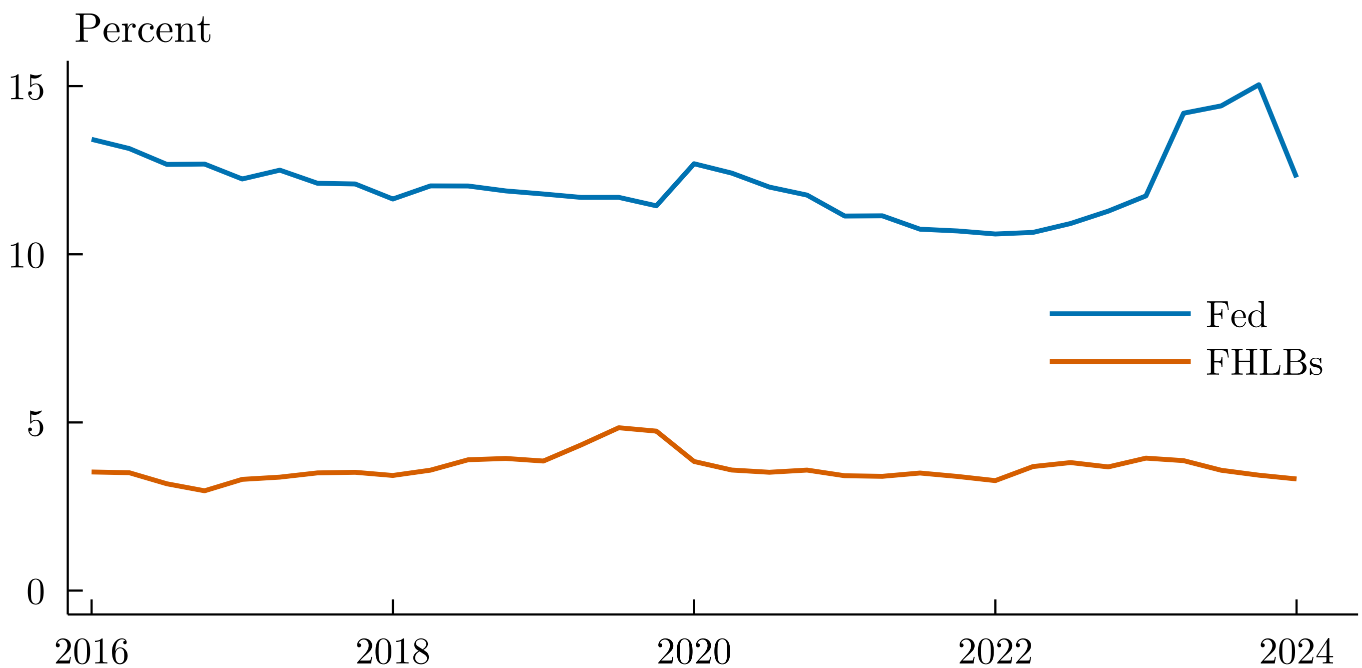

Figure A2: Capacity vs. Total Bank Assets. Plots the total amount of Fed and FHLB capacity reported in Fr2052a data against total assets as reported in call reports for our sample of banks.

