The Treasury Collateral Spread and Levered Safe-Asset Production*

Chase P. Ross†

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Abstract

Banks are vital suppliers of money-like safe assets, which they produce by issuing short-term liabilities and pledging collateral. But their ability to create safe assets varies over time as leverage constraints fluctuate. I write a simple model to describe private safe-asset production when intermediaries face leverage constraints. I directly measure leverage constraints using confidential supervisory data on high-frequency changes in the largest banks' repos. The collateral spread—the maturity-matched yield spread between Treasuries used as repo collateral more often and Treasuries used less often—averages about 0.5 basis points because it compensates for bank leverage risk.

JEL Codes: E40, E51, G12, G20

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†Board of Governors of the Federal Reserve System. Email: `chase.p.ross@frb.gov`

1 Introduction

Banks produce money-like safe assets using leverage and collateral. While the aggregate safe-asset supply fluctuates with the quantity of sovereign debt outstanding, it also fluctuates as banks face time-varying leverage constraints. I use a simple model to describe money-like safe-asset production when banks are leverage constrained and present the pricing implications of time-varying leverage constraints for safe assets used as collateral.

I study U.S. Treasury collateral backing repurchase agreements (repos), a type of short-term safe asset, and I document a *collateral spread*: Treasuries used as collateral trade at a discount—equivalent to a higher yield—compared to Treasuries not used as collateral, even after controlling for observables like maturity and liquidity. The average maturity-matched collateral spread is 0.53 basis points (bps). Variation in banks' leverage constraints leads to variation in banks' ability to produce private safe assets by levering up and pledging collateral—a source of risk for collateral.

Collateral dynamics matter because collateral is a basic input for the private sector's safe-asset production function. It is important to understand how the financial system produces safe assets because it is painful when safe-asset production breaks down, as it did during the Global Financial Crisis and the early stages of the 2020 pandemic.

A safe asset is a low-risk asset because it is information-insensitive. By design, investors have little incentive to produce private information on safe assets, and agents can use them as payment or to store value without fear of adverse selection (Gorton, 2017). Leverage and private safe-asset production are two sides of the same coin when equity issuance is costly. The costs of raising new external equity in the short term prevent banks from offsetting capital shocks with new equity issuance (Kashyap et al., 2010). Banks can produce safe assets only with incremental leverage or costly balance sheet adjustments because they do not issue equity regularly. Banks may be leverage constrained because of regulatory limits or market discipline when lenders refrain from providing additional funding to risky banks.

The analysis proceeds in two steps. First, I use CUSIP-specific collateral data collected from money market mutual fund investments in the tri-party repo market. The data provides two million CUSIP-month observations between 2011 and 2023, allowing me to identify which banks use which Treasury CUSIPs as repo collateral. For each Treasury CUSIP, I calculate its collateral ratio (CR), the share of a CUSIP's total market value used as repo collateral. In my sample, banks pledged 2.6 percent of each Treasury CUSIP, on average, as repo collateral to money funds. I calculate the Treasury collateral spread by comparing two yield curves: one estimated from high-CR Treasury CUSIPs and one from low-CR Treasury CUSIPs.

Second, I proxy for bank leverage constraints with confidential supervisory data on banks' repo exposures from the Federal Reserve's FR2052a *Complex Institution Liquidity Monitoring Report*. The dataset provides high-frequency information on the largest banks' balance sheets. Using this data, I show that the Treasury collateral spread is tightly linked to fluctuations in bank leverage constraints.

To better understand the collateral spread, I write a simple two-period model in the spirit of Krishnamurthy and Vissing-Jørgensen (2015) to describe expected returns in an economy where a bank produces short-term, money-like safe assets using its assets as collateral. The model shows that the collateral spread will be positive for two reasons, which I document in the data.

First, banks want to use the least money-like Treasuries as collateral since it is costly to lock up desirable Treasuries. In practice, Treasuries can be desirable if they are especially liquid (e.g., on-the-run), if they could be financed at negative rates (e.g., trading special), or if they are otherwise preferred by certain investors (e.g., specifics). Banks try to predict which Treasuries will be the least desirable and prefer to use those as collateral. Banks' collateral choices, which I empirically measure using the collateral ratio, provide a novel and systematic measure of which Treasuries are the least desirable.

Second, the model shows that the collateral spread will be positive because Treasuries' collateral value depends on bank leverage constraints and the covariance between the two. Spiking bank leverage constraints push down collateral values. All Treasuries hedge contractions in the safe-asset supply, but Treasuries used as collateral are worse hedges than Treasuries not used as collateral. The higher yield on Treasuries used as collateral compensates the holder for the risk that leverage constraints might increase, reducing its value as collateral. I show this bank leverage risk is priced.

The key empirical challenge to measuring the collateral spread is distinguishing between the two channels: to what extent do high-collateral-ratio Treasuries trade at a discount because they are the least desirable CUSIPs versus their poor covariance characteristics with bank leverage constraints? I run several tests to show both channels are at play. I confirm the first channel by showing that banks choose longer maturity and less liquid bonds to use as collateral. I confirm the second channel by showing that the collateral spread covaries with bank leverage constraints, not with measures of Treasury liquidity or the Treasury curve slope. I also use an event study to show that high-collateral-ratio bonds had lower returns than otherwise similar bonds during the European Sovereign Debt Crisis in 2011. Separately, I use quarter-ends as an exogenous shock to bank leverage constraints to show that high-collateral-ratio bonds trade at larger discounts when banks pull back to window-dress, a relationship that also holds after controlling for CUSIP observables.

It's helpful to compare with other Treasury basis trades to gain perspective on the collateral spread's 0.53 bps magnitude. The collateral spread is about 25 percent the size of the 5-year Treasury on-the-run/off-the-run spread and 60 percent the size of the cheapest-to-deliver basis (Barth and Kahn, 2021). In this context, the size of the collateral spread is plausible because it occupies a similar order of magnitude as other economically important Treasury spreads, albeit a bit smaller. A priori, the collateral spread should be smaller than these other Treasury spreads because the collateral spread (1) excludes all on-the-run Treasuries, so it does not include the substantial liquidity benefits that on-the-run issues carry, and (2) is value-weighted across all Treasury CUSIPs so it minimizes the effects of specific CUSIPs. It would be surprising if the collateral spread were larger than these other spreads since sophisticated levered investors closely study it, and the Treasury curve must be reasonably well-behaved.

In the final section, I study whether bank leverage risk appears for other types of collateral. The model predicts that the expected return of any security used as collateral will depend, in part, on its return covariance with bank leverage constraints. I use the money-fund data to study this dynamic for equities. I identify which stocks are used as collateral and provide evidence that these stocks covary with bank leverage risk after controlling for common equity risk factors.

Relation to the Literature This paper contributes to the literature by documenting Treasuries' collateral spread, its relationship with bank leverage, and providing details about the collateral allocation process in tri-party repo. Hu et al. (2019) use similar money fund data and focus on repo prices. They show that repo markets are competitive for safe assets but segmented for repos with risky collateral and that dealers optimize borrowing costs by strategically distributing collateral across fund families. Huber (2023) shows that dealers pay persistently different rates even for ostensibly homogenous repo trades and attributes it to dealers' market power. Krishnamurthy (2002) studies the on-the-run, off-the-run spread in Treasury bonds and documents the effect of investors' liquidity demands on the spread. Infante (2020) shows that increased demand for safe assets leads to a decrease in repos backed by Treasuries outstanding as the demand for safe assets compresses Treasuries' risk premia. Jank and Moench (2019) find that German banks respond to a falling safe-asset supply by increasing existing collateral reuse. Infante et al. (2018) show that the collateral multiplier for Treasury securities varies daily. Singh (2017) highlights the relationship between dealer balance sheet capacity and the financial system's ability to intermediate collateral. Christensen and Mirkov (2021) find safe but illiquid government bonds earn a large convenience yield, likely reflecting their ability to store value and serve as collateral. He et al. (2021) study the Treasury market's dysfunction during the Covid crisis and show that the safe-haven status of longer-term Treasuries may be eroding as intermediaries face binding leverage constraints.

This paper also contributes to the literature on the safe-asset supply. Diamond (2020) presents a model in which intermediaries choose the least risky portfolio, a diversified portfolio of nonfinancial firms' debt, to back their short-term debt issuance and shows that increased safe-asset demand increases intermediaries' leverage. Krishnamurthy and Vissing-Jørgensen (2015) show that demand for safe assets is an essential determinant of banks' short-term debt issuance, finding that Treasury issuance crowds out lending financed by short-term bank debt. Krishnamurthy et al. (2016) show that Treasuries are safe because the large number of Treasuries outstanding leaves investors with "nowhere else to go." Krishnamurthy et al. (2019) present a safe-asset determination model, finding that the sovereign's fundamentals and its outstanding debt are key determinants. Gorton et al. (2012) find that the safe-asset share of financial assets in the U.S. has been constant over the past 60 years, but its composition has changed from traditional bank liabilities to shadow bank liabilities. Krishnamurthy and Vissing-Jørgensen (2012) show that a scarcity of Treasuries relative to GDP pushes spreads between Treasuries and highly-rated corporate bonds higher as investors place a larger premium on the safety and liquidity aspects of U.S. sovereign debt. Gorton et al. (2015) show that more repos fail when the convenience yield is high. Gorton and Laarits (2018) find a safe-asset shortage post-crisis compared to pre-crisis. Sunderam (2015) shows that the financial sector produces more safe assets through asset-backed commercial paper when the convenience yield is high.

2 Institutional Details

I focus on repos, a type of safe asset produced by banks. A repo is a secured financing transaction in which the borrower (e.g., a bank or dealer) sells a security to a lender (e.g., a money market mutual fund) and agrees to repurchase it later, often the next day. The repo market is a large and central component of the financial system. Data from the Office of Financial Research shows that the U.S. repo market had at least $4 trillion of repos outstanding in 2023. Duffie (1996) describes repo mechanics in detail.

Intermediaries provide deposit account equivalents to institutional cash pools with repo, which has blossomed in popularity because institutions' large cash balances far exceed deposit insurance limits. Gorton et al. (2012) and Pozsar (2011) attribute the pre-crisis surge in repo to growth in institutional cash pools—pensions, endowments, and corporations—paired with a shrinking supply of Treasuries relative to GDP.

Table 1 uses a simplified bank balance sheet to show how a bank creates a safe asset by levering up and trading repo. In the pre-repo panel, the bank has $100 in Treasuries funded with $100 in equity. In the post-repo panel, the bank pledges its Treasuries as collateral in a repo to borrow $100 cash. The bank's leverage, equal to assets divided by equity, doubles after the repo. Holding equity levels constant, the bank must increase its leverage if it issues any more liabilities like repo. Kashyap et al. (2010) show that the costs of raising new external equity are important in the short term and prevent banks from offsetting capital shocks with new equity issuance. In this context, a bank cannot produce safe assets—its short-term liabilities—without incremental leverage or costly balance sheet adjustments that change the composition of its liabilities. Variation in the banking system's leverage constraint mechanically leads to variation in the banking system's ability to produce private safe assets.

The Repo Market The U.S. repo market is bifurcated into the tri-party and bilateral markets. In tri-party repo, a custodian sits between the lender and borrower to reduce operational burdens for smaller participants. According to the Federal Reserve Bank of New York, tri-party repo volume was $2.1 trillion in May 2020; tri-party repo collateral was 58 percent Treasuries, 40 percent agency MBS, and 2 percent agency debt. In bilateral repo, counterparties interact directly. Baklanova et al. (2016) and Copeland et al. (2014) estimate that the bilateral market was $1.9 trillion in March 2015 and find that 60 percent of the collateral was Treasuries, 20 percent was equities, and the rest was

ABS or corporate debt. Baklanova et al. (2015) give additional details on repo markets.

Tri-party trades are cash-driven because they are motivated by a cash lender's desire for a safe store of value. The bilateral market is security-driven because investors want a specific security. Investors might use a bilateral repo to acquire a Treasury trading *special*. Specific collateral CUSIPs might trade special because they are in high demand in the cash market: for example, investors want that specific Treasury because the bond is on-the-run or cheapest-to-deliver into a Treasury future.

Cash lenders in the tri-party market include money market funds, corporate treasuries, municipalities, and insurance companies. Cash borrowers include hedge funds and other levered investors, like mortgage real-estate investment trusts. The bank intermediates between cash lenders and cash borrowers to provide leverage to the bank's levered prime-brokerage clients. In return, cash lenders receive a set of high-quality collateral securities but not a specific security.

Repo collateral is either general or specific. General collateral encompasses a broad set of interchangeable high-quality securities, like U.S. Treasuries, agency mortgage-backed securities, or agency debt (e.g., Federal Home Loan Bank debt) but can also include more exotic securities and equities. In the typical cash-driven tri-party repo transaction, the cash lender limits acceptable collateral regarding maturity, issue concentration, liquidity, and other factors.

Collateral Optimization Financial market participants spend considerable time and resources selecting which CUSIPs to use as collateral and deciding how to allocate collateral efficiently across counterparties. Their goal is to have the lowest financing cost and the most unencumbered high-quality liquid assets. Repo borrowers leave their collateral inside their custodial account at the tri-party clearing bank—called the *box*—to facilitate same-day settlement. The custodian simply moves the collateral from the borrower's box to the lender's box.

Dealers prefer to place collateral with the lowest outside option in the box since desirable collateral can often be financed at cheaper rates. For example, banks can often finance a Treasury trading special at lower rates outside the box in security-specific bilateral repos. The custodian gives dealers tools to allocate collateral across secured trades efficiently, but many dealers use in-house methods. The Bank of New York Mellon (BNYM), the tri-party repo custodian in the U.S., provides a default collateral matching algorithm that is uncontroversial and endogenously designed to meet clients' (i.e., banks and dealers) demands.

Dealers carefully choose what collateral to put in the box because they cannot easily access it later. There is nontrivial friction in moving collateral in and out of the box. After post-crisis tri-party repo reforms, overnight collateral is locked up until 3:30 p.m. If collateral becomes desirable in dealer markets, the dealer must manually substitute unencumbered collateral from its box to the tri-party lock-up to ensure it has sufficiently collateralized all its repo deals at all times. The dealer must hold extra collateral in its box if it needs to substitute collateral already locked-up because custodians no longer provide intraday credit to finance collateral substitutions. Treasuries are often substituted because hedge funds and dealers often trade in ways that require substitutions. The friction involved in moving collateral in and out of the box means dealers spend considerable resources ranking collateral and making deliberate collateral decisions.

Dealers can use BNYM's collateral optimization tools to optimize across several dimensions. The matching requires three inputs: a list of all the dealer's collateral, a list of all the repo deals and what collateral is eligible for each deal, and the dealer's collateral preference ranking. BNYM, for example, offers its customers a cheapest-to-deliver optimization across portfolios. Other possible allocation preferences include allocating high-quality liquid assets for short-term trades and cheapest-to-deliver collateral for long-term trades; optimizing the collateral allocation based on the source of collateral (from the dealer's trading desk, its clients, or its treasury assets); and allocating low value-at-risk assets to fixed-income, currency, and commodity trades and high value-at-risk assets to tri-party trades. Many dealers prefer to use their own allocation method or to supplement BNYM's optimization tools.

Dealers rank which securities to pledge as collateral as part of the matching process, effectively ranking collateral from cheapest to richest to deliver. For example, the schedule provided in marketing material gives the following preference order: municipal bonds; ABS and CMOs; medium-term notes; corporate bonds; Ginnie Mae MBS REMIC; Ginnie Mae stripped MBS; MBS pass-throughs; GNMA MBS; TIPs bonds and notes; and, finally, Treasury bills, bonds, notes, and floating-rate notes.

Within Treasury collateral—the focus of this paper—dealers prefer to allocate the least liquid, longest-maturity, and odd-lot Treasuries so that the unencumbered assets remaining in the dealer's box are round lots of short-dated bills. Short-dated Treasuries are helpful if unexpected margin calls or calculation errors require additional delivery of securities.

Although cash lenders do not control what collateral they receive at the CUSIP-level, they control what collateral types they receive. For fixed income, lenders can choose acceptable collateral from 87 types of fixed-income securities across 17 buckets of securities. Cash lenders can also allow equity collateral. The lender can choose additional constraints for equity collateral, such as the maximum market capitalization percentage that borrowers can pledge and the collateral value as a share of that security's average traded volume. Lenders can specify even more granular cuts or make manual adjustments. The online appendix provides more details on the collateral types and the allocation process.

3 Model

3.1 Setup

I write a simple two-period model in the spirit of Krishnamurthy and Vissing-Jørgensen (2015). The model has two periods, t and $t+1$. Agents make decisions in period t before any dividends have been paid, and uncertainty resolves in period $t+1$. There are three components of the model:

a household sector, a bank, and a government. There are five assets, an *unboxed* Treasury bond θ_{ub}—denoted θ_{ub}^H if held by households and θ_{ub}^B if held by the bank—a *boxed* Treasury bond θ_b, a bank liability B, a Lucas tree with terminal value K that pays dividends k_t and k_{t+1}, and tradable equity in the bank E that pays dividends div_t and div_{t+1}. The bank liability B is analogous to a repurchase agreement, and the Lucas tree is equivalent to a real asset, either a business or land. It is cheaper for the bank to pledge the boxed bond as collateral underlying the bank repo B compared to the unboxed Treasury bond. The returns to the Treasury bonds, bank liability, Lucas tree, and bank equity are stochastic, but households know the Lucas tree dividends with certainty.

In period t, households and the bank make allocation decisions, and the tree pays dividend k_t. The allocation decisions in period t pin down the bank's dividend payments unless the bank's haircut changes. The bank pays div_t immediately after agents make their choices in period t. In period $t+1$ uncertainty resolves, the returns on the assets are known, the bank pays out div_{t+1}, and the tree pays out its dividend k_{t+1}.

The model generates its predictions from three features. First, the model assumes that households earn nonpecuniary utility from holding money-like safe assets, denoted $\mathcal{M}$:

$$\begin{aligned}
\mathcal{M}_t &= \pi_B B + \pi_{\theta_{ub}} \theta_{ub}^H + \pi_{\theta_b} \theta_b^H \\
\mathcal{M}_{t+1} &= \pi_B B(1+R_B) + \pi_{\theta_{ub}} \theta_{ub}^H (1+R_{\theta_{ub}}) + \pi_{\theta_b} \theta_b^H (1+R_{\theta_b}),
\end{aligned}$$

where π_i allows for varying money weights for different safe assets and $\pi_i > 0$ for any safe asset i. Such a feature can be motivated by the demand for a transaction medium as in Krishnamurthy and Vissing-Jørgensen (2015)—motivated by Krishnamurthy and Vissing-Jørgensen (2012)—and Stein (2012) and is consistent with the literature on money in the utility function from Tobin (1965).

Second, the model imposes a stochastic haircut requirement on the bank's deposit constraint. The bank is a technology that transforms collateral on its balance sheet—in the form of Lucas trees or Treasuries—into safe assets in the form of bank liabilities B subject to a haircut across its assets. If the bank could issue liabilities equal to its assets (i.e., without a haircut), it could lever infinitely and hold zero equity. The model assumes an exogenous haircut prevents the bank from leveraging up past a certain point and that the haircut can change between period t and $t+1$. The model also imposes that the bank cannot issue more equity, motivated by Kashyap et al. (2010)'s finding that equity issuance costs prevent banks from issuing equity to offset capital shocks in the short term.

The assumption that banks produce safe assets subject to a haircut is realistic. Banks can be leverage constrained through a regulatory channel by capital requirements (e.g., common-equity Tier 1 ratio) or leverage requirements (e.g., supplemental leverage ratio). Banks can also be leverage constrained through a market discipline channel. Even if regulatory constraints are not binding, private lenders may not want to supply more funding to risky banks. Macchiavelli and Zhou (2022) empirically show that money funds lend to different banks at varying repo haircuts and rates depending on their relationships.

