Where Collateral Sleeps*

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Abstract

Banks can use the discount window to fend off a run by prepositioning assets with the Fed and borrowing against them. Following the March 2023 bank runs, policymakers have considered mandatory prepositioning, arguably the largest update to the lender-of-last-resort toolkit in over a century. We study the forces that shape the largest banks' prepositioning. We show that run-prone uninsured-deposit flows causally drive prepositioning and that banks face a *prepositioning stigma*, even absent borrowing. Prepositioning is no panacea—banks still need good assets to borrow against—but it can help at the margin.

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> It's called "prepositioning." Remember the word; it's going to be important.
>
> (Izabella Kaminska, Politico, January 19, 2024)

1 Introduction

The discount window has been the central banker's classic lender-of-last-resort tool 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, to solvent banks. The details matter, though. Banks need collateral to borrow against, and borrowing from the discount window carries stigma, so banks are less inclined to use it (Armantier et al., 2015a).

Banks can voluntarily *preposition* their assets with the Fed. Prepositioning allows banks to quickly borrow from the discount window for two reasons. First, the Fed lends through the discount window only against collateral it has valued, a process that can be time-consuming. That valuation is done in advance for prepositioned collateral. Second, borrowing against prepositioned collateral does not rely on third-party financial plumbing, such as custodial banks or payment systems.

Since the March 2023 bank runs, prepositioning has become a focus for central bankers and market participants. It 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's rapid failure was caused, at least in part, by its collateral sleeping in the wrong place:

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

March 2023 taught markets that a dollar of good collateral in the wrong place is no different from no collateral at all. Alternatives have been proposed that banks should preposition assets with the Fed so collateral is immediately available if they need to borrow. If enacted, such requirements would represent the biggest innovation to the lender-of-last-resort toolkit in more than a century. Proponents argue that these requirements would improve the discount window's efficacy, despite its existing stigma.

In this paper, we study prepositioning to understand where banks keep their collateral and why. Our results show that the largest banks are deliberate in their prepositioning, responding to market forces. By revealed preference, banks prefer not to preposition large swaths of their assets. Although prepositioning with the Fed incurs an opportunity cost, it allows banks to buy insurance in case of a run. The quantity and composition of collateral sleeping at the Fed each night tell us how banks value that insurance.

We study prepositioning using two novel datasets: confidential supervisory prepositioning data and a comprehensive dataset spanning banks' voluntary public prepositioning disclosures from SEC filings. We document two motivating facts. First, the largest, most sophisticated banks routinely preposition a large share of assets—28 percent of their unencumbered assets—to the Federal Reserve.[1] These prepositioned assets serve as collateral against which a 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 preposition everything.

Second, most banks have not historically voluntarily disclosed their prepositioning, yet those that do tend to be riskier. This is a puzzle. If borrowing from the discount window carries stigma, why would a riskier bank voluntarily reveal that it has prepared to use it? We argue that banks weigh the stigma cost against its benefit: public disclosure of prepositioning signals that the bank has purchased run insurance, even if that insurance is costly. Banks disclose only when the signaling benefit outweighs the stigma cost.

We use a simple model to understand the forces that affect where collateral sleeps. The model shows how three forces help pin down banks' prepositioning: (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 prepositioning since prepositioned assets can't be used as collateral elsewhere; and (3) stigma, both for borrowing from the window and for simply prepositioning collateral.

Banks may be reluctant to pledge collateral to the Fed if it is more valuable in other collateral markets, like the repo market or back Federal Home Loan Bank (FHLB) advances.[2] This calculation depends, in part, on the relative financing rates and haircuts for that collateral. Banks' expectations about the future also matter since an optimistic bank may not expect to need the discount window. Stigma also plays a role, raising the bar that would compel a bank to preposition and use the discount window beyond the standard pecuniary costs stemming from financing rates and haircuts.

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

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

We use the simple model to frame our empirical work, evaluating each force individually before comparing them in a kitchen-sink regression. We show that bank prepositioning varies with the business cycle; for example, with banks prepositioning more when credit spreads are higher. While the business cycle can pose challenges to banks through higher defaults and fewer lending opportunities, prepositioning most specifically helps banks manage liquidity shocks. We infer the likelihood of a liquidity shock using high-frequency deposit flows and show that banks preposition more when they have more uninsured deposits.

Banks pay an opportunity cost when they preposition. A Treasury left on the Fed's books is a Treasury that a bank cannot use elsewhere. We 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. 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 never plan to use the window if it's sufficiently stigmatized, in which case they would see no need to preposition 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. Stigma plays an important role in such low take-up.

Importantly, though, we separate stigma into two flavors: borrowing stigma and prepositioning stigma. Discount window stigma, as typically discussed, refers to *borrowing stigma*: the stigma a bank incurs once it has actually borrowed from the window. By contrast, we define prepositioning stigma as the stigma from simply prepositioning with the Fed and publicly disclosing it. We present evidence of prepositioning stigma and show both flavors affect banks' prepositioning behavior.

We exploit variation in banks' exposure to borrowing stigma stemming 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. We find that banks with a larger share of assets in their Fed district preposition less.

And we find evidence of prepositioning stigma. First, we find that only 30 percent of banks disclose their prepositioning with the Fed in their public 10-Ks on average since 1995, but that share has increased in recent years. Many banks disclose their prepositioning only by commingling it with other types of prepositioning—namely, with the unstigmatized FHLBs.[3] Second, we show that banks that disclose Fed prepositioning tend to be riskier

[3]We call FHLBs 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)

and window-dress their prepositioning. Markets react negatively when banks start disclosing prepositioning. Banks trade off the benefit of public disclosure—a public signal that they have bought run insurance from the Fed—against the cost of prepositioning stigma. Indeed, we find that banks with more uninsured deposits, a proxy for run risk, are more likely to disclose their prepositioning.

Since banks' prepositioning is endogenous to macro conditions, regressions of prepositioning behavior yield biased estimates due to simultaneity and endogeneity biases, so they do not identify causal effects. To avoid these biases, our final analysis uses a granular, instrumental-variable approach to show that idiosyncratic uninsured deposit flows have a causal effect on prepositioning. Banks respond to idiosyncratic uninsured deposit outflows by increasing their prepositioning, a dynamic completely absent for insured deposit flows.

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 prepositioning rather than actual discount window borrowing. Few papers have studied prepositioning empirically. De Roure and McLaren (2021) study prepositioning in the 2010 Bank of England Funding for Lending Scheme. Hanson et al. (2024) study how to modify current regulations to require banks to preposition collateral to withstand uninsured deposit runs. Much of the work on prepositioning is from policymakers in the aftermath of the global financial crisis and the March 2023 bank turmoil (Tucker 2009, King 2018, Bowman 2024, Coelho and Restoy 2025). The G30 (2024) proposes that banks should be required to preposition 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 prepositioned collateral.

2 Model

We write a simple, two-period endowment model to understand the tradeoffs of prepositioning 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.

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.

2.1 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 prepositioned with the Federal Reserve, and another that is prepositioned with private collateral markets. For example, the private market could be the tri-party repo market or the FHLBs. Denote the amount of the assets the bank chooses to put at the Fed 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 prepositioned. 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 prepositioned assets at the discount window costs r^F and incurs a stigma cost. There is a haircut h^F to borrow against assets prepositioned at the discount window. Similarly, the household can use its assets prepositioned 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 the household can only borrow against its prepositioned assets in period 2, it cannot sell the asset.[4] 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 prepositioned 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 IA.A.

The second 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.[5] The

[4] 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 prepositioned. However, if we introduce counterparty risk—the risk that an asset prepositioned in the alternative market might not be returned by the counterparty—then the expected return on prepositioning in the alternative market would be lower.

[5] 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

household can borrow against assets in the alternative market at r^M in good states. We make the simplifying assumption that in bad states the household cannot borrow from the private collateral market ($h^M = 1$), consistent with the literature on repo market dislocations in bad states (Gorton and Metrick, 2012). Since borrowing from the Fed or alternative collateral markets requires the household to pay positive interest, we can think of r^F and r^M as negative.

Third, the model includes two different stigma costs: borrowing stigma and prepositioning 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 prepositioned with the Fed. Meanwhile, prepositioning stigma, $\sigma_p \mathbb{I}(Disclosure)$, is incurred whenever the household prepositions to the Fed and chooses to disclose it, regardless of whether the household borrows from the discount window. When the household chooses to disclose its prepositioning the household pays a prepositioning stigma cost in period 1 before the realization of the good or bad state. The alternative market incurs no stigma of either kind.

If prepositioning and disclosing it imposes a stigma cost, why would the household ever choose to disclose? There must be a benefit; in reality, we see a nontrivial share of banks disclosing their prepositioning. The benefit is that prepositioning is a form of costly insurance, and—in some cases—it is valuable for the bank to publicly signal it has purchased that costly insurance, even if that signal also imposes a stigma cost.

To capture the idea that disclosure can reassure market participants generally, and depositors specifically, we let the probability of the bad states depend on whether the bank discloses its prepositioning:

$$\pi(D) = \begin{cases} \pi_0, & \mathbb{I}(Disclosure) = 0 \\ \pi_0 - \Delta, & \mathbb{I}(Disclosure) = 1 \end{cases}$$

where $\Delta \leq \pi_0$. The household trades off two choices: (1) disclosing, paying the prepositioning stigma cost σ_p, but reducing the bad state odds by Δ, or (2) not disclosing, paying no prepositioning stigma cost, but facing a higher probability of the bad state. Importantly, though, we do not require that $\Delta > 0$, meaning that disclosing does not necessarily benefit the bank. If $\Delta < 0$, then the bank counter-productively increases the odds of a bad state by prepositioning. Hence, banks should never disclose when $\Delta < 0$.

the discount window are, in practice, higher compared to the private collateral market.

The household solves:

$$\max_{c_1,c_2,x^F,x^M,D\in\{0,1\}} u(c_1)+\beta\mathbb{E}[u(c_2)] \quad \text{subject to}$$
$$c_1 \leq e_1-(1+\sigma_p D)x^F - x^M$$
$$c_2^{bad} = e_2+(1+r^F-\sigma)(1-h^F)x^F$$
$$c_2^{good} = e_2+(1+r^M)(1-h^M)x^M.$$

The Lagrangian is

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

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

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

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

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

Equation 1 shows a tradeoff of prepositioning 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 preposition that asset in both markets simultaneously.

Intuitively, the household will prefer to not preposition 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 preposition 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.[6]

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. 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.

The model also makes clear that prepositioning provides a type of insurance against bank runs, but insurance that is both costly and with payoffs that are more limited in the bad states. Prepositioning is unlike insurance because the discount window loan is based on *current* market values, after a haircut. Since banks only borrow from the discount window in bad states—times when the market values are low—the bank can only borrow less than their collateral value in good states.

2.2 Model Predictions

Equating the two Euler conditions and substituting $c_2^{bad} = e_2 + \gamma x^F$ and $c_2^{good} = e_2 + \delta(X - x^F)$, we can solve for the amount of collateral pledged to the Fed x^F:

$$x^F = \frac{\pi(D)\gamma\, e_2 + \pi(D)\gamma\delta\, X - (1-\pi(D))\delta(1+\sigma_p D)\, e_2}{\gamma\delta\Big[\pi(D) + (1-\pi(D))(1+\sigma_p D)\Big]}, \tag{2}$$

where $\gamma = (1 + r^F - \sigma)(1 - h^F)$ and $\delta = (1 + r^M)(1 - h^M)$. 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' prepositioning 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. ${}^{\partial \hat{x}^F}/{}_{\partial \pi} > 0$.*

Prepositioning acts as a form of insurance since the bank can use prepositioned 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 preposition more collateral as a form of insurance.

[6]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 prepositioning of collateral at the discount window. This prediction can help us understand the choice of which assets are held with the Fed. For example, Treasuries typically have 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 preposition 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 prepositioned 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 preposition 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 prepositioning stigma* σ_p. $\partial\hat{x}^F/\partial\sigma_p < 0$.

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

3 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 include quantities across the banks' balance sheets by asset class, maturity, and other characteristics that vary by line item, but they do not include rates, prices, or CUSIPs. The data covers roughly three dozen large bank-holding companies, including both domestic and foreign companies, between 2016 and 2024. The largest banks—the eight U.S. global systemically important banks (GSIBs)—report daily data; the rest report monthly data. For brevity, we refer to the daily-reporting banks as "large" banks and the monthly-reporting banks as "medium-sized" banks. Details of data cleaning appear in IA.B.1.

Our focus is unencumbered collateral that banks preposition with a central bank to borrow against. This prepositioned collateral stands ready to create *capacity*, the financing a bank can raise from the central bank against its prepositioned 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, and
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 prepositioned collateral, its capacity falls by \$1 unless it prepositions more. The second point excludes collateral that banks must hold with a central bank to use the central bank payment services, for example, or to use daylight overdrafts. Copeland et al. (2024) show that high-frequency liquidity constraints stemming from payment activities are material. They also note that the largest banks are 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.

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

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

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 denotes the capacity provider (e.g., the Fed, FHLBs, or other central banks).

The numerator represents the prepositioned collateral with a specific central bank or GSE, and the denominator is the sum of all unencumbered assets and all prepositioned collateral across capacity providers and thus represents the pool of all possible collateral that could be prepositioned (excluding encumbered assets). Because some asset classes are ineligible to serve as collateral for discount window borrowing, we limit the denominator to asset classes that are pledgeable to the Fed, defined as the asset classes pledged in the data at least once. The excluded assets are largely equity securities and lower-rated sovereign bonds. However, since these ineligible assets represent a small share of banks' total assets, including or excluding them does not materially affect our results.

3.1 Capacity Facts

On average, banks preposition nearly $1.9 trillion—28 percent of eligible assets—with the Fed and $900 billion—14 percent—with the FHLBs. Figure 1 plots the capacity ratio aggregated across all assets and maturities, and Table 1 provides summary statistics. 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 upward following the 2023 banking turmoil. There is considerable range over the sample, with the Fed capacity ratio ranging from 23 to 34 percent. The number is surprising in contradictory ways: it's surprising that banks preposition such a large share of their assets, but simultaneously it's surprising they don't preposition all or nearly all of their unencumbered assets. Alternative capacity ratios (including versions with encumbered assets and total asset denominators) are in IA.C.1.

There is considerable dispersion across banks in their prepositioning. The right panel of Figure 1 plots the cross-sectional standard deviation across individual banks' capacity ratios: the average standard deviation is 29 percentage points. Given the average capacity ratio of 28 percent, the large standard deviation implies a wide range in banks' routine prepositioning behavior.

The confidential data does not cover the universe of 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, Table 2 gives aggregated prepositioning statistics provided by the Fed. The table shows that the total banking system has posted collateral with a lendable (post-haircut) value of $2.8 trillion, mostly from loan collateral ($1.8 trillion). The public data provide annual snapshots since 2021, but there is a clear upward trend in prepositioning, increasing from 8.2 percent of total commercial bank assets in 2021 to 12.1 percent in 2023. For comparison, our sample of banks prepositioned $2.9 trillion with the Fed at year-end 2023, against which they could borrow $2.2 trillion, implying that our sample captures 80 percent of total prepositioning, as shown in the bottom row of the table.

What banks pledge matters as much as how much they pledge. Figure 2 plots average capacity ratios by asset class and confirms our expectation 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 lowest collateral value, while those toward the bottom have the highest collateral value—at least as revealed by bank behavior. The large amount of safe assets prepositioned is also influenced by liquidity regulations—safe assets included in HQLA cannot be encumbered but can be prepositioned with the Fed.

Banks preposition 80 percent of their real-estate loans, largely to the FHLBs. This is unsurprising: whole mortgage loans are not useful as repo collateral, for example. Non-real-estate 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.[7] Then Treasuries (20 percent), agency (16 percent, including both agency debt and agency MBS), other (20 percent), and non-IG debt (15 percent). Sovereign bonds and equities both have smaller capacity ratios.

Capacity and Deposits Prepositioning helps banks satisfy sudden deposit outflows. The bottom four rows of Table 1 compare prepositioning to uninsured and total deposits. The post-haircut value of prepositioned assets with the Fed is 22 percent of uninsured deposits and 13 percent of total deposits. Figure 3 plots the ratio of the market value of prepositioned assets with the Fed relative to uninsured deposits. The ratio increased by half following March 2023. For completeness, immediately usable liquidity—defined as the market value of unencumbered assets, Fed and FHLB prepositioning (after haircuts), and unrestricted reserves—equals 112 percent of uninsured deposits and 67 percent of total deposits. Figures IA.8 and IA.9 plot the ratios and a waterfall chart comparing deposits with several liquidity sources.

4 Empirical Results

We now test the model's predictions. We first test each proposition in isolation. We then combine the propositions into a kitchen-sink regression to fully describe banks' prepositioning behavior. Finally, we use a granular instrumental variables approach to isolate the causal effect of deposit flows on banks' prepositioning decisions.

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

4.1 Prepositioning and the Business Cycle

All else equal, prepositioning collateral provides a form of insurance in bad states: it reduces 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 preposition more with the central bank when the probability of a bad state 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 3, which shows the correlation of changes in the Fed capacity ratios across several asset categories: 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 (BKX). A higher VIX, higher spreads, or lower bank stock returns are strongly associated with an increased capacity ratio. The last column shows that prepositioning and reserves tend to simultaneously increase.

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 prepositioning the securities that take the largest hit to their collateral value in bad states. Intraday overdrafts do not drive capacity ratios (Table IA.5), and banks do not routinely preposition a large share of their newly acquired assets (IA.C.2).

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.

4.2 Alternative Collateral Market

Prepositioning 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 prepositioning can change quickly as alternative collateral markets digest shocks and haircuts or financing rates adjust.

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

> 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 shows the alternative collateral market will draw more or less collateral depending on its relative haircut and rate (proposition 2). The proposition is a partial equilibrium prediction, holding the discount window's rate and haircuts fixed. 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.