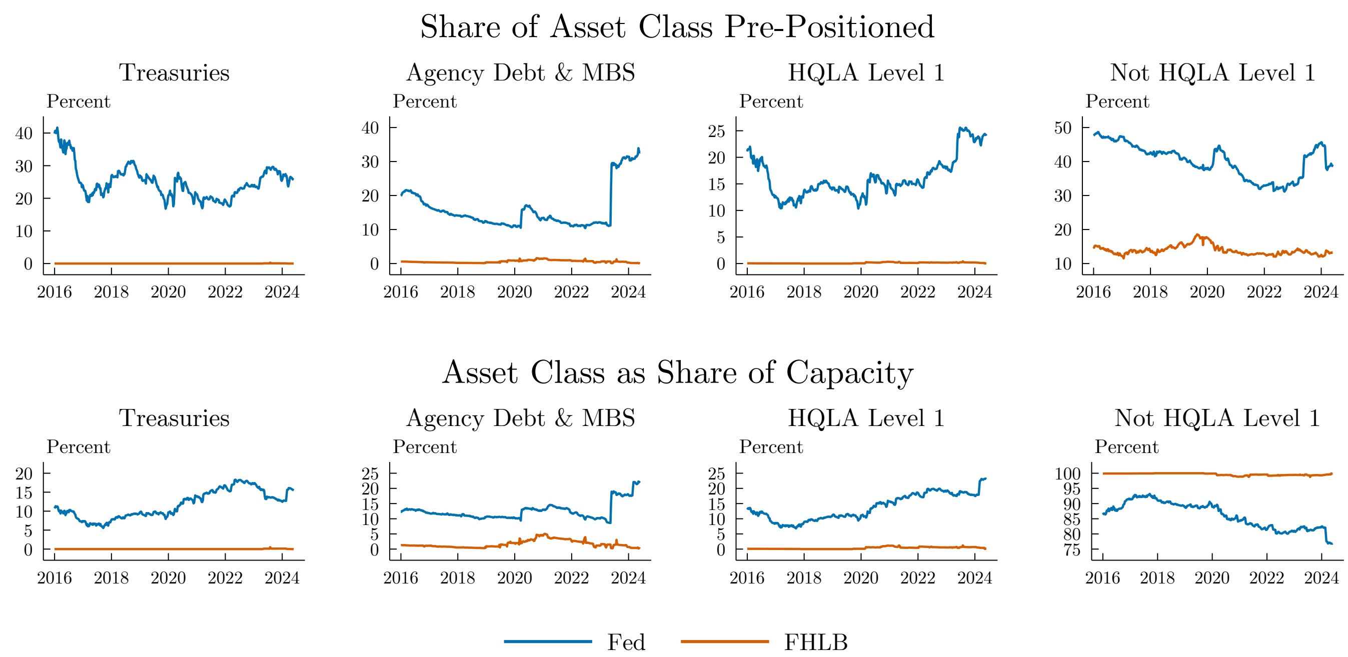

Figure A3: Capacity Composition by Asset Type. Top panel plots the share of an asset class that is pledged as collateral to the Fed or FHLB as a percent of the sum of total unencumbered assets and all pre-positioned collateral of that asset type. Bottom panel plots the share of capacity with the Fed or FHLB that each asset class constitutes. Plots are weekly averages of daily data.