Third, I assume that assets have exogenous money weights, denoted π_i, to account for the ability of that specific security to satisfy the household's money-like safe asset demand. For example, on-the-run Treasuries—which the model assigns a comparatively higher money weight—typically have higher prices and lower yields because households prefer more liquid safe assets, all else equal.

Households Households are endowed with a share of the bank, worth E, and K units of the Lucas tree that pay dividends in each period and have a terminal value of $K(1+R_K)$ in period $t+1$. The households can borrow from the bank, pledging λK as collateral, where $\lambda \in [0,1]$ is the haircut on the collateral the bank offers on its loans.

Households choose their optimal allocation across five choice variables: α, the amount of bank equity the households retain in the first period; λK, the size of the loan they get from the bank by pledging their tree as collateral; B, their holding of the bank liability; θ_b^H, their boxed Treasury holding; and θ_{ub}^H, their unboxed Treasury holding.

Agents receive nonpecuniary utility from holding money-like safe assets, $\Omega(\mathcal{M})$, where $\Omega'(\mathcal{M}) > 0, \Omega''(\mathcal{M}) < 0$, $\lim_{\mathcal{M}\to 0}\Omega'(\mathcal{M}) = \infty$, and $\lim_{\mathcal{M}\to\infty}\Omega'(\mathcal{M}) = 0$. In the standard two-period setup, an agent weighs the asset's cost and the associated consumption decline in the current period against the asset's payoff and the marginal utility in the two states. In this model, agents have an extra incentive to hold more money-like safe assets unrelated to their returns.

The household's problem is

$$U(c_t, c_{t+1}) = \max_{\alpha,\lambda K,B,\theta_{ub}^H,\theta_b^H} u\left(c_t + \Omega\left(\mathcal{M}_t\right)\right) + \beta \mathbb{E}_t\left[u\left(c_{t+1} + \Omega\left(\mathcal{M}_{t+1}\right)\right)\right], \tag{1}$$

where

$$\begin{aligned} c_t &= k_t + (1-\alpha)E + \alpha div_t + \lambda K - B - \theta_{ub}^H - \theta_b^H \\ c_{t+1} &= k_{t+1} + \alpha div_{t+1} + (1-\lambda)K(1+R_K) + B(1+R_B) + \theta_{ub}^H(1+R_{\theta_{ub}}) + \theta_b^H(1+R_{\theta_b}). \end{aligned}$$

Further define $C_t = c_t + \Omega(\mathcal{M}_t)$ and $C_{t+1} = c_{t+1} + \Omega(\mathcal{M}_{t+1})$. The first-order conditions for θ_{ub}^H, the household's choice of unboxed Treasury bonds are

$$1 = \Omega'(\mathcal{M}_t)\pi_{\theta_{ub}} + \mathbb{E}_t\left[\frac{\beta u'(C_{t+1})}{u'(C_t)}(1+R_{\theta_{ub}})(1+\Omega'(\mathcal{M}_{t+1})\pi_{\theta_{ub}})\right]. \tag{2}$$

The first-order conditions for both types of Treasuries and the bank liability B are similar because they satisfy the agent's safe-asset demand. For now, I will make the simplifying assumption that $\pi_{\theta_b} = \pi_{\theta_{ub}} = \pi_B = 1$.

Bank The bank is a technology that transforms its assets into money-like bank liabilities B. The bank's assets are boxed Treasuries, θ_b^B, unboxed Treasuries, θ_{ub}^B, and the loans the bank makes against Lucas tree collateral, λK. Define the bank's assets $A = \lambda K + \theta_b^B + \theta_{ub}^B$. The bank must pay some costs to administer its assets: $\phi(\lambda K)$, $\mu(\theta_{ub}^B)$, and $\mu(\theta_b^B - \kappa)$, where $\kappa > 0$ reflects that boxed Treasuries are cheaper for the bank to hold and pledge as collateral compared to unboxed Treasuries. The bank can transform unboxed Treasuries into boxed Treasuries by paying a flat fee. The bank faces a stochastic liability issuance limit in the form of an exogenous haircut h_t across the bank's entire collateral portfolio, equivalent to its assets, each period:

$$\begin{aligned} B &\leq (1-h_t)(\lambda K + \theta_{ub}^B + \theta_b^B) \\ B(1+R_B) &\leq (1-h_{t+1})\left(\lambda K(1+R_K) + \theta_{ub}^B(1+R_{\theta_{ub}}) + \theta_b^B(1+R_{\theta_b})\right). \end{aligned} \tag{3}$$

Haircuts h_t are stochastic; for example, the government may impose a haircut on B, forcing the bank to delever and pass on lower R_B to the households in period $t+1$.

The bank chooses three variables: the haircut λ it offers on Lucas trees for the loans it underwrites to households and the bank's Treasury positions, θ_b^B and θ_{ub}^B. The bank does not charge a haircut on its Treasury holdings, reflecting Holmström (2015)'s "no questions asked" principle. The bank's choices maximize its equity value, the expected sum of its dividends:

$$E = \max_{\lambda, \theta_b^B, \theta_{ub}^B} div_t + \beta \mathbb{E}_t \left[div_{t+1}\right] \tag{4}$$

where

$$\begin{aligned} div_t &= B - \lambda K - \theta_{ub}^B - \theta_b^B - \phi(\lambda K) - \mu(\theta_{ub}^B) - \mu(\theta_b^B - \kappa) \\ div_{t+1} &= \lambda K(1+R_K) + \theta_{ub}^B(1+R_{\theta_{ub}}) + \theta_b^B(1+R_{\theta_b}) - B(1+R_B). \end{aligned}$$

Government The government issues Treasury bonds in fixed total supply Θ, which are held by either the bank or the household: $\Theta = \theta_b^B + \theta_{ub}^B + \theta_b^H + \theta_{ub}^H$.

For tractability, I make several standard assumptions following Campbell (2017). I assume that households have time-separable power utility and constant relative risk aversion γ over consumption, consumption is conditionally lognormal, and consumption and asset returns are jointly conditionally homoskedastic. I assume that $\Omega(\mathcal{M}) = \log(\mathcal{M})$ and that log consumption growth follows

$$\log\left(\frac{C_{t+1}}{C_t}\right) \equiv \Delta c_{t+1} = \mu_c + \sigma_c \varepsilon_{t+1},$$

where the shocks $\varepsilon_{t+1} \sim \ iid \ \mathcal{N}(0,1)$.

Proposition. *The collateral spread is positive because it is compensation for bank leverage risk when* $\sigma_{c,\theta_b} = \sigma_{c,\theta_{ub}}$ *and* $\pi_{\theta_{ub}} > \pi_{\theta_b}$.

Proof. Assuming $\mu_h = 0$, standard arguments yield the geometric risk premium (ignoring the Jensen component) for the unboxed Treasury's return:

$$\mathbb{E}_t[r_{\theta_{ub},t+1} - r_{f,t+1}] \approx \gamma \sigma_{c,\theta_{ub}} - \sigma_{h,\theta_{ub}} - \omega'_{\theta_{ub}}(\mathcal{M}_t), \tag{5}$$

where $\log(1+\Omega'(\mathcal{M}_{t+1})\pi_{\theta_{ub}}) = \mu_h + \sigma_h \varepsilon_{t+1}$, $r_{\theta_{ub},t+1} = \log(1+R_{\theta_{ub},t+1})$, and $-\omega'_{\theta_{ub}}(\mathcal{M}_t) = \log(1-\Omega'(\mathcal{M}_t)\pi_{\theta_{ub}})$. Following Campbell (2017), $\sigma_{c,\theta_{ub}}$ is the conditional covariance of log unboxed Treasury returns and consumption growth, which under the homoskedastic assumption is equivalent to the unconditional covariance of innovations to $\mathrm{Cov}_t(c_{t+1} - \mathbb{E}_t c_{t+1},\, r_{\theta_{ub},t+1} - \mathbb{E}_t r_{\theta_{ub},t+1})$. I define $\sigma_{h,\theta_{ub}}$ analogously. A similar result holds for the boxed Treasury. The risk-free rate is given by $r_{f,t+1} = -\log(\beta) + \gamma\mu_c - 1/2\gamma^2\sigma_c^2 + \gamma\sigma_{c,h}$. I provide more details on the risk-free rate in the discussion at the end of this section.

The collateral spread is the difference between the boxed Treasury's and unboxed Treasury's returns:

$$\mathbb{E}_t[r_{\theta_b,t+1} - r_{\theta_{ub},t+1}] \approx \sigma_{h,\theta_{ub}} - \sigma_{h,\theta_b} + \log\left[\frac{\mathcal{M}_t - \pi_{\theta_b}}{\mathcal{M}_t - \pi_{\theta_{ub}}}\right]. \tag{6}$$

Because both types of Treasuries are safe assets, I make the simplifying assumption that σ_{c,θ_b} and $\sigma_{c,\theta_{ub}}$ are small and equal. The right-most term reflects the differences in the money weights of the two bonds. Because banks will use the least money-like bonds as collateral, I expect $\pi_{\theta_{ub}} > \pi_{\theta_b} > 0$, which implies the right-most term is positive when $\mathcal{M}_t > 1$.

The collateral spread is the difference in their haircut covariances when the bonds have identical money weights:

$$\mathbb{E}_t[r_{\theta_b,t+1} - r_{\theta_{ub},t+1}] \approx \sigma_{h,\theta_{ub}} - \sigma_{h,\theta_b} > 0. \tag{7}$$

The collateral spread is positive when $\sigma_{h,\theta_{ub}} > \sigma_{h,\theta_b}$. I empirically verify $\sigma_{h,\theta_{ub}} > \sigma_{h,\theta_b}$ and that σ_{c,θ_b} is approximately equal to $\sigma_{c,\theta_{ub}}$ in Table A1. Intuitively, $\sigma_{h,\theta_{ub}} > \sigma_{h,\theta_b}$ means that Treasuries used as collateral have worse returns when haircuts increase and so they are worse hedges than Treasuries not used as collateral. □

In practice, banks persistently use some Treasury CUSIPs as collateral, as discussed in section 2. Once repo borrowers place their Treasuries in the box (i.e., a boxed Treasury) at the tri-party repo clearing bank, those Treasuries tend to stay in the box. Because of the market structure, dealers use Treasuries placed in the box as collateral more often than unboxed Treasuries. Therefore, boxed Treasuries are more exposed to bank leverage risk shocks than unboxed Treasuries.

3.2 Model Predictions

The proposition provides two predictions that I test in the data.

Prediction 1 (Collateral Choice)**.** *Banks choose the least desirable Treasuries to use as collateral so that* $\pi_{\theta_{ub}} > \pi_{\theta_b}$.

Empirically, I will test whether measures of Treasury desirability explain banks' choice of collateral, including liquidity, duration, maturity remaining, and whether the Treasury is on-the-run, trading special, or cheapest-to-deliver.

Prediction 2 (Bank Leverage Risk Covariance)**.** *Treasuries used as collateral have higher expected returns—equivalent to lower prices or higher yields—because of their worse covariance with bank leverage risks:* $\sigma_{h,\theta_{ub}} > \sigma_{h,\theta_b}$.

Prediction 2 indicates that bank leverage risk causes high-collateral-use Treasuries to have higher expected returns than other Treasuries after controlling for differences in their desirability, as captured by π_θ.

3.3 Discussion

It is helpful to discuss three features of the model: the model's description of Treasury expected returns, the role of cyclical bank leverage, and the relationship between expected returns and yields in the model.

Equation 5 describes Treasury expected returns using three components: the Treasury bond's consumption covariance, its haircut covariance, and its money premium. Increasing haircuts h_t increases the money premium $\omega'(\mathcal{M})$, assuming $\mathcal{M} > 1$, and decreases expected Treasury returns.

The first term, $\gamma\sigma_{c,\theta_{ub}}$, is the unboxed Treasury consumption covariance term. It is standard in consumption-based asset pricing: if the covariance between an asset's returns and consumption growth is positive, then the asset is risky because it has lower returns when marginal utility is high. Investors require a risk premium to compensate for holding an asset with bad payoffs in bad states. Moreover, the risk premium is increasing in agents' risk aversion γ. Treasuries are safe assets with comparatively high returns during flight-to-safety states when marginal utility is high. A Treasury's consumption covariance is therefore low, and the bond carries a smaller risk premium than risky assets, such as equities.

The second term, $\sigma_{h,\theta_{ub}}$, is the covariance of innovations to the safe-asset supply with the Treasury's returns. Suppose $h_{t+t} > h_t$, banks are hit by a rising haircut which lowers $\mathcal{M}_{t+1}$. Money-like assets with lower returns when $\mathcal{M}_{t+1}$ is lower (e.g., if $\sigma_{h,\theta_{ub}} < 0$) are risky.

The third component, $\omega'_{\theta_{ub}}(\mathcal{M}_t)$, reflects the Treasury's money premium. It is decreasing in $\mathcal{M}_t$. Suppose in equilibrium there are few safe assets in the economy, then $\omega'_{\theta_{ub}}(\mathcal{M}_t)$ approaches infinity, and agents push up the price of Treasuries so much that expected returns turn negative. The money premium disappears when there are infinite safe assets: $\lim_{\mathcal{M}\to\infty} \omega'_{\theta_{ub}}(\mathcal{M}_t) = 0$.

Bank leverage cyclicality plays an important role in the model. It appears in the risk-free rate and the response of banks' safe asset production to haircut changes. The risk-free rate is given by

$$r_{f,t+1} = -\log(\beta) + \gamma\mu_c - {}^1\!/_2\gamma^2\sigma_c^2 + \gamma\sigma_{c,h}.$$

This risk-free rate differs from a standard model because of the last term in the expression, $\gamma\sigma_{c,h}$. The term reflects bank leverage cyclicality because it is the covariance of consumption and haircuts. Several papers document procyclicality in leverage, so good consumption growth occurs when bank leverage increases (equivalent to haircuts falling), implying $\sigma_{c,h} < 0$ (Adrian and Shin (2010) and Gorton and Metrick (2012)). I confirm this negative covariance between consumption growth and my measure of haircuts derived from repo exposures in Table A1. Adrian and Shin (2014) document that leverage is procyclical because intermediaries actively manage their leverage and dial down risk by deleveraging during market stress. This effect appears in the model by pushing down the risk-free rate because households have a stronger motive for precautionary savings.

Leverage cyclicality also appears in the effect of increasing haircuts on Treasury expected returns through $\omega'_{\theta_{ub}}(\mathcal{M}_t)$. When $A'(h_t) < 0$, the money premium is increasing in haircuts:

$$\frac{\partial \omega'_{\theta_{ub}}(\mathcal{M}_t)}{\partial h_t} = \pi_{\theta_{ub}} \left[(1-h_t)A'(h_t) - A(h_t)\right] \left[\frac{1}{\mathcal{M}_t} - \frac{1}{\mathcal{M}_t - \pi_{\theta_{ub}}}\right] > 0. \tag{8}$$

The model does not pin down the sign of $A'(h_t)$ because the model implicitly defines the bank's equilibrium portfolio of λK, θ_b^B, and θ_{ub}^B (which combine to A). Adrian et al. (2014) find that broker-dealer leverage is correlated with asset growth, so $A'(h_t) < 0$. When $\mathcal{M}_t > 1$ then $1/\mathcal{M}_t - 1/(\mathcal{M}_t - \pi_{\theta_{ub}}) < 0$ since $1 - h_t > 0$ and $A(h_t) > 0$. Combined, the partial is positive.

The partial clarifies two competing channels in the production of private safe assets after haircuts increase. If the economy is at equilibrium and haircuts increase, B falls, and $\mathcal{M}$ is too low. If $A'(h_t) > 0$, banks respond to the heightened safe-asset demand by expanding their balance sheet, despite the higher haircut, to earn the larger convenience yield by issuing money-like liabilities. In this case, agents do not need to bid up the price of Treasuries because B satiates their safe-asset demand. But if $A'(h_t) < 0$, then banks shrink their balance sheets as haircuts increase, B and $\mathcal{M}$ fall, and households bid up Treasuries because there is no alternative to satiate their safe-asset demand.

Finally, it is easy to cast the model in terms of Treasury yields instead of expected returns. Therefore, predictions that certain Treasuries have higher expected returns can also be rewritten to predict that those Treasuries have higher yields. For this reason, the model motivates empirical work on either Treasury returns or yields.

The online appendix provides comparative statics of the model in Figure A1 using estimated parameters from Table A1 and discusses the effect of the collateral spread on the convenience yield.

4 Data

I use data from two sources to test the model's predictions and measure the Treasury collateral spread. The first is collateral data from tri-party repos with money market funds. The second data set is confidential supervisory data collected by the Federal Reserve that provides high-frequency data on the largest banks' repos, among other items, which I use as a direct measure of bank leverage constraints. As robustness, I also indirectly measure bank leverage constraints using bank-intermediated basis trades.

4.1 Collateral Data

Beginning in November 2010, the Securities and Exchange Commission (SEC) required money market funds (MMFs) to disclose granular data on their portfolios every month in form N-MFP. The disclosure details the fund's portfolio at the end of the month, and the fund must file the form within five days after month-end. The SEC initially delayed publication of the data for 60 days but dropped the delay in September 2014. In October 2016, the SEC made small adjustments to the form and updated it to N-MFP2. The data is available publicly from the SEC.[1]

The N-MFP and N-MFP2 include details about the fund at an aggregate level, including its daily liquid assets and data on the fund's portfolio, often at the CUSIP level. When a fund owns a security outright, the form includes the issuer's name (e.g., "U.S. Treasury Note"), the title of the issue ("U.S. Treasury Note 2.454300%"), the legal entity identifier for the security, and the category of the security. The form also includes data on collateral used in repos. In the case of repo, the issuer is the counterparty ("Wells Fargo Bank NA"), and the form includes the value of the collateral, the coupon or yield, the collateral maturity date, the principal amount of the collateral, and the category of the collateral (e.g., asset-backed security, U.S. Treasury, equities). Infrequently, a fund denotes that hundreds of securities back a repo and does not list individual security details. The filings do not have security-level specific identifiers, so matching the collateral securities to other data requires manual cleaning from the fund-provided collateral description text.

I focus on Treasury nominal note and bond collateral in repos. Given the coupon rate and maturity, I match Treasuries to their CUSIPs. My data include roughly 15.4 million collateral-month observations across all collateral types, of which I match 2 million to Treasury CUSIPs and merge them with the daily CRSP Treasury data set.

I clean the data in the following way. There are five instances in which a Treasury coupon and maturity do not uniquely identify its coupon; in these cases, I use the CUSIP corresponding to the larger issue. I require the Treasury CUSIP to have both monthly return data and publicly-held outstanding data; if publicly-held outstanding data are missing, I instead use the total amount outstanding.

I hand-clean the repo counterparty data because the same firm may conduct repos using different legal entities. I manually identify 77 unique cash borrowers of the roughly 6,000 different names used as repo counterparties in the data, including banks, broker-dealers, government entities (the Federal Reserve, Freddie Mac, Federal Farm Credit Banks), mortgage real-estate investment trusts, and others. I exclude Treasury repos by the Federal Reserve because the Federal Reserve is not subject to leverage constraints like banks. I drop the few cases where a single transaction lists several repo counterparties.

