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. It has been used for over a century. During a bank run, Bagehot (1873) dictates that the central bank should lend freely against good collateral, at a penalty rate, and to solvent banks. The details matter, though. Banks need collateral to borrow against, and borrowing from the discount window causes the borrowing bank to become stigmatized; therefore, banks are less inclined to borrow (Armantier et al., 2015a). Following the March 2023 bank runs, alternatives have been proposed that banks should pre-position assets with the Fed so that the collateral is already there if they need to borrow.[1] Thus, the claim is that pre-positioning would improve the discount window's efficacy, regardless of its existing stigma. In this paper, we study pre-positioning to understand where banks keep their collateral and why.

Banks can voluntarily *pre-position* their assets with the Fed. Pre-positioning allows banks to quickly borrow from the discount window for two main 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, borrowing against pre-positioned collateral 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. Pre-positioning is especially important because bank runs are likely getting faster—Silicon Valley Bank (SVB) lost 87 percent of its deposits in just two days (Rose, 2023). The Federal Reserve noted that 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)

[1] For example, see Kaminska (2024) *A quiet revolution rocks central banking*, Politico. `https://www.politico.eu/article/pre-positioning-quiet-revolution-rocking-central-banking/`.

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—28 percent of their unencumbered assets—to the Federal Reserve.[2] 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

[2] 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.

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.[3] 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 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 liquidity shock using high-frequency deposit flows and show that banks pre-position more when they have more 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.[4] 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.

[3] 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.

[4] See "Discount Window Readiness" `https://www.federalreserve.gov/monetarypolicy/discount-window-readiness.htm`, which we summarize in Table 2.

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 if a bank is large within its Fed district. The Fed's weekly balance sheet provides borrowing data by district, and a smaller bank can better conceal their discount window borrowing. In our sample of confidential data from large banks, we find that banks with a larger share of assets in their Fed district pre-position less.

And we find evidence of pre-positioning stigma. First, we find that 14 percent of banks disclose their pre-positioning with the Fed in their public 10-Ks on average since 1995, but that number has increased in recent years. Many banks only disclose their pre-positioning by commingling it with other types of pre-positioning, namely with the unstigmatized FHLBs.[5] Second, we show that banks that disclose Fed pre-positioning tend to be riskier and window dress their pre-positioning, and markets react negatively when banks start disclosing pre-positioning. We argue that pre-positioning stigma is an important driving force in these relationships and how much banks pre-position.

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

[5]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.

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 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.[6] 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 as another tool to provide financing for high-quality collateral for banks (and others) (Afonso et al., 2022).

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

[6] 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`

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.[7]

3 How to Borrow from the Discount Window

The Fed's Operating Circular Number 10 describes how to borrow from the discount window.[8] 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 it is pledged.[9]

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.[10] 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

[7]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."

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

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

[10]Specifically, they can use Fedwire Securities, DTCC (if the firm is a member, otherwise firms 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).

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.[11] 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.

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 their 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 of up to 92 percent.[12]

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 described in step (1). The Fed encourages banks to complete it as soon as possible if they have not:[13]

> 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, it can take longer if the security had been previously pledged to a different counterparty. Such encumbrances

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

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

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

must be unwound before the bank can pre-position them 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 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:[14]

> 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

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

tri-party repo market or the FHLBs. Denote the amount of the assets the bank chooses to put at the Fed as x^F and denote the amount of the assets put in the alternative market as 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 borrow against its pre-positioned assets in period 2, it cannot sell the asset.[15] 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 the household 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 incurs 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 ($x^F = 0$).[16] The household can borrow against assets in the alternative market at r^M in good states. We

[15] 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.

[16] 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.

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.

The household solves:

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

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 for 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.[17]

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 involves 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.

[17] 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.

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 pre-positioning 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 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 collected for large bank-holding companies (BHCs) by 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 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. The data covers roughly three dozen large bank-holding companies, including both domestic and foreign companies, between 2016 to 2024. The largest banks—the eight U.S. global systematically important banks (GSIBs) report daily data—and the rest report monthly data. For brevity, we will refer to the daily-reporting banks as large banks and the monthly-reporting banks as medium-sized banks.[18]

We focus on banks that consistently report data through the full sample to reduce distortions stemming from changes in the set of reporting banks. We principally use data for the bank subsidiaries of each BHC, but we also use data from the consolidated parent company. The online appendix A.1.1 provides additional details on how we clean 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] Copeland et al. (2024) 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 management and do not use daylight overdrafts to manage their intraday reserve positions, possibly because they view daylight overdrafts as stigmatizing.

[18]The thresholds for daily and monthly reporting have changed over time. For additional details and historical thresholds, see `https://www.federalreserve.gov/apps/reportingforms/Report/Index/FR_2052a`.

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

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

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

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 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 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. 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 $1.9 trillion, 28 percent of their eligible assets, to the Fed and 14 percent to the FHLBs, on average. Figure 1 plots the capacity ratio aggregated across all assets and maturities. There is a modest downward trend through the sample, but there is a clear business cyclical component, with spikes during the initial stages of the COVID panic and a level shift up during the 2023 bank turmoil. There is considerable range over the sample, with the Fed capacity ratio ranging from 22 to 33 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. There is also considerable

[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.

disagreement across banks in their pre-positioning. Figure 2 plots the cross-sectional standard deviation across individual banks' capacity ratios: the average standard deviation is 29 percent. Given the average capacity ratio of 28 percent, the large standard deviation implies a wide range in banks' routine pre-positioning behavior.

It is also helpful to further separately study the behavior of the largest banks and medium-sized banks. Figures A1 and A2 plot capacity ratios for large banks and medium-sized banks, respectively. Large banks consistently pre-position more to the Fed, with an average capacity ratio of 34 percent compared to medium-sized banks' 22 percent average. Medium-sized banks tend to have more pre-positioned to the FHLBs, but after the turmoil of 2023, medium-sized banks shifted some pre-positioning away from the FHLBs and toward the Fed.

We focus on the capacity ratio measure using unencumbered assets since unencumbered assets can be pre-positioned without restriction. We can alternatively calculate the capacity ratio including both unencumbered and encumbered assets, which we show in the online appendix Figure A3.[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 24 percent with encumbered assets in the denominator, compared to 28 percent in the main measure. Table A3 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 using either the full bank panel with monthly data or the large bank panel with daily data.

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 A4. By this measure, the banks pre-positioned 12 percent of their assets at the Fed and 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 universe of the U.S. banks, but it covers a large and material slice of the banking system since the largest banks hold a large share of banking system assets. As a point of comparison, we present aggregated pre-positioning statistics provided from the Fed in Table 2. 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

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

upward trend pre-positioning, increasing from 8.2 percent of total commercial bank assets in 2021 to 12.1 percent in 2023. For comparison, our sample of banks pre-positioned $2.9 trillion with the Fed at 2023 year-end, against which they could borrow $2.2 trillion, implying our sample captures 80 percent of total pre-positioning, as shown in the bottom row of the table.

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 20 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 80 percent of their residential loans, largely to the FHLBs. This is unsurprising: whole mortgage loans are not useful as repo collateral, for example. Non-residential loans have an average capacity ratio of 59 percent, almost entirely to the Fed. Investment grade debt has the next highest capacity ratio at 30 percent.[22] Then Treasuries (20 percent), agency (16 percent, including both agency debt and agency MBS), other (16 percent), and non-IG debt (15 percent). Sovereign bonds and equities both have smaller capacity ratios.

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 could have higher collateral values in private collateral markets. The paper aims to understand this dynamic.

The result is not driven by the unique behavior of large or small banks. Figure A6 provides capacity ratios by asset class for large and medium-sized banks separately and shows they have broadly similar behavior. Notably, though, large banks pre-position safe assets—Treasuries and agency MBS—more often than smaller banks. This is perhaps surprising, since the largest banks should face the smallest frictions to deploying these assets into alternative collateral markets, like the repo market.

Table 3 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, agencies, and level 1 high-quality liquid assets (HQLA) because the standard deviation of the level of pre-positioning for these asset classes is larger relative to their mean than for non-HQLA

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

level 1 assets. All Fed capacity ratios are also more volatile than FHLB capacity ratios.[23].

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 pre-position more with the central bank when the probability of the bad states increases. A simple test of this proposition examines 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 row 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, and the return on the KBW bank stock index. A higher VIX, higher spreads, or lower bank stock returns are strongly associated with an increased capacity ratio.

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 daily data in the bottom panel show that banks tend to increase their capacity ratio in the short-term 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 A4,

[23] In the online appendix, we provide the same table for large and medium-sized banks in Tables A1 and A2, and we plot the capacity ratio time series for several asset classes (Figure A5 for all filers)

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? A combination of the two may be possible, as well. We can exploit a unique feature of the daily data: banks report forward asset purchases with granular settlement dates. If a bank bought a Treasury today that settles tomorrow, they will report it today. With this information, we can estimate banks' 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:

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

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. We use data from the largest banks for this regression since daily data is necessary to identify the previous day's settling purchases.

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 2 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 3 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 2 cents large or small? We think it's small for two reasons. One possibility is that banks do not pre-position their new assets because they immediately encumber them. This is not the case, though, since the last three columns repeat the regression with the dependent variable changed to the level of unencumbered assets. These coefficients are much larger—ranging between 39 and 55 cents, meaning that $1 of settling forward purchases increases unencumbered assets between 39 and 55 cents. Second, 2 cents is also small considering that banks pre-position 28 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 they instead pre-position dynamically, 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. Since the Fed's lending terms adjust slowly, 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 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

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

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 main 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 proxies for 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 for several broad asset class.[28] 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 0.7 percent haircut in the bilateral repo, 1.7 percent in the tri-party repo, 2.2 percent when pre-positioned at the Fed capacity, and 7.8 percent when pre-positioned at

[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."

[28]We calculate the average haircut for each collateral class by maturity bucket asset class across banks for each month using data from each bank's parent entity. We then exclude haircuts from secured funding markets that account for less than 1 percent of the total amount of secured funding as defined as the sum of collateral pledged to the bilateral and triparty repo market plus total collateral pre-positioned with the Fed and FHLB for each collateral class by maturity bucket pair. We then take a time series average of the resulting haircuts by maturity bucket and collateral bucket.

the FHLBs. Agency debt follows a similar rank ordering: bilateral (2.8 percent), tri-party repo (2.8 percent), the Fed (4.0 percent), and FHLBs (4.5 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. Similarly, many markets do not accept certain collateral types; hence, their haircut is functionally 100 percent. In this sense, the figure likely understates the spread of haircuts across different collateral markets.

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

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

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. We use data from the large banks that file daily data to minimize the variation in haircuts based on the banks' credit risk, which varies less across the large GSIBs than across the wider set of banks. 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 0.09 pp in the bilateral repo market, 0.15 in tri-party repo, 0.18 in FICC repo, 0.30 against the FHLB, and 1.66 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 at more punitive haircuts than the Fed's haircuts—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.[29]

Figure 5 plots the spread between the primary credit rate and financing rates across several collateral markets, where a larger spread means the collateral market offers cheaper financing compared to the discount window. The figure compares several financing rates: 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.[30] 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 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, with perhaps only $40 billion outstanding. Even though it is most desirable—shown by the large spread below 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, meaning the alternative markets typically offer cheaper financing rates than the discount window, ignoring the effect of varying haircuts.

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? Several papers have shown

[29] 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.

[30] 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.

that the answer to the former is emphatically yes, and we argue that the answer to the latter is likely also yes.

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 exposed to stigma 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 large it is relative the banking system 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 district-specific Reserve Bank balance sheet data weekly—at a somewhat less granular level—and market participants are attentive to individual Reserve Bank balance sheet growth.[31] Banks that constitute a small share of total assets in their Federal Reserve districts can more easily obscure their discount window borrowing, either because the bank itself is relatively small or because the district contains many other large banks.

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

[31] 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).

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 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 not likely to be such a large share of the bank's 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).[32]

We test the relationship between borrowing stigma and pre-positioning using a proxy for an individual bank's exposure to borrowing stigma, the bank's share of assets in its Federal Reserve district. We use publicly-available quarterly data from bank and credit union call reports, as well as foreign bank agency and branch FFIEC 002 filings, to calculate total assets in a Federal Reserve district. A bank's district asset share is the ratio of its assets in a given quarter compared to the total assets in its district:

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

We provide additional details on how we calculate total bank assets by Federal Reserve district in the online appendix.