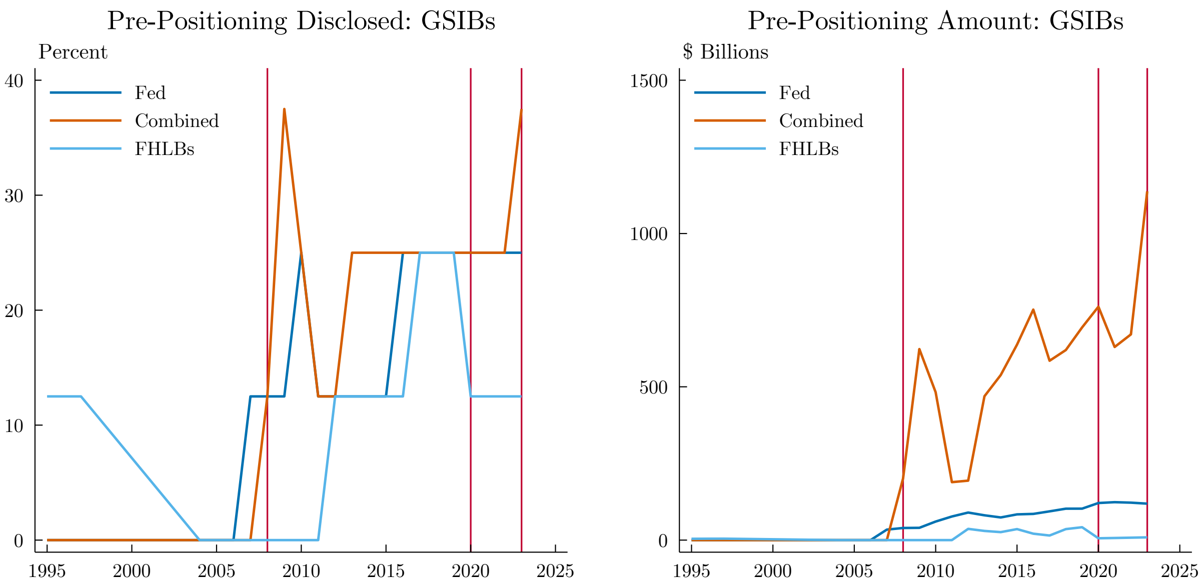

Figure A4: Public Pre-Positioning 10-K Information: Large Banks. Figure plots the share of banks reporting their pre-positioning by type for large banks, defined as globally systemically important banks. Figure derived only from public 10-K filings.

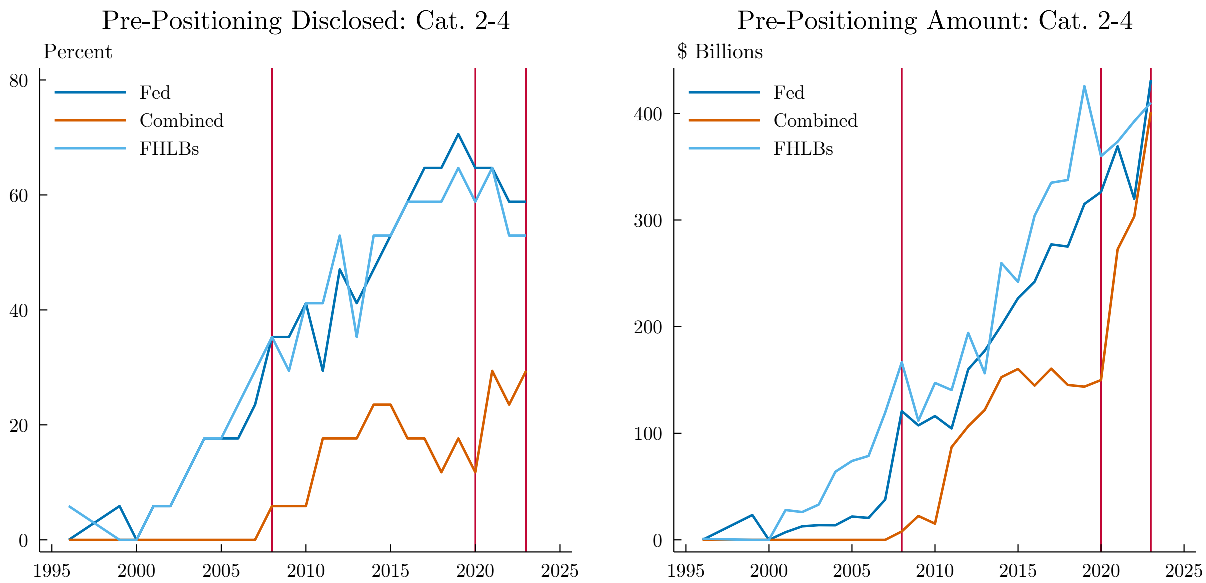

Figure A5: Public Pre-Positioning 10-K Information: Medium-sized Banks. Figure plots the share of banks reporting their pre-positioning by type for medium-sized banks, defined as category II, III, and IV banks. Figure derived only from public 10-K filings.