Table 2 presents summary statistics for the repo deals in my matched and merged sample, focusing on Treasury collateral. There are about 540,000 repo transactions in the sample, and those

[1] A previous version of this paper used data graciously cleaned and provided by the Office of Financial Research as part of its U.S. Money Market Monitor. See `https://www.financialresearch.gov/money-market-funds`.

repos have about 2 million collateral observations, implying the average repo uses about 4 different CUSIPs as collateral. For repos with Treasury collateral, there are about 250 cash lenders (money market mutual funds) and about 3,700 unique cash borrowers. In value-weighted terms, almost all Treasury CUSIPs are used as collateral in some non-zero amount. Treasuries used as collateral have slightly longer original maturity, remaining maturity, and duration than the full Treasury universe. The table also shows that on-the-run, second-on-the-run, and cheapest-to-deliver Treasuries are regularly used as collateral.

Collateral Use Persistence One way to test Prediction 1, that banks choose to use the least money-like Treasuries, is to check if dealers pledge the same Treasuries as collateral. I confirm the prediction because some Treasury CUSIPs are used as collateral persistently, even after controlling for observables, for two reasons. First, dealers agree on which Treasuries to place in the box because dealers implicitly agree on which Treasuries are least money-like, as suggested by Prediction 1. Second, the tri-party custodian facilitates same-day settlement by placing collateral from the borrower's box into the lender's box, both of which are accounts held on the custodian's balance sheet, so the collateral does not leave BNYM's balance sheet. Once the repo borrower puts some CUSIPs in their box, they tend to stay there. The CUSIP leaves the box if the dealer sells the security outright, changes strategy, or if the CUSIP starts trading special.

Once placed in a box for use as collateral, dealers use these Treasuries as collateral persistently in the time series within dealer and in the cross-section across dealers. I show collateral persistence by defining a variable Collateral Share$_{i,d,t}$ which reflects dealer d's use of CUSIP i in month t as a share of the total amount of collateral used by that dealer in that month:

$$\text{Collateral Share}_{i,d,t} = \frac{\text{CUSIP Collateral}_{i,d,t}}{\sum_i \text{CUSIP Collateral}_{i,d,t}}.$$

If a dealer used only two CUSIPs with values of \$90 and \$10 as collateral in a month, then Collateral Share$_{i,d,t} = 0.9$ for the first bond.

I show time-series persistence by regressing a dealer's date t collateral share of a specific CUSIP on that dealer's collateral share for the same CUSIP lagged by 1 month or 12 months, and I run the regression once for each dealer

$$\text{Collateral Share}_{i,d,t} = \alpha + \beta \text{Collateral Share}_{i,d,t-1} + \varepsilon_{i,d,t}.$$

I plot the β coefficient in Figure 1 for each dealer. The left panel shows that a dealer's collateral share is highly correlated from one month to the next. The right panel shows the same at a 12-month horizon. The persistence is statistically significant for all dealers in my sample at the 1-month horizon and most at the 12-month horizon. The average point estimate is 0.45 at the 1-month horizon and 0.19 at the 12-month horizon. The result is consistent with Prediction 1 so long as there is persistence in a Treasury's desirability. This is likely the case since most observables do not change rapidly from month to month, but there are some important cases where it does (e.g., becoming cheapest-to-deliver).

I also show collateral persistence in the cross-section: If a benchmark dealer boxes the Treasury, other dealers likely box the same Treasury. To test across dealer persistence, I use Société Générale as the benchmark dealer, although the results are similar for any large dealer. I run the following regression:

$$\text{Collateral Share}_{i,d,t} = \alpha + \beta \text{Collateral Share}_{i,SocGen,t} + \varepsilon_{i,d,t}.$$

I plot the t-statistic for β from the regression in Figure 2 against the monthly average repo collateral pledged by that dealer, highlighting global systemically important banks (G-SIBs) in blue. The larger a dealer's tri-party repo business, the more they agree on which Treasuries to use as collateral, consistent with Prediction 1. Almost all dealers with an average of more than \$5 billion of pledged Treasury collateral have significant collateral share correlations.

4.2 FR 2052a Complex Institution Liquidity Monitoring Report

I directly measure bank leverage constraints using high-frequency data on the repurchase market from confidential supervisory data collected in the FR2052a *Complex Institution Liquidity Monitoring Report*. The Federal Reserve collects the data as part of its regulatory framework to ensure the largest banks have sufficient liquidity and capital. The data provides information about banks' exposures and funding sources by asset class, with some information about counterparty and maturity profiles. The data provides exposure levels but neither price nor rate data. The data is available for the largest U.S. and foreign banks at a daily frequency. Three groups file the data daily: globally systematically important banks, category II banks, and category III banks with weighted average short-term funding of at least \$75 billion.[2] The data are confidential and not publicly available.

While the data encompasses several parts of banks' balance sheets, I focus on the aggregate amount of repos reported by the banks each day. The data aggregates across all types of repos, including tri-party and bilateral. I limit the sample to the set of banks that report daily data through the sample—running from early 2016 (when the data was first collected) to 2023, and I drop a handful of days where the data is incomplete. In some robustness tests, I also include other types of liabilities from the data.

The left panel of Figure 3 shows that the total repo market in the sample averages about \$2 trillion, peaking at \$3 trillion in late 2023. While my sample is limited to the largest US banks and foreign banks, these banks dominate the repo market. For comparison, the OFR estimates the repo market—spanning the DVP, GCF and tri-party markets—was \$4.6 trillion at 2023 year-end, while the FR2052a data had \$2.8 trillion of repo, so the banks in my sample span 60 percent of the

[2] The reporting instructions for FR 2052a are available at `https://www.federalreserve.gov/apps/reportingforms/Report/Index/FR_2052a`.

market.[3] The right panel presents bank repos as a share of total Treasuries outstanding since banks repos grow with the size of the banking system. The percent is increasing before Covid but then falls in 2020 as Treasury issuance jumped.

Do changes in repo outstanding map to changes in leverage constraints? Banks' repo intermediation is low-risk: a bank simultaneously lends cash against Treasuries from one counterparty (like a levered investor) and borrows cash in a second repo (with a money fund) by pledging those same Treasuries as collateral to raise the cash they lent in the first repo. The bank earns the spread between the two repo rates. The offsetting repos increase the bank's leverage even though it faces nearly no incremental risk—it is protected from counterparty risk since the trades are overcollateralized by Treasuries. As Duffie (2018) describes, higher leverage constraints compel the bank to charge more for intermediation, driving down repo volumes. Changes in repo volumes, then, reflect changes in leverage constraints, although it is important to control for changing demand.

One concern for using repos outstanding to proxy leverage constraints is that banks might be shifting their liability composition while keeping their total liabilities flat. In Table A2, I regress repo liabilities on non-repo liabilities and show that they are positively related in both level and changes, indicating banks are broadly increasing all types of liabilities simultaneously on average, rather than shifting from one type to another.[4] Moreover, the banks do not issue equity at a high frequency so it is highly unlikely banks pair increases in repo with equity issuance to keep their leverage ratios flat.

Another concern is that the changes in repos is principally driven by changes in demand for repos rather than leverage constraints. I handle this several ways, including controls for aggregate market conditions, the supply of Treasuries outstanding, and time fixed effects. I also confirm that the repo measure is highly correlated with other measures of bank leverage constraints, like that from Du et al. (2018) and Du et al. (2023), which I describe next.

4.3 Bank-intermediated Basis Trades

I supplement the supervisory data by indirectly measuring bank leverage constraints using several bank-intermediated basis trades. I proxy bank leverage constraints using bank-intermediated arbitrage returns across two markets: foreign exchange and corporate bonds. My choice of which arbitrages to include and how to aggregate them follows Du et al. (2023). The foreign exchange trades are covered-interest parity trades calculated following Du et al. (2018) for AUD, CAD, CHF, DKK, EUR, GBP, JPY, NZD, and SEK versus USD, at the one-month maturity using overnight indexed swap (OIS) rates. The corporate bond trades are the CDS-bond and CDS-CDX bases from JP Morgan Markets. The online appendix describes the trades in more detail. Importantly, I do not use any Treasury arbitrage trades so that regressions between Treasury collateral measures and the

[3] See `https://www.financialresearch.gov/short-term-funding-monitor/`.

[4] I define non-repo liabilities as the sum of non-repo secured liabilities (e.g., FHLB advances, firm shorts), unsecured liabilities (e.g., commercial paper, wholesale CDs), and deposits using the same confidential supervisory FR2052a data.

arbitrages are not confounded by dynamics specific to the Treasury market.

To minimize idiosyncrasies in a given market, I estimate bank leverage constraints by aggregating the basis trades to a single measure, which I call *PC1*, using the first principal component across the absolute value of the bases. I use the absolute value because the trades are, in principle, reversible, so dislocations in absolute value reflect leverage constraints. I plot the time series of *PC1* in Figure A2.

If repo borrowing and PC1 are both proxies for bank leverage constraints, then they should comove. Table 3 confirms this by regressing one on the other and finding a significant negative relationship across several specifications with different controls. The table shows the relationship is robust to including a control for other non-repo liabilities since an increase in repos does not increase the bank's leverage if it's offset by a decline in some other liabilities.

There are many advantages to using market data to estimate bank leverage constraints. First, the measure is based on market prices and does not depend on public balance sheet data. Balance sheet measures of leverage are typically limited to public companies and may not accurately reflect the economic leverage banks use.[5] Second, the constraint measure depends on products commonly traded by intermediaries worldwide, so the measure proxies for the leverage constraint for global intermediaries, not just U.S.-based firms. Pasquariello (2014) shows that financial dislocations, measured through arbitrages in stocks, foreign exchange, and money markets, indicate periods when the marginal utility of wealth is likely high.

The measure is not without drawbacks. It is limited to public data and only imperfectly captures funding costs. The data cannot estimate the effect of capital charges on the trades, as capital charges apply across the entire trading book rather than a single trade. And none of the basis trades are true arbitrages. They are exposed to noise-trader risk, horizon risk, and model risk.

5 Measuring the Treasury Collateral Spread

5.1 The Treasury Collateral Ratio

To measure the difference between high-collateral ratio and low-collateral ratio Treasuries, I define a sorting variable called the *collateral ratio* (*CR*). The model distinguishes between Treasuries as boxed or unboxed, which I proxy using collateral ratios. CUSIPs with high collateral ratios proxy for the model's boxed bonds, and CUSIPs with low collateral ratios proxy for unboxed bonds.

I calculate the collateral ratio for each Treasury CUSIP i to measure the intensity of that Treasury's use as collateral in month t:

$$CR_{i,t} = \left(\frac{\text{Market Value of Treasury CUSIP } i \text{ used as Repo Collateral}}{\text{Market Value of Treasury CUSIP } i}\right)_t . \tag{9}$$

[5]In the U.S., firms are allowed to net certain collateralized financing transactions. The transactions appear neither on their balance sheet nor in aggregate measures, like the Federal Reserve's Financial Accounts. Gorton et al. (2020) collect data on collateral pledged from six large broker-dealers' 10-Qs and show that collateral pledged—roughly equal to the volume of collateralized financing transactions—fell \$2.7 trillion from 2007Q2 to 2009Q1. In contrast, on-balance-sheet repo for the entire bank and broker-dealer industry fell by only half that amount over the same period. Fortunately, the confidential supervisory data is not netted.

The bottom of Table 2 presents summary statistics of the collateral ratio. There is considerable variation in *CR* across CUSIPs and across time. The average *CR* is 2.6 percent, with a cross-sectional standard deviation across CUSIPs of 2.3 percent and a time-series standard deviation of 1.1 percent (i.e., a CUSIP's own collateral ratio volatility over time). Figure 4 provides a box plot of the equal-weighted collateral ratios across CUSIPs by year; the average and variance of *CR* somewhat increase through the sample, the latter shown by the growing interquartile range.

Prediction 1 expects that banks choose the least desirable Treasuries to use as collateral, which I confirm in Table 4. The table shows the relationship between Treasury collateral ratios and observables by regressing one on the other. Treasury CUSIPs with higher collateral ratios are less liquid, have longer maturity remaining, are on-the-run, are cheapest-to-deliver, and are not trading special. Intuitively, the table confirms the prediction that banks' choose the least desirable CUSIPs to pledge as collateral, consistent with Greenwood et al. (2015)'s finding that long-term Treasuries are less money-like because of their higher interest-rate risk.[6]

It is perhaps surprising that on-the-run have higher collateral ratios since they are might be more desirable. One likely explanation is that they are more likely to be held in inventory by dealers. If specific collateral demands for these bonds doesn't exhaust dealers' inventories, then dealers will use it as general collateral. A dealer long on-the-run Treasuries might find financing for the position at a lower rate early in a trading session while other investors are short the CUSIP or while other dealers are looking for the CUSIP. The CUSIP is no longer desirable once the shorts are covered, and it will trade as general collateral.

Bonds that are trading special are less likely to be used as general collateral. The table shows that a 1 bp increase in the specialness of a CUSIP is associated with a collateral ratio that is 1.8 bps lower. This is consistent with the fact that dealers try to forecast the most desirable CUSIPs and refrain from using those as general collateral since dealer can borrow against a special CUSIP on cheaper terms because the special repo rate is below the general collateral repo rate.

An important concern is that the information captured in the collateral ratio is not novel or unique from other CUSIP observables. This is not the case, though, as evidenced by the low R^2s in Table 4. Even the final column, which includes all the measures as a horserace, has an R^2 of only 7 percent, and the constant is significantly different from zero. In this view, the collateral ratio provides new and novel information about which Treasuries are least desirable and, therefore, used more as collateral.

5.2 The Treasury Collateral Spread

A key empirical challenge is how to isolate the risk premium stemming from the collateral ratio that cannot be attributed to other characteristics like maturity and liquidity. For example, if the yield

[6] Cheapest-to-deliver data is from Bloomberg for 2y, 5y, 10y, and 30y Treasury futures. I define specialness as the spread between the DTCC GCF repo index and the volume-weighted repo rate on specific trades between 7:30am and 10:00am—the period when most specials trade—using data from the interdealer broker community. D'Amico and Pancost (2022) provide details on specialness.

curve is upward-sloping (as it was for much of the sample), then longer maturity bonds will have higher yields (and higher expected returns). In this case, a simple portfolio long high-CR bonds and short low-CR bonds would likely have positive expected returns, not because of risk captured by the collateral ratio but because the long leg has longer maturity CUSIPs than the short leg. Similar logic applies to liquidity spreads, since illiquid bonds have higher yields than liquid bonds. To avoid these issues, I estimate the risk premium stemming from collateral ratios using a yield curve estimated separately on high- and low-CR bonds to create a maturity-matched yield spread between the two: this is the Treasury collateral spread.

I estimate the collateral spread in four steps: First, I sort Treasuries into maturity buckets by rounding their remaining maturities to the nearest year. Second, I sort CUSIPs into terciles based on their lagged collateral ratio within each maturity bucket. The choice of terciles follows Asness et al. (2013). Money market funds release their data with a lag, so I lag the collateral ratio trait by one month to ensure the collateral ratio is in investors' information sets.

Third, I use Gürkaynak et al. (2007)'s model to estimate a yield curve separately for the high-CR tercile Treasuries and the low-CR tercile Treasuries. Following Gürkaynak et al. (2007), I exclude CUSIPs with less than three months to maturity, 20-year bonds, and both on-the-run and second-on-the-run CUSIPs so the yield curve estimates are not biased by their unusual liquidity. The procedure yields two par yield curves for each day.

Fourth, I calculate the spread between the high-CR and low-CR yields for each maturity bucket and then value-weight across the buckets by that bucket's market value of Treasuries compared to the total market value of all Treasuries outstanding in the previous month:

$$\text{Collateral Spread}_t = \sum_{b \in B} w_{b,t-1} \left(y_{b,t}^{HiCR} - y_{b,t}^{LoCR} \right) \tag{10}$$

where

$$w_{b,t} = \left(\frac{\text{Market Value of Treasury CUSIPs in } b}{\text{Market Value of all Treasury CUSIPs}} \right)_t ,$$

and B is the set of maturity buckets.

The top panel of Table 5 shows the average spread is 0.53 bps, ranging from -1.09 to 3.88 bps. For robustness, the table also provides the collateral spread when fixing the value weights to their average monthly value rather than allowing them to vary from month to month. The fixed-weight collateral spread is nearly identical, with an average of 0.56 bps. The bottom panel shows the collateral spread by tenor along with the average value-weight for each tenor. The collateral spread is hump-shaped over the curve, first decreasing in the front end, then increasing in tenor up to the 15-year tenor, and then falling again. The spread is positive at each tenor except for the 27-year through 30-year tenors. The longest maturities are likely the most imprecisely estimated tenor since there are so few CUSIPs that round to those year buckets, evident by the 30-year's nearly zero value weight. Value weights are highest for tenors under five years.

Figure 5 plots the collateral spread over the sample. The collateral spread is nearly always positive, meaning that high-CR Treasuries trade at a discount to maturity-matched low-CR Treasuries, consistent with a risk-based explanation. Over the 13-year sample, the collateral spread has been positive 91 percent of the time and had a negative average in only six months. The figure shows that the spread has been much more volatile over the last two years as inflation increased uncertainty surrounding the path of interest rates; the average collateral spread excluding 2022 and 2023 is somewhat lower at 0.44 basis points.

One useful point of comparison is the Covid "dash-for-cash" when investors rapidly sold Treasuries to raise cash in the initial panic of March 2020, leading to record strains in the market (Barone et al., 2023). The collateral spread during these months reflects this dash-for-cash. March 2020 was the most volatile period for the collateral spread up to that date. The average volatility of the spread—constructed as the standard deviation of the daily values within a month—peaked in March 2020 at 0.38 bps, compared to its pre-2020 average of 0.18 bps. The spread had large spikes during periods of acute stress, especially on March 18 and March 19, when the spread jumped by 0.64 bps and 0.54 bps, roughly two standard deviations. On March 15, the Federal Reserve announced it would purchase $500 billion of Treasuries, but by March 19, the Fed had already purchased more than $200 billion and markets grew concerned since nearly half of the Fed's total purchases were exhausted in only a few days. By the end of the week, including March 20, the Fed would ultimately purchase $272 billion of Treasuries against more than $530 billion in offers to sell from dealers.

Ultimately, the collateral spread fell somewhat after a wide array of policy interventions to calm markets. On March 23, the Fed announced unlimited purchases "in the amounts needed to support smooth market functioning." The Fed ramped up its repurchase operations against Treasuries, which peaked at more than $300 on March 17, putting a floor on the collateral value of Treasuries. Regulators also temporarily excluded Treasuries from banks' supplemental leverage ratios. Without these significant interventions, it's likely the collateral spread would have spiked even higher.

The collateral spread again briefly spiked during the SVB failure and its aftermath, although the trend is less clear. The spread is much more volatile in 2022 and 2023 because of the uncertainty around the path of inflation and interest rates. The banking turmoil was, in part, caused by that same uncertainty. It's not easy to ascribe the day-to-day movements to specific events given the short window in which many events occurred—the initial stress at SVB, the Fed's introduction of the BTFP, and the merger of UBS and Credit Suisse—but the collateral spread's volatility reached a new high in March 2023.

Table 6 provides evidence consistent with the importance of bank leverage for the Treasury collateral spread by regressing the collateral spread on several potential explanatory variables. Each independent variable is transformed into a z-score to make their coefficients comparable. The spread is strongly related to banks' repo borrowing relative normalized by Treasuries outstanding, shown in the first column. The collateral spread is larger when banks do less repo. This confirms a basic premise of the model that falling bank leverage constraints decrease the collateral spread because banks can do more repo borrowing when they are less constrained.

The table also shows that the collateral spread is weakly countercyclical, as it positively covaries with the VIX and liquidity (measured by the 10-year on-the-run bid-ask spread). It is negatively related to the 10-year/2-year Treasury curve slope even though the collateral spread is maturity-matched in the long and short legs and so not mechanically related to the slope; this negative relationship is driven entirely by the period 2022 and 2023, and excluding those years from the sample makes the relationship insignificant. The spread is also not a restatement of the cheapest-to-deliver Treasury basis, shown in column (5).