We show that banks pre-position less when they are more exposed to borrowing stigma. Table 7 shows the regression of capacity ratios on bank's market share measure using the quarter-by-bank panel. The first two columns use Federal Reserve capacity ratios as dependent variables, and the last two use FHLB capacity ratios. The independent variable is the district asset share, 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 a bank's share of its Federal Reserve district assets is associated with a Fed capacity ratio that is 2pp lower—an economically meaningful effect given the aggregate banking system averages a capacity ratio of roughly 28 percent.

[32] See also, WSJ (2023, March 18). "Fed Data: Most Emergency Lending Was in the West."

[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.

The remaining columns run several robustness tests and vary the inclusion of time fixed effects. Since FHLB borrowing via advances is not stigmatized, we should not see FHLB pre-positioning fall when a bank has a larger share of its district's assets. Columns (3) and (4) confirms this with a positive coefficient. Indeed, while banks with large district asset shares pre-position less with the Fed, they pre-position somewhat more with the FHLBs. A 1 standard deviation increase in district asset share corresponds to a 2pp increase in pre-positioning at the FHLB. The table shows that both banks more subject to borrowing stigma pre-position less, and those same banks tend to substitute toward the unstigmatized FHLBs.

An important feature of borrowing stigma is that banks can, in some cases, choose to interact with the Federal Reserve using a Federal Reserve Bank in a district that the bank's head office is not physically located in. We provide more details on the relevant regulation under which banks can change the Federal Reserve district bank with which they interact, including to borrow from the discount window, in the online appendix. Banks that make this switch tend to be banks that would otherwise have a large share of the assets in the district in which they are physically located. In the online appendix, Figure A7 plots the share of total banking assets held by banks that switch their regulatory district. About 30 percent of bank assets in recent years are held by banks that switched their supervisory Fed district.

The ability to switch district helps reduce borrowing stigma and thus very likely increases the amount of pre-positioning. This is clear by comparing switching bank's share of district assets in the district they choose compared to the district in which their head office is physically located. Since Q4 1997, when banks could start switching, the average switching bank had an average district share of 6.2 percent for their chosen district, compared to an average 9.9 percent in their physical location district. Since Table 7 shows that banks with lower district asset shares pre-position more, the ability for banks to switch district—thereby pushing down their district asset share—likely boosts pre-positioning by a material amount. We can estimate the effect using a back of the envelope approach: repeating the regression in column (1) of the table but without standardizing the independent variable to a z-score yields a beta of -0.17, implying a 1pp increase in district asset share decreases their Fed capacity ratio by 0.17pp. The coefficient implies that switching banks would pre-position about 0.63pp less ($0.17 \times (9.9 - 6.2)$), a small but meaningful effect especially given that switching banks tend to be large banks.

Pre-Positioning Stigma We find evidence that banks may view pre-positioning collateral as stigmatizing. Pre-positioning may be stigmatizing because it indicates a potential willingness to borrow from the window in bad states, and 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 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. The online appendix provides examples.

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.

The figures suggest 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 and 10-Q filings from 1995 to 2024. We limit the sample to the set of SEC filings from bank-affiliated filers. We identify bank-affiliated filers using companies with permnos that are identified as affiliated with commercial banks by the New York Fed, and mapping those to SEC CIK codes using the CRSP/Compustat link.[34] This restriction yields roughly 57,000 10-Ks and 10-Qs. We do basic cleaning on the raw SEC filings in the spirit of Loughran and McDonald (2016) to remove various formatting elements and tags. We provide additional details on the cleaning in the online appendix.

We then identify filings that disclose pre-positioning. We look for excerpts within a filing that include any of the strings "pledg", "pre-position", or "preposition", along with one of "federal reserve," "frb," "discount window," "fhlb," or "federal home loan bank." This process flags roughly about 25,000 10-Ks and 10-Qs with 83,000 candidate excerpts about pre-positioning. As robustness, we also checked other phrases, including "capacity," and "position," but found that pledging is by far the most common way banks describe their pre-positioning. We choose these strings to focus on instances in which the bank has certainly pre-positioned collateral. For example, Banks occasionally disclose they have available "lines of credit," "liquidity," or "funding," from FHLBs or the Federal Reserve, although these arrangements do not necessarily indicate the bank has pre-positioned collateral.

Given the number of filings and the variety in how firms report their pre-positioning data, we turn to a standard large-language model (LLM), ChatGPT 4o, to help process the data. We provide additional details on the prompt in the online appendix. In brief, we provide the LLM with the excerpt and ask it whether the bank has pre-positioned collateral to the Fed or FHLBs, and if so, how much. The process yields an estimated pre-positioned amount with the Fed, the FHLBs, or a combined Fed and FHLB number.

Cleaning data with the LLM requires several caveats. First and foremost, the LLM may inaccurately answer the prompt. We randomly select 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 disclosed 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 only 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 using annual filings, and we provide the aggregate summary statistics in Table A5. 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

[34]See `https://www.newyorkfed.org/research/banking_research/crsp-frb`.

and the FHLB. The "combined" line reflects banks that report a combined amount only.

The figure makes three facts clear: first, most publicly-traded banks do not disclose how much they pre-position with the Fed. Between 1995 and 2024, 14 percent of publicly-traded banks disclosed pre-positioning with the Fed. The most recent data shows about 35 percent of banks disclose. Such low levels of disclosure would be consistent with banks viewing pre-positioning disclosures as stigmatizing. 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. One challenge is distinguishing disclosure of pre-positioning from whether the bank actually pre-positions. However, in our sample of confidential data for three dozen banks, virtually all U.S.-based banks always have non-zero pre-positioning. We can therefore reject an alternative that disclosure rates are low because only some banks pre-position, even if all those that do pre-position disclose they do so.

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 before, 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.

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 $700 billion. The figure also shows that disclosed Fed pre-positioning tends to be smaller than disclosed FHLB pre-positioning at all points since 1995.

Notably, the most recent value of FHLB pre-positioning is about $850 billion, a large amount relative to the FHLB system's total debt outstanding of $1.2 trillion at year-end 2023. Were banks that disclose FHLB pre-positioning to implausibly simultaneously borrow from the FHLB, it would require the FHLB system to increase its borrowing by 50 percent, assuming a 30 percent haircut on pre-positioned assets (roughly the haircut shown in Figure 4 for residential loans). While this is clearly an unrealistic scenario, it highlights that pre-positioning at the FHLB, while unstigmatized, could be a less ideal source of emergency funding because it depends on the ability of the FHLB to issue incremental debt. Advances that require incremental debt issuance can involve frictions depending on the time of day. Moreover, large incremental FHLB borrowing could also prove impractical in extreme cases if banks' demand for FHLB advances was too large relative to the FHLBs balance sheet.

The online appendix breaks down the pre-positioning 10-K disclosures based on bank size: GSIBs, medium-sized banks, and all other banks.[35] 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 to 35 percent of the largest and smallest banks disclose Fed pre-positioning. Medium-sized banks are unique because they are more likely than not to disclose Fed pre-positioning, with about 50 percent disclosing in 2024.

Table 8 compares a bank's decision to publicly disclose pre-positioning with publicly-available measures of bank risk, including return on assets, total capital ratio, and (log of) total assets, all from call reports. The table includes quarter fixed effects to control for time variation in the risk measures. The first three columns show that banks which disclose Fed pre-positioning tend to be riskier in the sense that they have lower return on assets and lower capital ratios, and they also tend to be larger. By contrast, the last three columns repeat the regression for firms that disclose FHLB but not Fed pre-positioning. There is no similar relationship for these banks, since there is no relationship with ROA, and the banks have higher capital ratios and are smaller. The relationships are robust after controlling for the size of the bank. Combined, the table shows that riskier banks and larger banks are more likely to publicly disclose their pre-positioning with the Fed.

Next, we show that pre-positioning stigma is associated with lower abnormal stock returns. We show that banks earn negative abnormal returns the day they start disclosing Fed pre-positioning. This is not the case if the bank starts disclosing only FHLB or only combined pre-positioning.[36]

In Table 9, we regress a bank's abnormal excess returns on indicator variables for whether the bank started disclosing pre-positioning. We limit the regression to days of 10-K or 10-Q filings where earnings have already been reported. We calculate abnormal excess returns

[35]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.

[36]We merge the public filing data to CRSP return data using the CRSP/Compustat Linking Table which links permcos to the CIKs that are used in the 10-K filing data. We merge the I/B/E/S data using tickers.

relative to a Fama-French 3-factor model over a three-month window, excluding the two weeks before the 10-K or 10-Q filing. Column 1 shows that banks earn significantly lower abnormal returns on the day they start disclosing Fed pre-positioning. Compared to other days where banks report 10-K or 10-Q filings, starting to disclose Fed pre-positioning is associated with a 0.2 pp lower abnormal returns.

The simple univariate regression may overstate the effect of the pre-positioning disclosure if banks are more likely to begin disclosing when the bank's profitability or growth prospects have fallen. For this reason, we include a control for the quarter's earnings surprise in column 2. It may be surprising that earnings surprise is not significant. This is because the filing date, which is when the pre-positioning amount is available, is often many days after the earnings announcement, and the market has already digested information about whether the company beat or missed relative to expectations. Notice that including the earnings control significantly reduces the sample since only a subset of publicly traded banks have analyst coverage.[37]

As robustness, we show that the effect of pre-positioning stigma on returns is limited to cases of disclosing Fed pre-positioning. Bank returns are not lower on days where the bank starts disclosing only FHLB pledging or only the combined pledging amount (columns 3 to 6). The results suggest that pre-positioning stigma is limited to Fed pre-positioning.

In the online appendix section A.3, we provide additional evidence of pre-positioning stigma where banks that publicly disclose their pre-positioning tend to increase their pre-positioning in months that coincide with quarterly disclosure, but not other months.

6.4 Comparing the Pre-Positioning Forces

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 HQLA level 1 holdings, which we measure as the sum of

[37] The unexpected earnings variable from I/B/E/S reflects number of standard deviations the actual earnings is larger than the I/B/E/S surprise mean estimates for the quarter. An assumption is that the analyst forecast captures the bank's profitability or growth outlook. In columns 2, 4, and 6, we restrict to observations with unexpected earnings data.

unencumbered and pre-positioned HQLA level 1. We winsorize the deposit ratios at the 1st and 99th percentile to reduce the influence of outliers.

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 again winsorize the haircuts at the 1st and 99th 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 differences in the risk characteristics of other types of collateral. 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 captures the benefit of using collateral to borrow in secured markets compared to unsecured markets.

We also capture borrowing stigma exposure using the district asset share measure following the method described earlier. We compare how the three frictions measured above contribute to the share pre-positioned. We run the following regression:

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

where t is the date, b is the bank, and the dependent variable is the bank's Federal Reserve capacity ratio aggregated across all asset classes. 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. We separately run the regression on the large banks with daily data (where the time fixed effect is the date) and on all banks with monthly data (where the time fixed effect is the year-month).

Table 10 shows the regression result. The first three columns show the results for the daily large bank sample, the next three show the results across all banks in our sample. All specifications include bank fixed effects. The first column looks at pre-positioning aggregated across all collateral types. The main specification is shown in columns (1) and (4). The two columns show 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 they have more insured deposits and when their district asset share is higher. Intuitively, each force behaves as expected, but the relative magnitude is important: for large banks, a one standard deviation increase in uninsured deposits is associated with an 12pp higher capacity ratio, a larger effect than any other variable. The next largest are insured deposits (-9.9pp) and district asset share (-9.1pp). The full bank sample has similar results.

Importantly, the specifications all include bank fixed effects which 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 bank fixed effect provides a way to control for banks' preferences to pre-position if, for example, their business model makes them more or less vulnerable to rapid deposit flight or if they have persistently different risk-management approaches. 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 time fixed effects in the other columns. 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 have opposite effects on pre-positioning, while the Treasury haircut relationship is larger: a one standard deviation increase in a bank's Treasury haircut increases its pre-positioning by 1.3 to 1.5pp. The coefficient on borrowing stigma is consistently negative: banks with one standard deviation increase in stigma exposure as captured by district asset share measure pre-position between 4 and 13pp less, depending on the sample, with a larger effect for the large bank sample. The borrowing stigma effect is large, given the average capacity ratio is about 28 percent.

One important consideration is whether the bank's unrestricted reserves drive the variation in its capacity ratio, since a bank with more reserves may not need to pre-position as much to hedge against deposit flight. In columns (3) and (6), we also include a control for the bank's unrestricted reserve balances. Since larger banks will have larger reserves, we calculate the unrestricted reserve variable analogously to the deposit variables using a ratio to the bank's total HQLA level 1 holdings. 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. The negative and significant coefficient on reserves shows that banks with 1 standard deviation higher reserves have a capacity ratio that is lower by between 3 and 9pp.