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.[8] For capacity, banks report the amount of collateral they prepositioned 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.[9]

Figure 4 plots the average haircuts for collateral in the 1-month maturity bucket for several broad asset classes. 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. Federal Reserve haircuts are nearly always the largest. Treasuries, for example, have an average of a 0.2 percent haircut in the bilateral repo, 1.5 percent in the tri-party repo, and 2.2 percent when prepositioned at the Fed capacity.

[8]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.

[9]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."

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. For this reason, the figure likely understates the spread of haircuts across different collateral markets. A more like-for-like haircut comparison is in IA.C.3.

Borrowing rates are also important. The Fed sets the discount window's rate at a fixed spread to the upper bound of the target federal funds rate. Before the Covid pandemic, it was 50 bps above the upper target, but the Fed adjusted the spread to 0 during the initial panicked stages of the pandemic.

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. 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 relatively more expensive. Financing rates typically have a positive spread to the discount window rate, evidenced by each line nearly always staying above zero, meaning the alternative markets typically offer cheaper financing rates than the discount window, ignoring haircut differences.

4.3 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 would fail.

If stigma were sufficiently large, banks would never preposition collateral—regardless of whether prepositioning itself had stigma. If stigma were so large that banks would never borrow from the window, prepositioning 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 $150 billion from the discount window in March 2023.

We find that banks that are exposed to stigma preposition 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 to the banking system in its Federal Reserve district. The Federal Reserve does not provide high-frequency borrower-specific discount window data but it is required to provide weekly snapshots of its balance sheet, where discount window loans appear on the asset side of the Fed's balance sheet.[10] The individual Federal Reserve Banks operate the discount window, so a borrowing bank uses the window provided by its local Reserve Bank. 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.[11] 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.

We test the relationship between borrowing stigma and prepositioning using a proxy for an individual bank's exposure to borrowing stigma, the bank's share of total bank 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 bank assets in a Federal Reserve district. IA.B.2 provides data details.

A bank's district asset share is the ratio of its assets to the total district assets:

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

[10] Section 11(a)(1) of the Federal Reserve Act requires that the Fed "shall publish once each week a statement showing the condition of each Federal reserve bank . . . [s]uch statements shall show in detail the assets and liabilities of each Federal reserve bank. . . "

[11] The aggregate Fed system balance sheet separately lists primary credit as a 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).

We show that banks preposition less when they are more exposed to borrowing stigma. Table 4 shows the regression of capacity ratios on bank's market share measure using a 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.[12] 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 about 2pp lower—an economically meaningful effect given the aggregate banking system averages a capacity ratio of roughly 28 percent. Since FHLB borrowing via advances is not stigmatized, we should not see prepositioning with the FHLBs fall when a bank has a larger district asset share. Columns (3) and (4) confirm this.

A feature of borrowing stigma is that banks can interact with the Federal Reserve through a Reserve Bank outside the district where the bank's head office is located. 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, and 30 percent of bank assets in recent years are held by banks that switched their supervisory Fed district (Figure IA.10). IA.C.4 estimates that switching banks would preposition less if they could not switch.

4.4 Prepositioning Stigma

We find evidence that banks may view prepositioning collateral as stigmatizing. Prepositioning may be stigmatizing because it indicates a potential willingness to borrow from the window in bad states, and increased prepositioning could signal that the bank has grown riskier or weaker if disclosed. We show this in several ways. First, we collect data from the 10-Ks from public banks and find that historically only a small share of banks disclose their prepositioning. Second, we show that banks which start disclosing the Fed prepositioning suffer negative abnormal returns shortly after that disclosure becomes public. But why would banks voluntarily disclose their prepositioning if it's stigmatizing? We show that riskier banks are more likely to disclose, suggesting the signaling benefit outweighs the stigma cost only for riskier banks. We also show that the banks which disclose tend to window-dress their prepositioning, boosting it at quarter-ends that coincide with reporting dates.

Public Disclosures There is considerable variation in how firms publicly disclose their prepositioning. Many banks disclose nothing, some disclose an amount pledged to the FHLBs

[12] 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.

only, others to the Fed only, and many report a combined amount that commingles pledging to the Fed and FHLBs together. IA.B.3.1 provides examples.

We use automated textual methods to estimate the total amount of disclosed prepositioning across all publicly traded banks. We begin with the universe of 10-K and 10-Q filings from 1995 to 2025, spanning 59,000 10-Ks and 10-Qs from the SEC and about 850 from the FDIC. IA.B.3.2 provides details. Banks typically disclose either the prepositioned amount or the resulting post-haircut borrowing capacity.

Given the number of filings and the variety in how firms report prepositioning, we turn to a standard large-language model to help process the data, details in IA.B.3.2. Figure 6 shows the results; summary statistics appear in Table IA.8. The left-hand side of the figure shows the share of all filers that disclose their prepositioning with either the Fed, the FHLBs, or the combination of the Fed and the FHLB. The "combined" line reflects banks that report a combined amount—rather than a specific Fed and FHLB breakdown.

Many publicly-traded banks do not disclose how much they preposition with the Fed. Between 1995 and 2024, 30 percent of publicly-traded banks disclosed prepositioning with the Fed. Following the SVB bank run, the share reached an all-time high of 70 percent. That most banks historically did not disclose would be consistent with banks viewing prepositioning disclosures as stigmatizing. Low Fed prepositioning disclosure could reflect either nondisclosure or a simple lack of prepositioning. Either case would be consistent with prepositioning stigma. However, in our sample of confidential data for three dozen banks, virtually all U.S.-based banks always have non-zero prepositioning. We can therefore reject an alternative that low disclosure rates reflect a lack of prepositioning.

The figure also suggests the existence of prepositioning stigma because a larger share of banks disclose that they preposition with the FHLBs than with the Fed, and a sizable portion of filers only report a combined amount. Combined disclosures are useful to avoid stigma because the FHLBs are unstigmatized. If their combined prepositioning increases quarter-over-quarter, it is impossible to tell if that is because the bank has pledged more to the stigmatized Fed or to the unstigmatized FHLBs. Most of the largest banks disclose using the combined approach.

The number of banks disclosing prepositioning tends to jump after crisis periods, which is clear from the vertical lines in 2008, 2020, and 2023. With public data, we cannot distinguish whether more banks are simply disclosing their prepositioning amounts or more banks are choosing to preposition. Either case suggests that prepositioning stigma is falling over time. The right panel of Figure 6 plots the level of prepositioning disclosed by the 10-K filers. Over the last three years, the combined prepositioning amount has increased by more than $800 billion.

The most recent value of FHLB prepositioning is $1.2 trillion, 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 prepositioning to implausibly simultaneously borrow from the FHLB, the FHLB system would need to increase its borrowing by 70 percent, assuming a 30 percent haircut on prepositioned assets (a conservative value compared to the haircut shown in Figure 4 for real estate loans). The unrealistic scenario highlights that prepositioning at the FHLB, while unstigmatized, could be a less-than-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.

Bank Characteristics and Disclosure If disclosing prepositioning imposes a stigma cost, why would risky banks disclose? Table 5 compares disclosures with measures of bank risk, including capital ratios, the share of domestic deposits that are uninsured, loan-to-deposit ratios, the return on assets, 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 table shows that banks which disclose Fed prepositioning tend to be riskier because they have lower capital ratios, more uninsured deposits, more loans relative to deposits, and lower ROA. They also tend to be larger. Risky banks are more likely to disclose because the signaling benefit outweighs the stigma cost. The riskier the bank, the greater the net signaling benefit.

Abnormal Returns After Public Disclosure Next, we show that prepositioning disclosures impose a cost in the form of lower abnormal stock returns. We show that banks earn negative abnormal returns after they start disclosing Fed prepositioning. This is not the case if the bank starts disclosing only FHLB.[13]

In Table 6, we regress a bank's abnormal excess returns on indicator variables for whether the bank started disclosing prepositioning in the previous day.[14] We limit the regression to days in which at least one bank started providing prepositioning disclosures. We calculate abnormal excess returns relative to two models over a three-month window, excluding the

[13] 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.

[14] We lag the disclosure by a day because most bank filings in the SEC that have timestamps of when they are accepted by the SEC occur after market closes, with about 80 percent of the filings coming after market close in recent years. Note that the time the 10-K/10-Q filing is accepted by Edgar is different from the time of the earnings call.

two weeks before the date. We use a Fama-French 3-factor model and a CAPM-esque model that estimates abnormal returns of banks relative to the BKX bank stock index to strip out bank-industry shocks. We also include date and bank fixed effects to strip out date-specific shocks and each bank's average abnormal return, and we include a control for the bank's quarterly earnings surprise.

Columns (1) and (2) show that banks earn significantly lower abnormal returns on the day they start disclosing Fed prepositioning using either model. Compared to other days where banks report 10-K or 10-Q filings, banks that start disclosing Fed prepositioning have abnormal returns that are 31 to 38 bps lower.

As robustness, we show that the effect of prepositioning stigma on returns is limited to cases of disclosing Fed prepositioning. Columns 3 and 4 repeat the regression but for days when banks start disclosing FHLB prepositioning: there is no similar effect. The last two columns include both the Fed and FHLB dummies and finds that the Fed relationship has a similar magnitude. The results indicate that prepositioning stigma is limited to Fed prepositioning.

A potential confounding factor is that banks bundle other adverse news with their first prepositioning disclosure. We cannot rule out isolated cases, but systematic bias seems unlikely. In our sample of 759 publicly traded banks, roughly 380 distinct calendar dates mark the first disclosure; each bank can adopt only once, and these adoption dates are dispersed over time (Figure IA.15). We also control for the quarter's earnings surprise, and because 10-K/10-Q acceptance typically occurs after the earnings call, the call's headline information should already be reflected in prices and thus cannot mechanically drive the abnormal return on the disclosure date. For unrelated confounding factors to explain our results, the filings themselves would need to introduce new, negative information about bank condition that (1) was not revealed on the earnings call and (2) systematically coincides with the adoption dates. Together with bank and date fixed effects, these considerations make such systematic confounding unlikely.

Prepositioning Window-dressing We provide additional evidence of prepositioning stigma by comparing quarter-end pledging across disclosers and non-disclosers. We find that banks which publicly disclose their prepositioning tend to increase their prepositioning in months that coincide with quarterly disclosure, but not other months.

To test the behavior, we run the regression

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

Table 7 shows the results, which uses a merged panel of our FR2052a monthly bank data with the SEC prepositioning disclosure data.

The table shows that disclosing banks increase their prepositioning in months that appear in public 10-K/Q filings (column 1), but non-disclosers do not (column 3). The regression exploits banks' choice to disclose quarter-end—not quarter-average—prepositioning, so pledging in the month *before* the 10-K/Q month is not publicly disclosed. Measured month over month, disclosers raise capacity only in months that appear in public filings; measured quarter over quarter, columns 2 and 4 show that the three-month change is no different from zero for both groups. Thus, disclosers top-off at publicly disclosed quarter-ends—a form of window dressing.

Such window-dressing behavior is consistent with prepositioning stigma. Banks that disclose the level of prepositioning—which, as shown earlier, tend to be riskier—may want to show similar levels of prepositioning from quarter to quarter. Lower levels could indicate that the bank used some previously prepositioned 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 therefore feel pressure to consistently show they have large emergency liquidity buffers available.

4.5 Comparing the Prepositioning Forces

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

We proxy for the probability of a bad state using the Baa-Aaa spread and the bank's FDIC-insured or uninsured deposits. Deposits directly proxy for the bad state probability because 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 unencumbered assets that are pledgeable to the Fed and prepositioned HQLA level 1.

We proxy for alternative collateral market conditions by calculating the bank's average Treasury repo haircut. 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 primary credit rate and SOFR, which captures the benefit of using collateral to borrow from the discount window compared to other secured markets.

We also capture borrowing stigma exposure using the district asset share measure following the method described earlier. Unfortunately, we do not have a high frequency proxy for prepositioning stigma—banks change disclose strategies only infrequently.

We compare how the three frictions measured above contribute to the share prepositioned. We run the following regression:

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

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 8 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 main specification for the daily large bank sample is shown in column (1). Banks preposition more when the Baa-Aaa spread is higher, when they have more uninsured or less insured deposits. Conditions in alternative collateral markets matter, with banks prepositioning less when the spread between the primary credit rate and SOFR is larger and more when they face larger Treasury repo haircuts. Banks also preposition less when their district asset share is higher.

Each force behaves as the model predicts, but the relative magnitude is important: for large banks, a one standard deviation increase in uninsured deposits is associated with a 10pp higher capacity ratio, while a one standard deviation larger borrowing stigma exposure, as proxied by district asset shares, decreases prepositioning by 10pp. The remaining variables have more modest relationships by comparison. The full bank sample shown in the last three columns 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 preposition 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, which yields similar results.

In columns (3) and (6), we also include a control for the bank's unrestricted reserve balances because a bank with more reserves may not need to preposition as much to hedge against deposit flight. Since larger banks have more 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.

5 Granular Instrumental Variables

Our final analysis shows the effect of plausibly exogenous deposit flows on prepositioning. Since deposit flows are endogenous to financial conditions and the broader macroeconomic environment, the kitchen sink results in Table 8 reflect descriptive correlations rather than causal relationships. We now employ a granular instrumental variables approach, motivated by Kubitza et al. (2025)'s implementation of Gabaix and Koijen (2024), to identify the effect of deposit flows on prepositioning.

Conceptually, the granular IV approach exploits the fact that when depositor concentration is sufficiently high—meaning that a small set of depositors account for a disproportionately large share of deposits—idiosyncratic shocks to those specific large depositors create meaningful variation in a bank's aggregate deposit flows. Our identification strategy exploits that decisions by large depositors, driven by their idiosyncratic liquidity needs and cash management strategies, are plausibly exogenous to a bank's prepositioning choice, yet still affects the bank's total deposit base when depositor concentration is high.

Our data are available at granular depositor category levels rather than depositor-specific levels. Our preferred level of granularity is at the month by bank by depositor type by deposit account type by maturity bucket. There are 14 depositor types, 13 account types, and 6 maturity buckets.[15] Therefore, our identifying assumption is that depositors within a category have similar behavior. When depositor category concentration is sufficiently high, idiosyncratic shocks to that category will affect the bank's aggregate deposit base. Define a depositor category d as the cell at the depositor type by depositor account type by maturity bucket.

We impose two sample restrictions to ensure there is sufficient granular variation. First, we exclude deposit categories with less than \$10 million to remove the noise introduced by exceedingly small depositor categories. For uninsured (insured) deposits, this filter removes 28 (47) percent of depositor categories that account for only 0.02 (0.02) percent of total deposits. Second, we exclude foreign branches because our deposit data does not include their consolidated balance sheet, and their visible deposits tend to be concentrated in a handful of depositor categories which makes it difficult to identify idiosyncratic flows. Foreign branches have on average less than half as many depositor categories as the other banks.

Following Kubitza et al. (2025), we estimate the GIV in several steps. We calculate the deviation of a bank b's depositor category d's deposit flows from its trailing one-year average:

$$\Delta D_{bdt} = \frac{Deposits_{bdt} - \overline{Deposits}_{bdt}}{\overline{Deposits}_{bdt}}$$

where $\overline{Deposits}_{bdt}$ is the one-year trailing average, and we require that each bank has 12 months of deposit flow history. A bank has outflows when $\Delta D_{bdt} < 0$. We detrend by 12 months because deposit flows exhibit strong annual seasonality. We winsorize the deposit deviations at the 1st and 99th percentiles by depositor category to reduce the influence of outliers.

Next, we residualize ΔD_{bdt} by regressing it on bank, time, depositor category, and depositor

[15]Specifically, the depositor types include: bank, central bank, debt issuing special purpose entity, government sponsored enterprise, multilateral development bank, non-financial corporate, other, other financial entity, other supranational, public sector entity, retail, small business, sovereign, and supervised non-bank financial entity. The deposit account types include affiliated sweep accounts, non-affiliated sweep accounts, non-operational accounts, non-reciprocal brokered accounts, non-transactional non-relationship accounts, non-transactional relationship accounts, operational accounts, operational escrow accounts, other accounts, other product sweep accounts, other third-party deposits, reciprocal accounts, and transaction accounts. We group accounts into maturity buckets of one day or less, two to seven days, eight to 31 days, 32 to 91 days, 92 to 366 days, and more than 366 days. The reported data changed somewhat in May 2022, and we harmonize the depositor and account types to be consistent through the period.

category by time fixed effects:

$$\Delta D_{bdt} = \alpha_b + \gamma_t + \delta_d + \lambda_{d\times t} + \check{d}_{bdt}$$

where α_b are bank fixed effects, γ_t are time fixed effects, δ_d are depositor category fixed effects, and $\lambda_{d\times t}$ are depositor category-by-time fixed effects. The λ fixed effects absorb systematic shocks that affect specific depositor types across all banks in a given month—for example, seasonal patterns in corporate cash management. The residual $\check{d}_{bdt}$ represents idiosyncratic deposit flows that are orthogonal to bank characteristics and common depositor category trends and shocks across banks.

We then form the bank-specific granular instrument by comparing the difference between the size-weighted residual and equal-weighted residuals:

$$GIV_{bt} = \underbrace{\sum_d w_{bdt}\,\check{d}_{bdt}}_{\text{size-weighted } \check{d}_{bdt}} - \underbrace{\frac{1}{N}\sum_d \check{d}_{bdt}}_{\text{equal-weighted } \check{d}_{bdt}}$$

where $w_{bdt} = Deposits_{bdt}/\sum_d Deposits_{bdt}$ is the size weight of depositor category d at bank b in month t. We separately construct instruments for insured (GIV^I_{bt}) and uninsured deposits (GIV^U_{bt}) given the likely difference in their run risks. The uninsured deposit granular IV GIV^U_{bt} is estimated using residuals from a regression that focuses only on uninsured deposit categories and weights relative to total uninsured deposits, and likewise for the insured deposit granular IV.

Our first stage regression takes the form:

$$\Delta D^U_{bt} = \beta GIV^U_{bt} + X'C_t + \eta_b + \theta_t + \varepsilon_{bt}$$

where ΔD^U_{bt} is the bank's aggregate deposit flows as a percentage deviation from the trailing 12-month average and C_t is a vector of bank controls. Superscript U denotes uninsured deposits; we separately estimate an analogous specification that for insured deposit deviations ΔD^I_{bt} against the insured-derived GIV^I_{bt}.