Column (6) in Table 6 runs a horserace of all the variables and shows that repo has a strong relationship even after controlling for other variables: a 1 standard deviation increase in repos decreases the collateral spread by 0.22 bps, a large effect compared to the unconditional average spread of 0.53 bps. The last column excludes 2022 and 2023 and shows the relationship with the slope disappears, yet the strong negative correlation with repo remains.

There are several advantages to the described method for calculating the collateral spread. Most importantly, the collateral spread does not embed any term premium because its long and short legs have the same maturity. It also reduces the effect of liquidity differences across CUSIPs by excluding unusually liquid CUSIPs (on-the-run and second-on-the-run) and excluding unusually illiquid CUSIPs (20-year bonds).

The order of sorts used to calculate the collateral spread is important. Berk (2000) cautions against several potential pitfalls when estimating premia using sorts. Suppose a researcher sorts securities into portfolios based on the first variable and then double sorts on a second variable when the two variables are highly correlated. In that case, the first sort soaks up most of the variation in expected returns, while the second sort adds little incremental explanatory power for expected returns. The researcher, then, might errantly conclude that the first variable explains the cross-section of returns even if, in reality, the second factor does. The problem is especially notable if the second sorting variable is estimated, like a portfolio beta to an equity risk factor.

I order the sorts to address this concern. I first sort on maturity, then second sort on collateral ratios within each maturity bucket. I choose the order of the sorts because I know that the two sorting variables, maturity and collateral ratio, are correlated (column 3 in Table 4) and because a researcher should have strong priors that maturity, rather than collateral ratio, explains expected returns since the term structure is typically upward sloping, so longer maturity bonds have higher yields. If I had instead first sorted on collateral ratio—which would also implicitly sort on maturity—and then on maturity, I might errantly attribute a risk premium to the collateral ratio when, in fact, it stems from differences in the bonds' maturities. By sorting first on maturity and then on collateral ratios, the null is that the bonds' maturities explain the cross-section of returns and not the collateral ratio.

The disadvantage of sorting on maturities first and then second collateral ratios is that I might errantly reject that the collateral ratio characteristic is associated with a risk premium if the two are too closely correlated. Yet, I still find a significant collateral spread after constructing a maturity-neutral portfolio. If maturities and collateral ratios were too highly correlated, I would find no collateral spread.

Berk (2000) explains another related pitfall. Double sorts that first sort on characteristics (like book-to-market ratios) and then on estimated variables (like betas to an equity risk factor) are subject to an errors-in-variable problem since the characteristics are observed "perfectly" but the betas are estimated with error. If variation in the factor loadings is small, then sorts on the estimated betas would sort on measurement error and the researcher might errantly conclude that betas aren't related to risk premia. However, my methodology does not sort using estimated variables, so it does not suffer from this bias. The first sort is on maturity remaining, which is known with certainty since the sample includes only noncallable nominal Treasuries bonds and notes and the CUSIP observables are public. The second sort is on lagged collateral ratios, also public information. These dynamics would be a concern had I instead used month-ahead collateral ratios forecasts.

5.3 Collateral Spread Robustness

I run a battery of robustness tests to address potential concerns about the collateral spread estimation. A positive collateral spread means that bonds with higher collateral ratios trade at a relative discount to otherwise similar bonds. Although the methodology to estimate the spread is designed to reduce the effect of unusual CUSIP-specific factors—like being on-the-run or cheapest-to-deliver—one concern is that CUSIP-specific factors that are not observable may persistently bias the collateral spread estimate. Table 7 addresses this concern by showing that CUSIPs with higher collateral ratios trade at larger discounts even after including CUSIP fixed effects and several other controls. The table estimates pricing residuals using the Federal Reserve's public Gürkaynak et al. (2007)'s parameters.[7] The Federal Reserve's goal with the estimation is to create an off-the-run nominal yield curve, hence the Fed's model does not consider collateral ratios. I define the residual as

$$\text{Residual}_{i,t} = \text{Actual YTM}_{i,t} - \text{Estimated YTM}_{i,t}. \tag{11}$$

A bond with a positive residual has an actual yield that exceeds what the model expects, which equivalently means that it trades at a lower market price than expected. The positive and significant coefficient on the collateral ratio in each column indicates that a 1 pp increase in the collateral ratio is associated with a residual between 0.15 and 0.38 bps higher, meaning that the bond trades at a discount compared to the model. Column (6) is the main specification and includes a battery of controls and CUSIP fixed effects. Even with these controls, the relationship between collateral ratios and pricing residuals is strong: a 1 standard deviation increase in the collateral ratio is associated with a 0.21 bps increase in residual. Importantly, Table 7 provides another way to test Prediction 1

[7] See https://www.federalreserve.gov/data/nominal-yield-curve.htm.

which depends on market prices rather than characteristics that we would expect are less desirable a priori.

Another concern is that the collateral spread is measured with too much noise to be statistically different from zero. In the online appendix Table A3, I regress the value-weighted collateral spread and the spread at specific points on the curve on a constant and find that all measures are statistically different from zero and positive apart from the 30-year tenor, which, as mentioned before, has nearly no value-weight. Although the collateral spread's standard deviation (0.49 bps) may appear large relative to its mean (0.53 bps), the mean is well estimated when considering the standard error of the mean is .009 bps.

A related concern is that the Gürkaynak et al. (2007) model estimates the yield curve with too much noise in a way that might systematically bias the spread estimates. Since there are about 300 unique Treasury CUSIPs traded each day, sorting by CR into terciles means each curve is estimated from a large cross-section of about 100 CUSIPs. Table A4 shows that both yield curves are estimated with similar degrees of noise by regressing the different measures of pricing error for the high-CR yield curve on errors for the low-CR yield curve, where pricing errors are either the mean absolute pricing error or the root mean squared error. The table shows that pricing errors for the high- and low-CR curves are closely related and completely span one another since the constant is not different from zero.

A separate concern is that cheapest-to-deliver CUSIPs, on-the-run CUSIPs, or special repo rate CUSIPs are driving the result, which would be possible if these characteristics were restatements of the collateral ratio. I reestimate the entire yield curve in the online appendix Table A5, adjusting the sample to make sure these specific CUSIPs are not the main driving factors. The table estimates the collateral spread and its correlation with the main spread measure when (1) including the on-the-run Treasuries, which are excluded in the main estimate, (2) excluding all cheapest-to-deliver CUSIPs, and (3) excluding the 25 CUSIPs that have the largest special repo rates on average over the month. I choose the 25 CUSIPs threshold for special repo rates as a conservative upper bound on the number of CUSIPs that are on-the-run or cheapest-to-deliver on a given day. The table shows that the collateral spread estimated with these different filters are similar in magnitude, ranging from a low of 0.42 bps to a high of 0.58 bps, and highly correlated with the main measure. The collateral spread estimated with on-the-runs is the largest, likely reflecting the higher liquidity value of recently issued bonds.

5.4 Casting the Collateral Spread to Returns

It is easy to cast the Treasury collateral spread to the returns to an implementable trading strategy. The Treasury collateral spread is not directly tradable because it compares two synthetic Treasuries with identical maturities but different collateral ratios. In practice, two bonds rarely have identical maturities but different collateral ratio terciles. To create a tradable strategy, I sort the cross-section of Treasuries to form value-weighted collateral-ratio return strategies and show these covary strongly with the collateral spread. This strong relationship is mechanical because a bond's return is closely approximated by the product of its duration and (negative one times) the change in its yield: $r_{i,t} \approx -1 \times \Delta y_{i,t} \times duration_{i,t}$.[8]

I create a Treasury collateral-ratio return strategy by following the sort strategy used to calculate the spread. First, I sort Treasuries into maturity buckets by rounding their remaining maturities to the nearest year integer. Second, I sort CUSIPs into terciles based on their lagged collateral ratio within each maturity bucket. Third, I calculate the return on a strategy long the high-*CR* tercile and short the low-*CR* within each maturity bucket, where the long and short legs returns are value-weighted using the previous month's market value of that CUSIP. This produces returns for 30 strategies, one for each maturity bucket. Fourth, I aggregate across these 30 strategies by value-weighting each bucket using the market value of all the Treasuries in that tenor bucket, again lagged by one month:

$$\text{Collateral Strategy}_t = \sum_{b \in B} w_{b,t-1} \left(r_{b,t}^{HiCR} - r_{b,t}^{LoCR} \right)$$

where

$$w_{b,t} = \left(\frac{\text{Market Value of Treasury CUSIPs in } b}{\text{Market Value of all Treasury CUSIPs}} \right)_t,$$

where B is the set of maturity buckets. Notice that each step except for the third step (calculating the returns) mirrors the steps to calculate the collateral spread.

Figure 6 makes the negative relationship between the collateral spread and the collateral strategy plain. Table 8 formalizes the relationship by regressing one on the other in a series of spanning tests in the spirit of Haugen and Baker (1996) and Fama and French (2015). Columns (1) and (2) show the collateral strategy calculated this way does a good job spanning the collateral spread, and the result doesn't change after including controls for slope and liquidity in the second column. The controls are Fama and French (1993)'s *TERM*, the return difference between the 10-year and 2-year Treasury, and the 10-year on-the-run bid-ask spread, a proxy of liquidity. The first two columns show that the strategy does a good job approximating the return on the collateral spread in an implementable way and, importantly, does not significantly load on factors related to the slope of the Treasury curve or liquidity.

The collateral strategy has the advantage of reducing the effect of maturity remaining by sorting CUSIPs into year-width buckets. However, the disadvantage is that some year-width buckets are too sparse to form a long-short strategy. For example, if the 18-year maturity bucket only has 2 bonds, they cannot be sorted into terciles. In those cases, collateral strategy excludes the bucket.

As robustness, I create two related versions of the Treasury collateral-ratio return strategy using double sorts:

[8] Fabozzi et al. (2005), page 198, provides a full discussion of this common approximation.

1. Liquidity × CR: I independently sort each Treasury CUSIP into a liquidity tercile and a *CR* tercile using one-month lagged data. I measure liquidity using the monthly average of daily bid-ask spreads for each Treasury CUSIP, also lagged by one month. The return on this strategy is the double-sort:

$$\begin{aligned}\text{Liquidity} \times \text{CR} = & \frac{\text{Hi CR/Low Liq} + \text{Hi CR/Mid Liq} + \text{Hi CR/High Liq}}{3} \\ & - \frac{\text{Lo CR/Low Liq} + \text{Lo CR/Mid Liq} + \text{Lo CR/High Liq}}{3}.\end{aligned} \tag{12}$$

   This sort has the advantage that each of the double-sort portfolios will be less sparse, although there remain a handful of months when at least one double-sorted portfolio has no CUSIPs, in which case that portfolio is excluded from the strategy. The sort will also implicitly sort on maturity since liquidity and maturity are closely related. However, the sort controls only coarsely for maturity, so changes in the term structure might affect its returns.

2. Maturity × CR: I independently sort each Treasury CUSIP into a maturity remaining tercile and a *CR* tercile using one-month lagged data. The return on this strategy is a double-sort analogous to the Liquidity × CR strategy, and it has similar advantages and disadvantages.

Columns (3) through (6) in Table 8 show spanning tests for these alternative measures of the collateral strategy. They both span the collateral spread but *TERM* has an almost-significant coefficient, indicating that the full cross-section tercile sorts only imperfectly control for maturity differences.

As a final robustness test, Table 9 shows a nearest-neighbor match to estimate the collateral strategy more precisely. Tercile sorts are useful because they provide tractable ways to mimic investable strategies, but they collapse information along other dimensions. I sort Treasuries into two equal-sized buckets each month: high- or low-*CR* (lagged by a month), where the latter has many Treasuries with $CR = 0$. I match Treasuries to their nearest neighbor in the other bucket using the CUSIP's month-end values for duration, liquidity, maturity remaining, and indicators for whether it is trading special, cheapest-to-deliver, or on-the-run. The first three columns show the annualized average difference in monthly returns between Treasuries in the high and low halves using different distance metrics.

The nearest-neighbor match shows the average annualized return difference between high and low-CR CUSIPs ranges between 9 and 17 bps while controlling for the CUSIPs' observables. The last three columns repeat the analysis after changing the dependent variable to the pricing residual calculated with the Federal Reserve's public Gürkaynak et al. (2007)'s parameters. The last three columns show that high collateral ratio bonds have higher pricing residuals compared to their nearest neighbor and so trade at a relative discount. Given the average duration of bonds in the sample is about 5 years, column (4)'s estimated average treatment effect of 1.13 bps means that low-*CR* bonds trade at a 5.7 bps price premium over otherwise similar high-*CR* bonds ($5 \times 1.13 = 5.7$).

6 Empirical Results

I now test Prediction 2 to understand the relationship between the collateral spread and bank leverage constraints. The prediction says that the collateral spread will be positive because high-*CR* bonds have bad covariance characteristics with bank leverage risk. Intuitively, Treasuries are useful as collateral when intermediaries can pledge them, which mechanically requires the bank to use leverage. When banks become leverage constrained, the value of high-*CR* Treasuries fall compared to low–*CR* Treasuries.

6.1 The Collateral Spread Covaries with Bank Leverage Constraints

I directly test Prediction 2 in Table 10 using

$$\Delta\text{Collateral Spread}_t = \alpha + \beta\Delta(\text{Bank Leverage Measure}_t) + \gamma\prime X_t + \varepsilon_t \tag{13}$$

where X_t is a vector of controls, and the bank leverage measure is one of $\Delta \ln(\text{Repo}_t)$, $\Delta PC1_t$, or $\Delta(\text{Repo}_t/\text{Treasuries Outstanding}_t)$. The first four columns show that the collateral spread falls when banks increase their repo borrowing across several specifications: when banks do more repo the collateral spread falls. Column (4) estimates that a 1pp increase in $(\text{Repo}_t/\text{Treasuries Outstanding}_t)$ corresponds with the collateral spread falling by 0.10 bps, an economically large effect given the average collateral spread is 0.53 bps. The last two columns show that changes in the collateral spread and the arbitrage dislocations are tightly linked: a one standard deviation decrease in PC1 leads to a decline in the collateral spread that is 10 times its average daily change—nearly the same effect size as when using the repo measures in the first four columns. The result similarly holds including the full spectrum of controls and time fixed effects.

Several of the controls are especially important in ruling out alternative stories: one concern is that the collateral spread varies with riskiness in the banking system rather than collateral constraints. Columns (2), (4), and (6) include controls for riskiness of the banking system using changes in financials' CDS spreads, which is not significantly related to the collateral spread. Another concern is that the collateral spread simply increases as there are more Treasuries outstanding, which can strain the banks' ability to intermediate in markets, but the insignificant coefficient on $\Delta \ln(\text{Treasuries Outstanding}_t)$ excludes this possibility. The table also includes a control for non-repo liabilities using the confidential supervisory data, which has no significant effect. Finally, the table shows that *TERM* has no significant relationship with changes in the collateral spread.

6.2 Yields by Bank Constraint State

If the collateral spread is compensation for bank leverage risk, then high-*CR* bonds should have relatively lower prices—and higher yields—than low-*CR* bonds in bad states when marginal utility over money-like safe assets is high. Intuitively, bad states likely coincide with flights to safety so

Treasury yields should fall in general, but the model predicts that high collateral bond yields won't fall by as much, and they will be relatively cheaper when haircuts increase.[9] I now show that high-CR bonds trade at larger discounts to low-CR bonds when bank leverage constraints are high.

Table 11 shows the difference in high- and low-CR bonds' pricing residuals, as defined in equation 11. I calculate the value-weighted pricing residual for bonds in the top and bottom collateral ratio tercile. I define high and low bank constraint states using either the median ratio of repo borrowing to Treasuries outstanding (where a higher ratio indicates lower constraints) or the median bank-intermediated arbitrage PC1 (where a higher level indicates higher constraints).

The table makes two points. First, the "Hi Collateral Ratio" pricing residuals are larger than the "Lo Collateral Ratio" residuals in all states, meaning that the high collateral bonds always trade at a price discount to low collateral bonds. For example, high-CR bonds' residual is 3.56 bps larger than low-CR bonds in unconstrained states using the repo to Treasuries outstanding constraint measure.

Second, high collateral ratio bonds trade at a larger discount when leverage constraints are high, since the difference in pricing residuals is larger in constrained states (4.34 bps vs. 3.56 bps using the repo measure, 3.68 bps vs 2.79 bps using PC1). This difference is statistically significant using either constraint measure, as shown by the small p-values.

The test uses pricing residuals rather than yield-to-maturity as the dependent variable because yields are not directly comparable for bonds with different coupons, whereas the pricing residuals take this into account. Moreover, using pricing residuals also controls for systematic variation in yields that vary with maturity.[10]

6.3 European Crisis Event

I use the cross-sectional dimension of my collateral data to show that bank leverage constraint risk, rather than some other bond characteristic, is a key driver of the collateral spread. Bonds used as collateral must have worse returns in bad states if the collateral spread is compensation for bank leverage risk; otherwise, there is no risk that requires compensation. I show that bonds used as collateral by European banks during the initial panic stage of the European sovereign debt crisis had lower returns than otherwise similar bonds used as collateral by non-European banks.

I perform a difference-in-difference on Treasury returns to compare bonds used as collateral by European and non-European banks during the initial stage of the European sovereign debt crisis in July 2011. I use Stracca (2013)'s identification of euro crisis event dates. He identifies crisis events by comparing the average 10-year government bond yield spread for Italy and Spain versus German bunds. He identifies events using three criteria: there must be large jumps in the spreads

[9]The relationship can be seen by differentiating equation 6 with respect to h_t using the fact that $A'(h_t) < 0$ so that $\mathcal{M}'(h_t) < 0$. Assuming $\mathcal{M} > 1$, then the collateral spread is increasing in h_t since $\pi_{\theta_{ub}} > \pi_{\theta_b} > 0$.

[10]Specifically, the pricing residuals control for the effect that different coupons have on yield-to-maturity because the model estimates a discount function from a zero curve each day, then uses the discount function to calculate a model-implied price for each CUSIP using the bond's specific cash flow timing. This estimated price can then be cast into yield-to-maturity terms. The pricing residual, therefore, compares the model's estimate of the CUSIP's price—given that bond's CUSIP-specific cash flows—with its market price.

to bunds; the jumps should be associated with a significant political event; and the jump should not be explained "even potentially" by a non-euro-related event on the same day. The first adverse event Stracca (2013) identifies is on July 11, 2011, when "the crisis engulfs Italy."

I estimate the difference-in-difference regression:

$$r_{i,t} = \alpha + \gamma_1 \mathbb{I}(\text{Post}) + \gamma_2 \mathbb{I}(\text{Treated}) + \gamma_3 \mathbb{I}(\text{Post}) \times \mathbb{I}(\text{Treated}) + \beta' X_t + \varepsilon_{i,t}, \tag{14}$$

where t is a month, i is a Treasury CUSIP, and X_t is a vector of controls, including the CUSIP's duration, liquidity, remaining maturity, and indicators for being on-the-run, second-on-the-run, trading special, or cheapest-to-deliver. I set $\mathbb{I}(\text{Post}) = 1$ beginning July 11, 2011, and 0 otherwise.

I define the treatment group as CUSIPs that are intensively used as collateral by European banks. I calculate a CUSIP's European bank share as the share of a CUSIP used as collateral by European banks relative to that CUSIP's total use as collateral in April 2011, one quarter before the July event. I set $\mathbb{I}(\text{Treated}) = 1$ for bonds above the median European share in April 2011. The average European bank share is 96 percent for the treatment group and 43 percent for the control group. I run the difference-in-difference regression over a period of five months before and after the July 11 event. I estimate the difference-in-difference regression separately for high- and low-CR bonds. I use contemporaneous collateral ratios because I am interested in ex post outcomes.