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 uninsured deposits, they pre-position more. When they have more FDIC-insured deposits, they pre-position less. 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.

References

Gara Afonso, Lorie Logan, Antoine Martin, Will Riordan, and Patricia Zobel. The fed's latest tool: A standing repo facility. Technical report, Federal Reserve Bank of New York, 2022.

Sriya Anbil. Managing stigma during a financial crisis. *Journal of Financial Economics*, 130 (1):166–181, 2018.

Olivier Armantier and Charles A Holt. Overcoming discount window stigma: An experimental investigation. *The Review of Financial Studies*, 33(12):5630–5659, 2020.

Olivier Armantier, Eric Ghysels, Asani Sarkar, and Jeffrey Shrader. Discount window stigma during the 2007–2008 financial crisis. *Journal of Financial Economics*, 118(2):317–335, 2015a.

Olivier Armantier, Helene Lee, and Asani Sarkar. History of discount window stigma. 2015b.

Adam Ashcraft, Morten L Bech, and W Scott Frame. The federal home loan bank system: The lender of next-to-last resort? *Journal of Money, Credit and Banking*, 42(4):551–583, 2010.

Walter Bagehot. *Lombard Street: A description of the money market*. London: HS King, 1873.

Michael S Barr. Review of the federal reserve's supervision and regulation of silicon valley bank. *Board of Governors of the Federal Reserve System*, 28(1), 2023.

Michael S Barr. On building a resilient regulatory framework. *Board of Governors of the Federal Reserve System*, 2024.

Mark Carlson and Jonathan Rose. Stigma and the discount window. 2017.

James A Clouse. Recent developments in discount window policy. *Fed. Res. Bull.*, 80:965, 1994.

Adam Copeland, Darrell Duffie, and Yilin Yang. Reserves were not so ample after all. *Quarterly Journal of Economics*, 2024.

Calebe De Roure and Nick McLaren. Liquidity transformation, collateral assets and counterparties. *Central Bank Review*, 21(4):119–129, 2021.

Huberto M Ennis and Elizabeth Klee. The fed's discount window in. 2021.

W Scott Frame. *The federal home loan bank system and US housing finance*. SSRN, 2017.

G30. Bank failures and contagion: Lender of last resort, liquidity, and risk management. 2024.

Stefan Gissler and Borghan Narajabad. The increased role of the federal home loan bank system in funding markets, part 1: Background. 2017.

Gary Gorton and Andrew Metrick. Securitized banking and the run on repo. *Journal of Financial economics*, 104(3):425–451, 2012.

Samuel G Hanson, Victoria Ivashina, Laura Nicolae, Jeremy C Stein, Adi Sunderam, and Daniel K Tarullo. The evolution of banking in the 21st century: Evidence and regulatory implications. *Brookings Papers on Economic Activity*, 27, 2024.

Matthew S Jaremski, Gary Richardson, and Angela Vossmeyer. Signals and stigmas from banking interventions: Lessons from the bank holiday in 1933. Technical report, National Bureau of Economic Research, 2023.

Steven Kelly. Weekly fed report still drives discount window stigma. *Yale Program on Financial Stability*, 2024.

Mervyn King. Lessons from the global financial crisis. *Business Economics*, 53(2):55–59, 2018.

Tim Loughran and Bill McDonald. Textual analysis in accounting and finance: A survey. *Journal of Accounting Research*, 54(4):1187–1230, 2016.

Susan McLaughlin. Discount window stigma: What's design got to do with it? 2024.

Andrew Metrick and Paul Schmelzing. Banking-crisis interventions, 1257-2019. 2021.

Jonathan Rose. Understanding the speed and size of bank runs in historical comparison. *Economic Synopses*, 12, 2023.

Zeynep Senyuz, Sriya Anbil, and Alyssa G Anderson. The importance of repo trading relationships during market stress. *Available at SSRN 4572075*, 2023.

Paul Tucker. The repertoire of official sector interventions in the financial system-last resort lending, market-making, and capital. 2009.

8 Figures

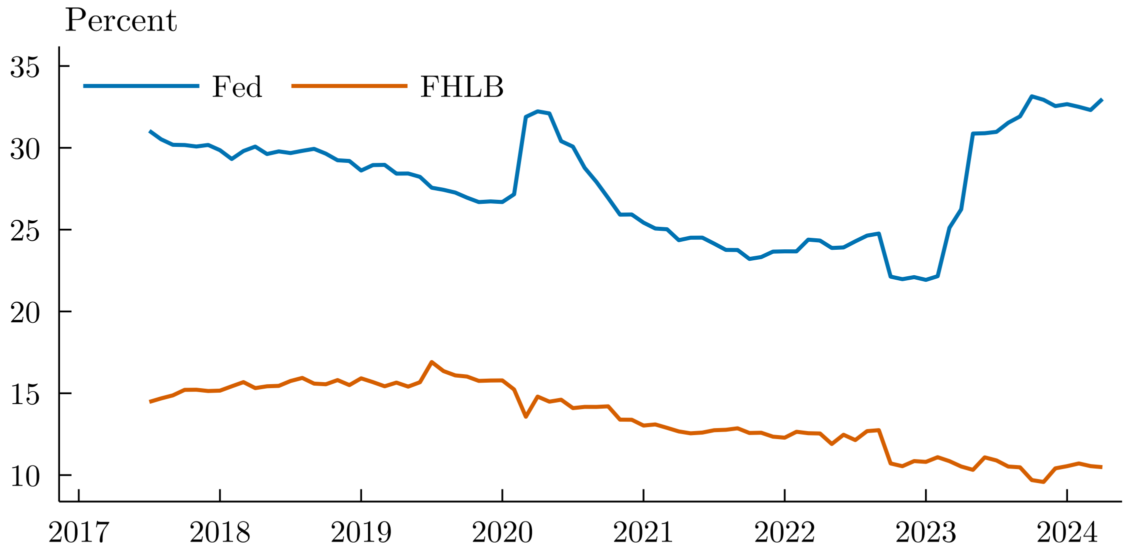

Figure 1: Capacity Ratio. Capacity Ratio$_t^p$ = (Pre-positioned Collateral/(Unencumbered Assets + All Pre-Positioned Collateral))$_t$ where both numerator and denominator are market values of the assets and p reflects the capacity provider (e.g., the Fed or the FHLBs). The numerator reflects the pre-positioned 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 monthly data. Includes all banks in our FR2052a sample; see data section for details.

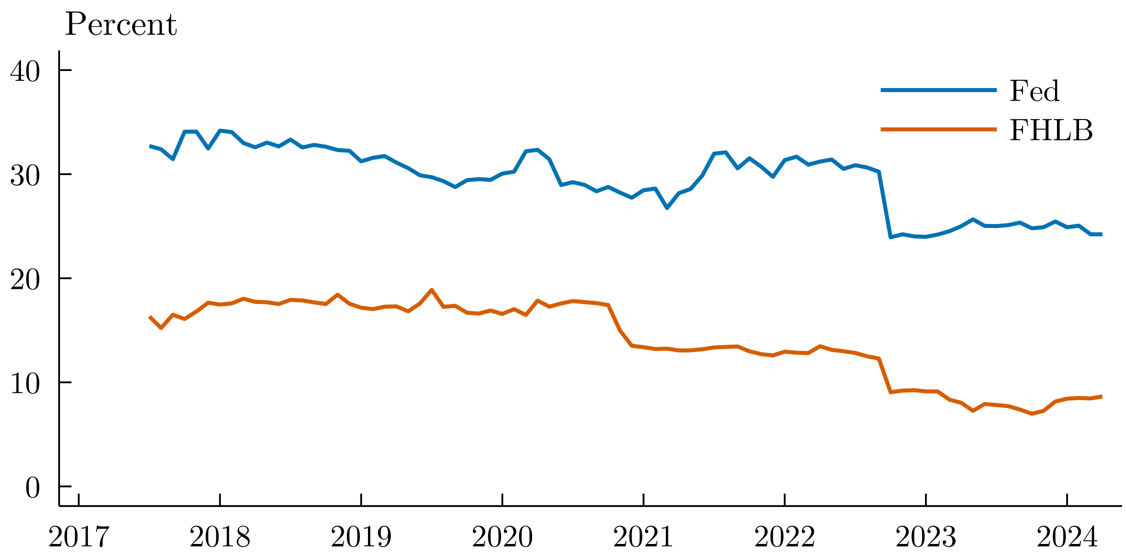

Figure 2: Cross-Sectional Standard Deviation of Capacity Ratio. Plot shows the standard deviation across individual banks' capacity ratios at a point in time. Capacity Ratio$_t^p$ = (Pre-positioned Collateral/(Unencumbered Assets + All Pre-Positioned Collateral))$_t$ where both numerator and denominator 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 monthly data. Includes all banks in our FR2052a sample; see data section for details.

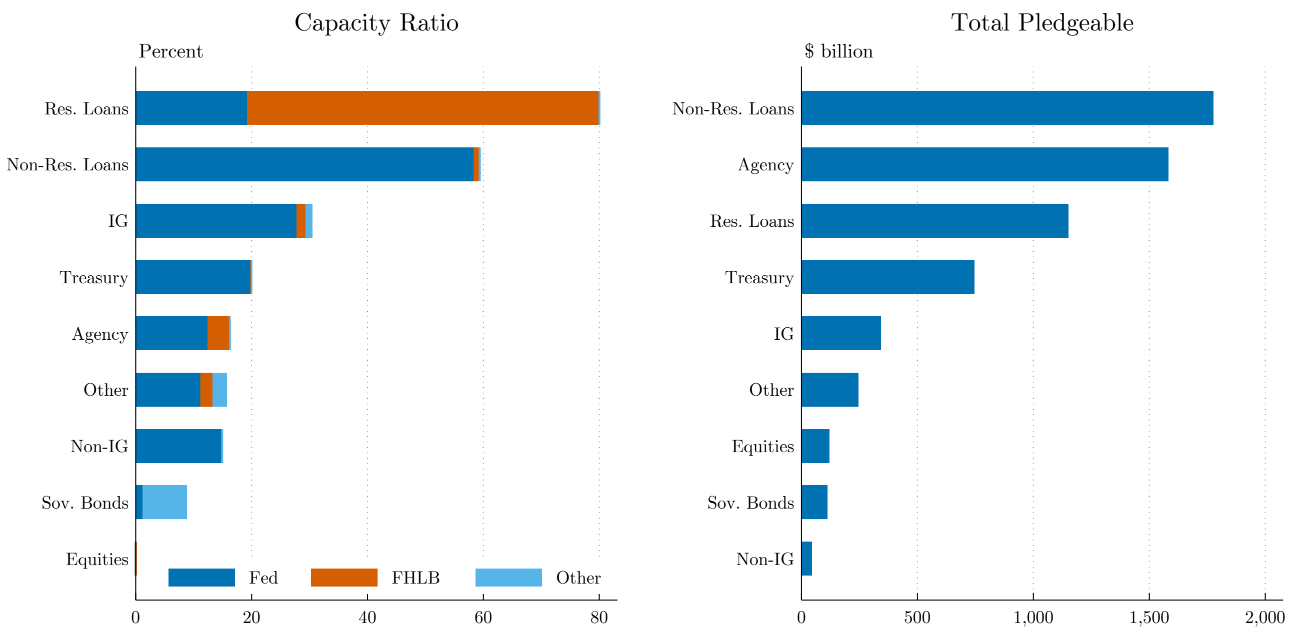

Figure 3: Average Capacity Ratio and Total Pledgeable by Asset Type and Provider. Left panel plots the average capacity ratio by provider and asset class, where capacity ratio is the capacity with that provider divided by the total amount of pledgeable assets. Right panel plots average total pledgeable assets, 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. Includes all banks in our FR2052a sample; see data section for details.