The second stage regression tests the effect of deposit flows on prepositioning:

$$\Delta\text{Capacity}_{bt} = \gamma\Delta\hat{D}^U_{bt} + X'C_t + \eta_b + \theta_t + \varepsilon_{bt}$$

where $\Delta\text{Capacity}_{bt}$ is the percentage deviation from the trailing 12-month average of capacity.

We expect that idiosyncratic deposit outflows lead to increased prepositioning, so that $\gamma < 0$; it would be counterintuitive if banks responded to deposit outflows by prepositioning less.

The instrument's relevance stems from the fat-tailed distribution of depositor categories within banks. Even though the average bank has 52 uninsured (47 insured) depositor categories each month, deposits are concentrated within these categories. The median bank's single largest uninsured (insured) category accounts for 15 (16) percent of its total deposits, and the five largest categories account for 38 (40) percent of total deposits. Such concentration ensures that idiosyncratic shocks to large depositor categories creates meaningful variation in the bank's aggregate deposit base.

The results of the regression are shown in Table 9. Panel A reports first-stage results. The first two columns present the first stage when instrumenting the bank's aggregate uninsured deposit flows with the uninsured GIV, and the second two use the analogous insured variables. The uninsured GIV has large F statistics, above 50, while the insured GIV has somewhat lower but still material F stats around 10. These F statistics confirm that the idiosyncratic deposit flows of large depositor categories captured in GIV is strongly related to aggregate deposit flows, especially for uninsured deposits. The columns show the results are robust to including several bank-specific controls, including the capital ratio, log of total assets, the lagged district share, (all calculated from call report data) and the ratio of reserves reported in FR2052a to total assets.

Columns (5) and (6) show the first stage regression when we jointly instrument both insured and uninsured deposit flows with both GIV measures, and columns (7) and (8) repeat the regression with bank-specific controls. These last four columns provide a horse race and show that the uninsured GIV is strongly related to uninsured deposit flows even when controlling for the insured GIV, and vice versa. These last four columns, though, show that the joint first stage F statistics falls to roughly 26, highlighting relatively weaker joint identification in the first stage. The horse race provides suggestive evidence that the effect operates through uninsured deposit flows rather than insured deposit flows, and we view the single-equation results (columns 1–2) as our preferred specifications.

Panel B shows the second stage regression, our main results. Columns (1) and (2) focus on the effect of uninsured deposit flows. One percentage point of instrumented outflow of uninsured deposit increases prepositioning by 0.8 percentage points. The economic magnitude is substantial: a one standard deviation in the median bank's uninsured deposit outflow (3 percent) implies increased prepositioning of 2.4 percentage points—a large effect compared to average prepositioning of 28 percent. Notably, though, the effect is entirely restricted to uninsured deposits: instrumented insured deposit flows have no relationship with prepositioning behavior. This is consistent with expectations that uninsured depositors are more likely to run (Drechsler et al., 2023). The results are similar when jointly instrumenting insured and uninsured deposit flows with the insured and uninsured GIVs as shown in the last two columns; the second stage in column (5) uses changes in uninsured and insured deposits estimated in the first stages columns (5) and (6) in Panel A, and the second stage in column (6) uses estimated deposit changes using Panel A columns (7) and (8).

As a check, Panel C provides the uninstrumented OLS regression, which is subject to endogeneity concerns that the instrument is designed to avoid. However, the panel confirms that the OLS and IV estimates occupy similar orders of magnitude. Unlike the instrumented regressions, the OLS finds a significant relationship between prepositioning and insured deposit flows in some specifications, though the coefficient is about 9 times larger for uninsured deposits compared to insured deposits.

Were the instrumented coefficients positive, then banks would *decrease* their prepositioning following deposit outflows. Such dynamics are counterintuitive. We can conduct a simple test of the logic using a regression during March and April 2023, at the height of the SVB-related stress. Table IA.10 shows that banks with more uninsured deposit outflows increased their prepositioning, while banks with insured deposit outflows decreased it. This simple regression is subject to endogeneity, though, since the banks that had deposit inflows may well have received those inflows because they were the safest banks, and safe banks may aggressively increase prepositioning in bad states.

The exclusion restriction requires that category-specific idiosyncratic shocks affect prepositioning only through their impact on aggregate deposit flows, which we argue is plausible after controlling for bank and time fixed effects. That is, the instrument satisfies the exclusion restriction if $\check{d}_{bdt}$ captures only idiosyncratic shocks. If $\check{d}_{bdt}$ reflects aggregate conditions, the exclusion restriction is violated. We check the exclusion restriction several ways. First, we note that the IV results are robust to different residualization specifications that include bank characteristics, like capital ratios and log total assets. Second, we conduct a simple placebo test: for each bank b, we assign its GIV_{bt} to the alphabetically next bank by ticker symbol (wrapping the last ticker back to the first). For example, we assign Bank A's GIV to Bank B, and Bank Z's GIV to Bank A. If the instrumental variables reflect aggregate factors rather than bank-specific idiosyncratic flows, we would expect the placebo to retain significant results. We regress the bank's actual GIV on its alphabetical placebo GIV in Table IA.11 and find no relationship for either the insured or uninsured GIVs, consistent with the variables not reflecting aggregate factors. We run the IV regression using the alphabetical placebo in Table IA.12 and find no relationship: none of the instrumented variables' coefficients are different from zero, and the F statistics are all below 10, with several rounding to zero.

These results provide causal evidence that banks actively manage their prepositioning in response to deposit flows, with the response strongest for the most run-prone type: uninsured deposits. The effects are large and indicate that deposit flows require banks to materially adjust their prepositioning.

6 Conclusion

We show that banks' prepositioning behavior is deliberate and responsive to market forces. In bad states, they preposition more. When they have more uninsured deposits, they preposition more. When they have more FDIC-insured deposits, they preposition less. But stigma weighs on prepositioning, as does the value of that collateral elsewhere. Banks must balance the benefits and costs of prepositioning, and we show they do just that.

More prepositioning 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 prepositioned with the Fed. Yet even if prepositioning is no panacea, it likely helps on the margin. Central bankers—and the real economy that depends on the stability of the financial system—should take every margin they can get.

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7 Figures

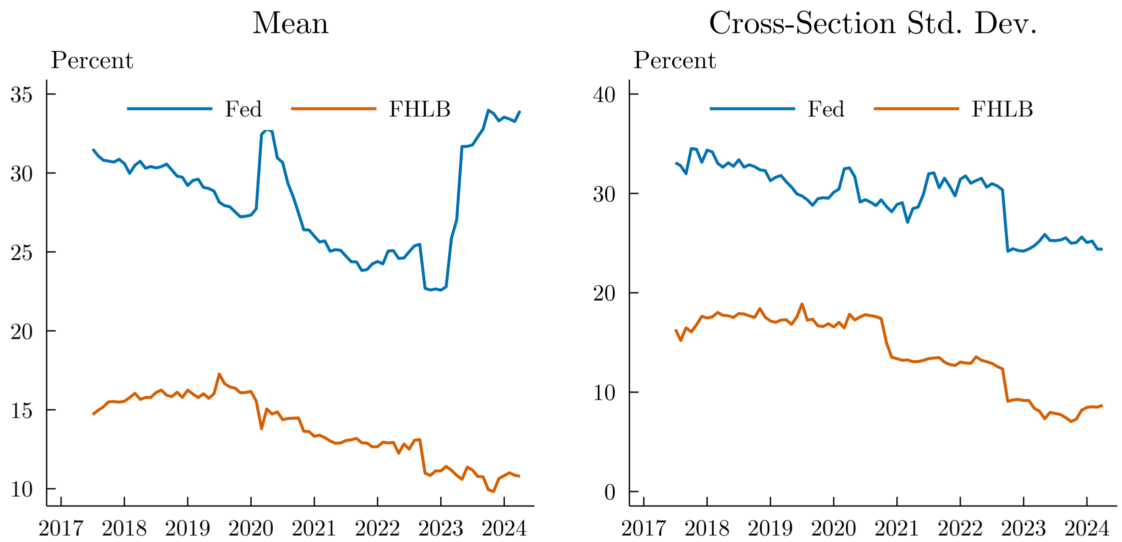

Figure 1: Capacity Ratio. Capacity Ratio$_t^p$ = (Prepositioned Collateral/(Unencumbered Assets + All Prepositioned Collateral))$_t$ where both numerator and denominator are market values of the assets and p reflects the capacity provider (e.g., the Fed or the FHLBs). The numerator reflects the prepositioned collateral with a specific central bank or GSE, and the denominator is the sum of all unencumbered assets and all prepositioned collateral across all capacity providers that are pledgeable at the Fed. We calculate Capacity Ratio$_t^p$ separately for the Fed and the FHLBs. Plots are monthly data. Left panel plots the average aggregated across all banks and the right panel plots the standard deviation across individual banks' capacity ratios at a point in time. Includes all banks in our FR2052a sample; see data section for details.

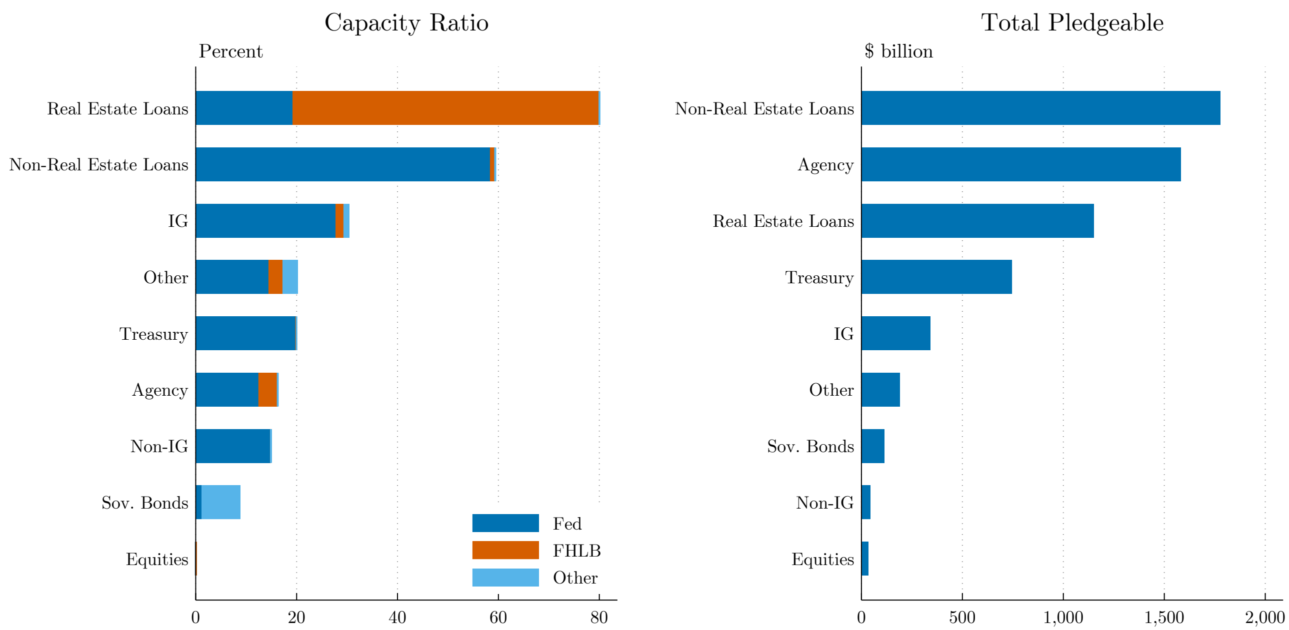

Figure 2: Average Capacity Ratio and Total Pledgeable by Asset Type and Provider. Left panel plots the average capacity ratio by provider and asset class, where capacity ratio is the capacity with that provider divided by the total amount of pledgeable assets. Right panel plots average total pledgeable assets, the sum of unencumbered assets and prepositioned 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.

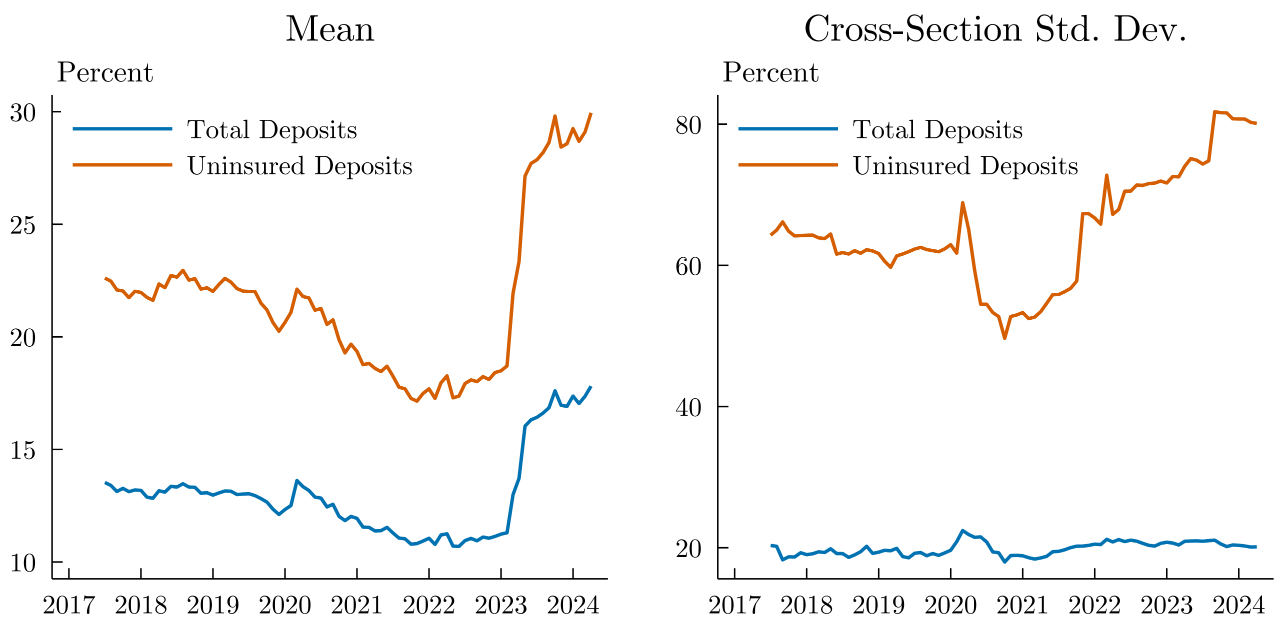

Figure 3: Capacity vs. Deposits. Left panel plots the average capacity with the Fed relative to deposits, either total deposits or uninsured deposits. Right panel plots standard deviation in bank-specific Fed capacity vs. deposit ratios after winsorizing at the 5th and 95th percentile. Includes all banks in our FR2052a sample; see data section for details.

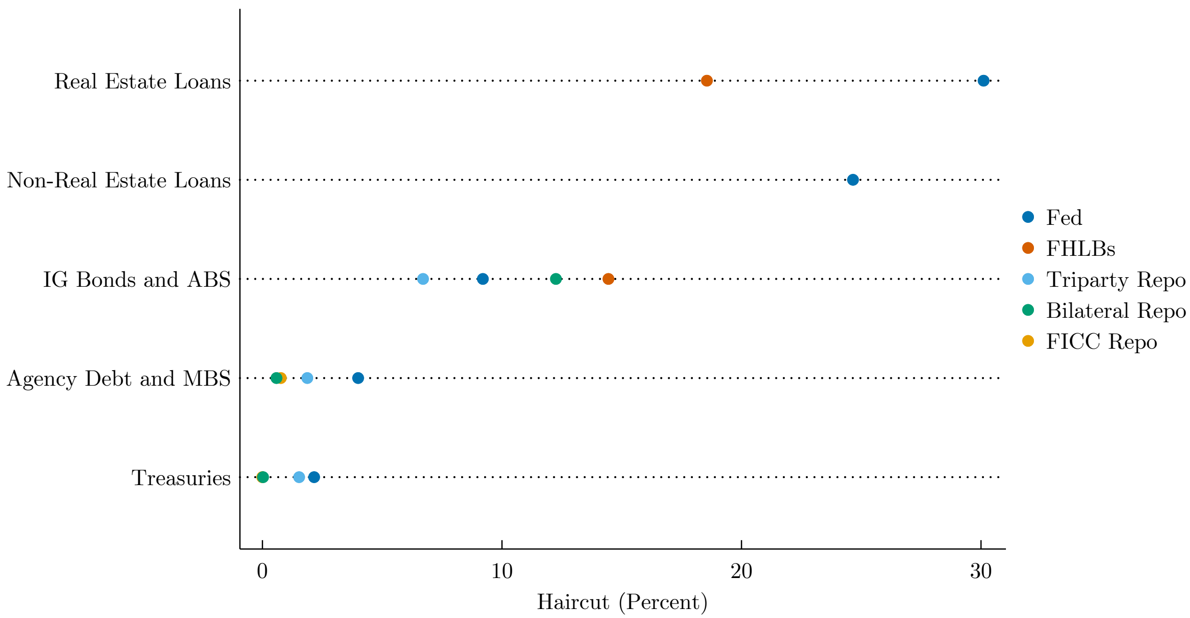

Figure 4: Haircuts Across Collateral Markets. Figure plots the average haircut on 1-month tenor collateral across several asset classes and collateral markets. We calculate the average haircut for each collateral class aggregating across the largest banks each date. We then exclude haircut observations from secured funding markets that have less than \$10 billion in total borrowing across the banks. We then take a time series average of the resulting haircuts by maturity bucket and collateral bucket. Repo haircuts are calculated from the consolidated entities; other haircuts are calculated at the bank subsidiary level. Includes large banks in our FR2052a sample; see data section for details.