The test assumes only European banks were treated, meaning that only European banks became leverage constrained. Ex post CDS spreads show that this assumption is a reasonable approximation. Classifying treated banks as those with the largest CDS spread changes does not materially change the results.

Table 12 presents the regression results. The first three columns use high-CR bonds, and the last three columns use low-CR bonds, and the columns vary the fixed effects and whether the regression is weighted with by market value of each CUSIP. The main result is shown in the $\mathbb{I}(\text{Post}) \times \mathbb{I}(\text{Treated})$ row in the first three columns: Among high-CR bonds, high European bank share bonds had lower returns than similar bonds used as collateral by non-European banks. European banks' high-CR bonds had lower average monthly returns by 57 to 64 bps.

Bonds not used as collateral—low-CR bonds—do not have a significant interaction term in columns (4) through (6), so they do not have as large of a return differential depending on whether European or non-European banks pledged them. Why not? Although these bonds are pledged relatively more by European banks, they are still not pledged much at all: the average (max) collateral ratio for the high-collateral ratio bonds in the first three columns is 2.8 (8.4) percent but only 0.49 (0.87) percent for the low collateral ratio bond. The low collateral ratio bonds—even those that are pledged relatively more by the treated European banks—are simply not used as collateral enough to be meaningfully affected by the shock.

As the euro crisis accelerated, interest rates fell, and risk-off sentiment drove a flight-to-safety, boosting the returns across all types of Treasuries. Therefore, the $\mathbb{I}(\text{Post})$ coefficient is positive in all specifications and significantly positive in many. Figure 7 visualizes the parallel trends assumption of the difference-in-difference regression. In the top-left panel, there is no evident trend in the treated or control groups' returns before July 2011; after the event, the difference grows dramatically.

Dollar funding played a significant role in European banks becoming leverage constrained over this period; the liquidity shock was a specific manifestation of a bank leverage shock. Correa et al. (2017) show how dollar funding shocks caused banks to cut lending to U.S. firms. European banks facing a liquidity shock needed dollars to pay down their dollar-denominated debt and delever, so they sold their dollar-denominated short-term trading assets, especially Treasuries. Market commentary from that period shows that European bank deleveraging concerns reached beyond money funds (Van Steenis et al., 2011). In October and November 2011, the euro-dollar basis was at extreme levels, indicating European banks were willing to pay a large premium for dollars. As a robustness check, I exclude October and November 2011 from the difference-in-difference regression and find similar results.

In the online appendix, I estimate the Treasury collateral spread for bonds used as collateral by European banks and separately for those used as collateral by all other banks. I separate CUSIPs into two buckets each month based on the share of that CUSIP that is used as collateral by European banks. I then repeat the collateral spread estimation using the two filtered samples. The approach has the advantage of estimating a "treated" collateral spread and a separate "control" collateral spread. The disadvantage of the approach is it estimates yield curves from a cross-section that is half that of the full cross-section, so it is less precisely estimated.

Table A6 uses these collateral spread estimates in a simple event study by regressing the collateral spread (treated or control) on a dummy variable equal to 1 beginning July 11, 2011, the beginning of the stress event. The time frame is the same as the difference-in-difference, running from February 2011 to November 2011. The table shows that the treated collateral spread significantly increases after the stress, meaning that high-CR bonds pledged more by European banks traded at larger discounts after the stress. The effect is especially large when comparing with the control collateral spread which falls after the stress. The table also regresses the difference between the treated and control collateral spreads on the post dummy and confirms that the treated collateral spread increased more than the control spread as implied by the first two columns. As a robustness, the last three columns of the table run a placebo using the same regression setup but shifting the sample and post dummy to the following year, 2012. There is no similar pattern in this placebo period.

6.4 Quarter-End Leverage Constraints

Quarter ends provide a natural experiment to identify the effects of bank leverage constraints on collateral. Often, increases in bank leverage constraints coincide with a flight to safety and increased risk aversion, which boosts Treasuries' prices. Such dynamics are typically absent on quarter ends. Quarter ends affect leverage constraints as banks window dress, but they are not systematically correlated with bad times and a concomitant flight to safety.

Many papers have documented the regulatory frictions that drive quarterly window-dressing, namely leverage ratio and risk-weighted capital requirements. Banks have an incentive to window dress when these ratios are measured with a point-in-time snapshot, like the last day of a quarter. Du et al. (2018), for example, document that covered-interest parity violations for short-dated FX contracts spike at quarter ends as banks delever. Regulations for European banks, for example, measured leverage ratios using the point-in-time quarter-end value. Several papers document that quarterly window-dressing in repo markets principally occurs in foreign rather than U.S. banks.[11]

Since foreign banks are important repo providers (see Figure 2), quarter-ends represent a material increase in bank leverage constraints for the repo market that are not endogenous to other bad shocks. I can identify the effect of leverage constraints on collateral prices by looking at dislocations during this brief window. I test the hypothesis that increased bank leverage should push prices down for high collateral ratio bonds using the regression

$$\begin{aligned}\text{Residual}_{i,t} = \alpha &+ \beta_1 \left(\text{Collateral Ratio}_{i,t-1} \times \mathbb{I}(\text{Quarter-End}_t)\right) \\ &+ \beta_2 \text{Collateral Ratio}_{i,t-1} + \beta_3 \mathbb{I}(\text{Quarter-End}_t) + \gamma\prime X_t + \varepsilon_{i,t}.\end{aligned}$$

The dependent variable is the yield-to-maturity residual (as previously defined). The independent variables of interest are the collateral ratio (lagged by 1 month, to reflect the investors' information set), a dummy equal to 1 on the last day of the quarter, an interaction of the two, and a vector of controls X_t.

The coefficient of interest is β_1, shown in the first row of Table 13. Since quarter-ends proxy for bank leverage constraint shocks, if $\beta_1 > 0$ then high collateral ratio bonds trade at a larger price discount (or a higher yield) on quarter ends compared to other Treasuries that are not used as collateral. The regression confirms this. Column (1) estimates the mispricing for a bond with a collateral ratio one standard deviation above average increases by 0.3 bps on quarter-ends compared to other Treasuries. Importantly, the regression controls for the fact that high collateral ratio bonds tend to trade at a discount as documented in Table 7. This is also clear in the positive and significant coefficient on the uninteracted Collateral $\text{Ratio}_{i,t-1}$ term. The remaining columns repeat the regression by varying the fixed effect and control specifications and all find similar effects. Note that the columns with time fixed effects cannot separately identify the quarter-end dummy or maturity control since they are collinear with that date's fixed effect, so there is no corresponding coefficient for those columns.

[11]See Munyan (2017), Kotidis and Van Horen (2018), Correa et al. 2020, Anbil and Senyuz (2022), and Bassi et al. (2024). U.S. banks window-dress on margins other than repo. Berry et al. (2020) shows that U.S. G-SIBs manage their GSIB surcharges down by reducing their over-the-counter derivatives, but since the effect of repo on U.S. GSIB's surcharges scores are largely calculated using daily averages, they have no incentive to window dress their repo business to lower their surcharge.

7 Other Collateral Types

An important question is whether bank leverage risk also plays a role for asset classes beyond Treasuries. This paper studies Treasuries because they constitute the majority of repo collateral, and bank leverage risk dynamics are likely easier to observe for Treasuries since they are claims on same issuer—the U.S. government—so there are no firm-specific risks varying across Treasury CUSIPs. Data on Treasury returns is also reliable and available with high frequency.

I find suggestive evidence that similar dynamics are at play in equities, where stocks that are used as collateral have higher returns when banks' repo increases after controlling for common stock risk factors. But equity repo collateral is an imperfect laboratory to study leverage risk, with both advantages and disadvantages. An important advantage to studying equity repo collateral compared to other types of non-Treasury repo collateral is that equities have reliable and high-frequency price data. Reliable and high-frequency price data is often not available for less liquid corporate bonds, agency MBS, and ABS—often, these securities simply trade too infrequently to have high-frequency data.[12] Compared to Treasuries, though, equities have different risk factor loadings that vary in the cross-section and time series, so it is important to control for these risks. Equities also constitute a smaller share of repo collateral, so a priori we should expect the effect of bank leverage risk on their collateral value to be small compared to Treasuries.

Table 14 provides a snapshot of the assets used as collateral in the money-fund market and in the broader repo market captured by the FR2052a data. The table shows the December 2023 value for money funds and the average of daily values from the first half of December 2023 for the FR2052a data to avoid possible year-end distortions. The datasets likely have considerable overlap, but the N-MFP data includes repos with banks that are not included in the FR2052a data, while the FR2052a data spans all types of repos, not just money-fund transactions.[13]

Treasuries are the largest type of collateral in the data, amounting to 38 percent ($1.1 trillion) in the FR052a data and 76 percent ($2 trillion) of collateral pledged in N-MFP filings. This is why I principally focus on Treasuries in the paper. Equity collateral is a magnitude smaller, averaging roughly 3 percent ($95 billion) of collateral pledged in the FR2052a data and 0.2 percent ($5 billion) in the N-MFP data. The difference in collateral composition across the two datasets is likely an artifact of market segmentation and market power, where certain types of counterparties can demand higher quality collateral than others (Hu et al., 2019). Agency mortgage-related debt is also a large share of collateral in both datasets, standing at 14 percent in FR2052a ($404 billion) and 21 percent ($569 billion) in N-MFP. Foreign sovereign bonds also constitute an important share of the FR2052a data because the data spans the banks' global operations, including foreign repo markets that use local sovereign bonds. Corporate debt and agency debt account for at least 1 percent of the total

[12]For example, He and Song (2022) document the role of agency MBS as safe assets by mainly focusing on new issues because they are much more liquid than seasoned agency MBS.

[13]The FR2052a repo data may include transactions where the bank's counterparty uses a repo to borrow a specific security to sell it short. However, the effect of short-selling transactions should be limited since they are typically classified as securities lending transaction which are recorded separately in the FR2052a data.

amount pledged in FR2052a.

Even though equity collateral is small in the N-MFP data, bank leverage risk should depend on collateral use across all segments of the repo market, not just the tri-party repo market in which money-funds participate. In this view, the $95 billion is a lower bound since it spans only the handful of banks that file daily FR2052a reports. There is also considerable time series variation in equities posted as collateral. Figure 8 shows that equity collateral peaked at $190 billion in 2021 but has been falling since.

That equities can be an important form of collateral is also revealed by the documentation money-fund clients give the tri-party bank about their collateral preferences—essentially a list of stocks that the money-fund is willing to accept as repo collateral. They can provide granular cuts on what type of equities they receive across several dimensions: the equity type (common stock, preferred stock, ETFs, ADRs, etc.), which exchange the stock trades on (NYSE, NYSE Arca, NASDAQ, pink sheets, etc.), which indices the stock must belong to, or whether the stock is convertible. Money-funds can also specify the maximum amount of a stock pledged to them based on market cap or trading volume.

A related risk for collateral is "bundling" different types of securities together to back the same repo. For example, if a Treasury and an MBS were both used as collateral for the same repo, then that Treasury's collateral risk could be higher than for another Treasury that isn't bundled alongside risky assets. Such dynamics may be important but are likely muted at least for Treasuries since the data suggests they are only infrequently bundled with other collateral. In the money-fund data, conditional on a repo having a nonzero amount of Treasury collateral, the average (median) share of Treasury collateral backing that repo is 88 percent (100 percent). In this view, money-fund repos backed by Treasuries are overwhelmingly backed by only Treasuries. Unfortunately, the Fr2052a data does not present transaction-level data, so it is not possible to study collateral bundling outside of the money-fund market with these datasets.

Model Intuition I can adjust the model to provide a simple framework to understand collateral risk by writing the geometric risk premium for a stock p following the same logic as equation 5:

$$\mathbb{E}_t[r_{p,t+1} - r_{f,t+1}] \approx \gamma\sigma_{c,p} - \sigma_{h,p}. \tag{15}$$

Since equities are not considered safe assets, I make the simplifying assumption that a stock's money weight π_p is zero, which implies $\omega_p'(\mathcal{M}_t) = 0$. This is consistent, for example, with Holmström (2015)'s description of safe assets as information insensitive and equities as information sensitive. Equities are likely used less as collateral in the tri-party repo market precisely because they are information sensitive.

The key difference between this expression for equities and for Treasuries is the firm-specific consumption covariance term $\gamma\sigma_{c,p}$. For Treasuries, the term is small or zero since safe assets have low consumption covariance. Here, however, I need to control for firm-specific covariances that are unrelated to their covariance with bank leverage constraints (the σ_h terms).

Equity Collateral Data I clean the collateral description strings in the N-MFP to identify common stocks, and then I fuzzy merge these stocks with the CRSP stock data using the company's name. I exclude collateral that are likely preferred stocks, warrants, ETNs, and ETFs, and I clean the collateral description strings in several ways to remove generic terms (e.g., "holdings"). I fuzzy match the resulting collateral strings to the CRSP company name strings, where the CRSP data is the universe of ordinary common shares (share codes 10 and 11). The online appendix provides more cleaning details.

Over the period 2011 to 2023, CRSP has roughly 8,700 unique company names and the money-fund data has 21,400 unique strings that describe equities. I use fuzzy matching to match 8,200 N-MFP strings to CRSP. A significant share of the unmatched securities are ETFs, ETNs, and foreign stocks. Unsurprisingly, stocks from larger companies and with less volatile returns tend to be used as collateral more often. I choose the fuzzy match cutoff thresholds to balance the risk of including incorrect matches versus the risk of throwing out correct matches. Importantly, the results below are consistent using a variety of different cutoff thresholds, and the results are stronger when including only perfect matches at the cost of a much smaller matched sample.

Results I test whether bank leverage risk appears in firm-specific stock returns in Table 15 by running the regression

$$r_{i,t} - r_{f,t} = \alpha + \beta_1 \Delta \ln(\text{Repo}_t) + \beta_2(Mkt_t - r_{f,t}) + \beta_3(SMB_t) + \beta_4(HML_t) + \beta_5(MOM_t) + \varepsilon_{i,t}$$

where the left hand side is a firm's excess return and the right hand side is daily innovations in repo and several risk factors. The regression controls for firm-specific variation in the consumption covariance term ($\gamma\sigma_{c,p}$) by including several standard equity risk factors including the excess return on the market portfolio, value (HML), size (SMB), and momentum (MOM). I run the regression at the date by company level.

The first two columns of Table 15 run the regression on the full sample of equities, not conditioning on whether that company's stock has been used as collateral and find that repo growth is significantly positively related to firm returns. The first column uses Fama and French (1996)'s 3-factor model and finds a 1pp increase $\Delta \ln(\text{Repo}_t)$ corresponds to a 1.3 bps increase in stock returns, all else equal. The second column adds the momentum factor and finds similar results. Intuitively, the first two columns are consistent with all equities' collateral value increasing as banks increase their repo, even if those stocks are not actively being used as collateral. That the coefficient is a magnitude smaller for repo growth than for the common stock factors is consistent with the expectation that the effect of bank leverage risk is smaller for equities given their comparatively limited role as repo collateral.

Columns (3) and (4) limit the sample to stocks that are used as collateral and finds similar but stronger results. Column (3) limits the sample to stocks have been used as collateral at some point before the current month, reflecting the set of information available to investors. Once a stock has been used at least once as collateral, I include it in this sample: I denote this sample as "rolling." Alternatively, Column (4) instead limits to stocks that are used at least once in the entire sample, denoted in the sample row with "full."

Finally, the last two columns show that stocks which are not used collateral do not vary with repo growth. Column (5) uses the rolling sample approach to identify stocks never used as collateral (like column 3) up to the current month. Column (6), analogous to column (4), limits the sample to stocks that are never used as collateral at any point in the full sample. Regardless of the sample, the last two columns confirm stocks which are not used collateral do not vary with repo growth and finds no significant effect and a much smaller coefficient on repo growth, as expected.

An alternative approach would be to limit the sample to stocks that in the previous month were in the top tercile of collateral use, like the previous work with Treasuries. The disadvantage of this approach is the sample size is much smaller given the limited volume of stocks used as collateral each month. Since the volume of equities used in each month is so limited in the sample, it is not possible to create well-balanced collateral ratio terciles—most stocks are not used as collateral in a given month. Instead, the regression assumes that stocks used as collateral once tend to be used as collateral, even if that is not captured in the money-fund data. This seems plausible given the FR2052a data has equity collateral volume that is roughly 20 times larger.

As robustness, I also check that the results do not change materially if I require a stricter level of fuzzy matching, for example, by requiring the Levenshtein distance is greater than or equal to 95 (compared to the base case requirement of 85 described in the appendix). This stricter fuzzy matching makes the results stronger although at the cost of making the matched sample smaller.

Bank leverage risk likely plays a role in all types of asset classes that are used as collateral. Although agency MBS and corporate bonds have less high frequency data, especially for seasoned issues, I expect similar dynamics appear in these markets given their nontrivial volumes as repo collateral.

8 Conclusion

Governments do not always issue enough safe assets, like Treasuries. Bank-produced liabilities satisfy the remaining safe-asset demand. When short-term equity issuance is costly, banks must use leverage and collateral to produce money-like safe assets. Banks' ability to make incremental safe assets varies considerably from day to day because their leverage constraints vary from day to day.

Banks produce private safe assets using collateral, often repos backed by Treasuries. I show that Treasuries used as collateral load on bank leverage risk because banks cannot pledge more collateral when they are leverage constrained: pledging requires incremental leverage. Safe-asset production, then, is implicitly inefficient because Treasuries' collateral values depend on bank leverage constraints. Banks use long-term safe assets—like Treasury bonds—as collateral to make money-like short-term safe assets—like repos—but those long-term safe assets become riskier when banks use them as collateral.

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9 Figures

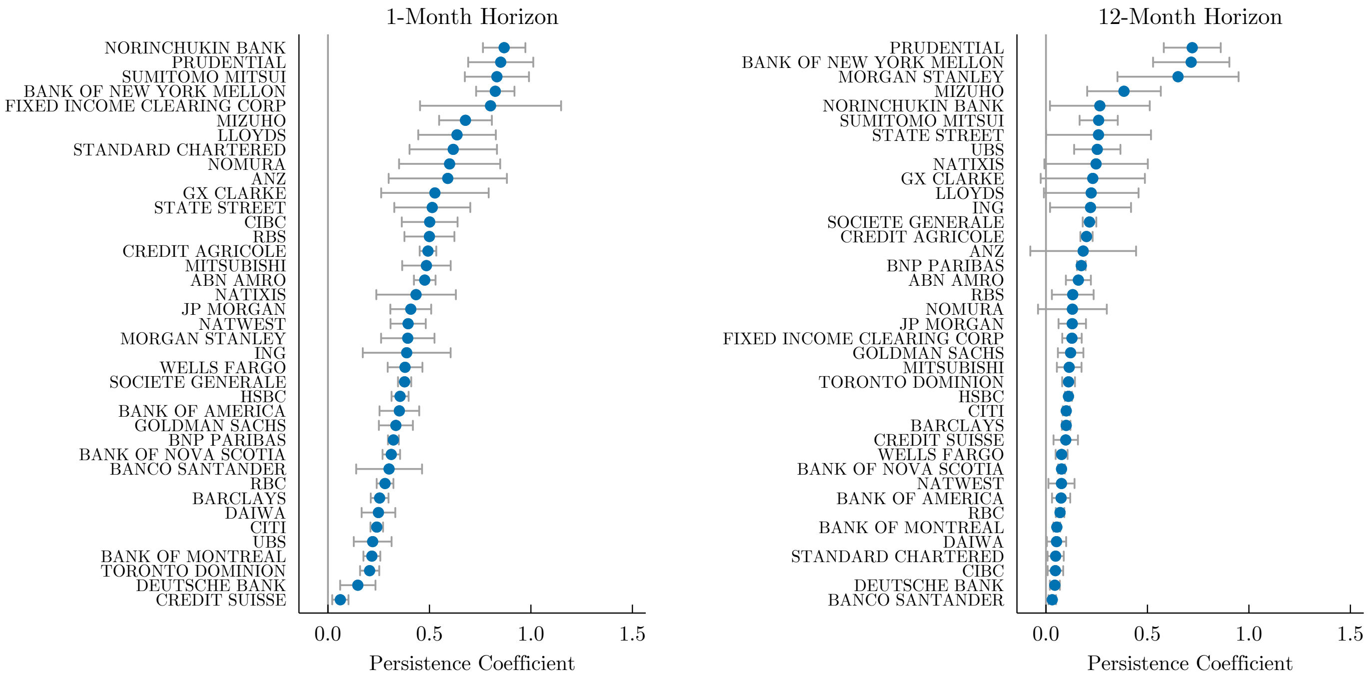

Figure 1: Time-Series Persistence of Boxed Treasuries. Plot gives the estimated beta coefficient with 95% confidence intervals from the regression $\text{Collateral Share}_{i,d,t} = \alpha + \beta \text{Collateral Share}_{i,d,t-1} + \varepsilon_{i,d,t}$, where $\text{Collateral Share}_{i,d,t}$ is the collateral share of CUSIP i for dealer d at time t across all the Treasuries used as collateral by that dealer at that time: $\text{Collateral Share}_{i,d,t} = \text{CUSIP Collateral}_{i,d,t} / \sum_i \text{CUSIP Collateral}_{i,d,t}$. Includes dealers and cash borrowers with at least 100 CUSIP by month observations. Figure derived from the publicly available N-MFP money fund filings.