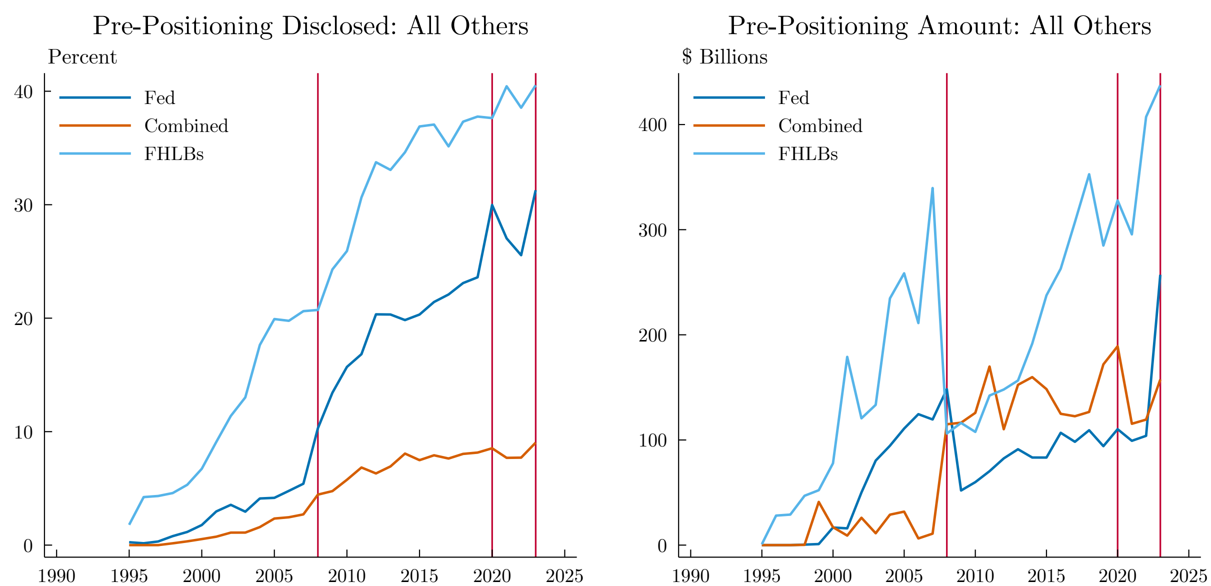

Figure A6: Public Pre-Positioning 10-K Information: All Other Banks. Figure plots the share of banks reporting their pre-positioning by type for all other banks that are neither GSIBs nor category II, III, or IV banks. Figure derived only from public 10-K filings.

	Fed Capacity Ratio excl. Encumbered$_t$	FHLB Capacity Ratio excl. Encumbered$_t$
	(1)	(2)
Fed Capacity Ratio incl. Encumbered$_t$	1.316***	
	(253.40)	
FHLB Capacity Ratio incl. Encumbered$_t$		1.126***
		(52.33)
Constant	-2.870^{***}	0.626***
	(-19.35)	(3.80)
N	509	509
R^2	0.99	0.84

Table A1: Comparing Capacity Ratios with and without encumbered assets. Table shows the regression of Capacity Ratio$_t$ without encumbered assets in the denominator (the benchmark measure) on the Capacity Ratio$_t$ including encumbered assets. Data is daily from May 2022. t-statistics are reported with robust standard errors where * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

	Correlation of ΔCapacity Ratio$_t^{\text{Fed},k}$ with:	
k	$\Delta \ln(\text{Avg. Collateralized Daylight Drafts})_t$	$\Delta \ln(\text{Peak Daylight Drafts})_t$
All	−0.10	−0.08
HQLA 1	−0.08	−0.11

Table A2: Correlation of Capacity Ratios and Daylight Drafts. Table shows correlation of the change in the Fed capacity ratio with the change in the (logs) of average collateralized daylight overdrafts and peak collateralized overdrafts. Data is at weekly frequency. Daylight overdraft data are available from `https://www.federalreserve.gov/paymentsystems/psr_dlod.htm`.