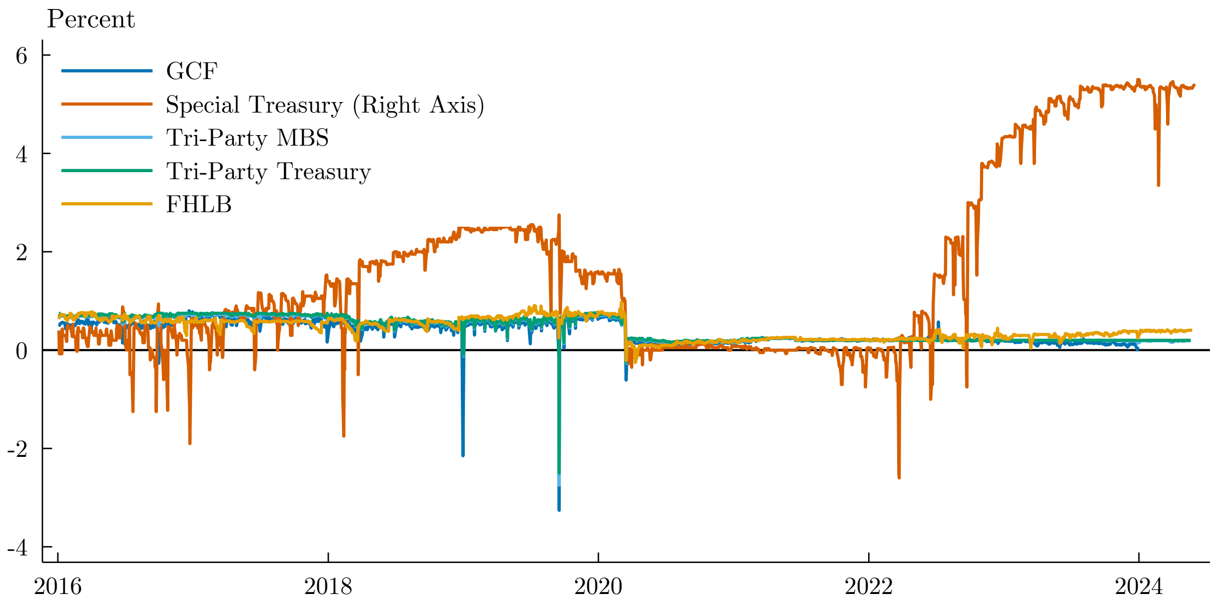

Figure 5: Financing Rates Across Collateral Markets. Figure plots the spread between the primary credit rate and the collateral market financing rate, where the financing rates are (1) general collateral finance (GCF) rate from DTCC, (2) the overnight repo rate for on-the-run 2-year Treasuries from JP 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.

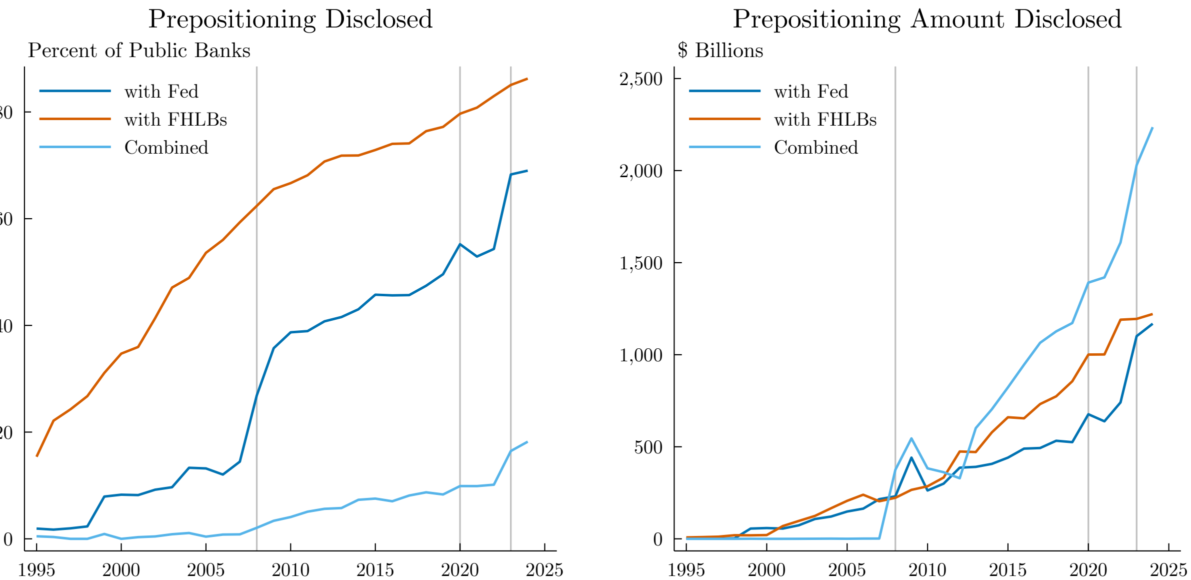

Figure 6: Prepositioning Disclosed in Public 10-Ks. Figure plots the share of banks reporting their prepositioning by type. Figure derived only from public 10-K filings. Vertical lines denote 2008, 2020, and 2023.

8 Tables

			All	Treasuries	Agency	HQLA L1	Non-HQLA L1
(a):	*Prepositioned At Fed ($bn)*	Mean	1,871	160	210	216	1,655
		Std. Dev.	434	61	140	106	329
(b):	*Prepositioned At FHLBs ($bn)*	Mean	887	1	73	14	874
		Std. Dev.	84	3	33	9	81
(c):	*Unencumbered*	Mean	3,864	674	1,475	1,250	2,615
		Std. Dev.	1,046	240	322	255	854
$(a)/(a+b+c)^{\dagger}$:	*Capacity Ratio Fed*	Mean	28.4	19.2	12.1	14.0	32.6
		Std. Dev.	3.3	3.2	8.0	5.3	3.7
$(b)/(a+b+c)^{\dagger}$:	*Capacity Ratio FHLB*	Mean	13.8	0.1	4.0	0.9	17.6
		Std. Dev.	2.0	0.3	1.5	0.5	2.9
$(a)/\sum(a)$:	*Share of Total Prepositioned 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 Prepositioned at FHLBs*	Mean		0.1	8.0	1.5	98.5
		Std. Dev.		0.3	3.2	0.9	0.9
$(1-h^{Fed}) \times a/$Uninsured Deposits:	*Prepositioned At Fed After Haircut vs. Uninsured Deposits*	Mean	21.6	2.2	3.0	3.0	18.6
		Std. Dev.	3.4	0.6	1.8	1.2	2.7
$(1-h^{Fed}) \times a/$Total Deposits:	*Prepositioned At Fed After Haircut vs. Total Deposits*	Mean	13.0	1.3	1.8	1.8	11.2
		Std. Dev.	1.9	0.3	1.0	0.7	1.5
$((1-h^{Fed})a+(1-h^{FHLB})b+c+reserves)/$Uninsured Deposits:	*Prepos. at Fed and FHLB + Unenc. + Reserves vs. Uninsured Deposits*	Mean	111.6	36.1	50.0	45.8	90.2
		Std. Dev.	8.9	6.2	4.5	4.9	8.8
$((1-h^{Fed})a+(1-h^{FHLB})b+c+reserves)/$Total Deposits:	*Fed Capacity + FHLB Capacity + Unenc. vs. Total Deposits*	Mean	67.2	21.8	30.2	27.6	54.3
		Std. Dev.	5.5	4.0	3.2	3.3	5.3

Table 1: Prepositioning Summary Statistics. Table shows summary statistics for prepositioned 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 prepositioning at other central banks, which is typically small or zero. Bottom two rows compare the sum of post-haircut values of prepositioning at the Fed and FHLBs plus the market value of unencumbered assets plus unrestricted reserves against total deposits or uninsured deposits. Unencumbered assets include those pledgeable at the Federal Reserve. Includes all banks in our FR2052a sample; see data section for details.

	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 Prepositioning Summary Statistics. Table shows the publicly available summary statistics provided by the Federal Reserve for banks and credit unions compared to the aggregate prepositioning 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`.

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	0.20*	0.32**	−0.42***	0.15
Treasuries	0.21*	0.24*	−0.32**	0.22*
HQLA 1	0.19	0.28**	−0.40***	0.20*
Non-HQLA1	0.20*	0.31**	−0.38***	0.07

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	0.08***	0.06**	−0.06*	0.08***
Treasuries	0.04	0.01	−0.05*	0.00
HQLA 1	0.05*	0.02	−0.05*	−0.01
Non-HQLA1	0.07**	0.06**	−0.05*	0.08***

Table 3: 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. Stars denote significance where * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

	Fed Capacity Ratio$_t^b$		FHLB Capacity Ratio$_t^b$	
Share of District Assets$_{t-1}^b$	-1.87^{***}	-2.10^{***}	1.56^{***}	1.70^{***}
	(-3.32)	(-3.66)	(5.18)	(5.64)
N	1,399	1,399	1,399	1,399
Within R^2	0.00	0.01	0.01	0.02
Time Fixed Effect	No	Yes	No	Yes

Table 4: Prepositioning 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 two columns use the Fed capacity ratio, as previously defined. The last two columns change the dependent variable to the FHLB capacity ratio, which reflects prepositioning 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				
	Capital Ratio$_t^b$	Uninsured Share$_t^b$	Loan-to-Deposit$_t^b$	ROA$_t^b$	ln(Assets)$_t^b$
$\mathbb{I}$(Disclose Fed Pre-positioning$_t^b$)	-0.98^{***}	1.62^{***}	2.93^{***}	-0.04^{**}	0.27^{***}
	(-6.92)	(6.30)	(14.49)	(-2.52)	(12.60)
N	37,115	29,043	38,167	38,168	38,168
Within R^2	0.00	0.00	0.00	0.00	0.00
Time Fixed Effect	Yes	Yes	Yes	Yes	Yes

Table 5: Prepositioning 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 prepositioning to the Fed. ROA is net income (RIAD4340) over assets, capital ratio is total equity capital (RIAD3210) divided by risk-weighted assets (RCFDA223 up to 2015Q1, then RCFDG641), uninsured share is the share of uninsured domestic deposits (RCON5597) relative to total domestic deposits (RCON2200) in percent; we set it at 100 percent in the handful of cases when this ratio is above 100 percent; loans (RCFD2122) to deposit ratio is loans divided by total consolidated deposits (RCFD2200). Uninsured deposit data begins 2002. R^2 is within-R^2. t-statistics are reported in parentheses using robust standard errors clustered by quarter where * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. All data in the regression are derived from publicly available data.

	Abnormal Excess Return					
	BKX	FF3	BKX	FF3	BKX	FF3
$\mathbb{I}(\text{Start Fed Disclosure})^b_{t-1}$	-0.376^{*}	-0.316^{*}			-0.381^{*}	-0.309
	(-1.91)	(-1.68)			(-1.85)	(-1.58)
$\mathbb{I}(\text{Start FHLB Disclosure})^b_{t-1}$			-0.0763	-0.0993	0.0158	-0.0199
			(-0.58)	(-0.75)	(0.13)	(-0.17)
Unexpected Earnings$_t$	-0.00153	-0.00191	-0.00175	-0.00212	-0.00153	-0.00191
	(-0.62)	(-0.84)	(-0.71)	(-0.93)	(-0.62)	(-0.84)
N	123,062	126,248	122,701	125,879	123,062	126,248
Within R^2	0.00	0.00	0.00	0.00	0.00	0.00
Bank Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
Time Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes

Table 6: Abnormal Returns Around Prepositioning 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 prepositioning. FHLB disclosure days exclude days where banks also start disclosing Fed prepositioning. Column titles denote the model used to estimate abnormal returns: either a CAPM-esque single factor model using the BKX bank stock index or the 3-factor Fama–French model; both estimated over a rolling 3-month period. R^2 is within-R^2. t-statistics are reported in parentheses using robust standard errors clustered by date and bank where * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

	Disclosers		Non-Disclosers	
	$\Delta\ln(\text{Fed Capacity})^b_{t-1\to t}$	$\Delta\ln(\text{Fed Capacity})^b_{t-3\to t}$	$\Delta\ln(\text{Fed Capacity})^b_{t-1\to t}$	$\Delta\ln(\text{Fed Capacity})^b_{t-3\to t}$
$\mathbb{I}(\text{Month with Quarterly Disclosure}^b_t)$	6.716*	−3.967	0.0190	−0.896
	(1.70)	(−0.65)	(0.03)	(−0.81)
N	1,184	1,156	815	791
Within R^2	0.03	0.03	0.03	0.06
Controls	Yes	Yes	Yes	Yes

Table 7: Prepositioning Disclosers Increase Capacity at Quarter-Ends. Table shows the regression $\Delta\ln(\text{Capacity (Level)})^{Fed,b}_{t-j\to t} = \alpha + \beta_1\mathbb{I}(\text{Month with Quarterly Disclosure})^b_t + \varepsilon^b_t$ 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 prepositioning 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 prepositioning 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. Controls include Baa−Aaa spread and VIX. 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						
$Baa - Aaa_t$	1.21**			−0.04		
	(2.33)			(−0.07)		
Insured Deposits$_t^b$	−8.11***	−8.63***	−4.36	−12.63***	−13.05***	−7.97***
	(−4.34)	(−4.78)	(−1.53)	(−8.73)	(−8.82)	(−4.04)
Uninsured Deposits$_t^b$	10.04***	10.16***	10.39***	6.10***	6.04***	10.64***
	(5.70)	(5.88)	(6.07)	(4.61)	(4.46)	(7.37)
Alternative Collateral Market						
$PCR_t - SOFR_t$	−0.70**			−0.99***		
	(−2.22)			(−2.75)		
Treasury Repo Haircut$_t^b$	0.75***	1.38***	1.37***	0.32	1.05***	1.11***
	(2.85)	(4.34)	(4.42)	(0.93)	(2.87)	(3.11)
Stigma						
District Asset Share$_t^b$	−10.35***	−13.07***	−12.10***	−6.29***	−7.60***	−7.40***
	(−3.24)	(−4.03)	(−3.66)	(−4.85)	(−5.78)	(−5.66)
Controls						
Unrestricted Reserves$_t^b$			−4.41**			−9.55***
			(−2.56)			(−4.07)
N	16,584	16,792	16,792	2,022	2,022	2,022
R^2	0.11	0.12	0.12	0.25	0.28	0.33
Time FE	No	Yes	Yes	No	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes

Table 8: Sizing the Prepositioning 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 2) 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 PCR and SOFR; 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 * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Panel A: First Stage

	(1) ΔD^U	(2) ΔD^U	(3) ΔD^I	(4) ΔD^I	(5) ΔD^U	(6) ΔD^I	(7) ΔD^U	(8) ΔD^I
Uninsured GIV_{bt}	0.17^{***}	0.16^{***}			0.18^{***}	-0.01	0.17^{***}	-0.02
	(7.45)	(7.27)			(7.27)	(-0.54)	(7.10)	(-0.79)
Insured GIV_{bt}			0.53^{***}	0.53^{***}	-0.04^{***}	0.53^{***}	-0.04^{***}	0.53^{***}
			(3.22)	(3.18)	(-3.52)	(3.18)	(-3.34)	(3.14)
N	2,412	2,407	2,411	2,406	2,411	2,411	2,406	2,406
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
F-Stat	55.5	52.8	10.4	10.1	26.7	7.5	25.9	6.4
Joint F-Stat					26.9		25.8	
Controls	No	Yes	No	Yes	No	No	Yes	Yes

Panel B. Second Stage. Dependent Variable: ΔCapacity$_{bt}$

	(1)	(2)	(3)	(4)	(5)	(6)
ΔUninsured Deposits$_{bt}$	-0.75^{***}	-0.80^{***}			-0.70^{***}	-0.70^{***}
	(-2.67)	(-2.84)			(-2.76)	(-2.95)
ΔInsured Deposits$_{bt}$			0.02	-0.00	0.02	-0.01
			(0.38)	(-0.03)	(0.28)	(-0.12)
N	2,412	2,407	2,411	2,406	2,411	2,406
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	No	Yes	No	Yes	No	Yes

Panel C. OLS. Dependent Variable: ΔCapacity$_{bt}$

	(1)	(2)	(3)	(4)	(5)	(6)
ΔUninsured Deposits$_{bt}$	-0.45^{***}	-0.45^{***}			-0.48^{***}	-0.47^{***}
	(-2.87)	(-2.71)			(-3.08)	(-2.87)
ΔInsured Deposits$_{bt}$			-0.02	-0.04^{*}	-0.02	-0.05^{**}
			(-1.28)	(-1.90)	(-1.48)	(-2.20)
N	2,412	2,407	2,411	2,406	2,411	2,406
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	No	Yes	No	Yes	No	Yes

Table 9: Granular Instrumental Variable: Prepositioning and Deposit Flows. Table shows the granular instrumental variables regression of prepositioning on deposit flows. See text for variable construction. Panel A presents the first stage regression of deposit flows, either uninsured (D^U) or insured D^I, on the uninsured GIV and insured GIV. Panel B presents the second stage of prepositioning on instrumented deposit flows. The first four columns of Panel B correspond to the first stage in the same column in Panel A; column 5 in Panel B corresponds to Panel A's columns 5 and 6, and column 6 in Panel B corresponds to Panel A's columns 7 and 8. Panel C presents the uninstrumented OLS regression. Sample includes all banks at a monthly frequency. Controls include capital ratio, the ratio of reserves to total assets, log of total assets, and the bank's district asset share. Kleibergen-Paap rk Wald F statistics reported. t-statistics are reported in parentheses using robust standard errors clustered by month where * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Internet Appendix to

Where Collateral Sleeps

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The Internet Appendix consists of four sections. Section IA.A provides institutional details on the discount window, including the mechanics of borrowing from the window. Section IA.B provides additional details about the data. Section IA.C provides additional discussion and results to supplement the main text. Section IA.D presents additional tables and figures.

IA.A Institutional Details for the Discount Window

IA.A.1 Brief History of the Window

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

But the Fed grew concerned that banks were becoming too reliant on the discount window—sometimes borrowing non-stop—so the Fed introduced several rules to reduce its use. Armantier et al. (2015b) summarize several ways the Fed did this. First, the Fed used "direct pressure" on banks to limit discount window borrowing. In the 1950s, the Fed created rules that would not allow banks to fund their routine business using the discount window. In the 1970s, the Fed required banks to exhaust all other sources of private credit before 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 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.[16] 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 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.[17]

IA.A.2 How to Borrow from the Discount Window

The Fed's Operating Circular Number 10 describes how to borrow from the discount window.[18] 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

[16] 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`

[17] 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."