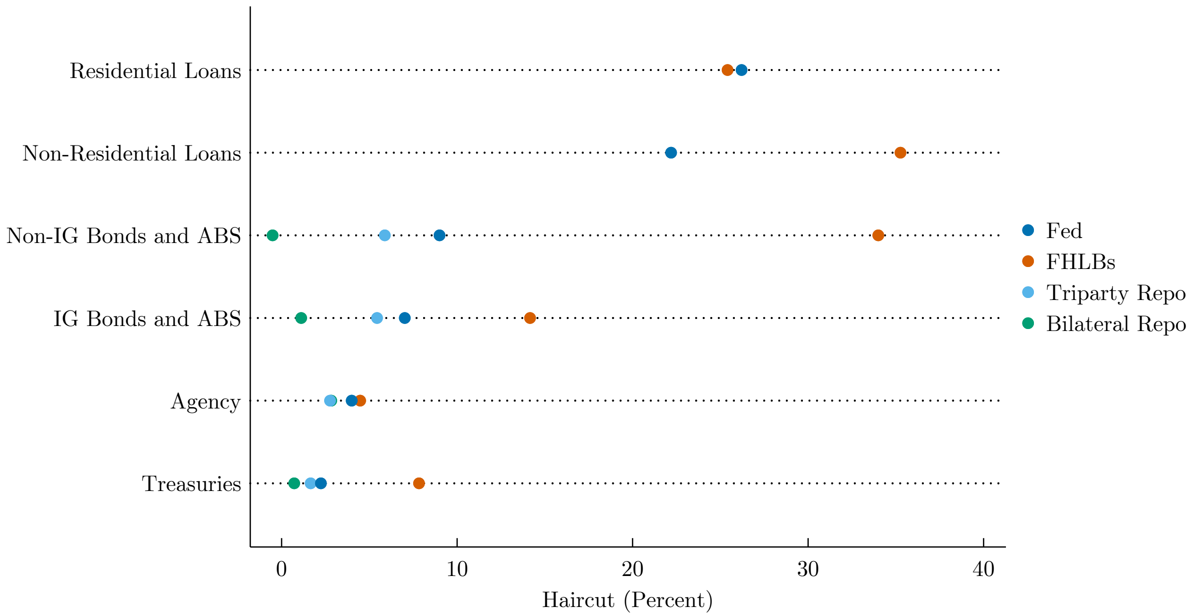

Figure 4: Haircuts Across Collateral Markets. Figure plots the average haircut on 1-month tenor collateral across several asset classes and collateral markets. We exclude small markets by adding together tri-party repo, bilateral repo, FICC repo, FHLB capacity, and Federal Reserve capacity, and dropping collateral markets that have less than 1 percent of the total in a given month. Includes all banks in our FR2052a sample; see data section for details.

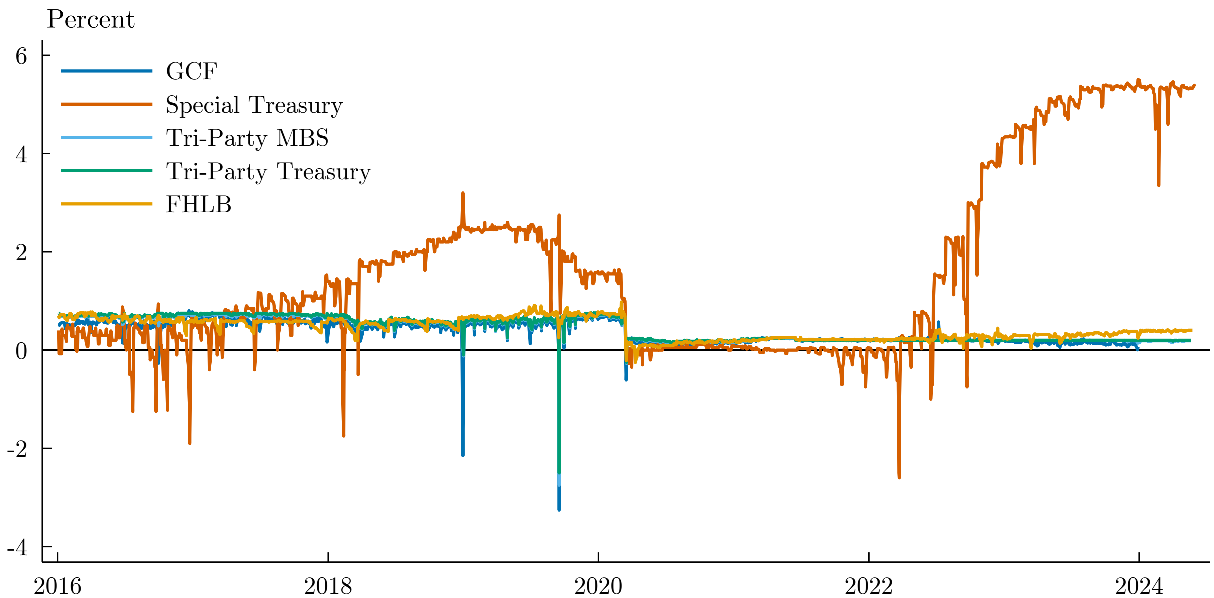

Figure 5: Financing Rates Across Collateral Markets. Figure plots the spread between the primary credit rate and the collateral market financing rate, where the financing rates are (1) general collateral finance (GCF) rate from DTCC, (2) the overnight repo rate for on-the-run 2-year Treasuries from JP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

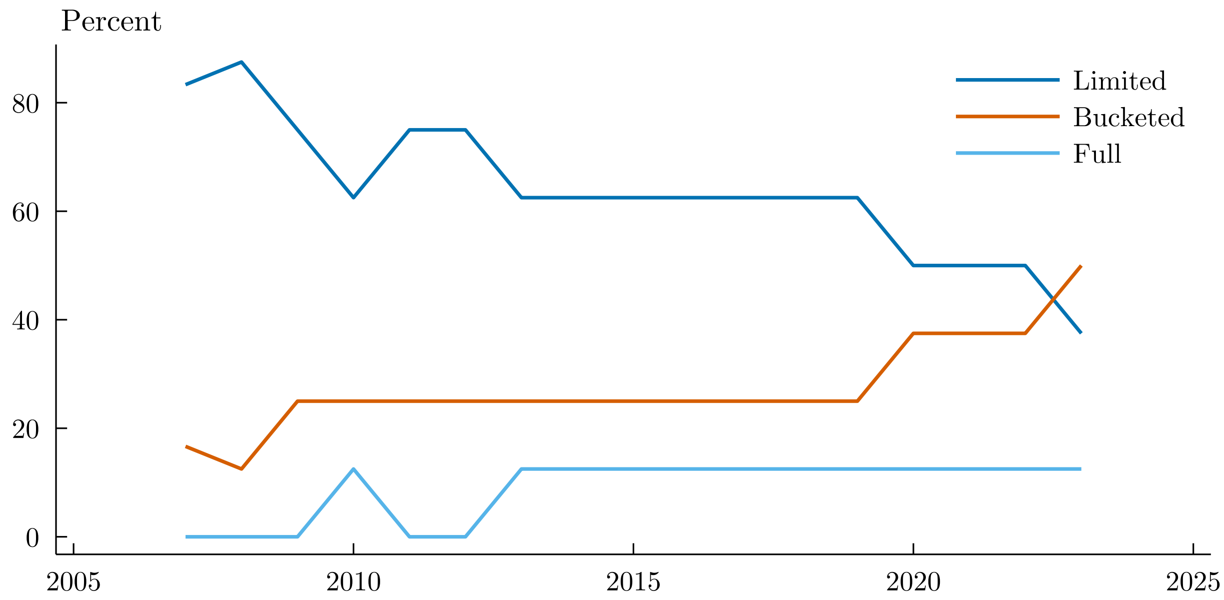

Figure 6: U.S. GSIB Public 10-K Pre-Positioning Style. Figure plots the share of banks reporting their pre-positioning by type. Figure derived only from public 10-K filings.

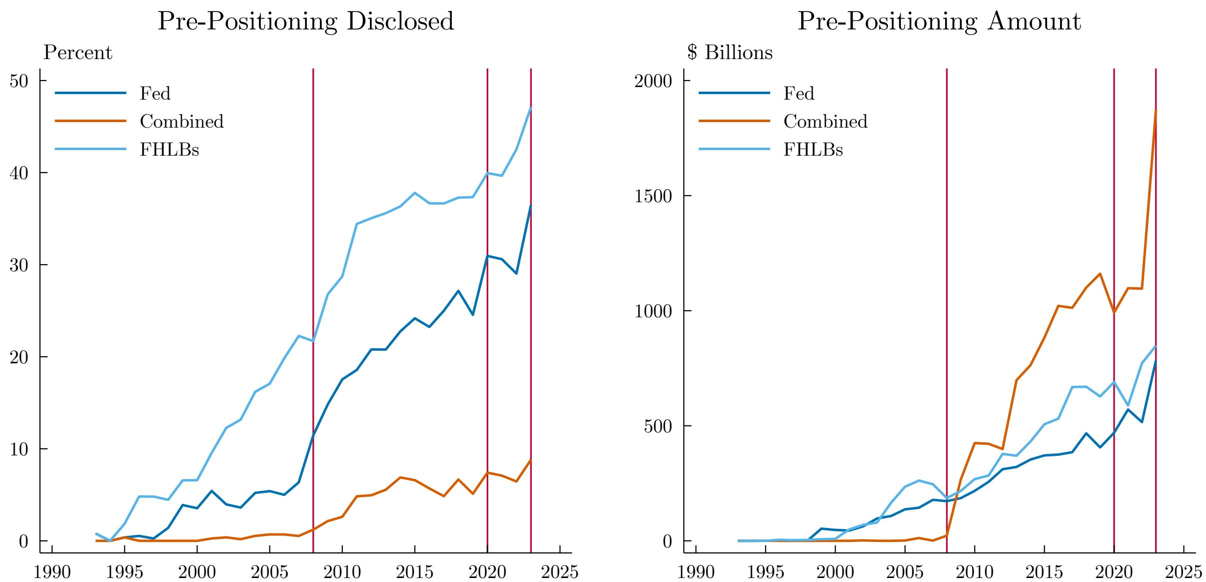

Figure 7: Pre-Positioning Disclosed in Public 10-Ks. Figure plots the share of banks reporting their pre-positioning by type. Figure derived only from public 10-K filings. Vertical lines denote 2008, 2020, and 2023.

9 Tables

		Operating Hours		Processing Time	
	Form	Pledges	Withdrawals	Pledges	Withdrawals
Securities	Fedwire Securities Services	8:30 am ET to 7:00 pm ET	8:30 am ET to 3:15 pm 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 1:00 pm ET†	Before 1:00 pm ET†	varies	varies
	Euroclear	Before 12:15 pm ET†	Before 10:00 am 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 the same day. †: cutoff time for same-day pledges or withdrawals.

	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
Lendable value of collateral in FR2052a sample ($ billions)	1,472	1,471	2,205
Sample Coverage of total lendable value (percent)	77.3	71.4	80.0

Table 2: Aggregate Banking System Pre-Positioning Summary Statistics. Table shows the publicly available summary statistics provided by the Federal Reserve for banks and credit unions compared to the aggregate pre-positioning reported in our sample of FR2052a reporting banks. Total commercial bank assets are non-seasonally adjusted total assets in the last weekly public H.8 report from the Federal Reserve in the given year. See `https://www.federalreserve.gov/monetarypolicy/discount-window-readiness.htm`.

			All	Treasuries	Agency	HQLA L1	Non-HQLA L1
(a):	*Pre-Positioned At Fed ($bn)*	Mean	1,871	160	210	216	1,655
		Std. Dev.	434	61	140	106	329
(b):	*Pre-Positioned At FHLBs ($bn)*	Mean	887	1	73	14	874
		Std. Dev.	84	3	33	9	81
(c):	*Unencumbered*	Mean	4,024	674	1,475	1,295	2,730
		Std. Dev.	1,100	240	322	261	901
$(a)/(a+b+c)^{\dagger}$:	*Capacity Ratio Fed*	Mean	27.7	19.2	12.1	13.6	31.9
		Std. Dev.	3.2	3.2	8.0	5.1	3.7
$(b)/(a+b+c)^{\dagger}$:	*Capacity Ratio FHLB*	Mean	13.5	0.1	4.0	0.9	17.2
		Std. Dev.	2.0	0.3	1.5	0.5	2.9
$(a)/\sum(a)$:	*Share of Total Pre-Positioned at Fed*	Mean		8.3	10.5	11.0	89.0
		Std. Dev.		2.0	3.8	2.8	2.8
$(b)/\sum(b)$:	*Share of Total Pre-Positioned at FHLBs*	Mean		0.1	8.0	1.5	98.5
		Std. Dev.		0.3	3.2	0.9	0.9

Table 3: Pre-Positioning Summary Statistics. Table shows summary statistics for pre-positioned assets and unencumbered assets. Summary statistics are calculated from monthly observations between 2017 and 2024. 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. Includes all banks in our FR2052a sample; see data section for details.