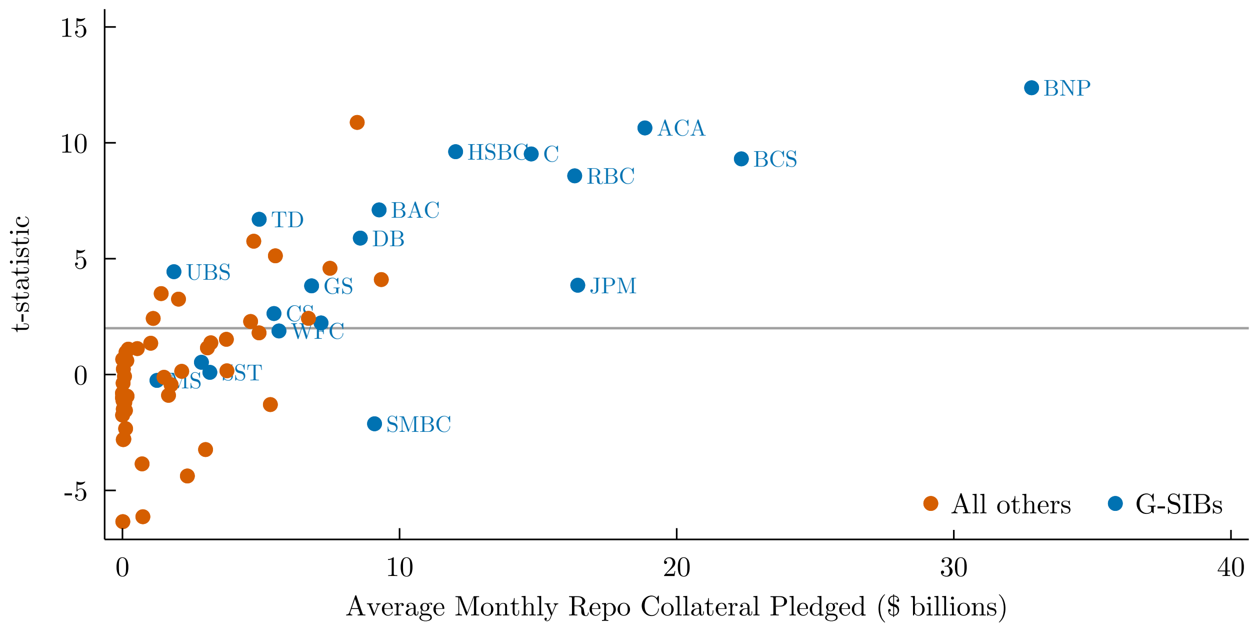

Figure 2: Cross-Sectional Persistence of Boxed Treasuries. Plot gives the t-statistics of the beta coefficient from the regression Collateral $\text{Share}_{i,d,t} = \alpha + \beta\text{Collateral Share}_{i,SocGen,t} + \varepsilon_{i,d,t}$, where Collateral $\text{Share}_{i,d,t}$ is the collateral share of CUSIP i for dealer d at time t across all the Treasuries used as collateral by that dealer at that time, and Société Générale is the benchmark dealer to which all other dealers are compared. Blue dots denote global systemically important banks (G-SIBs) while red dots represent all other dealers. Average repo collateral is the monthly average Treasury collateral pledged by that dealer in my sample. Includes dealers and cash borrowers with at least 100 CUSIP by month observations and excludes the Fixed Income Clearing Corporation. Figure derived from the publicly available N-MFP money fund filings.

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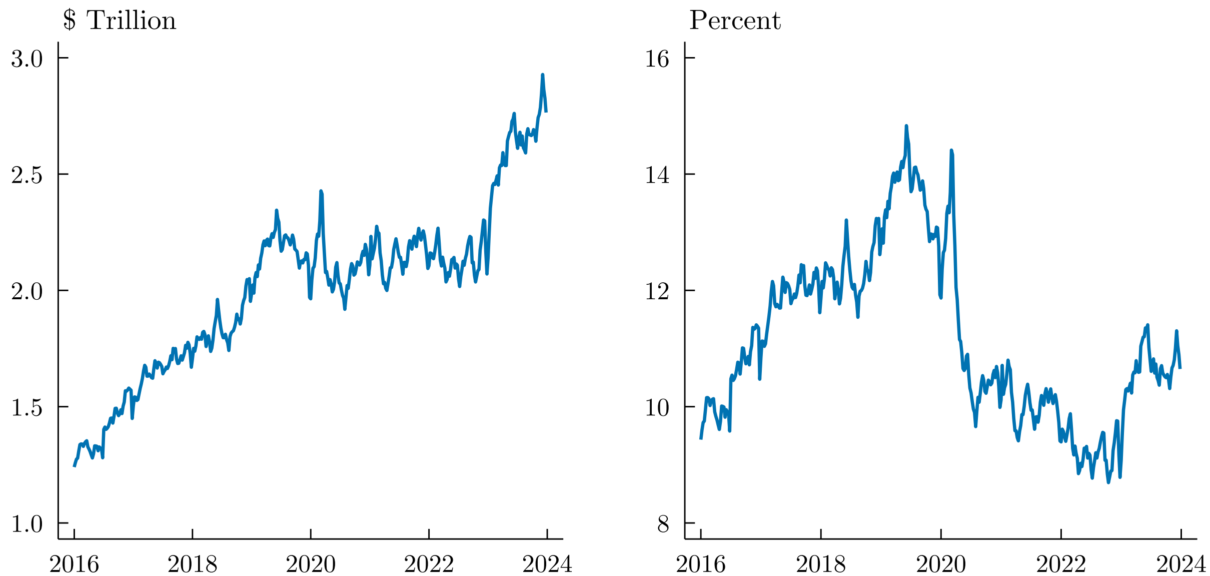

Figure 3: Total Repo Borrowing. The left panel plots the total amount of repo borrowing by the largest banks from FR2052a. The right panel is the ratio of repo borrowing to total Treasuries outstanding. Plots are weekly averages of daily data.

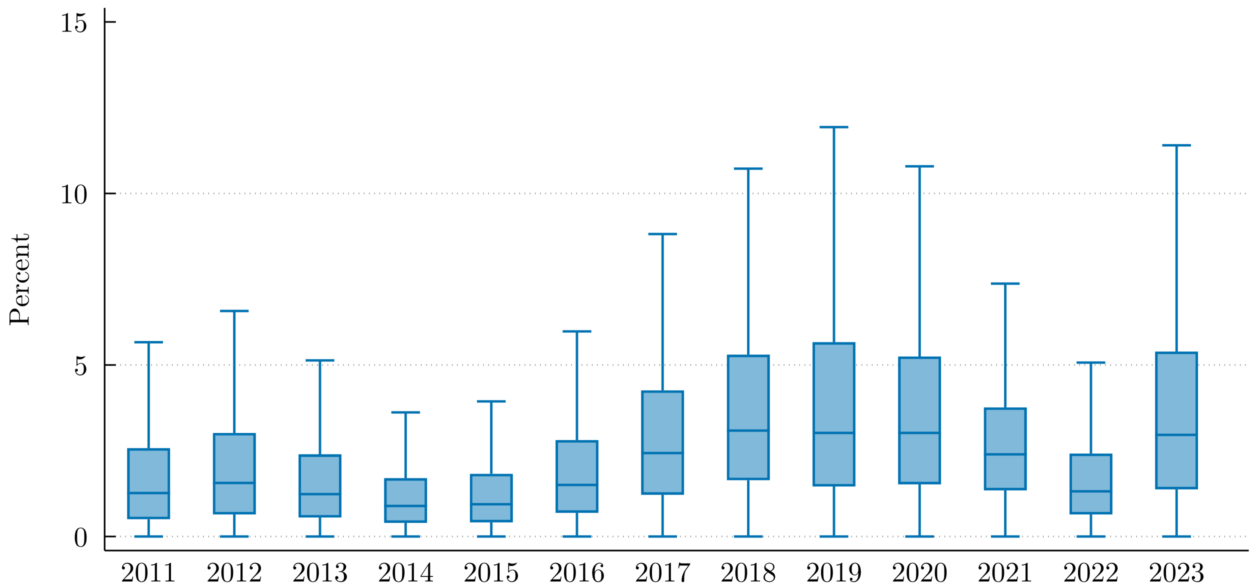

Figure 4: Time-Series Variation in Collateral Ratio. Box plot of the collateral ratio at the month-CUSIP level by year, equal-weighted across CUSIPs. The blue bar in the middle of the box is the average collateral ratio in that year, the blue box is the interquartile range, and the lines up and down trace out the lower- and upper-adjacent values.

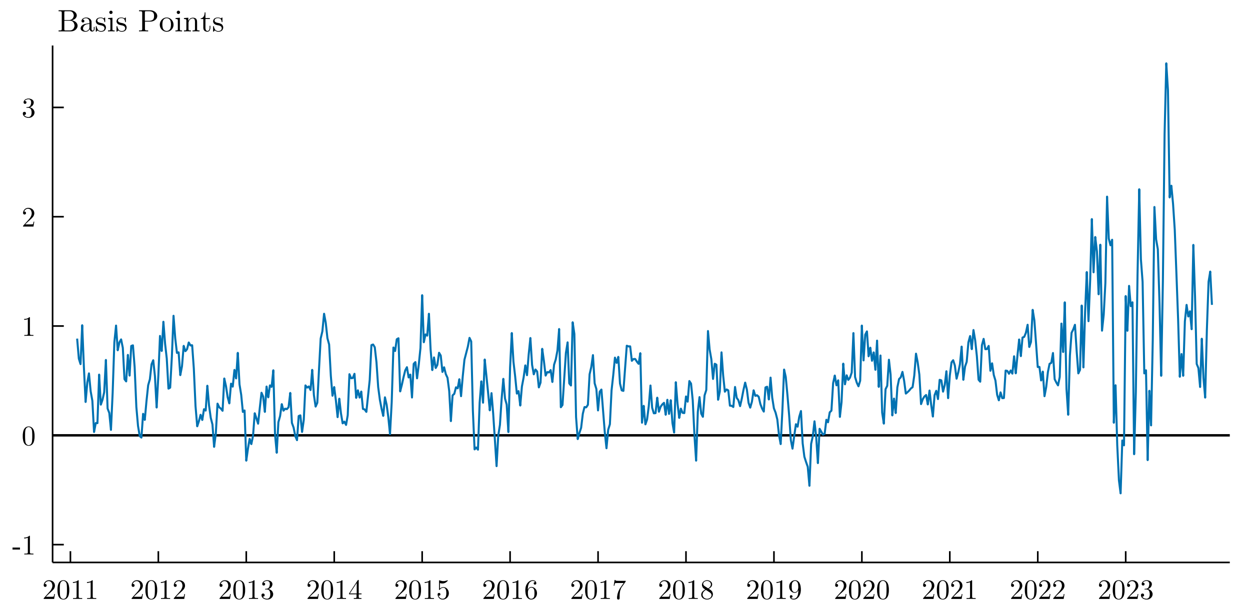

Figure 5: Treasury Collateral Spread. Figure plots the Treasury collateral spread, which is the value-weighted maturity-matched yield spread between Treasuries used more often as repo collateral and Treasuries used less often. Value-weights are the market value of Treasuries outstanding by maturity bucket. See section 5.2 for details. Plot is weekly averages of daily data.

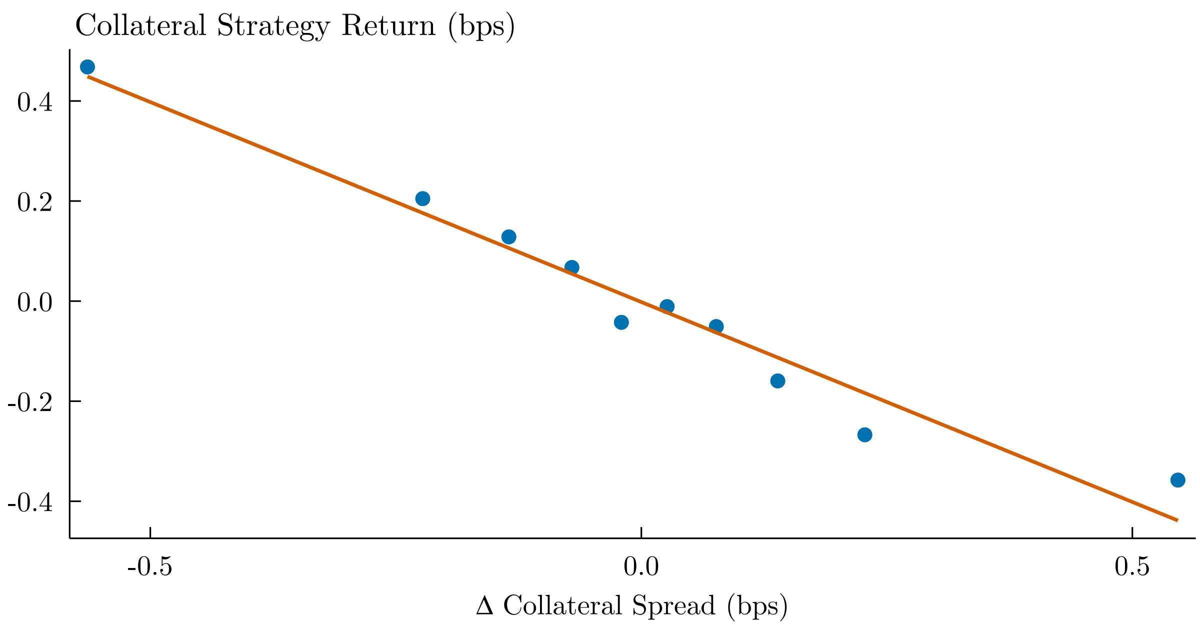

Figure 6: Casting the Treasury Collateral Spread to Returns. Figure plots a binscatter of the daily returns in the Treasury collateral strategy (double sorted by maturity bucket and collateral ratio) and the change in the Treasury collateral spread.

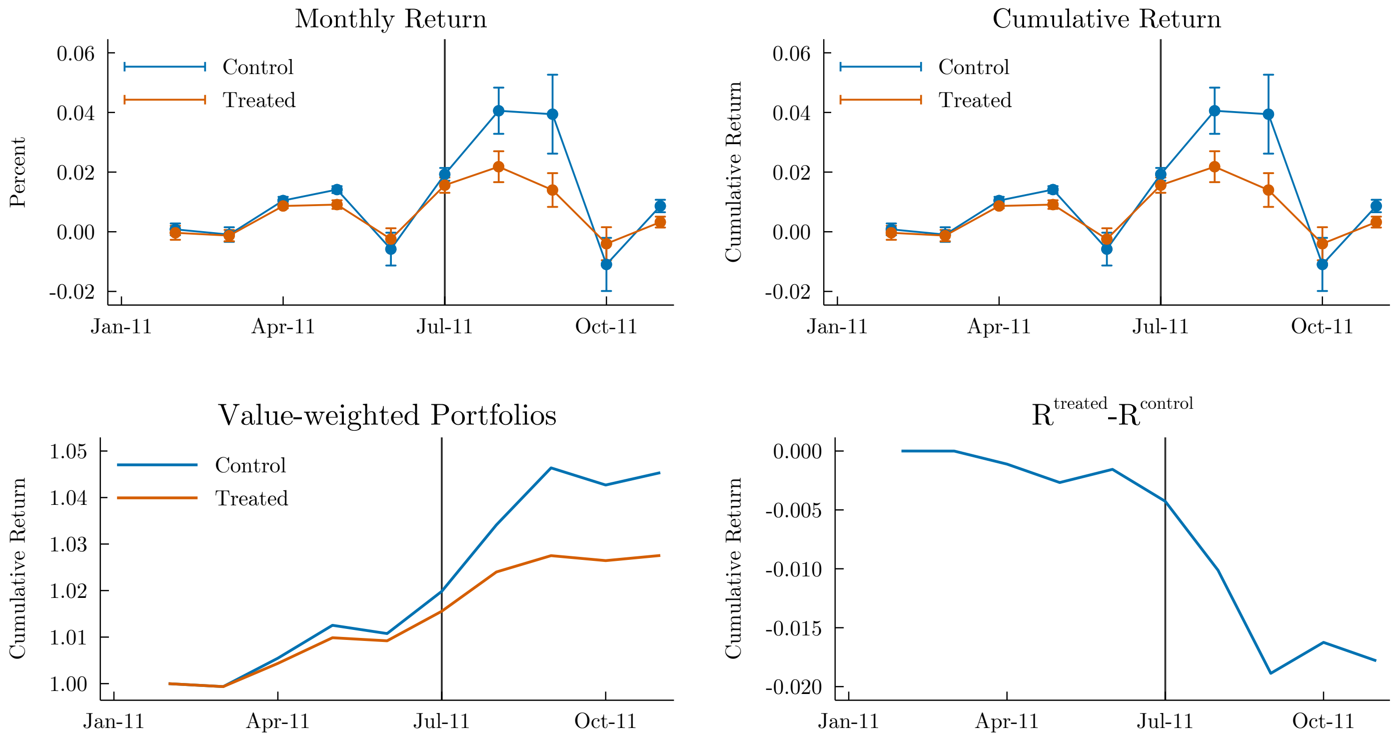

Figure 7: Parallel Trends around July 2011 Euro Sovereign Debt Crisis Event. The top-left panel shows the predictive margins of monthly returns for treated and control bonds estimated from equation 14 and shown in column (2) of Table 12, where a treated bond is a bond that is more often pledged as collateral by European banks and is in the top tercile of contemporaneous *CR*. The top-right panel shows the same predictive margins for treated and control bonds in terms of cumulative returns. The bottom-left panel shows the value-weighted return for the portfolio of treated and control bonds in the sample of column (2) of the table. The bottom-right panel shows the difference in the value-weighted cumulative return long the treated portfolio and short the control portfolio from the bottom-left panel.