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

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

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. 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 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 IA.1 describes the operating hours and processing times across platforms. Loans are often held through borrower-in-custody arrangements, but a third party or Reserve bank can also be a custodian.

3. Collateral Valuation Before the Fed can lend against collateral, it calculates a fair value estimate for each asset and then applies a haircut to calculate the asset's lendable value. For more details, see `https://www.frbdiscountwindow.org/Pages/Collateral/collateral_valuation`. 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 prepositioned 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. For the full set of haircuts, see `https://www.frbdiscountwindow.org/Pages/Collateral/collateral_valuation`.

4. Borrowing A firm requests a discount window loan by contacting its Reserve Bank. 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. It takes time to complete the initial set-up. The Fed encourages banks to complete it as soon as possible if they have not. While the time it takes to preposition securities is generally short, it can take longer if the security had been previously pledged to a different counterparty. Such encumbrances must be unwound before the bank can preposition 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.

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.

Even with enough collateral prepositioned 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.

IA.B Data Details

IA.B.1 FR 2052a Complex Institution Liquidity Monitoring Report

Our sample is the set of banks that consistently file through the full sample at the consolidated bank-holding company level 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. 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 meaningfully 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 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.

IA.B.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 and data available from the Chicago Fed to map each bank to its Federal Reserve district.[19] 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 is not always the same as the district in which its head office is physically located. As described in the

[19]FFIEC attribute data is available at `https://www.ffiec.gov/npw/FinancialReport/DataDownload`.

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[20]

> *(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.

Banks also sometimes change their district, and the FFIEC attribute data generally only provides the most recent vintage of the mapping of RSSDs to their district. We handle this two ways. For dates up to 2021, we use the Chicago Fed's commercial bank data for "Geographic and Structure" data, using RSSD9032, which is available at a bank by quarter frequency. We then use the Wayback Machine to manually download roughly quarterly snapshots of the FFIEC attributes file, and append these two sources together to create a panel of bank by quarter district mappings.

[20] `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.[21] 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.

Two points are worth noting. First, simply using the most recent FFIEC attributes data to map banks to their Fed district yields nearly identical results, since banks infrequently switch their regulatory district. Second, we rely exclusively on public sources to map banks to their district since, 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 FR2052a 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.

IA.B.3 10-K/Q Data

IA.B.3.1 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 end-of-period HQLA assets; additional unencumbered securities, including

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

> 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 prepositioning 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 prepositioning 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.

IA.B.3.2 10-K/Q Data Details

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.[22] This restriction yields roughly 59,000 10-Ks and 10-Qs from the SEC and about 850 from the FDIC. We do basic cleaning on the raw filings in the spirit of Loughran and McDonald (2016) to remove various formatting elements and tags.

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.

Unlike the SEC filings, the raw FDIC filings are less standardized. We clean the raw FDIC filings using a similar procedure adapted to their less standardized structure. We parse each filing to strip markup, HTML entities, control characters, and non-standard characters. When possible, we extract available metadata—like the FDIC certificate number, bank name, form type, period end date, and the date filed. We manually map FDIC certificate numbers to RSSD identifiers.

We identify excerpts within a filing that contain at least one "context" term—such as "pledg", "preposition", "preposition", "capacity", "liquidity", "collateral", "readiness", or "discount window"—together with at least one Federal Reserve-related phrase ("federal reserve", "frb", "frbs", "discount window", "f.r.b") or Federal Home Loan Bank–related phrase ("federal home loan bank", "federal home loan banks", "fhlb", "f.h.l.b", "fhlbs"). For each match, we retain the sentence along with one surrounding sentence before and after, remove boilerplate text and duplicates, and exclude non-10-K/Q submissions. This process flags about 44,000 10-Ks and 10-Qs with 260,000 candidate excerpts about prepositioning.

We then combine all the relevant extracts from a single filing into one combined excerpt which we provide to ChatGPT (o3-2025-04-16) with the following prompt:

> You will receive an excerpt from a U.S. bank's public filing.
>
> Your task: **extract the most recent figures that relate to collateral the bank has set aside *for potential future borrowing*** from either
>
> - the Federal Reserve (Fed, FRB, Federal Reserve Banks, Discount Window) and other central banks
> - the Federal Home Loan Banks (FHLB, FHLBs).

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

Distinguish **the value of collateral actually pledged** from the **borrowing capacity** that the pledge could generate. The borrowing capacity typically reflects a haircut to the value of the pledged collateral.

Please follow this schema for your output:

Fed_Prepositioned_Value
Extract the dollar amount of assets pledged to the Federal Reserve, possibly including other central banks

- DEFAULT ASSUMPTION: Assets pledged to the Fed or other central banks are for borrowing capacity unless explicitly stated otherwise
- Extract amounts unless the text specifically states the pledging is only for non-borrowing purposes, such as open market operations, payment system access, clearing and settlement, or any other explicitly stated non-borrowing purpose
- Examples:
  - "Assets pledged at Federal Reserve Banks: $30 billion" → EXTRACT $30 billion
  - "Assets pledged to the Fed for payment system access: $30 billion" → DO NOT EXTRACT
  - "The firm pledged $30 billion for open market operations with the Fed" → DO NOT EXTRACT
  - "Assets pledged to Federal Reserve Banks and other central banks: $35 billion" → EXTRACT $35 billion
- This field should also include amounts pledged to other central banks if these are reported as a combined figure with Federal Reserve pledges, or if the context makes it clear they are grouped with Fed pledges for the purpose of disclosing potential borrowing capacity (e.g., "pledged to Federal Reserve Banks and other central banks")
- If mentioned but no figure given, mark as "Not Specified"
- If no Fed pledging mentioned, mark as "Not Relevant"

Fed_Borrowing_Capacity
Extract the dollar amount of the resulting borrowing capacity (value after haircuts) specifically available from the Federal Reserve's discount window and from other central banks, based on pledged collateral, for potential future borrowing (i.e., total capacity minus any outstanding borrowings)

- If the excerpt specifies available capacity at the Fed, possibly with other central banks, but gives no numeric figure, write "Not Specified"
- If the excerpt does not mention available borrowing capacity specifically at the Fed or other central banks (or is otherwise irrelevant), write "Not Relevant"

FHLB_Prepositioned_Value
Extract the dollar amount of assets pledged to the Federal Home Loan Banks, with these guidelines:

- DEFAULT ASSUMPTION: Assets pledged to the FHLB are for borrowing capacity unless explicitly stated otherwise

- Extract amounts unless the text specifically states the pledging is for any other stated non-borrowing purposes (similar to the exclusions listed for Fed_Prepositioned_Value, e.g., securing existing specific obligations or other explicitly stated non-borrowing FHLB-specific purposes)
- If mentioned but no figure given, mark as "Not Specified"
- If no FHLB pledging mentioned, mark as "Not Relevant"

FHLB_Borrowing_Capacity
Extract the dollar amount of the resulting borrowing capacity (value after haircuts) specifically available from the FHLB, based on pledged collateral, for potential future borrowing (i.e., total capacity minus any outstanding borrowings)

- If the excerpt specifies available capacity at the FHLB but gives no numeric figure, write "Not Specified"
- If the excerpt does not mention available borrowing capacity specifically at the FHLB (or is otherwise irrelevant), write "Not Relevant"

Combined_Prepositioned_Value
Extract the combined amounts pledged specifically to the Federal Reserve (and other central banks) and FHLBs but no other entities in that specific combined figure, with these guidelines:

- DEFAULT ASSUMPTION: Combined Fed+FHLB pledged amounts are for borrowing capacity unless explicitly stated otherwise (following the same exclusion logic as Fed_Prepositioned_Value if specific non-borrowing purposes are stated for the combined amount)
- If such a combined amount is given, record it here.
- If the excerpt states that collateral is pledged to both but no numeric total is given, write "Not Specified"
- If the excerpt combines Fed+FHLB collateral with collateral pledged to other institutions beyond other central banks in a single figure, such that you cannot isolate the amount pledged only to Fed+FHLB and other central banks, write "Not Specified"
- If the combined collateral is explicitly stated to be *only* for non-borrowing purposes (e.g., "The $X billion pledged to the Fed and FHLBs is solely for facilitating interbank clearing"), mark "Not Relevant". If the combined prepositioned amount is for both borrowing and non-borrowing purposes, record it here
- If the excerpt is irrelevant to a combined collateral value pledged exclusively to the Fed (possibly including other central banks) and FHLB, write "Not Relevant"

Combined_Capacity
Use this only if the excerpt explicitly states a single, combined available borrowing capacity (value after haircuts, minus outstanding borrowings) specifically and exclusively from the Federal Reserve (and other central banks) and FHLBs (and no other entities) for potential future borrowings.

- If such a combined amount is given, record it here

- If the excerpt states that combined capacity is available but no numeric total is given, write "Not Specified"
- If the excerpt refers to capacity that includes other institutions or sources (other than other central banks), or lumps it together so you cannot isolate *just* Fed+FHLB+other central bank capacity, write "Not Specified"
- If the excerpt is irrelevant to available capacity exclusively from both Fed and FHLB, write "Not Relevant"

Confidence_Level
(10 = exact, 1 = highly uncertain)

—

Important Clarifications

1. **Prepositioned Value vs. Capacity:** Prepositioned Value is typically the market/fair value of the assets pledged *before* haircuts. Capacity is the resulting borrowing power *after* haircuts. Look for keywords like "prepositioned", "fair value," "market value," "pledged securities," "pledged loans" for Prepositioned value, and "borrowing capacity," "available credit," "liquidity available from pledging," "cash obtainable by borrowing" for Capacity.
2. **Default Assumption**
   - When banks report "assets pledged" to the Federal Reserve, other central banks, and/or FHLBs without specifying a purpose, assume these are for borrowing capacity. Only exclude amounts when the text explicitly states they are only for other specific purposes like: open market operations, payment system access, clearing and settlement, or any other explicitly stated non-borrowing purpose.
   - The burden of proof is on EXCLUSION, not inclusion. When in doubt, include the pledged amount.
3. **Other Central Banks Rule**
   - *Include in Fed fields*: Only when explicitly combined with Federal Reserve figures (e.g., "pledged to Federal Reserve Banks and other central banks: $X billion")
   - *Exclude from Fed fields*: When reported separately (e.g., "pledged to Fed: $X billion, pledged to ECB: $Y billion")
   - *Simple test*: If you can't separate the Fed amount from the "other central banks" amount, include the total in Fed fields.
4. **Exclude Collateral Pledged for Existing Outstanding Borrowings**
   - If the excerpt *only* discusses collateral that is securing *existing* or *outstanding* loans/borrowings, do *not* extract it.
   - In that case, mark the relevant field(s) as "Not Relevant" or "Not Specified" (whichever applies—see below).
5. **"Not Specified" vs "Not Relevant"**
   - "Not Specified" means the bank states it has prepositioned or borrowing capacity with the entity, but gives no dollar amount. For example: "We maintain pledged collateral at the Fed"

- “Not Relevant” means the excerpt does not include information on borrowing capacity and related prepositioning; it can also apply if the amount is explicitly only for a non-borrowing purpose.

6. **Zero vs. Not Specified**
   - If the excerpt explicitly states “$0” is prepositioned, record **“0”**.
   - If the excerpt mentions that collateral is prepositioned but *does not* state an amount, record **“Not Specified”**.
7. **Multiple Time Periods**
   If the excerpt provides multiple time frames (e.g., 2023 vs. 2024) for prepositioned collateral, prioritize the *most recent* data.
8. **Confidence Level**
   - If you are certain the extracted amount is correct, rate 10.
   - If there is ambiguity or partial information, you might choose a lower confidence.
9. **Ranges**
   If the bank reports a range, use the smaller number.
10. **Approximate vs. exact:**
    When both an approximate and an exact value appears, use the exact amount. (e.g., “approximately $1.0 billion ($998.2 million)” should extract $998.2 million).
11. **Fair value vs. amortized value**
    If the value of prepositioned collateral is reported both at fair value and amortized value, use the fair value.

Example Scenarios

Scenario A (Capacity Only):
“The Bank had available borrowing capacity at the FHLB of approximately $10 billion as of December 31, 2024.”

- Fed_Prepositioned_Value: Not Relevant
- Fed_Borrowing_Capacity: Not Relevant
- FHLB_Prepositioned_Value: Not Specified
- FHLB_Borrowing_Capacity: $10 billion
- Combined_Prepositioned_Value: Not Relevant
- Combined_Capacity: Not Relevant
- Confidence_Level: 10

Scenario B (Collateral Securing Outstanding Borrowing - Exclude):
“At year-end, the Bank pledged $5 billion of collateral to the Federal Reserve for outstanding discount window borrowings.”

- Fed_Prepositioned_Value: Not Relevant
- Fed_Borrowing_Capacity: Not Relevant

- FHLB_Prepositioned_Value: Not Relevant
- FHLB_Borrowing_Capacity: Not Relevant
- Combined_Prepositioned_Value: Not Relevant
- Combined_Capacity: Not Relevant
- Confidence_Level: 10

Scenario C (Combined Capacity):
"We have approximately $12 billion of combined borrowing capacity available from the Federal Reserve and the FHLB for contingent funding needs."

- Fed_Prepositioned_Value: Not Relevant
- Fed_Borrowing_Capacity: Not Relevant
- FHLB_Prepositioned_Value: Not Relevant
- FHLB_Borrowing_Capacity: Not Relevant
- Combined_Prepositioned_Value: Not Specified
- Combined_Capacity: $12 billion
- Confidence_Level: 9

Scenario D (Total Pledged (not necessarily for capacity) vs. Borrowing Capacity):
"The Bank has pledged assets of $251.3 billion at Federal Reserve Banks and other central banks and FHLBs. As of December 31, 2024, the Bank's borrowing capacity at the FHLBs and Federal Reserve discount window was approximately $100 billion."

- Fed_Prepositioned_Value: Not Specified
- Fed_Borrowing_Capacity: Not Specified
- FHLB_Prepositioned_Value: Not Specified
- FHLB_Borrowing_Capacity: Not Specified
- Combined_Prepositioned_Value: $251.3 billion
- Combined_Capacity: $100 billion
- Confidence_Level: 9

We separately feed each filing's excerpts to the LLM which yields three separate estimates for filing. The LLM nearly always returns a single number for each field, but in some cases it returns text (e.g., "10 billion" or "approximately 10 billion"). We parse the responses into standardized dollar amounts. A small number of responses are strings that cannot be standardized programmatically, so we manually convert these edge case strings into numeric values.

For each filing-field pair, we aggregate across the three runs with simple rules. If all three numeric values perfectly match, we keep that value. If they differ only by rounding (coefficient of variation less than 0.05, say because one model returned \$1 billion and the other return \$998 million), we keep the most precise figure based on significant digits in the original string. If two of three either match exactly or are "close" in this sense, we keep their common value. When a filing–field mixes text labels ("Not Specified"/"Not Relevant") and numbers, we keep the response that is most common (e.g., if two of the three LLM responses agree that it is "not relevant", we use that). We correct likely unit omissions when one run differs from the others by a factor of 1e3 or 1e6. After these adjustments, there are only a small number of disagreements remaining. In these cases, we keep the largest value of the three to avoid mechanically understating levels when a run drops units. Applying these rules, the three runs are identical in about 88 percent of filing–field pairs; nearly all other differences are small rounding differences. We then collapse to one observation per filing–field.

Cleaning data with the LLM requires several caveats. First, banks substantially vary in how they report prepositioning, requiring judgement even a human would apply inconsistently. We include the entire prompt in the Internet Appendix, which describes several edge cases. Second, the LLM may inaccurately answer the prompt. We randomly select 2,000 excerpts of the sample and verify that it is correct about 96 percent of the time. We also manually verify its accuracy for the largest 25 banks since these banks likely dominate aggregate disclosed prepositioning if they disclose. Third, we run the LLM on each filing three separate times and check for consistency. The LLM estimates perfectly agree about 90 percent of the time.

There are two cases when the LLM performs poorly: first, in a small number of cases, firms report their prepositioning only in a table rather than in a sentence. The LLM is less accurate in these cases since we focus on excerpts that have keywords. 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).

IA.C Additional Discussion and Results

IA.C.1 Alternative Measures of the Capacity Ratio

It is also helpful to further separately study the behavior of the largest banks and medium-sized banks. Figures IA.1 and IA.2 plot capacity ratios for large banks and medium-sized banks, respectively. Large banks consistently preposition more to the Fed, with an average capacity ratio of 35 percent compared to medium-sized banks' 22 percent average. Medium-sized banks tend to have more prepositioned to the FHLBs, but after the turmoil of 2023, medium-sized banks shifted some prepositioning away from the FHLBs and toward the Fed. In Figure IA.3, we plot the FHLB capacity ratio when adjusting the denominator to reflect the set of assets pledgeable to the FHLBs instead of those pledgeable to the Fed. The average FHLB capacity ratio calculated this way is similar but somewhat higher, averaging 16 percent.

We focus on the capacity ratio measure using unencumbered assets since unencumbered assets can be prepositioned without restriction. We can alternatively calculate the capacity ratio including both unencumbered and encumbered assets, which we show in Figure IA.4. 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 26 percent with encumbered assets in the denominator, compared to 28 percent in the main measure. Table IA.4 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 prepositioned 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 Figure IA.5. By this measure, the banks prepositioned 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.

Figure IA.7 provides capacity ratios by asset class for large and medium-sized banks separately and shows they have broadly similar behavior. Notably, though, large banks preposition safe assets—Treasuries and agency MBS—more often than smaller banks.

IA.C.2 Estimating Routine Prepositioning with Forward Purchases

Do banks simply top off their prepositioning with existing loans in bad states? Or, when they make a new loan, do they preposition 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 prepositioning 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 prepositioned collateral on date t on the market value of forward asset purchases that will settle on date t as reported on the previous business day:

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

where t is the date, $t+n$ is the maturity, b is the bank, k is the asset class, and i is the currency. X_t is a vector of controls, including date, bank, and product (defined at the asset class by currency by maturity level) 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, and limit to products for which banks report forward purchases.