Panel A: All Banks (Monthly)				
	Correlation of ΔCapacity Ratio$_t^{Fed,k}$ with:			
k	VIX	Baa-Aaa	Bank Index Stock Return	$\Delta\ln$(Unrestricted Reserves)
All	0.22*	0.33***	−0.43***	0.17
Treasuries	0.21*	0.24*	−0.32**	0.21*
HQLA 1	0.19	0.28**	−0.40***	0.19
Non-HQLA1	0.21*	0.32**	−0.39***	0.10

Panel B: Large Banks (Daily)				
	Correlation of ΔCapacity Ratio$_t^{Fed,k}$ with:			
k	VIX	Baa-Aaa	Bank Index Stock Return	$\Delta\ln$(Unrestricted Reserves)
All	0.09***	0.06**	−0.08***	0.08***
Treasuries	0.04	0.01	−0.05*	0.00
HQLA 1	0.05*	0.02	−0.05*	−0.01
Non-HQLA1	0.08***	0.06**	−0.08***	0.08***

Table 4: Fed Capacity Ratio Correlations. Table shows correlation of the change in the Fed capacity ratio, either aggregated across all assets or limited to specific asset classes, with the VIX, Baa−Aaa corporate bond spread, bank index stock return using the KBW bank stock index, and unrestricted reserves. Top panel includes all banks in our FR2052a sample at a monthly frequency; bottom panel includes large banks at a daily frequency. 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$^{b,k}_{t,t+n}$	0.02***	0.03***	0.01**	0.55***	0.51***	0.39***
	(3.10)	(4.40)	(2.36)	(3.45)	(3.70)	(3.82)
N	3,713,702	923,714	2,789,988	3,713,702	923,714	110,492
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 ΔCapacity (Level)$^{b,k}_{t,t+n}$ = $\alpha + \beta$Settling Forward Purchases$^{b,k}_{t,t+n} + \gamma\prime X_t + \varepsilon^k_{t,t+n}$. Panel is at the date-bank-asset type-maturity bucket level. Fixed effects 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. Sample includes large banks at a daily frequency. 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$_{t,t+n}^{b,i,k}$	0.09***	0.18***	0.15***	0.30***	1.66***
	(12.94)	(9.71)	(50.89)	(18.24)	(84.05)
N	114,847	17,933	101,037	21,426	197,049
R^2	0.00	0.00	0.09	0.05	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 * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

	Fed Capacity Ratio$_t^b$		FHLB Capacity Ratio$_t^b$	
District Asset Share$_{t-1}^b$	-2.31^{***}	-2.56^{***}	1.59^{***}	1.70^{***}
	(-4.09)	(-4.45)	(5.31)	(5.65)
N	1,393	1,393	1,393	1,393
Within R^2	0.01	0.01	0.01	0.02
Time Fixed Effect	No	Yes	No	Yes

Table 7: Pre-Positioning Decreases with Stigma Exposure. Table presents the regression of a bank's capacity ratio on its share of assets in its Federal Reserve district. The first column columns use the Fed capacity ratio, as previously defined. The last two columns change the dependent variable to the FHLB capacity ratio, which reflects pre-positioning at the FHLBs. Capacity ratio variables are quarterly averages. Bank asset share is calculated using the total assets by Fed district by quarter and is lagged by one quarter and is standardized as a z-score for legibility. Includes all banks in our FR2052a sample; see data section for details. t-statistics are reported in parentheses using robust standard errors where * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

	Fed Disclosures			FHLB Disclosures		
	ROA_t^b	Capital Ratio_t^b	$\ln(\text{Assets})_t^b$	ROA_t^b	Capital Ratio_t^b	$\ln(\text{Assets})_t^b$
$\mathbb{I}(\text{Disclose Fed Pre-positioning}_t^b)$	-0.0345^{*}	-0.139^{***}	55.95^{***}			
	(-1.76)	(-3.03)	(23.09)			
$\mathbb{I}(\text{Disclose FHLB Pre-positioning}_t^b)$				-0.00390	0.131^{**}	-9.041^{***}
				(-0.28)	(2.03)	(-3.28)
N	41,957	41,957	41,957	37,694	37,694	37,694
Within R^2	0.00	0.00	0.01	0.00	0.00	0.00
Time Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes

Table 8: Pre-Positioning Disclosure vs. Bank Risk Observables. Table shows the regression of several call report bank observables on a dummy equal to 1 for when the bank publicly disclosed its pre-positioning to the Fed or FHLB (but not the Fed). ROA is net income (RIAD4340) over assets, capital ratio is total equity capital (RIAD3210) divided by total assets. Coefficients scaled by 10,000 for readability. R^2 is within-R^2. t-statistics are reported in parentheses using robust standard errors where * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. All data in the regression is derived from publicly available data.

	Abnormal Excess Return					
$\mathbb{I}(\text{Start Fed Disclosure})_t^b$	-0.209^{*}	-0.215^{*}				
	(-1.86)	(-1.85)				
Unexpected Earnings$_t$		-0.000480		-0.00112		-0.00112
		(-0.12)		(-0.28)		(-0.28)
$\mathbb{I}(\text{Start FHLB Disclosure Only})_t^b$			-0.00512	-0.0853		
			(-0.07)	(-1.06)		
$\mathbb{I}(\text{Start Combined Disclosure Only})_t^b$					-0.0785	0.0977
					(-0.45)	(0.62)
N	47,980	24,739	47,174	24,189	47,174	24,189
Within R^2	0.00	0.00	0.00	0.00	0.00	0.00

Table 9: Abnormal Returns Around Pre-Positioning Disclosure. Table shows the regression of abnormal returns on the release day of 10-K and 10-Q filings on an indicator variable denoting when a bank begins to disclose pre-positioning. FHLB and combined disclosure days exclude days where banks also start disclosing Fed pre-positioning. Abnormal returns are calculated relative to the 3-factor Fama French model over a rolling 3-month period. R^2 is within-R^2. t-statistics are reported in parentheses using robust standard errors clustered by bank where * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

	Large Banks (Daily)			All Banks (Monthly)		
	(1)	(2)	(3)	(4)	(5)	(6)
Bad State Risk						
Baa$-$Aaa$_t$	2.05***			1.12***		
	(5.43)			(3.33)		
Insured Deposits$_t^b$	−9.90***	−8.36***	−5.34**	−12.01***	−13.03***	−8.32***
	(−5.94)	(−4.88)	(−2.02)	(−7.89)	(−9.05)	(−4.39)
Uninsured Deposits$_t^b$	11.69***	9.84***	9.89***	6.02***	6.18***	10.43***
	(7.43)	(5.96)	(5.98)	(4.56)	(4.58)	(6.49)
Alternative Collateral Market						
EFFR$-$GCF$_t$	0.10			0.34***		
	(0.92)			(3.67)		
Treasury Repo Haircut$_t^b$	0.93***	1.50***	1.49***	0.61*	1.32***	1.37***
	(3.33)	(4.77)	(4.84)	(1.69)	(3.50)	(3.70)
Borrowing Stigma						
District Asset Share$_t^b$	−9.14***	−13.42***	−12.80***	−4.32***	−6.77***	−6.64***
	(−2.77)	(−4.09)	(−3.85)	(−3.13)	(−4.66)	(−4.60)
Controls						
Unrestricted Reserves$_t^b$			−3.01*			−8.79***
			(−1.88)			(−3.58)
N	15,832	16,792	16,792	1,930	2,022	2,022
R^2	0.15	0.12	0.12	0.23	0.28	0.33
Time FE	No	Yes	Yes	No	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes

Table 10: Sizing the Pre-Positioning Forces. Table shows the regression of Capacity Ratio$_t^{b,Fed}$ 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 HQLA level 1 holdings; 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), 3) we also reflect the alternative collateral market using the spread between the effective fed funds rate and the general collateral financing rate; 4) borrowing stigma exposure (proposition 4) using a bank's share of assets in its Federal Reserve district. We also include unrestricted reserves normalized by the size of the bank's HQLA level 1 holdings as a control. We winsorize the deposit ratios, repo haircuts, and reserve ratio at the 1st and 99th percentile to reduce the influence of outliers. The first three columns use the sample of large banks at a daily frequency; last three columns use the sample of all banks at a monthly frequency. 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 through the full sample at the consolidated bank-holding company level. For the daily version of the data, we include BHCs that report data at a daily frequency consistently between 2016 and 2024. For the monthly version of the data, we include BHCs that report data consistently between July 2017 and 2024, since monthly filers were only required to provide data in July 2017, a year and a half after the largest banks. We exclude BHCs that are acquired by another BHC when the acquiring BHC is not included in our data. We exclude internal transactions. We drop a handful of dates with outliers.

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 includes 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 to provide 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.

To calculate capacity ratios, we primarily focus on bank subsidiaries in the FR2052a data. To do this, we manually match FR2052a reporting entities to their bank RSSD ID. The FR2052a data provides data at the "material entity" level, defined as:

> A material entity is each consolidated bank, branch or non-bank entity that is a material contributor to a firm's funding and liquidity operations, based on factors including size, complexity, business activities, and overall risk profile.

Larger BHCs generally need to provide information on a several material entities, while smaller BHCs provide data on a more limited set of their subsidiaries. We identify the relevant bank subsidiary in several steps. Often the bank subsidiary is itself a material entity, in which case we directly match the bank's RSSD ID using the name of the bank. In other cases, it is common for the company to provide data on only one material entity, a consolidated entity, in which case we map that consolidated entity to the bank RSSD ID. One concern is that when a company provides only a single consolidated entity, it provides the balance sheet for its bank subsidiary combined with other subsidiaries, for example a broker-dealer subsidiary. However, any bias introduced by this aggregation is small since other subsidiaries are necessarily non-material since they are not separately reported.

In other cases, a company may report a consolidated bank entity which aggregates across the balance sheets of several smaller bank subsidiaries, each with distinct RSSD IDs. In this case, we map the entity to all of its constituent bank subsidiaries RSSD IDs so long as (1) those subsidiaries' RSSD IDs have a valid entry in the FFIEC attribute file which provides a map to their Federal Reserve district (discussed below), and (2) so long as the subsidiary has at least $50 million of total assets in their call report at any point between 2016 to 2024. If the company reports both a bank material entity and a separate consolidated bank material entity—which would occur, for example, if the company owns two banks, one material and the other not material—we match the material bank entity rather than a consolidated bank entity. Finally, we also exclude entities that appear for only a single month.

Foreign banks often have two types of material entities that can use the discount window: branches/agencies and bank subsidiaries. We treat branches/agencies and bank subsidiaries that are owned under the same parent foreign company as distinct entities since bank subsidiaries owned by foreign parents through intermediate holding companies operate relatively independently from their foreign parent.

Some variables—like repo haircuts—also require identifying the overarching parent entity for a given bank. For U.S. banks, this is always available as a consolidated entity. For foreign banks, we choose either the largest entity in asset terms or the material entity with the longest reporting time span, in case there are several with similar asset levels—in some cases, this is the company's consolidated agencies and branches, in other cases it is the company's consolidated U.S. operations.

A.1.2 Bank Assets by Supervisory Federal Reserve District

We calculate total assets by Federal Reserve district in several steps. First, we collect total assets from several types of reports: call reports for domestic banks using variable RCFD2170 (total consolidated assets); FFIEC 002 reports for U.S. branches and agencies of foreign banks using RCFD2170; and credit union call report variable CUSA2170. We exclude quarters before 1980 since the data is sparse for some periods in the 1970s.

This data creates a quarterly panel at the bank level, which we then merge with FFIEC attribute data to map each bank to its Federal Reserve district.[38] We restrict our sample to those that have both quarterly financial data and also appear in the FFIEC attribute data.

Importantly, the Federal Reserve district from which the bank could borrow from is not always the same as the district in which its head office is physically located. As described in the FFIEC attribute documentation:

> Changes in Regulations D and I, effective October 1, 1997, allow depository institutions to denote a Federal Reserve office other than where the entity is physically located for purposes of Federal Reserve membership and/or reserve account maintenance.

Regulation I, for example, states[39]

> *(c)* ***Location of the Bank***
>
> (c)(1) **General rule.** For purposes of this part, a national bank or a State bank is located in the Federal Reserve District that contains the location specified in the bank's charter or organizing certificate, or as specified by the institution's primary regulator, or if no such location is specified, the location of its head office, unless otherwise determined by the Board under paragraph (c)(2) of this section.
>
> (c)(2) **Board determination.** If the location of a bank as specified in paragraph (c)(1) of this section, in the judgment of the Board of Governors of the Federal Reserve System (Board), is ambiguous, would impede the ability of the Board or the Reserve Banks to perform their functions under the Federal Reserve Act, or would impede the ability of the bank to operate efficiently, the Board will determine the Federal Reserve District in which the bank is located, after consultation with the bank and the relevant Reserve Banks. The relevant Reserve Banks are the Reserve Bank whose District contains the location specified in paragraph (c)(1) of this section and the Reserve Bank in whose District the bank is proposed to be located. In making this determination, the Board will consider any applicable laws, the business needs of the bank, the location of the bank's head office, the locations where the bank performs its business, and the locations that would allow the bank, the Board, and the Reserve Banks to perform their functions efficiently and effectively.