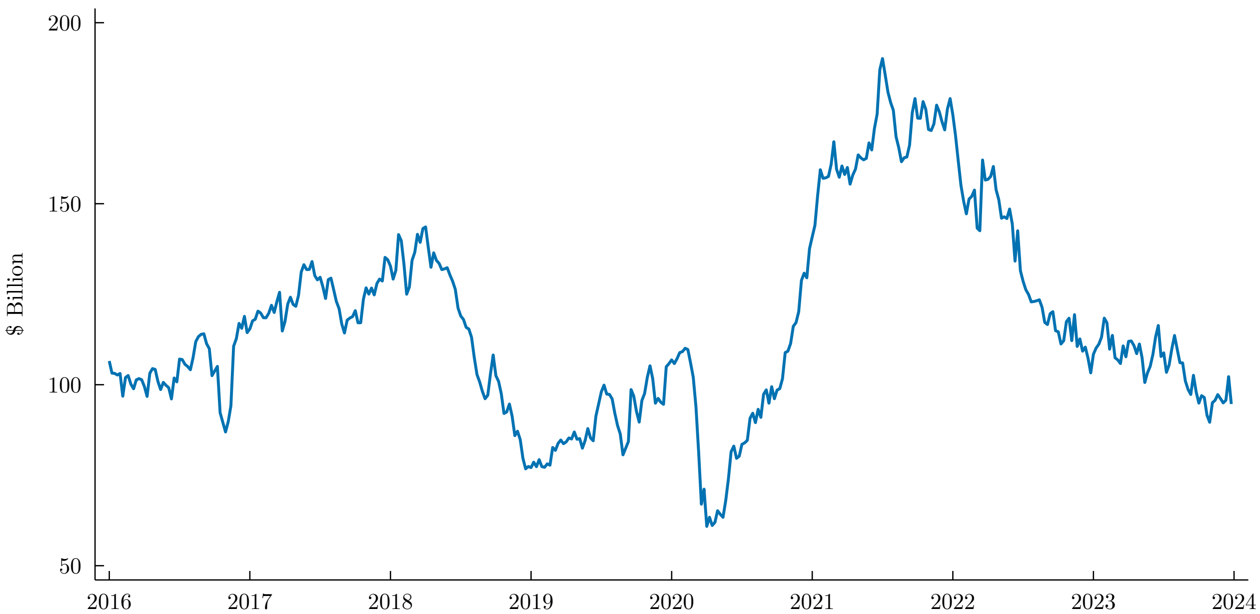

Figure 8: Equity Repo Collateral. Figure plots the volume of repos with equity collateral from FR2052a. Plot is weekly averages of daily data.

10 Tables

Pre-Repo				Post-Repo			
Assets ($)		**Liabilities ($)**		**Assets ($)**		**Liabilities ($)**	
Cash	0	Repo	0	Cash	100	Repo	100
Treasuries	100	Equity	100	Treasuries	0	Equity	100
Repo-Encumbered Treasuries	0			Repo-Encumbered Treasuries	100		
Total	100	Total	100	Total	200	Total	200
		Leverage	1			*Leverage*	2

Table 1: Safe-Asset Production via Bank Leverage. Figure shows a simplified bank's balance sheet before and after a repo transaction. In the pre-repo left panel, the bank has $100 in Treasuries funded with $100 in equity. In the post-repo transaction, the bank pledges its Treasuries as collateral in a repo to borrow $100 cash. Leverage is equal to assets divided by equity.

		Collateral Ratio > 0	Full Treasury Sample
Treasuries (daily average)	Unique CUSIPs	294	297
	Market Value (USD billions)	8,861	8,930
	Original Maturity (years)	11.58	11.53
	Remaining Maturity (years)	6.40	6.35
	Duration (years)	5.14	5.10
	On-the-run CUSIPs	6.14	6.23
	Second On-the-run CUSIPs	6.21	6.21
	Cheapest-to-deliver CUSIPs	3.97	3.97
Repo Transaction (full sample)	N (Month-Collateral level)	1,999,198	
	N (Month-Repo level)	537,064	
	# Funds (Lenders)	248	
	# Counterparties (Borrowers)	3,724	
	# Borrower-Lender Pairs	9,240	
Repo Transaction (monthly)	Collateral Value (avg, USD millions)	357	
	Repo Value (avg, USD millions)	351	
	Collateral Value (sum, USD billions)	1,183	
	Repo Value (sum, USD billions)	1,159	
	Avg. Haircut	3.02%	
	Std. Dev Haircut (time-series)	0.36%	
Collateral Ratio (monthly)	Average	2.62%	2.60%
	Max (avg, monthly)	16.40%	
	Std. Dev. (cross-section)	2.32%	
	Std. Dev. (time-series of monthly mean)	1.08%	

Table 2: Repo Data Summary Statistics. Summary statistics of repo data and Treasury collateral use. Data from monthly money market mutual fund filings. Sample period from January 2011 to December 2023 and spans all Treasury repurchases. Full Treasury sample includes noncallable Treasury notes and bonds. Haircuts are winsorized at the 1 and 99% level to reduce the influence of outliers.

	Dependent Variable: $\Delta \ln(\text{Repo}_t)$			$\Delta(\text{Repo}_t/\text{Treasuries Outstanding}_t)$		
	(1)	(2)	(3)	(4)	(5)	(6)
Bank Leverage Measures						
$\Delta PC1_t$	-0.165^{***}	-0.172^{***}	-0.168^{**}	-0.020^{***}	-0.021^{***}	-0.020^{**}
	(-2.66)	(-2.95)	(-2.51)	(-2.80)	(-3.04)	(-2.50)
Controls						
$\Delta \ln(\text{Non-Repo Liabilities}_t)$		0.337^{***}	0.340^{***}		0.033^{***}	0.034^{***}
		(4.01)	(3.90)		(3.69)	(3.69)
$\Delta\text{Financial CDS}_t$			0.562			0.035
			(0.32)			(0.19)
$\Delta\text{Bid-Ask Spread}_t$			-1.094			-0.111
			(-1.50)			(-1.47)
$\Delta \ln(\text{Treasuries Outstanding}_t)$			-38.050			-15.110^{***}
			(-1.24)			(-4.55)
$TERM_t$			0.090			0.008
			(1.07)			(0.90)
N	1,975	1,975	1,871	1,975	1,975	1,871
R^2	0.05	0.06	0.07	0.05	0.06	0.08
Month FE	Yes	Yes	Yes	Yes	Yes	Yes

Table 3: Repo and Bank-Intermediated Arbitrages. Table presents the results from regressing repo measures on $\Delta PC1_t$; PC1 is the first principal component in the expected returns across several bank-intermediated arbitrage trades. Repo measures are multiplied by 100. Non-repo liabilities are the sum of non-repo secured liabilities, unsecured liabilities, and deposits from FR2052a. Financial CDS is the average CDS spread across U.S. financials denominated in USD using the primary curve and coupon from Markit, bid-ask spread is for the 10-year on-the-run Treasury in cents using data from the interdealer broker community, Treasuries outstanding is calculated using data from Treasury Direct, and term is the return difference between 10-year and 2-year fixed-term Treasury indices from CRSP. Constant omitted. t-statistics shown using heteroskedastic and autocorrelation consistent standard errors using the Newey and West (1994) automatic lag selection procedure where * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

	Dependent Variable: Collateral $\text{Ratio}_{i,t}$						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Bid-Ask $\text{Spread}_{i,t}$	0.194***						0.0550**
	(4.21)						(2.36)
$\text{Age}_{i,t}$		0.00523					0.00500
		(0.47)					(0.44)
Maturity $\text{Remaining}_{i,t}$			0.0761***				0.0652***
			(11.33)				(8.60)
$\mathbb{I}(\text{On-the-Run}_{i,t})$				2.975***			3.884***
				(13.66)			(4.61)
$\mathbb{I}(\text{Cheapest-to-deliver}_{i,t})$					1.189***		1.144***
					(3.89)		(3.28)
$\text{Specialness}_{i,t}$						−0.0177***	−0.0158***
						(−13.03)	(−12.05)
Constant	1.869***	2.658***	2.204***	2.623***	2.669***	2.774***	2.071***
	(9.72)	(40.49)	(39.12)	(49.52)	(51.47)	(51.31)	(21.97)
N	47,239	47,239	47,239	47,239	47,239	44,739	44,739
R^2	0.02	0.00	0.04	0.02	0.00	0.02	0.07

Table 4: Collateral Ratio Covariances. Table presents the results from regressing CUSIP-month collateral ratios (in percent) on the CUSIP's month-end observables: bid-ask spread (in cents), age (in years), maturity remaining (in years), indicator variables for whether the CUSIP is on-the-run or cheapest-to-deliver, and the CUSIP's specialness spread in basis points, defined as the spread between the DTCC GCF repo index and the volume-weighted repo rate on trades between 7:30am and 10:00am using data from the interdealer broker community. Cheapest-to-deliver data is from Bloomberg for 2y, 5y, 10y, and 30y Treasury futures. Standard errors clustered by CUSIP where * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Panel A: Aggregated Spread				
	Mean (bps)	Std. Dev.	Min	Max
Collateral Spread, Value-Weight	0.53	0.49	-1.09	3.88
Collateral Spread, Fixed-Weight	0.56	0.48	-1.13	3.88

Panel B: Spreads by Tenor				
	Spread (bps)		Value Weight (%)	
Tenor	Mean	Std. Dev.	Mean	Std. Dev
1	0.82	1.66	22.3	2.4
2	0.51	0.94	15.7	1.3
3	0.15	0.91	11.6	0.9
4	0.05	0.80	10.7	0.8
5	0.20	0.79	8.1	0.8
6	0.50	1.05	6.8	0.8
7	0.88	1.43	4.3	0.5
8	1.29	1.80	3.2	0.6
9	1.69	2.10	3.6	0.6
10	2.05	2.33	0.3	0.3
11	2.35	2.49	0.2	0.2
12	2.59	2.59	0.2	0.2
13	2.75	2.64	0.2	0.2
14	2.85	2.65	0.2	0.2
15	2.89	2.63	0.2	0.2
16	2.86	2.58	0.2	0.2
17	2.77	2.50	0.2	0.2
18	2.63	2.38	0.3	0.2
19	2.44	2.24	0.3	0.3
20	2.22	2.07	0.4	0.3
21	1.96	1.88	0.5	0.4
22	1.67	1.67	0.6	0.4
23	1.35	1.46	0.7	0.5
24	1.02	1.27	0.9	0.6
25	0.67	1.15	1.2	0.5
26	0.31	1.15	1.4	0.5
27	-0.06	1.30	1.7	0.5
28	-0.43	1.57	2.0	0.5
29	-0.80	1.94	2.3	0.4
30	-1.17	2.36	0.0	0.1

Table 5: Treasury Collateral Spread Summary Statistics. Panel A presents summary statistics for the Treasury collateral spread. The first row is the value-weighted spread, where value-weights are calculated using the market value of Treasuries by tenor in the previous month. Second row shows the collateral spread where weights are fixed by averaging over the monthly values for the full sample. Panel B shows the collateral spread and value weight by tenor.

	Dependent Variable: Collateral Spread_t						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Repo/UST	-0.19^{***}					-0.22^{***}	-0.16^{***}
	(-5.20)					(-5.35)	(-5.33)
VIX		0.04				-0.08^{**}	-0.04^{*}
		(1.22)				(-2.12)	(-1.81)
Bid-Ask Spread			0.08^{***}			0.12^{**}	0.10^{***}
			(2.66)			(2.30)	(3.02)
Slope				-0.13^{**}		-0.25^{**}	-0.02
				(-2.51)		(-2.52)	(-0.36)
Cheapest-to-Deliver Basis					0.01	-0.01	0.02
					(0.43)	(-0.27)	(1.13)
Constant	0.59^{***}	0.53^{***}	0.53^{***}	0.53^{***}	0.53^{***}	0.44^{***}	0.51^{***}
	(12.51)	(13.84)	(14.11)	(14.94)	(13.69)	(9.01)	(22.23)
N	1,988	3,231	3,175	3,231	3,230	1,934	1,447
R^2	0.12	0.01	0.02	0.07	0.00	0.25	0.21
Sample	Full	Full	Full	Full	Full	Full	Pre-2022

Table 6: Treasury Collateral Spread Covariances. Table presents the results from regressing the Treasury collateral spread on several variables: Repo/UST is the ratio of repo borrowing from the FR2052a data relative to Treasuries outstanding, bid-ask spread is from the 10-year on-the-run Treasury using data from the interdealer broker community in cents, slope is the difference in the yields for 10-year and 2-year Treasuries, cheapest-to-deliver basis is the 10-year cheapest-to-deliver basis net of carry from JP Morgan Markets. All independent variables are standardized to z-scores using their moments from 2011 to 2023. t-statistics shown using heteroskedastic and autocorrelation consistent standard errors using the Newey and West (1994) automatic lag selection procedure where * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

	Dependent Variable: Yield-to-maturity Residual$_{i,t}$ = Actual$_{i,t}$ − Predicted$_{i,t}$ (bps)					
	(1)	(2)	(3)	(4)	(5)	(6)
Collateral Ratio$_{i,t-1}$	0.27***	0.38***	0.35***	0.32***	0.15***	0.21***
	(9.33)	(11.40)	(9.66)	(10.97)	(5.28)	(7.99)
Controls						
Duration$_{i,t}$					2.20***	2.35***
					(9.57)	(11.83)
Bid-Ask Spread$_{i,t}$					−0.04	−0.30***
					(−0.43)	(−3.63)
Maturity Remaining$_{i,t}$					−1.43***	
					(−9.80)	
$\mathbb{I}$(Special$_{i,t}$)					−0.40***	−0.83***
					(−4.61)	(−10.69)
$\mathbb{I}$(Cheapest-to-deliver$_{i,t}$)					−0.05	0.25
					(−0.08)	(0.83)
$\mathbb{I}$(First On-the-run$_{i,t}$)					−2.37***	−3.14***
					(−10.26)	(−12.17)
$\mathbb{I}$(Second On-the-run$_{i,t}$)					−0.95***	−1.12***
					(−4.87)	(−5.92)
N	962,229	962,229	962,229	962,229	962,229	962,229
R^2	0.00	0.07	0.07	0.13	0.02	0.14
CUSIP FE	No	No	Yes	Yes	No	Yes
Date FE	No	Yes	No	Yes	No	Yes

Table 7: Pricing Residuals and Collateral Ratio. Table presents the regression of CUSIP pricing residuals on several independent variables. Pricing residuals are estimated using the Federal Reserve's public Gürkaynak et al. (2007) estimates where Residual$_{i,t}$ = Actual YTM$_{i,t}$ − Estimated YTM$_{i,t}$. Regression is at CUSIP by day level. Collateral ratio is the previous month's value, and liquidity is the average bid-ask spread in cents over the previous month. A CUSIP is defined as trading special if its repo rate is more than 1 bp lower than the DTCC GCF repo index, where its repo rate is calculated using volume-weighted repo rate on specific trades between 7:30am and 10:00am with data from the interdealer broker community. Cheapest-to-deliver data is from Bloomberg for 2y, 5y, 10y, and 30y Treasury futures. Constant omitted. t-statistics shown using robust standard errors clustered by CUSIP where * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

	Dependent Variable: ΔCollateral Spread$_t$					
	(1)	(2)	(3)	(4)	(5)	(6)
Double-Sorted Collateral Strategies						
Maturity Bucket × CR	-10.73^{***}	-10.87^{***}				
	(-7.99)	(-8.13)				
Maturity × CR			-0.37^{**}	-0.45^{***}		
			(-2.17)	(-2.59)		
Liquidity × CR					-0.09^{**}	-0.17^{**}
					(-2.00)	(-2.30)
Controls						
TERM		-0.01		0.02		0.03
		(-0.36)		(0.93)		(1.30)
ΔBid-Ask Spread		-0.02		-0.01		-0.01
		(-1.14)		(-0.82)		(-0.75)
Constant	-0.00	-0.00	0.00	0.00	0.00	-0.00
	(-0.02)	(-0.13)	(0.05)	(0.00)	(0.16)	(-0.06)
N	3,228	3,120	3,228	3,120	3,228	3,120
R^2	0.06	0.06	0.00	0.00	0.00	0.00

Table 8: Treasury Collateral Spread Spanning Tests. Table presents the results from regressing the Treasury collateral spread on double-sorted collateral strategies, and controls TERM (the 10-year Treasury return minus the 2-year Treasury return, both from the CRSP fixed-term indices), and the bid-ask spread is from the 10-year on-the-run Treasury using data from the interdealer broker community in cents. ΔCollateral Spread$_t$ is in bps and collatearl strategies' returns are in percent. t-statistics shown using heteroskedastic and autocorrelation consistent standard errors using the Newey and West (1994) automatic lag selection procedure where * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

	Return			YTM Residual (Actual-Predicted)		
	(1)	(2)	(3)	(4)	(5)	(6)
Average Treatment Effect	14.02^{**}	9.27^{***}	17.47^{***}	1.13^{***}	1.06^{***}	1.15^{***}
	(2.49)	(3.11)	(3.44)	(5.89)	(4.51)	(6.29)
Observations	46,295	46,295	46,295	46,295	46,295	46,295
R^2	Mahalanobis	Euclidean	Inverse Variance	Mahalanobis	Euclidean	Inverse Variance

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 9: Collateral Spread Estimated with Nearest-Neighbor Match. Table shows the results of nearest-neighbor matching across Treasuries sorted into one of two buckets each month: high- and low-*CR* (lagged by a month). I then match Treasuries to their nearest neighbor using month-end values for duration, liquidity (the average bid-ask spread over the previous month), maturity remaining, and indicators for whether it is trading special, cheapest-to-deliver, or on-the-run. Columns show the difference between Treasuries in the high- and low-*CR* halves using different distance metrics. The first three columns show the effect on annualized returns in bps and the last three show the effect on the yield residual in bps, where $\text{Residual}_{i,t} = \text{Actual YTM}_{i,t} - \text{Estimated YTM}_{i,t}$. A CUSIP is defined as trading special if its repo rate is more than 1 bp lower than the DTCC GCF repo index, where its repo rate is calculated using volume-weighted repo rate on specific trades between 7:30am and 10:00am with data from the interdealer broker community. Cheapest-to-deliver data is from Bloomberg for 2y, 5y, 10y, and 30y Treasury futures. t-statistics are reported in parentheses using robust standard errors.