If $\beta = 1$, then all changes in prepositioning are simply explained by banks prepositioning all their settling forward purchases with the Fed. A priori, this is implausible since the change in the market value of prepositioned securities should depend on the prepositioned securities on date $t-1$, the change in the market value of those securities from $t-1$ to t, and the new securities prepositioned 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 preposition.

Table IA.6 shows the regression results. The main result is in column (1), which shows that roughly 0.4 cents of every dollar of newly settled purchases are prepositioned with the Fed. One concern is that banks are unable to quickly preposition 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.

The estimated magnitude is especially small for two reasons. One possibility is that banks do not preposition their new assets because they immediately encumber them. We reject this in the last three columns by repeating the regression with the dependent variable changed to the level of unencumbered assets. These coefficients are much larger—ranging between 29 and 37 cents, meaning that $1 of settling forward purchases increases unencumbered assets between 29 and 37 cents. Second, 0.4 cents is also small considering that banks preposition 28 cents for every dollar of their eligible assets. The table shows that banks are largely not simply prepositioning their new assets as a rote matter of their standard operations, suggesting that they instead preposition dynamically, when their expectations for the future grow dimmer.

IA.C.3 Haircut Comparison Across Collateral Markets

We can better compare haircuts across markets by comparing haircuts on narrow subsets of assets with similar characteristics. Table IA.7 regresses haircuts in private collateral markets against the Fed haircut:

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

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 IA.7 confirms this intuition. A 1 pp increase in the Fed is related to an increase of 0.06 pp in the bilateral repo market, 0.16 in tri-party repo, 0.18 in FICC repo, 0.29 against the FHLB, and 0.45 for unencumbered assets. The regression shows that the Fed charges higher haircuts than all other alternative collateral markets.

IA.C.4 Banks with Switched Fed Districts

Under some conditions, banks can interact with the Fed system using a Federal reserve regional bank other than one in which its headquarters are physically located. Such "switches" require the Fed's approval. 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 Internet Appendix, Figure IA.10 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 likely increases prepositioning. 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 6.0 percent for their chosen district, compared to an average 9.8 percent in their physical location district. Since Table 4 shows that banks with lower district asset shares preposition more, the ability for banks to switch district—thereby pushing down their district asset share—can boost prepositioning 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 -0.14, implying a 1pp increase in a bank's district asset share decreases their Fed capacity ratio by 0.14pp. The coefficient implies that switching banks would preposition about 0.54pp less $(0.14 \times (9.8 - 6.0))$, a small but meaningful effect especially given that switching banks tend to be large banks.

IA.D Appendix Figures and Tables

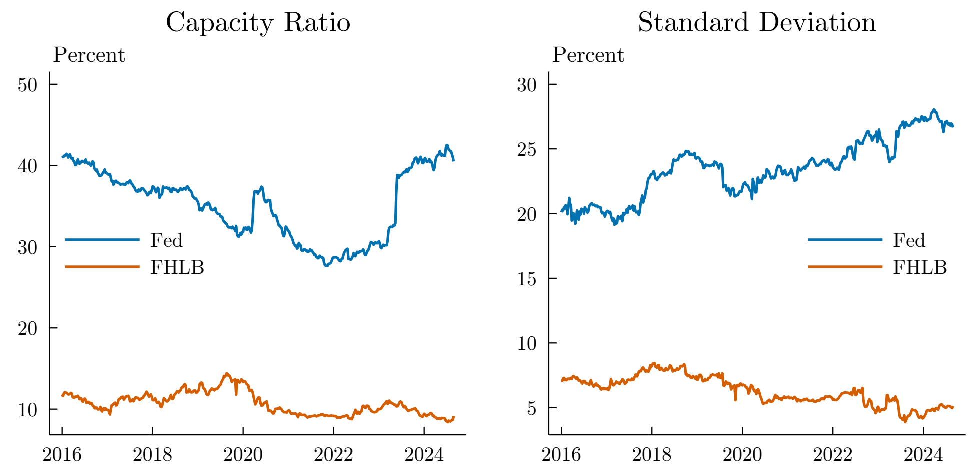

Figure IA.1: Large Banks: Capacity Ratio and Cross-Sectional Standard Deviation of Capacity Ratio. Capacity Ratio$_t^p$ = (Prepositioned Collateral/(Unencumbered Assets + All Prepositioned Collateral))$_t$ where both numerator and denominator are market values of the assets and p reflects the capacity provider (e.g., the Fed or the FHLBs). The numerator reflects the prepositioned collateral with a specific central bank or GSE, and the denominator is the sum of all unencumbered assets and all prepositioned 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.

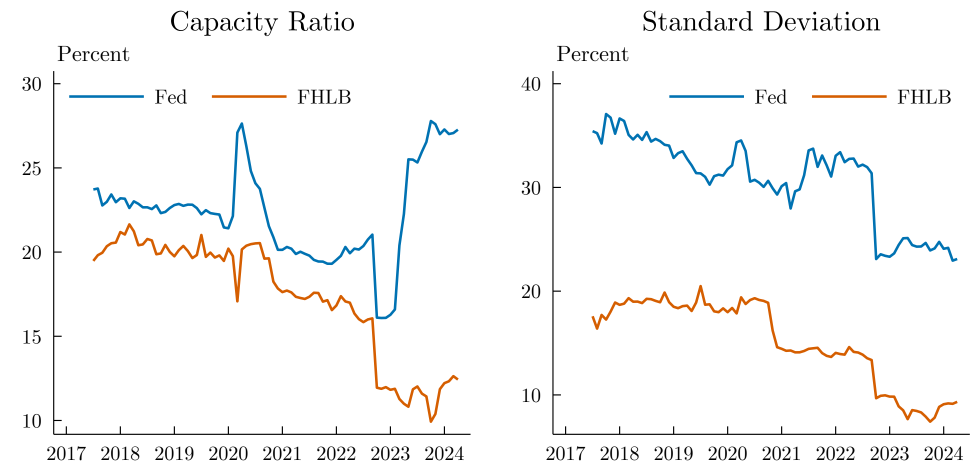

Figure IA.2: Medium-Sized Banks: Capacity Ratio and Cross-Sectional Standard Deviation of Capacity Ratio. Capacity Ratio_t^p = (Prepositioned Collateral/(Unencumbered Assets + All Prepositioned Collateral))$_t$ where both numerator and denominator are market values of the assets and p reflects the capacity provider (e.g., the Fed or the FHLBs). The numerator reflects the prepositioned collateral with a specific central bank or GSE, and the denominator is the sum of all unencumbered assets and all prepositioned 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.

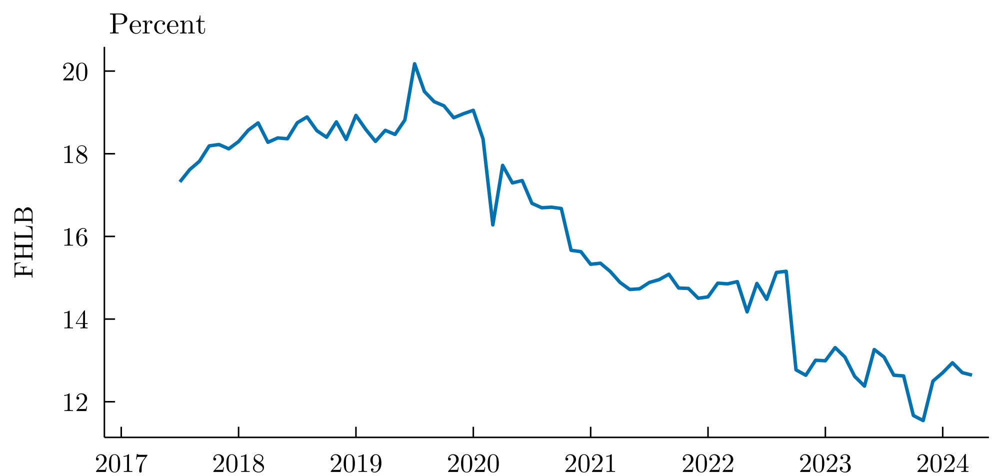

Figure IA.3: FHLB Capacity Ratio with adjusted denominator. Capacity Ratio_t^p = (Prepositioned Collateral/(Unencumbered Assets + All Prepositioned Collateral))$_t$ where both numerator and denominator are market values of the assets and p reflects the capacity provider (e.g., the Fed or the FHLBs). The numerator reflects the prepositioned collateral with the FHLBs, and the denominator is the sum of all unencumbered assets and all prepositioned collateral across all capacity providers that are pledgeable at the FHLB (as opposed to the Fed, as we use for the main estimates). Plots are monthly data. Includes all banks in our FR2052a sample; see data section for details.

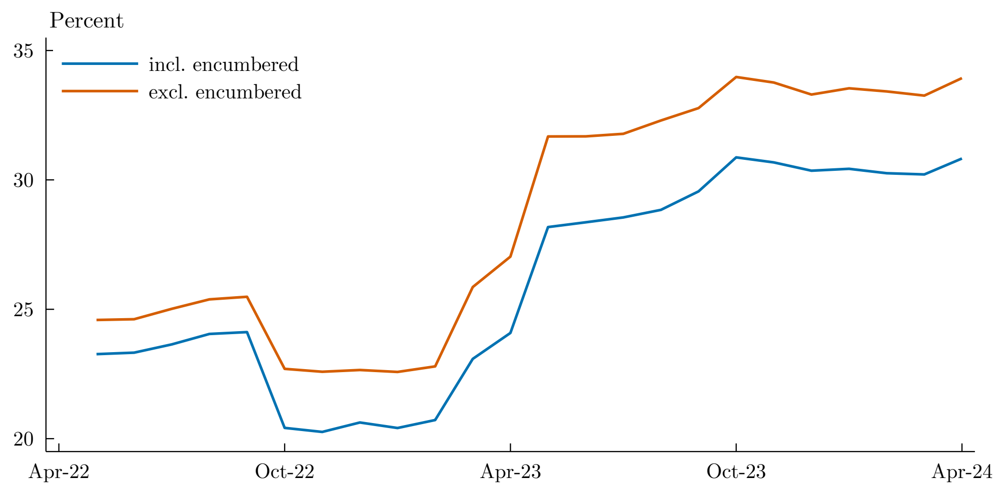

Figure IA.4: Capacity Ratio including Encumbered Assets. Capacity Ratio_t^p = (Prepositioned Collateral/(Unencumbered Assets + Encumbered Assets + All Prepositioned Collateral))$_t$ where both numerator and denominator are market values of the assets and p reflects the capacity provider (e.g., the Fed or the FHLBs). The numerator reflects the prepositioned collateral with a specific central bank or GSE, and the denominator is the sum of all unencumbered assets, encumbered assets, and all prepositioned collateral across all capacity providers. Data on encumbered assets are available beginning only in May 2022. 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.

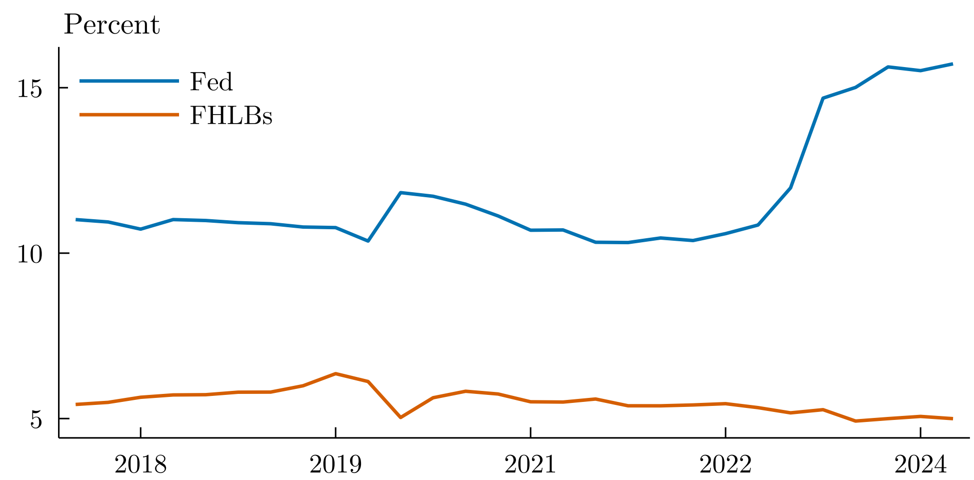

Figure IA.5: Capacity vs. Total Bank Assets. Plots the total amount of Fed and FHLB capacity reported in FR2052a data against total assets as reported in call reports for our sample of banks.

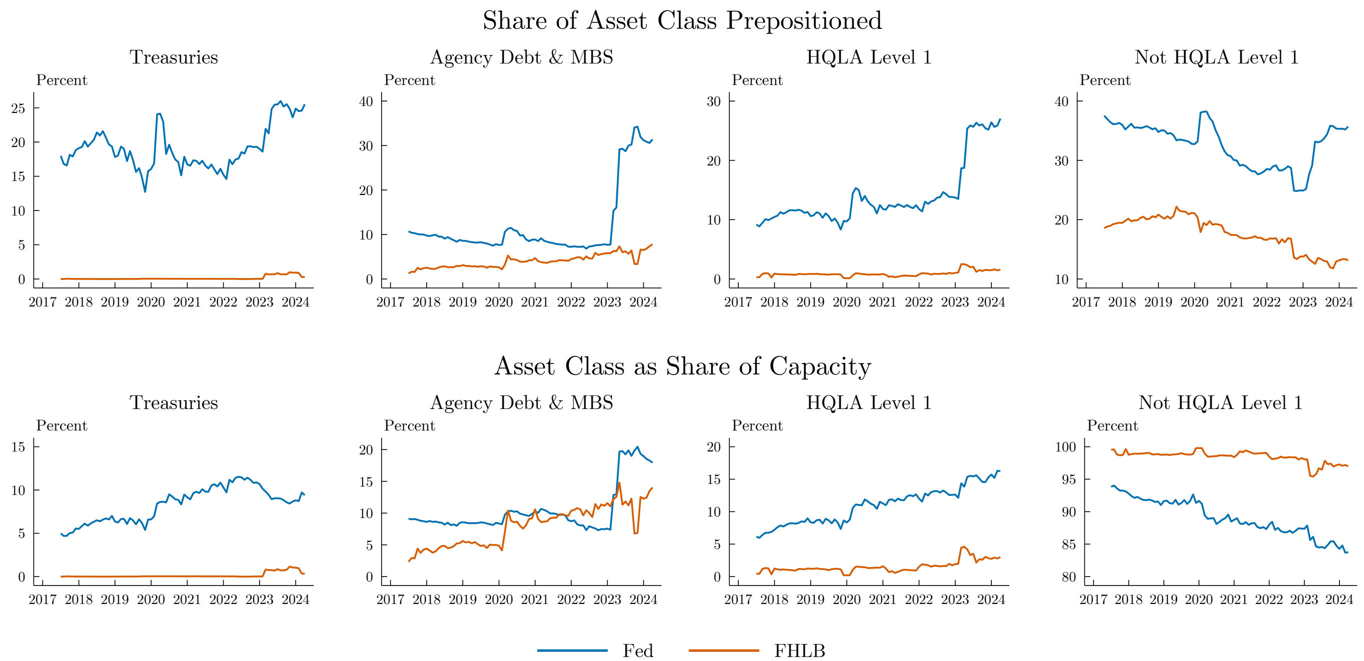

Figure IA.6: Capacity Composition by Asset Type for All Banks. Top panel plots the share of an asset class that is pledged as collateral to the Fed or FHLB as a percent of the sum of total unencumbered assets and all prepositioned collateral of that asset type. Bottom panel plots the share of capacity 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.

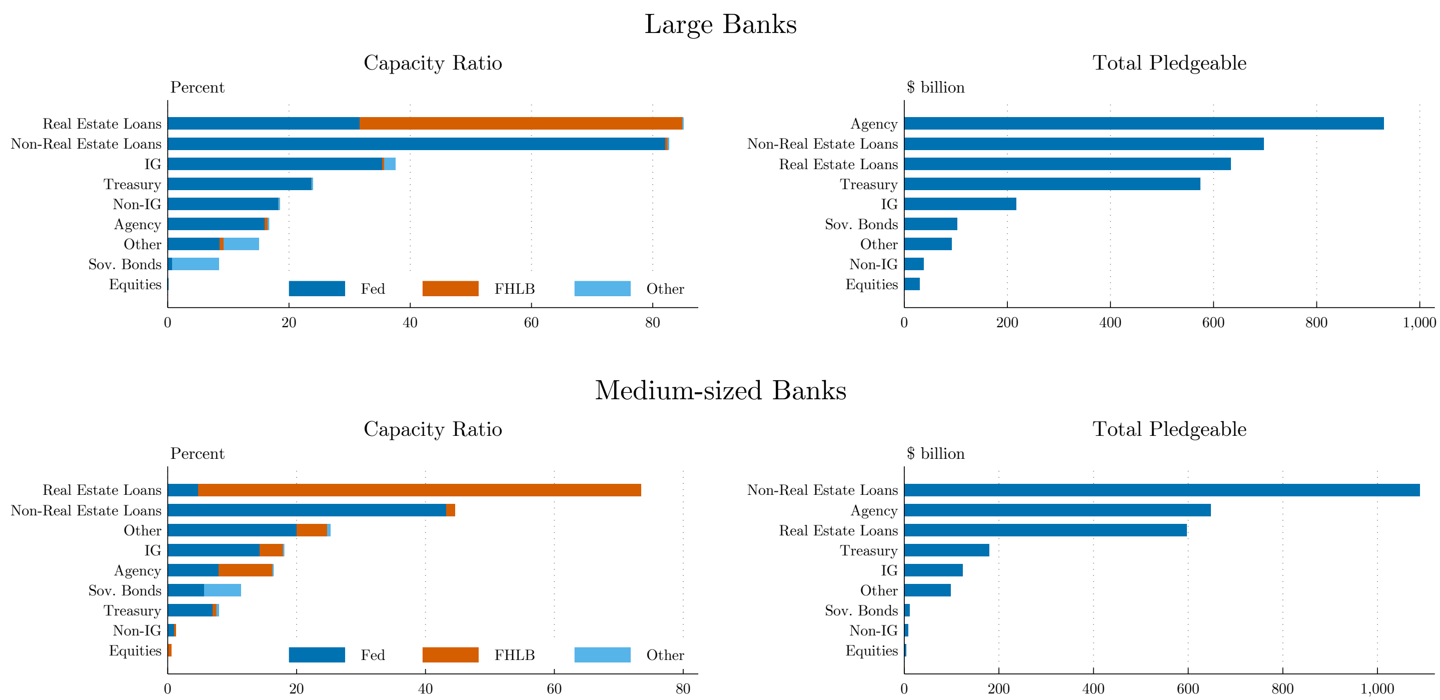

Figure IA.7: Average Capacity Ratio and Total Pledgeable by Bank Size. Left panel plots the average capacity ratio by provider and asset class, where capacity ratio is the capacity with that provider divided by the total amount of pledgeable assets. Right panel plots average total pledgeable assets, the sum of unencumbered assets and prepositioned 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.