[38] FFIEC attribute data is available at `https://www.ffiec.gov/npw/FinancialReport/DataDownload`.
[39] `https://www.ecfr.gov/current/title-12/chapter-II/subchapter-A/part-209/section-209.2`

We set FFIEC 002 filers' Federal Reserve district equal to the district where the branch/agency is physically located (DIST_FRS); for call report filers (domestic banks and credit unions) we set the Federal Reserve district equal to the district is physically located for quarters before Q4 1997 (DIST_FRS) and equal to the "Federal Reserve Regulatory District Code" (AUTH_REG_DIST_FRS) beginning in Q4 1997, except when the entity has no value for AUTH_REG_DIST_FRS, in which case we use the district the bank is physically located in (DIST_FRS).

We verify our mapping of banks to their Federal Reserve district by checking against publicly-available discount window transaction data which provides information on the Federal Reserve district from which the bank borrowed beginning in 2011, available with a two-year lag.[40] Since the publicly available data does not have the borrower's RSSD ID, we instead match using their ABA number. Our mapping correctly matches the actual district from which the bank borrowed in 99.9 percent of the borrowers for which we can match using their ABA number.

Note, however, that the FFIEC attribute data provides only the most recent mapping from an RSSD ID to its Federal Reserve district; it does not provide the historical mapping in the case that a bank changed its regulatory Federal Reserve district. While this introduces some bias in our estimates—we can only map RSSDs to their regulatory Fed district with the most recently available data—it accurately reflects what is public knowledge, and hence provides a valid proxy for the public's understanding of bank assets by district. By construction, our measure of stigma exposure cannot rely on non-public information, else it would be invalid.

We calculate the total assets in each quarter for each regulatory district to estimate a bank's share of assets in its regulatory Federal Reserve district. In the rare case that a FR2025a bank entity has subsidiary banks in separate Federal Reserve districts, we calculate the entity's value-weighted average bank share of district assets, where the value-weights are the entity's assets in a given district. In the case that the filer has several branches located in different Federal Reserve districts, we similarly value weight based on their total assets reported in the FFIEC 002 report.

A.2 10-K/Q Disclosure Examples

- 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

[40] The publicly available data is available at `https://www.federalreserve.gov/regreform/discount-window.htm`.

> 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.

A.3 Additional Tests for Pre-positioning Stigma

Another way to examine pre-positioning stigma is shown in Table A6 which studies quarter-end window dressing in capacity based on whether a firm is a discloser or not. We merge our FR2052a monthly bank sample with the SEC pre-positioning disclosure data. The table shows the regression

$$\Delta \ln(\text{Capacity (Level)})^{Fed,b}_{t-1\to t} = \alpha + \beta_1 \mathbb{I}(\text{Month with Quarterly Disclosure})^b_t + \varepsilon^k_t.$$

The table shows that disclosing banks increase their pre-positioning in months that coincide with public quarterly filings (column 1), but there is no such dynamic for banks that do not publicly disclose Fed pre-positioning (column 3). This regression takes advantage of the fact that capacity from the month *before* the quarter-end month does not get publicly disclosed, since pre-positioning disclosures focus on the level at quarter-end. Moreover, rather than looking at the month-over-month change on quarter-ends, we can instead look at the quarter-over-quarter change, which is the change in capacity over a three-month period. Column (2) shows that the change in capacity calculated using quarter-end capacity values is not significantly different from zero for either disclosers or non-disclosers. The evidence shows that disclosing banks window-dress their pre-positioning, boosting their capacity levels at quarter-end.

Such window-dressing behavior is consistent with pre-positioning stigma. Banks that disclose the level of pre-positioning (which we have previously shown tend to be riskier banks) may feel that it is important to show similar levels of pre-positioning from quarter to quarter. Why? Lower levels of pre-positioning could indicate that the bank used some previously pre-positioned assets in other secured funding markets or that the bank has borrowed from the discount window, meaning that the bank has fewer marginal sources of liquidity than in the previous quarter. Disclosing banks may feel it is important to consistently show they have large emergency liquidity available and are reluctant to show lower values of emergency liquidity available quarter-over-quarter.

A.4 10-K Data Details

We clean the raw SEC filings following a process described in Loughran and McDonald (2016). In particular, we exclude all <TYPE> tags of GRAPHIC, ZIP, EXCEL, JSON, PDF; we remove DIV, TR, TD, and FONT tags; we remove all XML documents and XBRL text; we exclude certain boilerplate language at the beginning and end of the documents; and standardize the text to remove markup tags and other non-standard characters. We exclude a handful of filings that do not have valid metadata in the file header.

We look for sentences within a filing that includes the string “pledg” along with one of “federal reserve,” “frb,”, “discount window,” “fhlb,” or “federal home loan bank.” We provide each excerpt to the ChatGPT (model iteration gpt-4o-2024-08-06) with the following prompt:

> You will be provided with an excerpt from a financial document from a bank.
>
> Your goal is to identify and extract the amounts of collateral pledged (also called pre-positioned to the Federal Reserve (also called Fed or FRB) or the Federal Home Loan Banks (also called FHLB or FHLBs)) for potential borrowing.
>
> Please follow the schema provided for your output:
>
> - Fed_Specific_Amt: The specific amount of collateral pledged to the Federal Reserve. If no monetary amounts are present but the excerpt indicates that the bank pledges collateral to the Federal Reserve, use "Not Specified." If the excerpt is irrelevant, use "Not Relevant."
> - FHLB_Specific_Amt: The specific amount of collateral pledged to the Federal Home Loan Banks. If no monetary amounts are present but the excerpt indicates that the bank pledges collateral to the Federal Home Loan Banks, use "Not Specified." If the excerpt is irrelevant, use "Not Relevant."
> - Fed_and_FHLB_Combined_Amt: The combined amount of collateral pledged to both the Federal Reserve and Federal Home Loan Banks. Use this field only if a combined amount is explicitly provided. If no monetary amounts are present but the excerpt indicates that the bank pledges collateral to both the Federal Reserve and the Federal Home Loan Banks, use "Not Specified." If the amount includes collateral pledged to other entities in addition to the Federal Reserve and Federal Home Loan Banks, also use "Not Specified." If the excerpt is irrelevant, use "Not Relevant."
> - Confidence_Level: Your confidence level in the accuracy of the extracted amounts, on a scale of 1 (low) to 10 (high). If the excerpt is irrelevant to the task, use "Not Relevant."
>
> Additional considerations:
>
> - For amounts from two different time periods, prioritize the most recent amounts.

Since a single filing may reference pre-positioning in several different excerpts—for example, they may separately disclose the aggregate amount of pre-positioning and the amount of pre-positioning of hold-to-maturity assets—we collapse the data to the filing level by taking the largest pre-positioning value in that filing.

A.5 Figures

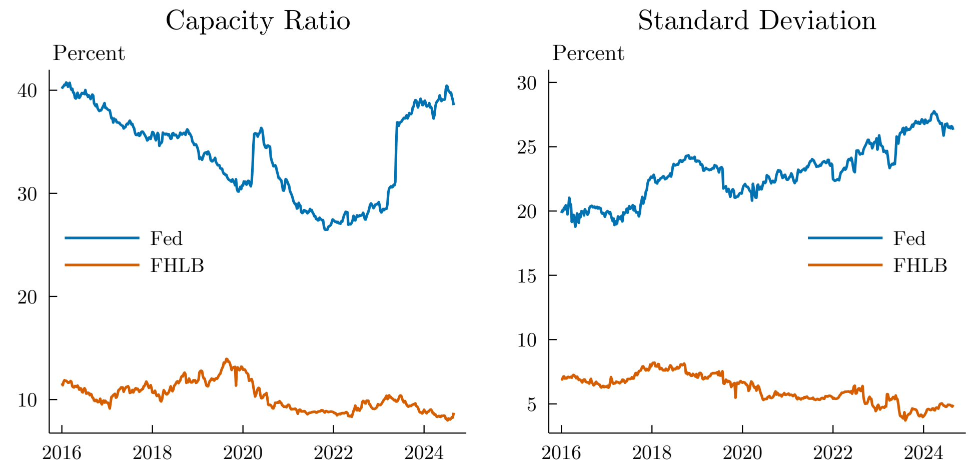

Figure A1: Large Banks: Capacity Ratio and Cross-Section Standard Deviation of Capacity Ratio. Capacity Ratio$_t^p$ = (Pre-positioned Collateral/(Unencumbered Assets + All Pre-Positioned Collateral))$_t$ where both numerator and denominator are market values of the assets and p reflects the capacity 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. Left panel shows the aggregate capacity ratio across the banks, and right panel shows the standard deviation across individual banks' capacity ratios at a point in time. Plots are weekly averages of daily data. Large banks are defined as daily filers of FR2052a.

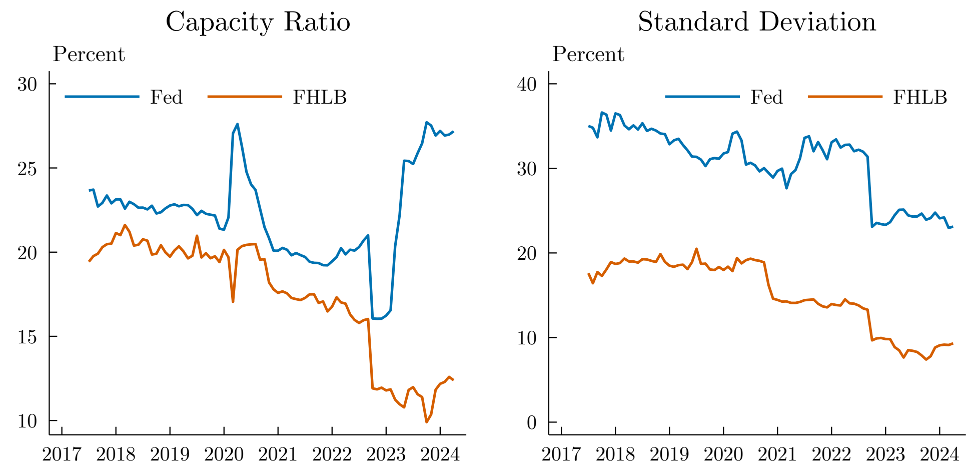

Figure A2: Medium-Sized Banks: Capacity Ratio and Cross-Section Standard Deviation of Capacity Ratio. Capacity Ratio$_t^p$ = (Pre-positioned Collateral/(Unencumbered Assets + All Pre-Positioned Collateral))$_t$ where both numerator and denominator are market values of the assets and p reflects the capacity 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. Left panel shows the aggregate capacity ratio across the banks, and right panel shows the standard deviation across individual banks' capacity ratios at a point in time. Plots are monthly data. Medium-sized banks are defined as monthly filers of FR2052a.

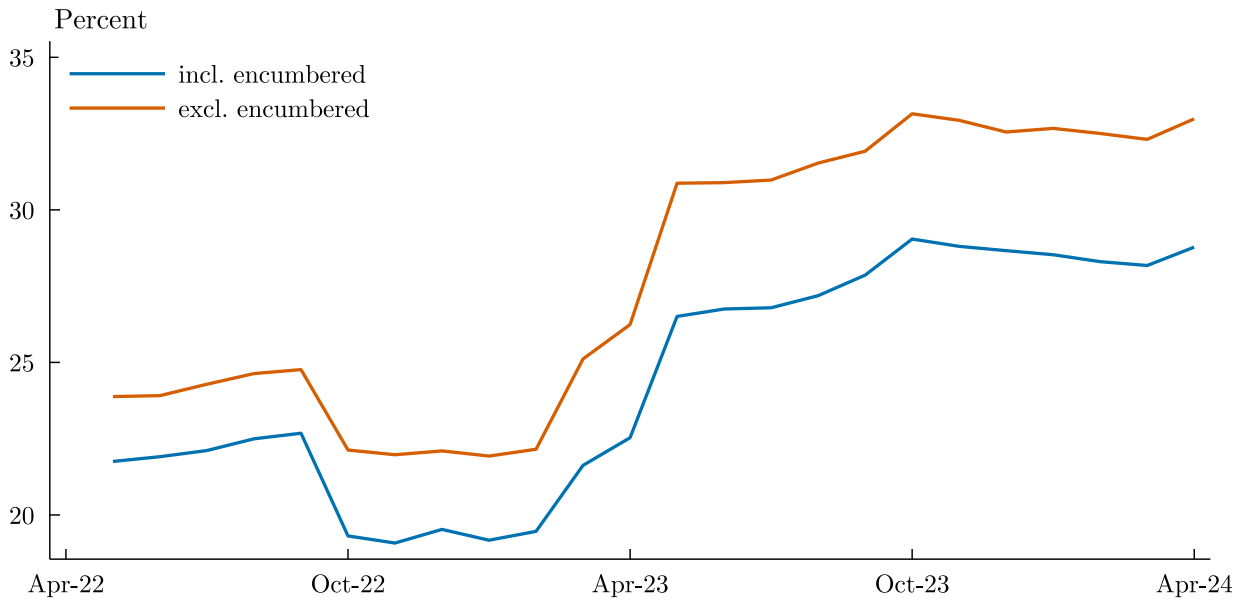

Figure A3: Capacity Ratio including Encumbered Assets. Capacity Ratio_t^p = (Pre-positioned Collateral/(Unencumbered Assets + Encumbered Assets + All Pre-Positioned Collateral$))_t$ where both numerator and denominator are market values of the assets and p reflects the capacity provider (e.g., the Fed 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 monthly data. Includes all banks in our FR2052a sample; see data section for details.