	All	Treasuries	Non-HQLA L1	All	Treasuries	Non-HQLA L1	All	Treasuries	Non-HQLA L1
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Bad State Risk									
$\text{Baa} - \text{Aaa}_t$	1.06***	0.78*	1.08**	0.72*	1.51***	0.65			
	(2.64)	(1.69)	(2.04)	(1.71)	(4.99)	(1.29)			
$\text{Insured Deposits}_t^b$	−0.59	−7.70***	−0.60	6.90***	6.07***	5.64***	7.15***	7.94***	5.28***
	(−0.94)	(−8.56)	(−0.79)	(4.56)	(4.91)	(3.75)	(4.55)	(5.63)	(3.41)
$\text{Uninsured Deposits}_t^b$	18.79***	16.21***	22.27***	10.06***	6.70***	9.69***	11.30***	6.19***	11.78***
	(24.59)	(12.62)	(25.36)	(6.64)	(4.36)	(5.08)	(7.99)	(3.93)	(6.26)
Alternative Collateral Market									
$\text{EFFR}_t - \text{GCF}_t$	−0.09	−0.42*	0.01	0.05	−0.61**	0.18			
	(−0.53)	(−1.74)	(0.04)	(0.31)	(−2.38)	(1.07)			
$\text{Treasury Repo Haircut}_t^b$	1.86***	5.39***	1.24***	1.60***	1.91***	1.10***	1.55***	2.05***	0.87**
	(4.64)	(6.75)	(3.55)	(5.69)	(6.97)	(3.23)	(4.76)	(6.45)	(2.24)
Stigma									
HHI_t^b	−2.79***	−8.83***	−1.10**	−18.84***	−4.23**	−15.06***	−22.24***	−5.20**	−18.30***
	(−7.26)	(−13.89)	(−2.44)	(−7.67)	(−2.32)	(−5.17)	(−9.71)	(−2.46)	(−6.40)
Controls									
$\text{10-Year Treasury Yield}_t$	1.73***	−0.14	1.55***	1.80***	−0.33*	1.67***			
	(5.06)	(−0.39)	(3.54)	(5.76)	(−1.77)	(4.48)			
$\ln(\text{Treasuries Outstanding})_t$	−2.70***	−0.04	−3.20***	−0.73*	2.93***	−1.24***			
	(−9.76)	(−0.11)	(−8.69)	(−1.86)	(14.11)	(−2.90)			
$\text{Unrestricted Reserves}_t^b$	−16.06***	−20.89***	−18.49***	−11.39***	−17.24***	−6.87***	−12.82***	−16.23***	−8.98***
	(−20.08)	(−8.42)	(−21.90)	(−4.55)	(−3.31)	(−3.93)	(−5.41)	(−3.27)	(−5.44)
N	14,002	13,906	14,002	14,002	13,906	14,002	14,510	14,413	14,510
R^2	0.66	0.50	0.74	0.32	0.30	0.22	0.33	0.20	0.23
Time FE	No	No	No	No	No	No	Yes	Yes	Yes
Bank FE	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes

Table A3: Sizing the Pre-positioning Forces with controls. Table repeats the regression in Table 9 adding three controls: the level of Treasury yields, Treasuries outstanding, and unrestricted reserves normalized by the size of the bank's capacity plus its unencumbered assets (the same denominator we use for the capacity ratio measure). Table shows the regression of Capacity Ratio_t^k on several potential explanatory variables: 1) the probability of a bad state (proposition 1) using the Baa-Aaa spread and the bank's FDIC insured or uninsured deposits, where the deposits are normalized by the size of the bank's capacity plus its unencumbered assets (the same denominator we use for the capacity ratio measure); 2) the alternative collateral market (proposition 3) by calculating the bank's average Treasury haircut across all repo markets with data (tri-party, bilateral, FICC, and other), the haircuts at the 5 percentile and 95 percentile to reduce the influence of unrealistic outliers; 3) we also reflect the alternative collateral market using the spread between the effective fed funds rate and the general collateral financing rate; 4) stigma exposure using the HHI measure that captures the concentration of a bank's FRS district. The first three columns have no fixed effects, the next three have bank fixed effects, and the final three have both time and bank fixed effects. R^2 is within-R^2. t-statistics are reported in parentheses using robust standard errors clustered by month where * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.