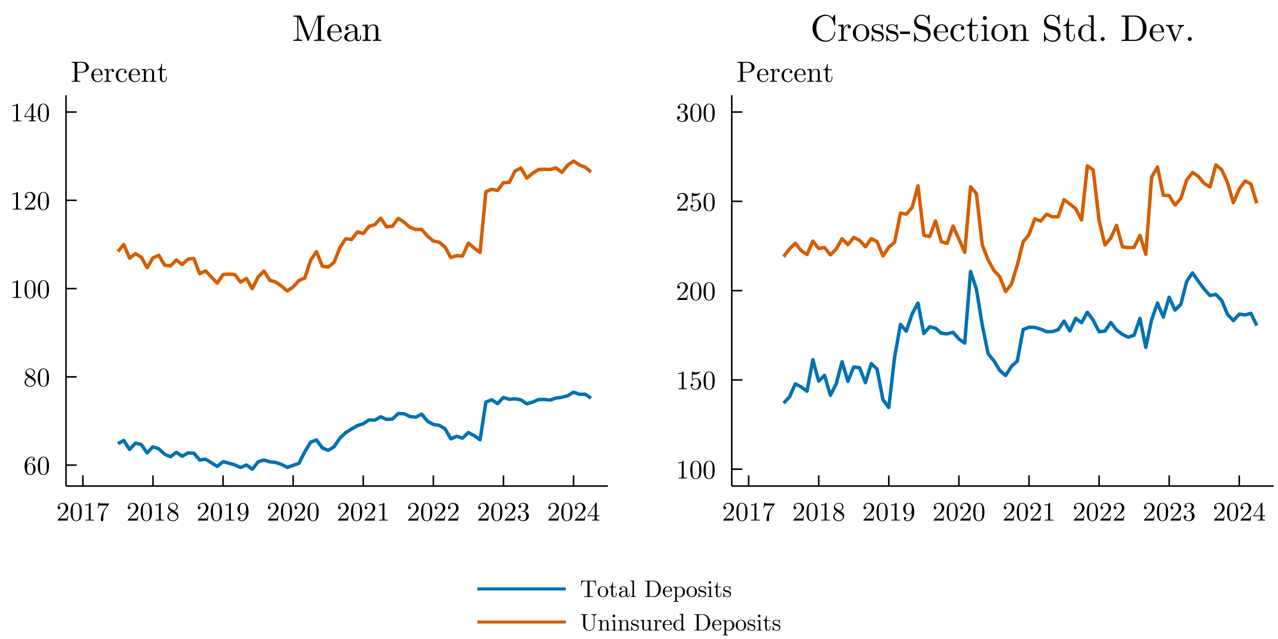

Figure IA.8: Liquidity Sources vs. Deposits. Left panel plots the ratio of (post-haircut Fed prepositioning + post-haircut FHLB prepositioning + unrestricted reserves + the market value of unencumbered assets that are pledgeable at the Fed) relative to deposits, either total or uninsured. Right panel plots standard deviation in bank-specific ratios after winsorizing at the 5th and 95th percentile. Includes all banks in our FR2052a sample; see data section for details.

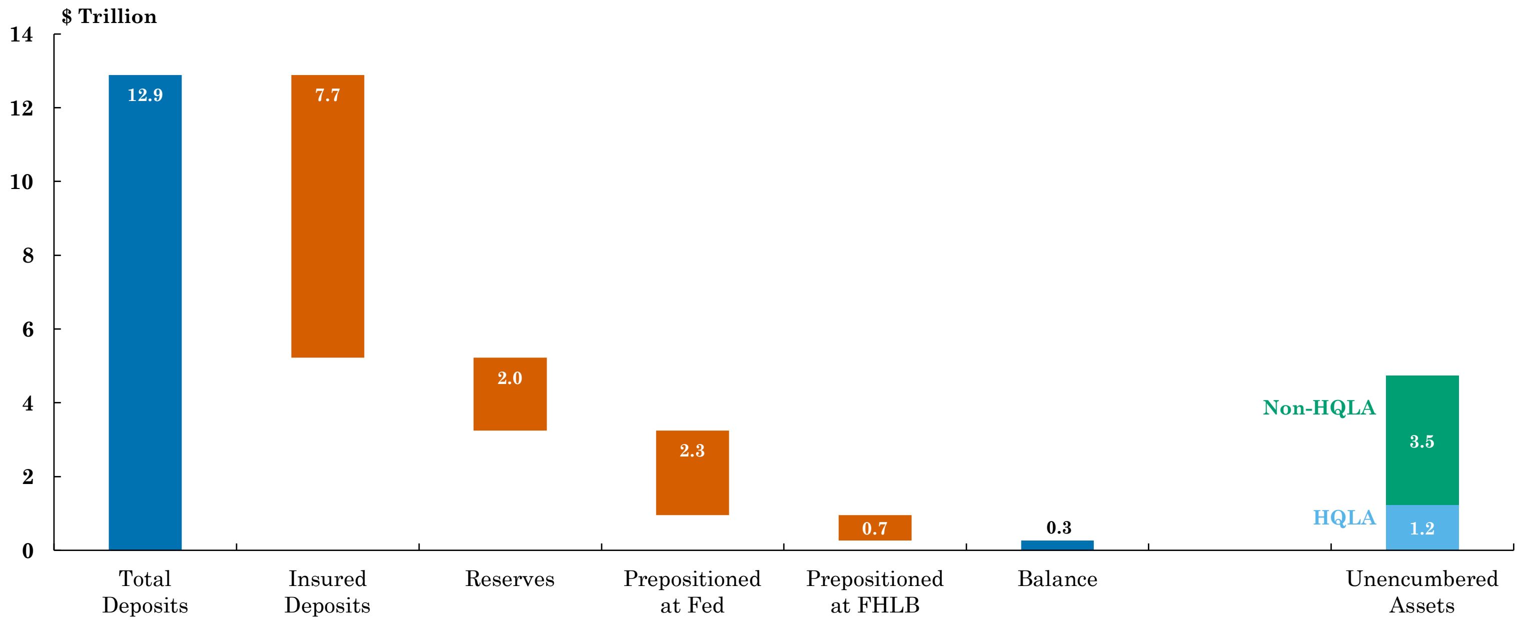

Figure IA.9: Deposit Waterfall. Figure compares deposits against post-haircut Fed and FHLB prepositioning, the market value of unencumbered assets that are pledgeable to the Fed, and reserves. Data for April 2024. Includes all banks in our FR2052a sample; see data section for details.

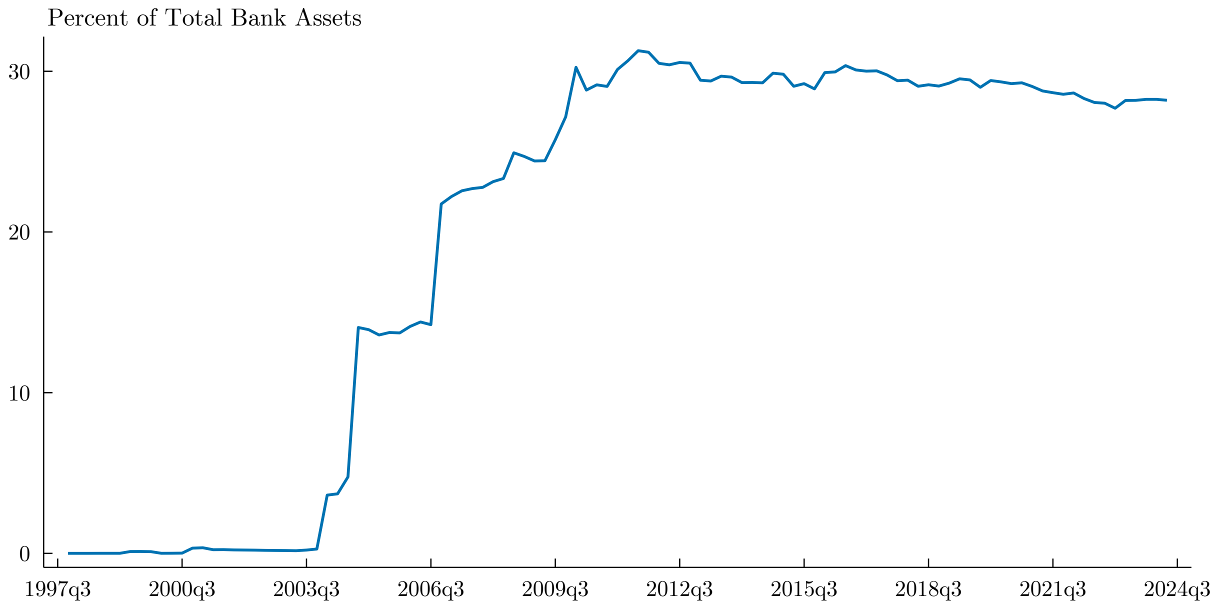

Figure IA.10: Share of Bank Assets Held By Switching Banks. Figure plots the share of total bank assets held by banks with supervisory Federal Reserve districts different from the district in which its head office is physically located. Figure derived entirely from public data, including call report and FFIEC attribute data.

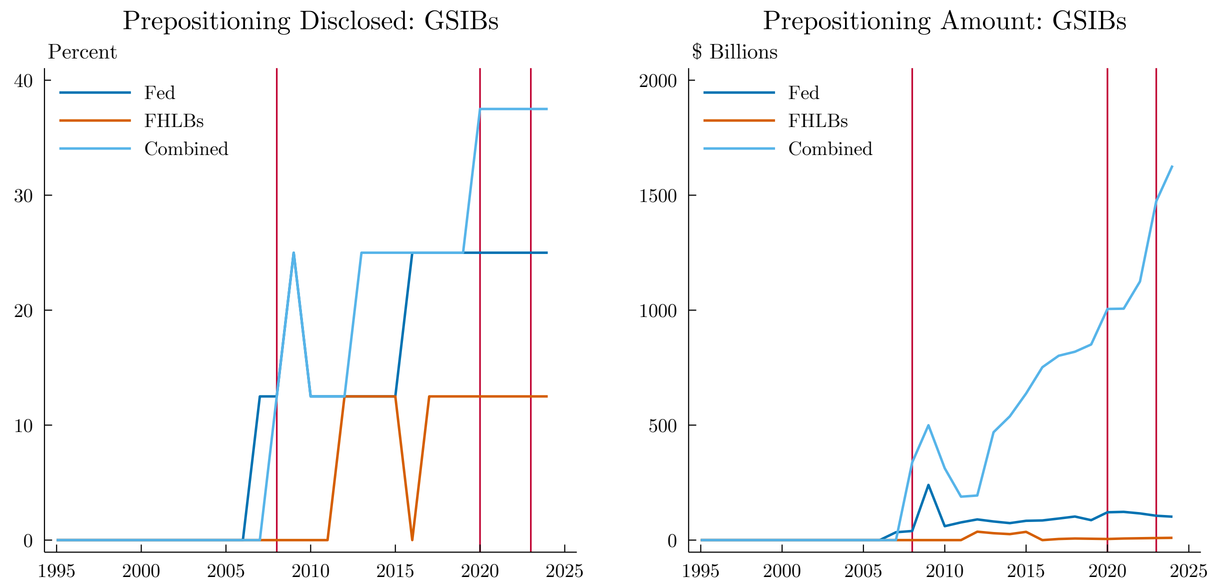

Figure IA.11: Public Prepositioning 10-K Information: Large Banks. Figure plots the share of banks reporting their prepositioning by type for large banks, defined as globally systemically important banks. Figure derived only from public 10-K filings.

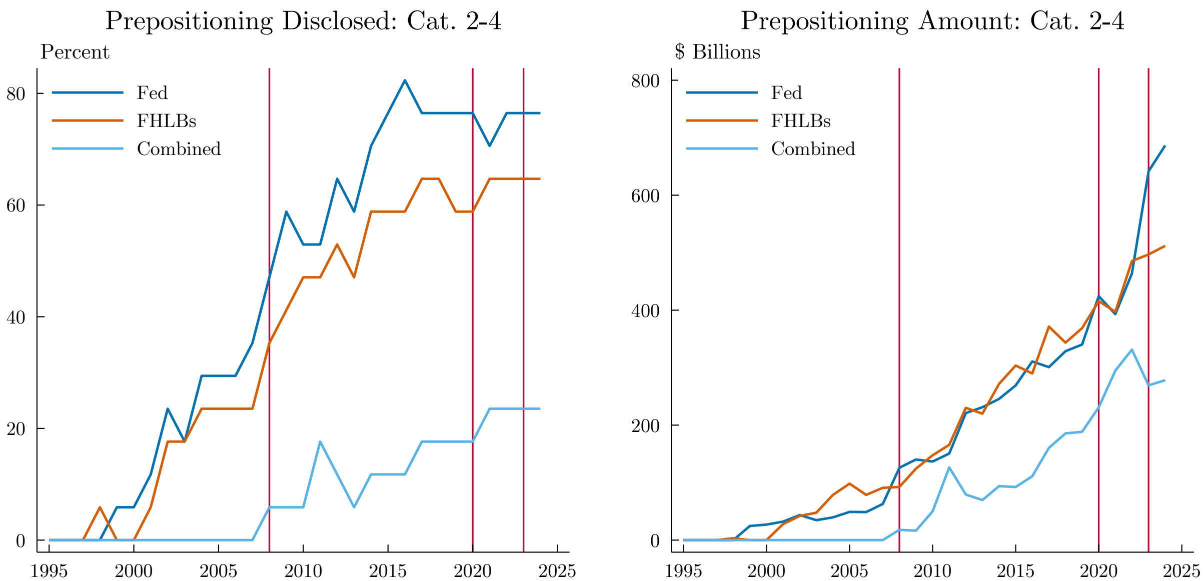

Figure IA.12: Public Prepositioning 10-K Information: Medium-sized Banks. Figure plots the share of banks reporting their prepositioning by type for medium-sized banks, defined as category II, III, and IV banks. Figure derived only from public 10-K filings.

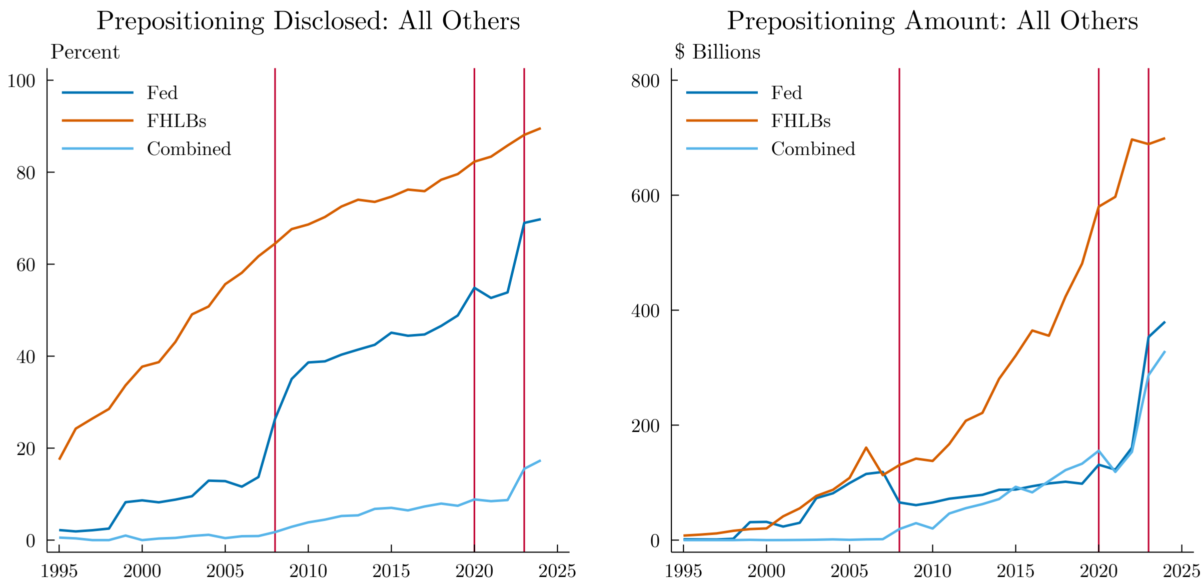

Figure IA.13: Public Prepositioning 10-K Information: All Other Banks. Figure plots the share of banks reporting their prepositioning by type for all other banks that are neither GSIBs nor category II, III, or IV banks. Figure derived only from public 10-K filings.