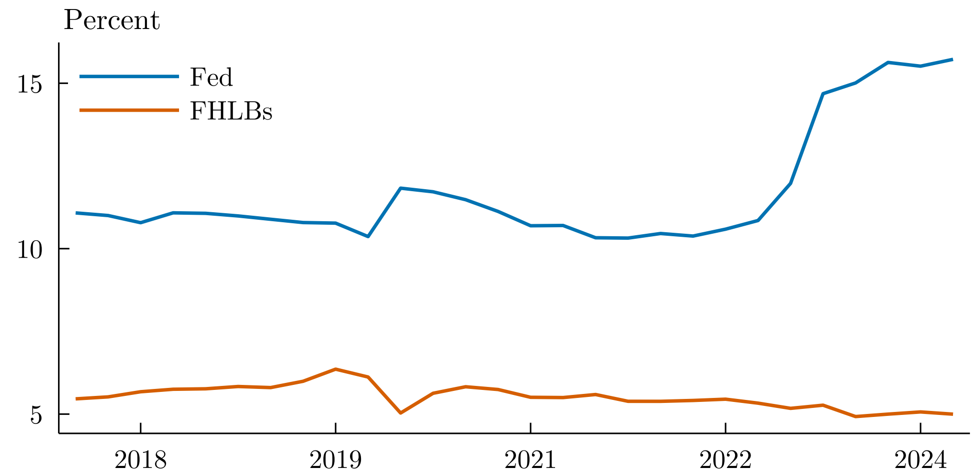

Figure A4: Capacity vs. Total Bank Assets. Plots the total amount of Fed and FHLB capacity reported in FR2052a data against total assets as reported in call reports for our sample of banks.

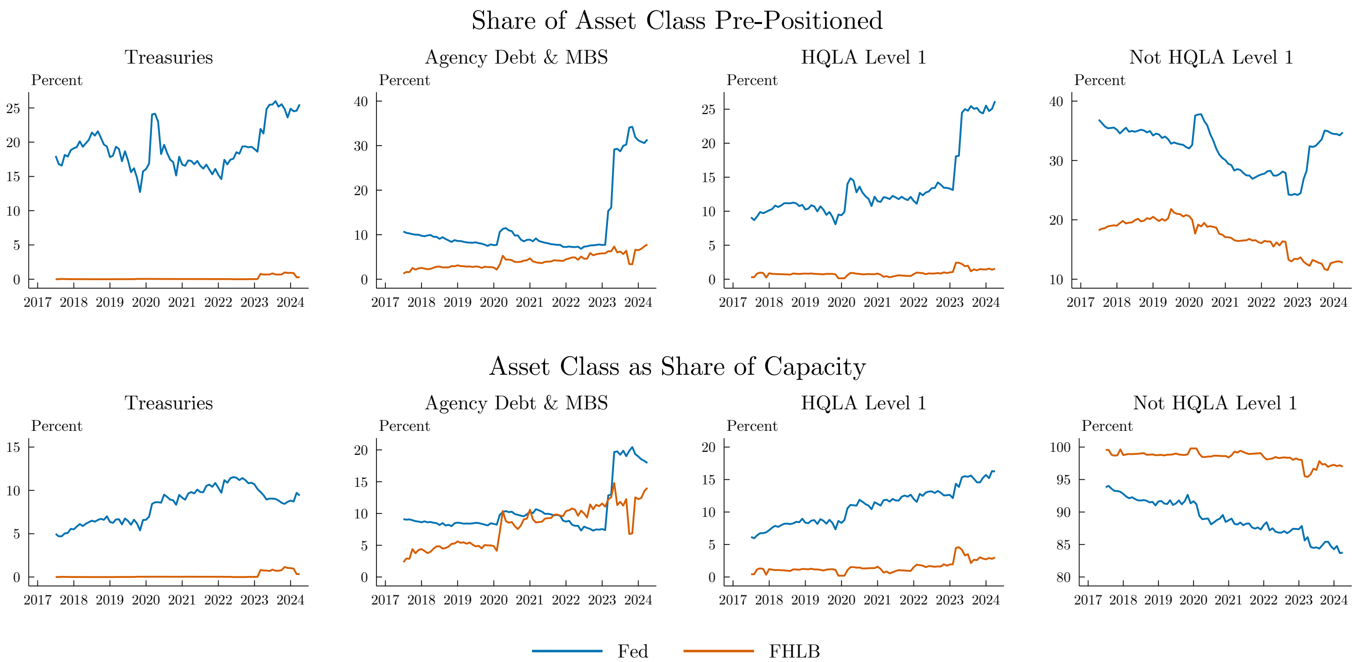

Figure A5: Capacity Composition by Asset Type for All Banks. Top panel plots the share of an asset class that is pledged as collateral to the Fed or FHLB as a percent of the sum of total unencumbered assets and all pre-positioned collateral of that asset type. Bottom panel plots the share of capacity with the Fed or FHLB that each asset class constitutes. Plots are monthly data. Includes all banks in our FR2052a sample; see data section for details.

Figure A6: Average Capacity Ratio and Total Pledgeable by Bank Size. Left panels 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 pledgeable assets. Right panel plots average total pledgeable assets, 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. Large banks are defined as daily filers of FR2052a; medium-sized banks are defined as monthly filers of FR2052a.

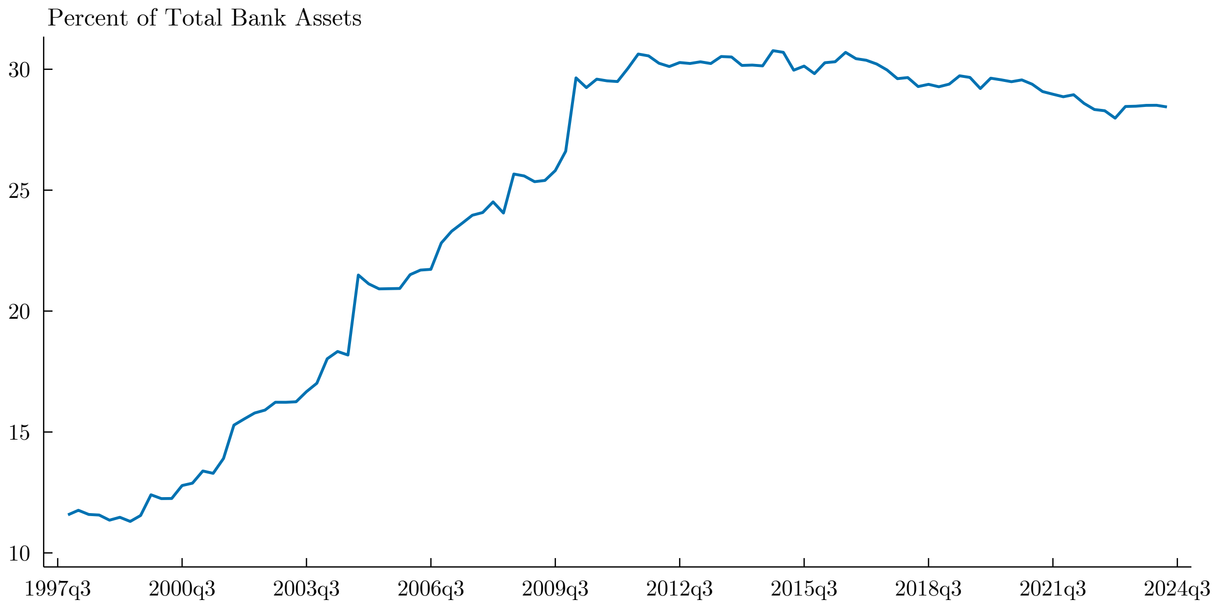

Figure A7: Share of Bank Assets Held By Switching Banks. Figure plots the share of total bank assets held by banks with supervisory Federal Reserve districts different from the district in which its head office is physically located. Figure derived entirely from public data, including call report and FFIEC attribute data.

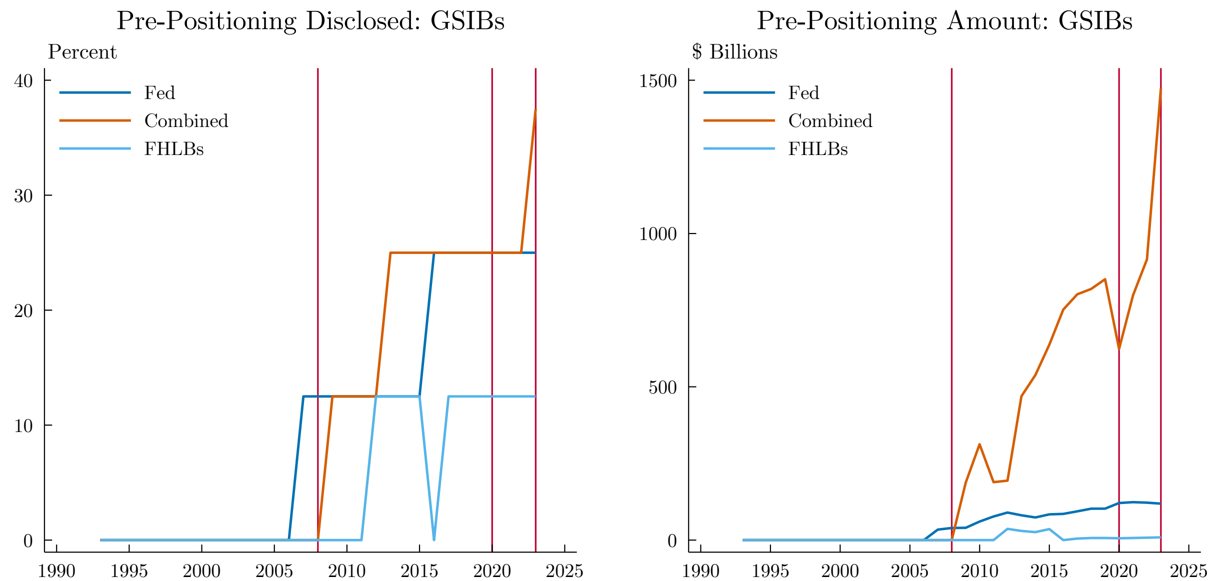

Figure A8: Public Pre-Positioning 10-K Information: Large Banks. Figure plots the share of banks reporting their pre-positioning by type for large banks, defined as globally systemically important banks. Figure derived only from public 10-K filings.