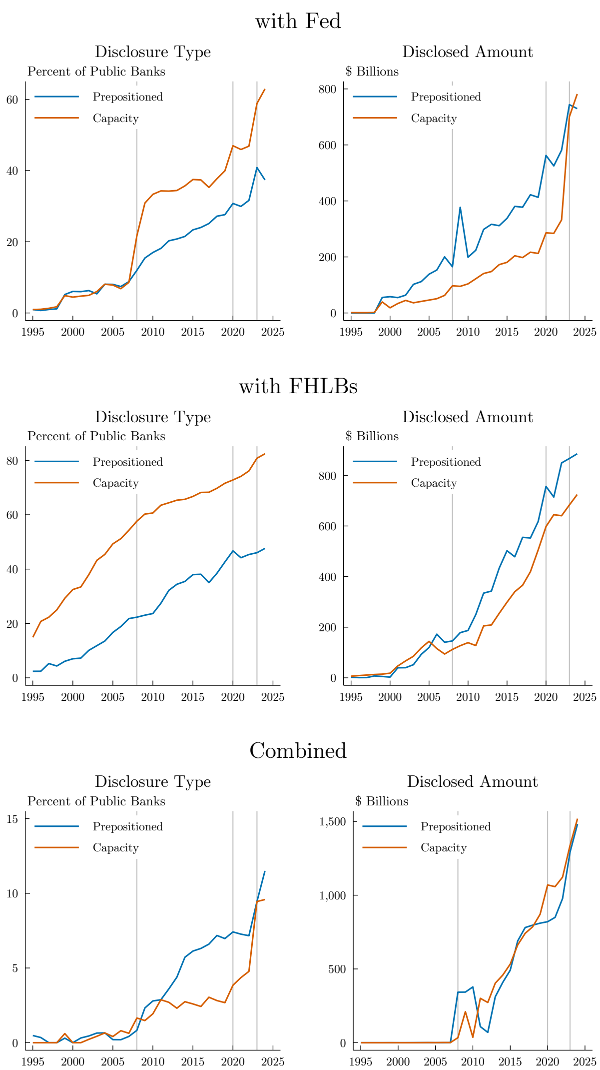

Figure IA.14: Public Prepositioning 10-K Disclosure Strategy. Figure plots the share (and dollar value) of banks reporting their prepositioning either with the prepositioned amount or with the capacity amount. Figure derived only from public 10-K filings.

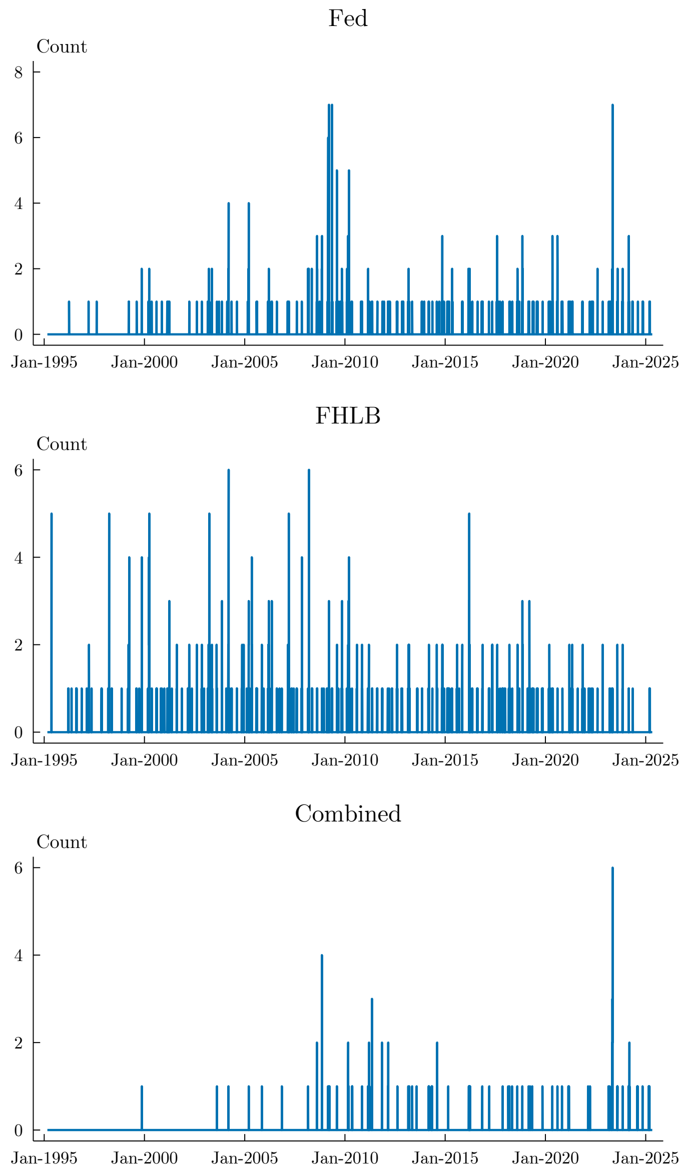

Figure IA.15: Count of Banks Beginning Disclosure by Date. Figure plots the count of banks that start disclosing their Fed, FHLB, or combined prepositioning. Figure derived only from public 10-K filings.

	Form	Operating Hours		Processing Time	
		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 IA.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.

			All	Treasuries	Agency	HQLA L1	Non-HQLA L1
(a):	*Prepositioned At Fed ($bn)*	Mean	1,151	137	149	164	986
		Std. Dev.	227	57	62	76	159
(b):	*Prepositioned At FHLBs ($bn)*	Mean	349	0	6	1	347
		Std. Dev.	48	0	5	1	48
(c):	*Unencumbered*	Mean	1,797	437	776	761	1,036
		Std. Dev.	465	218	176	216	255
$(a)/(a+b+c)^{\dagger}$:	*Capacity Ratio Fed*	Mean	35.1	24.9	16.2	16.9	41.9
		Std. Dev.	4.2	4.6	6.5	4.0	4.8
$(b)/(a+b+c)^{\dagger}$:	*Capacity Ratio FHLB*	Mean	10.7	0.0	0.6	0.1	14.7
		Std. Dev.	1.4	0.0	0.4	0.1	1.5
$(a)/\sum(a)$:	*Share of Total Prepositioned at Fed*	Mean		11.6	12.5	13.7	86.3
		Std. Dev.		3.5	2.5	4.1	4.1
$(b)/\sum(b)$:	*Share of Total Prepositioned at FHLBs*	Mean		0.0	1.6	0.3	99.7
		Std. Dev.		0.0	1.2	0.3	0.3
$(1-h^{Fed})\times a$/Uninsured Deposits:	*Prepositioned At Fed After Haircut vs. Uninsured Deposits*	Mean	21.0	2.9	3.2	3.5	17.6
		Std. Dev.	2.8	0.7	1.0	1.1	2.9
$(1-h^{Fed})\times a$/Total Deposits:	*Prepositioned At Fed After Haircut vs. Total Deposits*	Mean	13.5	1.9	2.1	2.2	11.2
		Std. Dev.	1.7	0.5	0.7	0.7	1.7
$((1-h^{Fed})a+(1-h^{FHLB})b+c+reserves)$/Uninsured Deposits:	*Prepos. at Fed and FHLB + Unenc. + Reserves vs. Uninsured Deposits*	Mean	88.6	32.9	41.7	41.2	68.1
		Std. Dev.	3.9	6.0	4.1	5.1	4.0
$((1-h^{Fed})a+(1-h^{FHLB})b+c+reserves)$/Total Deposits:	*Fed Capacity + FHLB Capacity + Unenc. vs. Total Deposits*	Mean	56.8	21.1	26.8	26.4	43.7
		Std. Dev.	2.7	4.0	2.7	3.4	2.4

Table IA.2: Large Banks: Prepositioning Summary Statistics. Table shows summary statistics for prepositioned 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 prepositioning at other central banks, which is typically small or zero. Bottom two rows compare the sum of post-haircut values of prepositioning at the Fed and FHLBs plus the market value of unencumbered assets plus unrestricted reserves against total deposits or uninsured deposits. Unencumbered assets include those pledgeable at the Federal Reserve. Includes large banks in our FR2052a sample; see data section for details.

			All	Treasuries	Agency	HQLA L1	Non-HQLA L1
(a):	*Prepositioned At Fed ($bn)*	Mean	708	13	61	41	667
		Std. Dev.	227	12	81	41	190
(b):	*Prepositioned At FHLBs ($bn)*	Mean	523	1	67	12	511
		Std. Dev.	62	3	31	8	62
(c):	*Unencumbered*	Mean	1,957	193	644	443	1,514
		Std. Dev.	679	38	166	70	668
$(a)/(a+b+c)^{\dagger}$:	*Capacity Ratio Fed*	Mean	22.3	6.3	7.9	8.3	25.3
		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	20.5
		Std. Dev.	3.5	1.1	3.2	1.5	4.9
$(a)/\sum(a)$:	*Share of Total Prepositioned 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 Prepositioned at FHLBs*	Mean		0.2	12.4	2.4	97.6
		Std. Dev.		0.5	5.2	1.5	1.5
$(1-h^{Fed})\times a/$Uninsured Deposits:	*Prepositioned At Fed After Haircut vs. Uninsured Deposits*	Mean	24.2	0.6	2.6	1.8	22.4
		Std. Dev.	6.5	0.5	3.5	1.7	4.9
$(1-h^{Fed})\times a/$Total Deposits:	*Prepositioned At Fed After Haircut vs. Total Deposits*	Mean	12.9	0.3	1.4	0.9	11.9
		Std. Dev.	3.1	0.2	1.8	0.9	2.3
$((1-h^{Fed})a+(1-h^{FHLB})b+c+reserves)/$Uninsured Deposits:	*Prepos. at Fed and FHLB + Unenc. + Reserves vs. Uninsured Deposits*	Mean	161.1	43.3	68.3	56.5	138.6
		Std. Dev.	25.2	5.5	5.2	4.0	26.4
$((1-h^{Fed})a+(1-h^{FHLB})b+c+reserves)/$Total Deposits:	*Fed Capacity + FHLB Capacity + Unenc. vs. Total Deposits*	Mean	86.1	23.2	36.7	30.3	74.1
		Std. Dev.	12.6	3.3	3.8	2.5	13.4

Table IA.3: Medium-Sized Banks: Prepositioning Summary Statistics. Table shows summary statistics for prepositioned 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 prepositioning at other central banks, which is typically small or zero. Bottom two rows compare the sum of post-haircut values of prepositioning at the Fed and FHLBs plus the market value of unencumbered assets plus unrestricted reserves against total deposits or uninsured deposits. Unencumbered assets include those pledgeable at the Federal Reserve. 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	1.135***		1.197***	
	(52.47)		(364.31)	
FHLB Capacity Ratio incl. Encumbered_t		0.865***		1.092***
		(35.54)		(124.04)
Constant	−0.949	2.367***	−2.217***	0.287***
	(−1.48)	(8.97)	(−20.03)	(3.89)
N	24	24	564	564
R^2	0.99	0.98	0.99	0.96

Table IA.4: 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 in parentheses using robust standard errors where * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Panel A: All Banks (Monthly)		
	Correlation of ΔCapacity Ratio$_t^{\text{Fed},k}$ with:	
k	$\Delta \ln(\text{Avg. Collateralized Daylight Drafts})_t$	$\Delta \ln(\text{Peak Daylight Drafts})_t$
All	−0.08	−0.04
HQLA 1	−0.08	−0.04

Panel B: Large Banks (Weekly)		
	Correlation of ΔCapacity Ratio$_t^{\text{Fed},k}$ with:	
k	$\Delta \ln(\text{Avg. Collateralized Daylight Drafts})_t$	$\Delta \ln(\text{Peak Daylight Drafts})_t$
All	−0.06	−0.11
HQLA 1	−0.07	−0.11

Table IA.5: 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. Significance is reported with stars where * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Daylight overdraft data are available from `https://www.federalreserve.gov/paymentsystems/psr_dlod.htm`.

	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$^{b,k}_{t,t+n}$	0.004**	0.005	0.004**	0.323***	0.290***	0.369***
	(2.18)	(1.49)	(2.44)	(11.85)	(12.18)	(6.78)
N	3,344,952	801,576	2,543,376	3,344,952	801,576	2,543,376
R^2	0.00	0.00	0.00	0.02	0.02	0.03

Table IA.6: Most Forward Purchases Are Not Prepositioned. Table shows the regression ΔCapacity (Level)$^{b,k}_{t,t+n}$ = $\alpha + \beta$Settling Forward Purchases$^{b,k}_{t,t+n} + \gamma\prime X_t + \varepsilon^{b,k}_{t,t+n}$. Panel is at the date by bank-asset type by maturity bucket by currency level. Includes date, bank, and product fixed effects (where product is defined as the asset type by maturity bucket by currency). Sample limited to products for which banks report forward purchases. 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 pledgeable at the Fed. Sample includes large banks at a daily frequency. t-statistics are reported in parentheses using robust standard errors clustered by date 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$^{b,i,k}_{t,t+n}$	0.06***	0.18***	0.16***	0.29***	0.45***
	(6.78)	(9.71)	(51.51)	(19.28)	(90.02)
N	115,239	17,933	100,749	21,301	186,153
R^2	0.00	0.00	0.09	0.05	0.16

Table IA.7: 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. Sample includes large banks. 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 using robust standard errors clustered by date where * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

All Filers, 1995-2024		Fed	FHLB	Combined
Share of Filers Disclosing (percent)	Average	30.1	58.8	4.8
	Max	69	86	18.2
Total Level Disclosed ($ billion)	Average	341.1	437.1	570.9
	Max	1,168.5	1,221.3	2,236.1

Table IA.8: Public Prepositioning Disclosure Summary Statistics. Table provides summary statistics of the publicly disclosed prepositioning in annual reports from 1995 to 2024. Table derived only from public SEC filings. We define disclosure as the bank providing information on either the value of pledged assets or their post-haircut borrowing capacity. Some banks report only the prepositioned amount, others report only the capacity it generates. For banks that report both, we do not double count; instead we take the larger of the two values.

	Large Banks (Daily)			All Banks (Monthly)		
	(1)	(2)	(3)	(4)	(5)	(6)
Bad State Risk						
$Baa - Aaa_t$	1.53^{***}			0.56		
	(3.49)			(1.10)		
Insured Deposits_t^b	-7.79^{***}			-8.27^{***}		
	(-4.10)			(-6.43)		
Uninsured Deposits_t^b	9.78^{***}			5.75^{***}		
	(5.50)			(5.40)		
Alternative Collateral Market						
$PCR_t - SOFR_t$		-0.31			0.15	
		(-1.00)			(0.37)	
Treasury Repo Haircut_t^b		0.67^{**}			1.07^{***}	
		(2.03)			(2.71)	
Stigma						
District Asset Share_t^b			-16.10^{***}			-2.07^{***}
			(-4.75)			(-2.77)
N	16,592	16,600	16,792	3,060	2,916	4,093
R^2	0.09	0.01	0.03	0.06	0.00	0.00
Time FE	No	No	No	No	No	No
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes

Table IA.9: Sizing the Prepositioning Forces, one-by-one. Table repeats the regression in Table 8 against the prepositioning forces one by one. R^2 is within-R^2. t-statistics are reported in parentheses using robust standard errors clustered by month where * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

	(1) $\Delta\text{Capacity}_{bt}$	(2) $\Delta\text{Capacity}_{bt}$	(3) $\Delta\text{Capacity}_{bt}$
ΔUninsured Deposits$_{bt}$	-2.04^{*}		-2.78^{**}
	(-1.80)		(-2.56)
ΔInsured Deposits$_{bt}$		0.64	1.63^{***}
		(1.67)	(4.17)
Constant	16.40^{*}	25.39^{***}	1.69
	(1.95)	(2.88)	(0.20)
N	62	62	62
R^2	0.13	0.02	0.22

Table IA.10: Prepositioning vs. Deposit Flows After SVB. Table shows the regression of the change in capacity on uninsured or insured deposit flows, where variables are measured by their deviation from their one-year average, as described in section 5. Sample is limited to March and April 2023. Sample includes all banks at a monthly frequency. t-statistics are reported in parentheses using robust standard errors where * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

	(1) Uninsured GIV_{bt}	(2) Insured GIV_{bt}
Next Bank Uninsured GIV_{bt}	-0.00	
	(-0.24)	
Next Bank Insured GIV_{bt}		-0.01
		(-0.47)
Constant	5.77^{***}	6.44^{***}
	(9.09)	(9.66)
N	2,355	2,355
R^2	0.00	0.00

Table IA.11: Actual GIV vs. the Placebo GIV. Table shows the regression of the actual GIV for bank b in month t on the placebo GIV, which is the GIV of the alphabetically next bank in the same month based on ticker symbol. t-statistics are reported in parentheses using robust standard errors where * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Dependent Variable: ΔCapacity$_{bt}$						
	(1)	(2)	(3)	(4)	(5)	(6)
ΔUninsured Deposits$_{bt}$	113.98	−28.68			37.41	4.32
	(0.06)	(−0.24)			(0.11)	(0.55)
ΔInsured Deposits$_{bt}$			1.50	3.71	−53.90	−11.24
			(0.63)	(0.59)	(−0.11)	(−0.55)
N	2,082	2,079	2,081	2,078	2,081	2,078
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
F-Stat	0.0	0.1	7.2	0.9	0.0	0.2
Bank FE	No	Yes	No	Yes	No	Yes

Table IA.12: Granular Instrumental Variable Placebo. Table shows the granular instrumental variables regression of prepositioning on deposit flows. Regressions are identical to those in Table 9 except for each bank b, we assign its GIV_{bt} to the alphabetically next bank by ticker symbol (wrapping the last ticker back to the first). Panel A presents the first stage regression of deposit flows, either uninsured (D^U) or insured D^I, on the uninsured GIV and insured GIV. Panel B presents the second stage of prepositioning on instrumented deposit flows. The first four columns of Panel B correspond to the first stage in the same column in Panel A; column 5 in Panel B corresponds to Panel A's columns 5 and 6, and column 6 in Panel B corresponds to Panel A's columns 7 and 8. Panel C presents the uninstrumented OLS regression. Sample includes all banks at a monthly frequency. Controls include capital ratio, the ratio of reserves to total assets, log of total assets, and the bank's district asset share. Kleibergen-Paap rk Wald F statistics reported; last two columns report joint F-statistics given we use both uninsured and insured GIV as instruments. The single variable F-stats for column 5 are 5.3 (uninsured) and 3.7 (insured); for column 6 they are 4.5 (uninsured) and 0.7 (insured). t-statistics are reported in parentheses using robust standard errors clustered by month where * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.