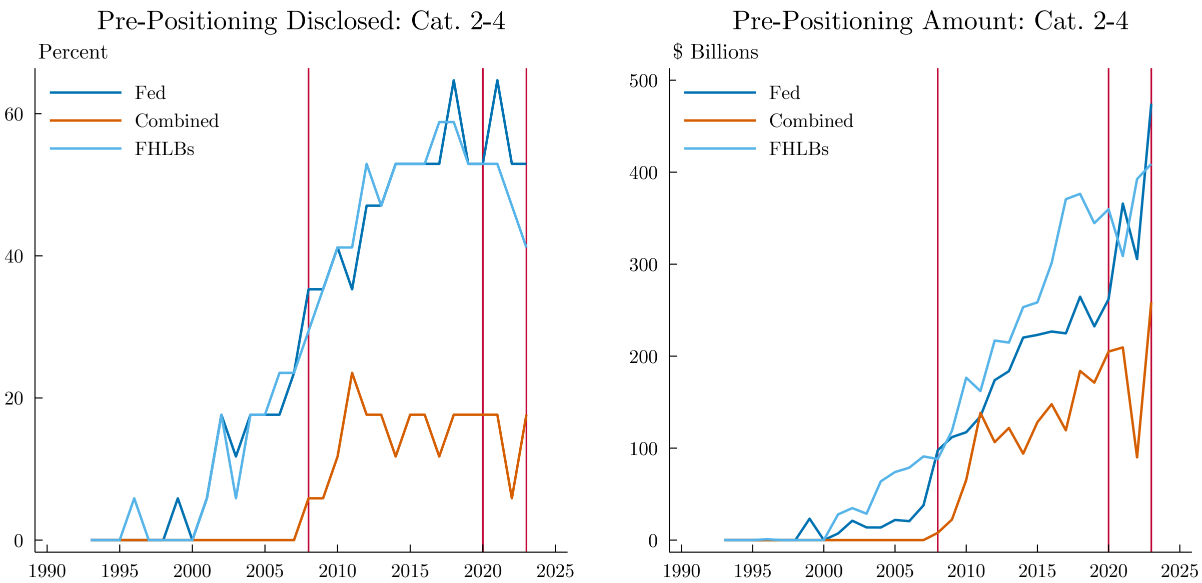

Figure A9: Public Pre-Positioning 10-K Information: Medium-sized Banks. Figure plots the share of banks reporting their pre-positioning by type for medium-sized banks, defined as category II, III, and IV banks. Figure derived only from public 10-K filings.

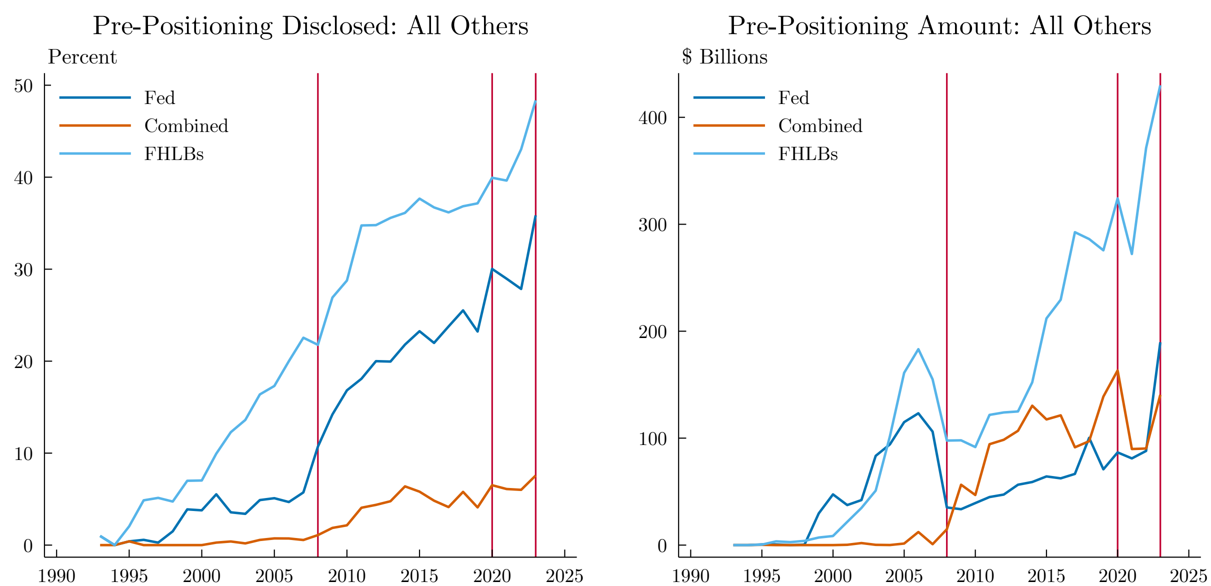

Figure A10: Public Pre-Positioning 10-K Information: All Other Banks. Figure plots the share of banks reporting their pre-positioning by type for all other banks that are neither GSIBs nor category II, III, or IV banks. Figure derived only from public 10-K filings.

			All	Treasuries	Agency	HQLA L1	Non-HQLA L1
(a):	*Pre-Positioned At Fed ($bn)*	Mean	1,133	137	149	164	969
		Std. Dev.	188	57	62	76	121
(b):	*Pre-Positioned At FHLBs ($bn)*	Mean	349	0	6	1	347
		Std. Dev.	48	0	5	1	48
(c):	*Unencumbered*	Mean	1,934	437	776	801	1,133
		Std. Dev.	519	218	176	228	299
$(a)/(a+b+c)^{\dagger}$:	*Capacity Ratio Fed*	Mean	33.5	24.9	16.2	16.2	40.0
		Std. Dev.	4.1	4.6	6.5	3.8	4.8
$(b)/(a+b+c)^{\dagger}$:	*Capacity Ratio FHLB*	Mean	10.3	0.0	0.6	0.1	14.3
		Std. Dev.	1.3	0.0	0.4	0.1	1.5
$(a)/\sum(a)$:	*Share of Total Pre-Positioned at Fed*	Mean		11.7	12.7	13.9	86.1
		Std. Dev.		3.6	3.1	4.5	4.5
$(b)/\sum(b)$:	*Share of Total Pre-Positioned at FHLBs*	Mean		0.0	1.6	0.3	99.7
		Std. Dev.		0.0	1.2	0.3	0.3

Table A1: Large Banks: Pre-Positioning Summary Statistics. Table shows summary statistics for pre-positioned assets and unencumbered assets. Summary statistics are calculated from daily observations between 2016 and 2024. 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. Includes large banks in our FR2052a sample; see data section for details.

			All	Treasuries	Agency	HQLA L1	Non-HQLA L1
(a):	*Pre-Positioned At Fed ($bn)*	Mean	708	13	61	41	667
		Std. Dev.	227	12	81	41	190
(b):	*Pre-Positioned At FHLBs ($bn)*	Mean	523	1	67	12	511
		Std. Dev.	62	3	31	8	62
(c):	*Unencumbered*	Mean	1,966	193	644	443	1,522
		Std. Dev.	683	38	166	70	672
$(a)/(a+b+c)^{\dagger}$:	*Capacity Ratio Fed*	Mean	22.2	6.3	7.9	8.3	25.2
		Std. Dev.	2.8	4.9	10.4	8.1	2.9
$(b)/(a+b+c)^{\dagger}$:	*Capacity Ratio FHLB*	Mean	17.3	0.6	8.4	2.4	20.4
		Std. Dev.	3.5	1.1	3.2	1.5	4.8
$(a)/\sum(a)$:	*Share of Total Pre-Positioned at Fed*	Mean		1.7	6.8	5.1	94.9
		Std. Dev.		0.9	6.2	2.9	2.9
$(b)/\sum(b)$:	*Share of Total Pre-Positioned at FHLBs*	Mean		0.2	12.4	2.4	97.6
		Std. Dev.		0.5	5.2	1.5	1.5

Table A2: Medium-Sized Banks: Pre-Positioning Summary Statistics. Table shows summary statistics for pre-positioned assets and unencumbered assets. Summary statistics are calculated from monthly observations between 2018 and 2024. 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. Includes medium-sized banks in our FR2052a sample; see data section for details.

	All Banks (Monthly)		Large Banks (Daily)	
	Fed CR excl Encumbered$_t$	FHLB CR excl Encumbered$_t$	Fed CR excl Encumbered$_t$	FHLB CR excl Encumbered$_t$
Fed Capacity Ratio incl. Encumbered$_t$	1.189***		1.324***	
	(53.62)		(313.29)	
FHLB Capacity Ratio incl. Encumbered$_t$		0.891***		1.111***
		(37.12)		(100.15)
Constant	−1.242*	2.356***	−3.217***	0.730***
	(−2.01)	(9.62)	(−25.51)	(8.88)
N	24	24	564	564
R^2	0.99	0.98	0.99	0.93

Table A3: Comparing Capacity Ratios with and without encumbered assets. Table shows the regression of Capacity Ratio$_t$ without encumbered assets in the denominator (the main measure) on the Capacity Ratio$_t$ including encumbered assets. Data begins May 2022. t-statistics are reported with robust standard errors where * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Panel A: All Banks (Monthly)		
	Correlation of ΔCapacity $\text{Ratio}_t^{\text{Fed},k}$ with:	
k	$\Delta \ln(\text{Avg. Collateralized Daylight Drafts})_t$	$\Delta \ln(\text{Peak Daylight Drafts})_t$
All	−0.10	−0.06
HQLA 1	−0.09	−0.05

Panel B: Large Banks (Weekly)		
	Correlation of ΔCapacity $\text{Ratio}_t^{\text{Fed},k}$ with:	
k	$\Delta \ln(\text{Avg. Collateralized Daylight Drafts})_t$	$\Delta \ln(\text{Peak Daylight Drafts})_t$
All	−0.05	−0.12
HQLA 1	−0.07	−0.11

Table A4: Correlation of Capacity Ratios and Daylight Overdrafts. 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. Top panel includes all banks in our FR2052a sample at a monthly frequency, using the last daylight overdraft observation in a given month; bottom panel includes large banks at a weekly frequency, matching the level of frequency of publicly-available daylight overdraft data. t-statistics are reported in parentheses where * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Daylight overdraft data are available from `https://www.federalreserve.gov/paymentsystems/psr_dlod.htm`.

All Filers, 1995-2024		Fed	FHLB	Combined
Share of Filers Disclosing (percent)	Average	13.7	23.0	2.9
	Max	36.5	47.1	8.8
Total Level Disclosed ($ billion)	Average	227.0	295.8	427.4
	Max	783.3	848.0	1,872.9

Table A5: Public Pre-positioning Disclosure Summary Statistics. Table provides summary statistics of the publicly disclosed pre-positioning in annual reports from 1995 to 2024. Figure derived only from public SEC filings.

	Disclosers		Non-Disclosers	
	$\Delta\ln(\text{Fed Capacity})^b_{t-1\to t}$	$\Delta\ln(\text{Fed Capacity})^b_{t-3\to t}$	$\Delta\ln(\text{Fed Capacity})^b_{t-1\to t}$	$\Delta\ln(\text{Fed Capacity})^b_{t-3\to t}$
$\mathbb{I}(\text{Month with Quarterly Disclosure}^b_t)$	3.037**	0.258	0.219	−0.117
	(2.21)	(0.14)	(0.33)	(−0.10)
N	915	897	989	957
R^2	0.01	0.00	0.00	0.00

Table A6: Pre-Positioning Disclosers Increase Capacity at Quarter-Ends. Table shows the regression $\Delta\ln(\text{Capacity (Level)})^{Fed,b}_{t-j\to t} = \alpha + \beta_1\mathbb{I}(\text{Month with Quarterly Disclosure})^b_t + \varepsilon^k_t$ where j is either 1 (month on month changes) or 3 (quarter on quarter changes). The first two columns look at banks that disclosed their Fed pre-positioning and the last two columns look at banks that did not disclose. We define a bank as a disclosing bank when it discloses its Fed pre-positioning using the most recently available quarterly disclosure, which coincides with the current month for months that are also quarter-ends. Since we do not have SEC filings for the foreign-affiliated banks and branches or agencies, we are limited to the companies that are publicly-traded in the U.S. Coefficients multiplied by 100 for legibility. t-statistics are reported in parentheses using robust standard errors clustered by month where * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

	Large Banks (Daily)			All Banks (Monthly)		
	(1)	(2)	(3)	(4)	(5)	(6)
Bad State Risk						
Baa$-$Aaa$_t$	1.50***			0.66		
	(3.46)			(1.31)		
Insured Deposits^b_t	$-$7.17***			$-$8.29***		
	($-$3.81)			($-$6.53)		
Uninsured Deposits^b_t	9.22***			5.84***		
	(5.21)			(5.35)		
Alternative Collateral Market						
EFFR$-$GCF$_t$		$-$0.05			0.60***	
		($-$0.27)			(2.74)	
Treasury Repo Haircut^b_t		0.86**			1.50***	
		(2.44)			(4.24)	
Borrowing Stigma						
District Asset Share^b_t			$-$14.52***			$-$5.35***
			($-$4.00)			($-$3.62)
N	16,592	15,856	16,792	3,060	2,780	4,075
R^2	0.09	0.01	0.03	0.06	0.01	0.00
Time FE	No	No	No	No	No	No
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes

Table A7: Sizing the Pre-positioning Forces, one-by-one. Table repeats the regression in Table 10 against the pre-positioning forces one by one. R^2 is within-R^2. t-statistics are reported in parentheses using robust standard errors clustered by month where * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.