	Dependent Variable: ΔCollateral Spread_t					
	(1)	(2)	(3)	(4)	(5)	(6)
Bank Leverage Measures						
$\Delta \ln(\text{Repo}_t)$	-0.013^{**}	-0.011^{*}				
	(-2.20)	(-1.92)				
$\Delta(\text{Repo}_t/\text{Treasuries Outstanding}_t)$			-0.112^{**}	-0.101^{**}		
			(-2.27)	(-2.11)		
$\Delta PC1_t$					0.022^{**}	0.025^{*}
					(2.03)	(1.70)
Controls						
ΔFinancial CDS_t		0.484		0.481		0.420
		(0.82)		(0.81)		(0.72)
ΔBid-Ask Spread_t		0.184		0.185		0.184
		(1.25)		(1.25)		(1.22)
$\Delta \ln(\text{Treasuries Outstanding}_t)$		-3.473		-4.566		-3.335
		(-0.47)		(-0.62)		(-0.45)
$\Delta \ln(\text{Non-Repo Liabilities}_t)$		-0.006		-0.007		-0.011
		(-0.26)		(-0.28)		(-0.46)
$TERM_t$		-0.042		-0.042		-0.045
		(-1.15)		(-1.15)		(-1.21)
N	1,975	1,871	1,975	1,871	3,226	1,871
R^2	0.00	0.01	0.00	0.01	0.00	0.01
Month FE	No	Yes	No	Yes	No	Yes

Table 10: Covariance of Bank Leverage Constraints and Collateral Spread. Table presents the results from regressing changes in the collateral spread (in bps) on repo growth measures and $\Delta PC1_t$. PC1 is the first principal component in the expected returns across several bank-intermediated arbitrage trades. Repo measures are multiplied by 100. Non-repo liabilities are the sum of non-repo secured liabilities, unsecured liabilities, and deposits from FR2052a. Financial CDS is the average CDS spread across U.S. financials denominated in USD using the primary curve and coupon from Markit, bid-ask spread is for the 10-year on-the-run Treasury in cents using data from the interdealer broker community, Treasuries outstanding is calculated using data from Treasury Direct, and term is the return difference between 10-year and 2-year fixed-term Treasury indices from CRSP. Constant omitted. t-statistics shown using heteroskedastic and autocorrelation consistent standard errors using the Newey and West (1994) automatic lag selection procedure where * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Bank Constraint State	Portfolio	Days	Pricing Residual (bps)	Std. Error	T-test	p-value
Constraint Measure: Repo/Treasuries Outstanding						
Unconstrained	Low Collateral Ratio	994	−5.13	0.15		
	Hi Collateral Ratio	994	−1.57	0.05		
	Hi − Low Collateral Ratio	994	3.56	0.13		
Constrained	Low Collateral Ratio	994	−6.38	0.24		
	Hi Collateral Ratio	994	−2.04	0.08		
	Hi − Low Collateral Ratio	994	4.34	0.19		
Hi − Low Collateral Ratio: Constrained vs. Unconstrained		994	0.78	0.23	3.43	0.00
Constraint Measure: PC1						
Unconstrained	Low Collateral Ratio	1,615	−4.24	0.13		
	Hi Collateral Ratio	1,615	−1.45	0.05		
	Hi − Low Collateral Ratio	1,615	2.79	0.10		
Constrained	Low Collateral Ratio	1,615	−5.13	0.13		
	Hi Collateral Ratio	1,615	−1.45	0.04		
	Hi − Low Collateral Ratio	1,615	3.68	0.11		
Hi − Low Collateral Ratio: Constrained vs. Unconstrained		1,615	0.88	0.15	5.96	0.00

Table 11: Collateral Ratio-Sorted Portfolio Pricing Residuals by Bank Leverage Constraint State. Table presents the value-weighted pricing residual in basis points for high- and low-CR portfolios across bank leverage constraint states. Pricing residuals are estimated using the Federal Reserve's public Gürkaynak et al. (2007) estimates where $\text{Residual}_{i,t} = \text{Actual YTM}_{i,t} - \text{Estimated YTM}_{i,t}$. The top panel defines bank leverage constraint states by the median level of repo borrowing to Treasuries outstanding, where a high amount of repo borrowing relative to Treasuries is a low constraint state. Bottom panel defines bank leverage constraint state by the median PC1, which is calculated across several bank-intermediated arbitrages, where a high level of PC1 indicates a constrained state. T-test and p-value correspond to two-sided tests: $H_0 : (y^{\text{High-CR}} - y^{\text{Low-CR}})^{\text{Constrained}} - (y^{\text{High-CR}} - y^{\text{Low-CR}})^{\text{Unconstrained}} = 0$ vs. $H_a : (y^{\text{High-CR}} - y^{\text{Low-CR}})^{\text{Constrained}} - (y^{\text{High-CR}} - y^{\text{Low-CR}})^{\text{Unconstrained}} \neq 0$.

	High Collateral Ratio			Low Collateral Ratio		
	(1)	(2)	(3)	(4)	(5)	(6)
Diff-in-Diff						
$\mathbb{I}(\text{Post}_t)$	80.97***	69.86***	32.89**	7.66	11.93	65.41***
	(4.66)	(3.95)	(2.59)	(0.64)	(0.68)	(5.60)
$\mathbb{I}(\text{Treated}_i)$	21.64***	20.27**	16.56**	−2.67	0.34	−0.73
	(2.61)	(2.38)	(2.21)	(−0.51)	(0.05)	(−0.14)
$\mathbb{I}(\text{Post}_t) \times \mathbb{I}(\text{Treated}_i)$	−57.39***	−64.00***	−61.29***	2.42	3.27	2.95
	(−2.74)	(−2.83)	(−2.81)	(0.21)	(0.19)	(0.20)
Bond Characteristics						
$\text{Duration}_{i,t}$	36.42***	34.40***	32.57***	28.86***	25.09***	28.55***
	(7.93)	(6.18)	(6.66)	(5.95)	(4.37)	(6.30)
$\text{Bid-Ask Spread}_{i,t}$	−26.04***	−29.10***	−22.14***	−5.58*	−6.74*	−1.42
	(−4.13)	(−3.60)	(−2.63)	(−1.83)	(−1.73)	(−0.39)
$\mathbb{I}(\text{On-the-run}_{i,t})$	−8.51	30.37	−20.26	62.89***	61.35***	4.71
	(−0.33)	(1.03)	(−0.67)	(12.26)	(11.24)	(0.66)
$\mathbb{I}(\text{Second-on-the-run}_{i,t})$	−19.69	−6.24	−11.88	−54.62	−59.91	−23.65
	(−0.74)	(−0.22)	(−0.57)	(−1.38)	(−1.40)	(−0.70)
$\mathbb{I}(\text{Cheapest-to-deliver}_{i,t})$	−12.49	−0.92	−29.15	−28.95	−38.03*	−5.14
	(−0.44)	(−0.04)	(−1.09)	(−1.15)	(−1.76)	(−0.34)
$\mathbb{I}(\text{Special}_{i,t})$	49.56***	56.72***	18.33	12.09*	29.62***	18.43**
	(4.42)	(3.90)	(1.52)	(1.81)	(3.15)	(2.23)
$\text{Maturity Remaining}_{i,t}$	−9.61***	−8.56**	−7.36**	−7.50*	−4.34	−6.51
	(−3.51)	(−2.54)	(−2.55)	(−1.82)	(−0.91)	(−1.60)
Observations	1,066	1,066	1,066	1,148	1,148	1,148
R^2	0.25	0.24	0.50	0.22	0.23	0.50
Month FE	No	No	Yes	No	No	Yes
Weighted	No	Yes	Yes	No	Yes	Yes

Table 12: Collateral Returns around July 2011 Euro Sovereign Debt Crisis Event. $r_{i,t} = \alpha + \gamma_1 \mathbb{I}(\text{Post}) + \gamma_2 \mathbb{I}(\text{Treated}) + \gamma_3 \mathbb{I}(\text{Post}) \times \mathbb{I}(\text{Treated}) + \beta' X_t + \varepsilon_{i,t}$ where t is month and i is a Treasury CUSIP and X_t is a vector of controls. $r_{i,t}$ is the monthly return in basis points. I define $\mathbb{I}(\text{Post}) = 1$ if the date is after July 11, 2011 and 0 otherwise. I defined the CUSIP as treated, $\mathbb{I}(\text{Treated}) = 1$, if the Treasury CUSIP is intensively used by collateral by European banks. Sample limited to all Treasuries used as collateral one quarter before the July event—in April 2011—and sorts bonds into two halves based on the share of that CUSIP used as collateral by European banks compared to that CUSIP's total use as collateral. $\mathbb{I}(\text{Treated}) = 1$ for bonds above the median European share in April 2011. Sample is the five months before and after the July event. Weighted columns are weighted by the CUSIP's market-value as a share of total Treasuries by month, lagged by a month. Controls include average bid-ask spread in the previous month in cents, and month-end values for duration, maturity remaining, and indicators for CUSIPs that are cheapest-to-deliver, on-the-run, second-on-the-run, or trading special at month-end. A CUSIP is defined as trading special if its repo rate is more than 1 bp lower than the DTCC GCF repo index, where its repo rate is calculated using volume-weighted repo rate on specific trades between 7:30am and 10:00am with data from the interdealer broker community. Cheapest-to-deliver data is from Bloomberg for 2y, 5y, 10y, and 30y Treasury futures. Constant omitted. t-statistics shown using robust standard errors clustered by CUSIP where * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

	Dependent Variable: Yield-to-maturity $\text{Residual}_{i,t} = \text{Actual}_{i,t} - \text{Predicted}_{i,t}$ (bps)					
	(1)	(2)	(3)	(4)	(5)	(6)
$\text{Collateral Ratio}_{i,t-1} \times \mathbb{I}(\text{Quarter-End}_t)$	0.05^{**}	0.08^{**}	0.05^{**}	0.06^{**}	0.04^{**}	0.05^{*}
	(2.50)	(2.53)	(2.41)	(2.09)	(2.10)	(1.77)
$\text{Collateral Ratio}_{i,t-1}$	0.27^{***}	0.38^{***}	0.35^{***}	0.32^{***}	0.14^{***}	0.21^{***}
	(9.30)	(11.34)	(9.63)	(10.90)	(5.26)	(7.93)
$\mathbb{I}(\text{Quarter-End}_t)$	-0.36^{***}		-0.35^{***}		-0.31^{***}	
	(−3.22)		(−3.14)		(−2.81)	
Controls						
$\text{Duration}_{i,t}$					2.20^{***}	2.35^{***}
					(9.57)	(11.83)
$\text{Bid-Ask Spread}_{i,t}$					−0.04	-0.30^{***}
					(−0.43)	(−3.63)
$\text{Maturity Remaining}_{i,t}$					-1.43^{***}	
					(−9.80)	
$\mathbb{I}(\text{Special}_{i,t})$					-0.40^{***}	-0.83^{***}
					(−4.60)	(−10.69)
$\mathbb{I}(\text{Cheapest-to-deliver}_{i,t})$					−0.05	0.25
					(−0.09)	(0.83)
$\mathbb{I}(\text{First On-the-run}_{i,t})$					-2.37^{***}	-3.13^{***}
					(−10.25)	(−12.15)
$\mathbb{I}(\text{Second On-the-run}_{i,t})$					-0.95^{***}	-1.12^{***}
					(−4.88)	(−5.93)
N	962,229	962,229	962,229	962,229	962,229	962,229
R^2	0.00	0.07	0.07	0.13	0.02	0.14
CUSIP FE	No	No	Yes	Yes	No	Yes
Date FE	No	Yes	No	Yes	No	Yes

Table 13: Window Dressing Table. Table presents the regression of $\text{Residual}_{i,t} = \alpha + \beta_1 \text{Collateral Ratio}_{i,t-1} \times \mathbb{I}(\text{Quarter-End}_t) + \beta_2 \text{Collateral Ratio}_{i,t-1} + \beta_3 \mathbb{I}(\text{Quarter-End}_t) + \gamma\prime X_t + \varepsilon_{i,t}$. Pricing residuals are estimated using the Federal Reserve's public Gürkaynak et al. (2007) estimates where $\text{Residual}_{i,t} = \text{Actual YTM}_{i,t} - \text{Estimated YTM}_{i,t}$. The independent variables are the collateral ratio (lagged by a month), a dummy equal to 1 on the last day of the quarter, and an interaction of the two. Controls include the CUSIP's duration, average bid-ask spread in the previous month in cents, maturity remaining, and indicators for trading special, cheapest to deliver, and first or second on the run. A CUSIP is defined as trading special if its repo rate is more than 1 bp lower than the DTCC GCF repo index, where its repo rate is calculated using volume-weighted repo rate on specific trades between 7:30am and 10:00am with data from the interdealer broker community. Cheapest-to-deliver data is from Bloomberg for 2y, 5y, 10y, and 30y Treasury futures. Constant omitted. t-statistics shown using robust standard errors clustered by CUSIP where * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

N-MFP			FR2052a		
	$ Billions	Share (%)		$ Billions	Share (%)
Treasuries	2,059	76.1	Treasuries	1,104	38.1
Agency MBS and CMO	569	21.0	Foreign Sovereigns	1,033	35.7
Corporate Debt	29	1.1	Agency MBS and CMO	404	13.9
Other Instrument	14	0.5	Corporate Debt	117	4.0
Agency Debt	12	0.4	Equities	95	3.3
Asset-Backed Securities	10	0.4	Agency Debt	70	2.4
Private Label CMOs	8	0.3	Private Label CMBS/RMBS	28	1.0
Equities	5	0.2	Asset-Backed Securities	25	0.9
Money Market	2	0.1	Other	20	0.7
Total	2,708	100	Total	2,896	100

Table 14: Repo Collateral Composition. Table presents the collateral composition for repos reported in the money fund N-MFP data and in the FR2052a data. N-MFP data is for December 2023, and FR2052a data is average of daily values in the first half of December 2023. I classify collateral classes in the FR2052a data into buckets that are similar to the categories provided in the N-MFP.

	All Stocks		Collateral Value > 0		Collateral Value = 0	
	(1)	(2)	(3)	(4)	(5)	(6)
Δ ln(Repo)	0.013**	0.012**	0.015***	0.016***	0.008	0.002
	(2.22)	(2.26)	(2.58)	(2.72)	(1.40)	(0.35)
Mkt-Rf	0.915***	0.903***	0.942***	0.932***	0.832***	0.803***
	(72.48)	(66.11)	(70.38)	(71.30)	(50.96)	(39.60)
HML	0.188***	0.162***	0.164***	0.124***	0.158***	0.277***
	(12.95)	(10.93)	(10.47)	(7.92)	(8.36)	(12.85)
SMB	0.814***	0.785***	0.808***	0.823***	0.743***	0.661***
	(41.85)	(37.47)	(36.61)	(39.77)	(32.27)	(23.66)
MOM		−0.078***	−0.083***	−0.083***	−0.068***	−0.083***
		(−7.45)	(−8.04)	(−7.96)	(−5.32)	(−6.21)
Constant	−0.000	−0.000	0.002	0.003	−0.004	−0.011
	(−0.05)	(−0.04)	(0.31)	(0.35)	(−0.57)	(−1.44)
N	7,490,875	7,490,875	4,578,355	5,744,796	2,912,520	1,746,079
R^2	0.07	0.07	0.08	0.08	0.06	0.06
Collateral Sample	n/a	n/a	Rolling	Full	Rolling	Full

Table 15: Spanning Tests of Repo and Common Equity Risk Factors. Table presents the regression of excess stock returns on repo growth and asset pricing factors: $r_{i,t} - r_{f,t} = \alpha + \beta_1 \Delta \ln(\text{Repo}_t) + \beta_2(Mkt_t - r_{f,t}) + \beta_3(SMB_t) + \beta_4(HML_t) + \beta_5(MOM_t) + \varepsilon_{i,t}$. Regression run at the day by company level from January 2016 to December 2023 (the period that repo data is available from FR2502a). The first two columns run the regression on the full sample of equities, not conditioning on whether that company's stock has been used as collateral. Column (3) limits the sample to stocks have been used as collateral at some point before the current month, reflecting the set of information available to investors, denoted "rolling." Alternatively, Column (4) instead limits to stocks that are used at least once in the entire sample, denoted "full." Column (5) uses the rolling sample approach to identify stocks never used as collateral (like column 3) up to the current month. Column (6), analogous to column (4), limits the sample to stocks that are never used as collateral at any point in the full sample. t-statistics shown using robust standard errors clustered by company and date where * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

A Online Appendix

A.1 Collateral Optimization

In the tri-party repo market, lenders cannot control which specific collateral they receive. For both equity and fixed-income collateral, lenders can specify more granular cuts or make manual adjustments. The buckets include Treasuries, agency debentures, international agencies, trust receipts, cash, GNMA, agency mortgage backs, agency REIMCs/CMOs, government trust certificates, SBA, sovereign debt, agency credit risk securities, municipal bonds, private-label CMOs, ABS, corporate bonds, and money market instruments. Each bucket provides more granularity. Within Treasuries, there are five types: bills, bonds, notes, strips, and synthetic Treasuries. Within agency REMICs/CMOs, lenders can choose among 15 types. The types are residuals, inverse IO floaters, IOettes, interest-only, principle-only, inverse floaters, super floaters, companion floaters, sequential and other floaters, PAC and other scheduled floaters, Z bonds, companion bonds, sequential bonds, TAC bonds, PAC and other scheduled bonds.

Cash lenders can choose the acceptable credit rating for municipal bonds, private-label CMOs, ABS, corporate bonds, and money market instruments. The lender also sets an appropriate margin for each collateral-type, and they can exclude securities in default and counterparty securities.

Cash lenders can choose whether they will accept common stock (by exchange), preferred, ETFs, UITs, ADRs, warrants or rights, mutual funds, equity indices, convertible bonds, or preferred stocks.

The general collateral optimization process takes several steps. Dealers combine their inventory held at BNYM and elsewhere along with their exposures. They give BNYM a collateral eligibility schedule that shows what collateral is acceptable for each transaction. The inputs create position eligibility data, showing which collateral is eligible for each trade, considering margins and concentration limits. The clearing bank allocates collateral by combining position eligibility with the dealer's collateral rank preference in the collateral prioritization schedule. Finally, BNYM physically moves the collateral to the appropriate box. If dealers choose to include positions held away from BNYM in the optimization, they will also need to use SWIFT, or something similar, to move positions.

A.2 Model Details

Proposition. *The convenience yield—the difference in expected returns for the Lucas trees and safe assets—is increasing in bank leverage constraints, h_t, and attenuated by bank leverage risk when $\mathcal{M}_t > 1, A'(h_t) < 0,$ and $\sigma_{h,\theta_b} \leq 0$.*

Proof. The difference in the expected returns for K and the boxed Treasury θ_b is

$$\mathbb{E}_t[r_{K,t+1} - r_{\theta_b,t+1}] \approx \gamma(\sigma_{c,K} - \sigma_{c,\theta_b}) + \sigma_{h,\theta_b} + \omega'(\mathcal{M}_t) \tag{A1}$$

which is increasing in h_t if $\mathcal{M}_t > 1$ and $A'(h_t) < 0$. Intuitively, as h_t increases, banks become more constrained and cannot issue more safe assets. When $A'(h_t) < 0$ banks shrink their balance sheets as haircuts increase, B and $\mathcal{M}$ fall, and households bid up Treasuries because there is no alternative to satiate their safe-asset demand. Agents bid up the price of Treasuries in the first period, which pushes down expected returns for Treasuries and creates a wedge between r_K and r_{θ_b}. □

The convenience yield estimates $\omega'(\mathcal{M}_t)$. The convenience yield is attenuated if it does not control for haircut covariance σ_{h,θ_b} because $\sigma_{h,\theta_b} \leq 0$, which I empirically verify in Table A1. A similar result holds if I change the definition of convenience yield to use the unboxed Treasury yield, but the attenuation bias is smaller because $\sigma_{h,\theta_b} < \sigma_{h,\theta_{ub}} < 0$.

Parameter Estimation Table A1 shows estimated covariances using annualized monthly data. To estimate the covariances, I use the Fama–French market factor and personal consumption expenditures (PCE). I convert the series to real terms using the PCE inflation index, the preferred measure of inflation of the Federal Reserve's FOMC. The result are annual percent changes in real terms. The data cover the period from 2011 to 2023.

The boxed Treasury return is calculated using the estimated yield on a 5-year Treasury when estimating the yield curve using Treasuries with collateral ratios—the share of the total Treasury CUSIP market value used as tri-party repo collateral with a money market fund—in the top tercile, lagged by one month. The return is then approximated by $-1 \times \Delta y_t \times duration_t$, where duration is 4 years. Similarly, the unboxed Treasury portfolio is calculated using Treasuries that are in the bottom tercile of collateral use. To measure haircut covariances, I proxy innovations to h_t with innovations to the repo to Treasury measure used in Table 3 multiplied by -1.

The covariance of Treasury returns and consumption growth, after rounding to two decimal points, are small and equal across the unboxed and boxed Treasuries (-0.02 and -0.02), but the covariance of their returns and bank leverage constraints are different: -0.69 and -0.76, respectively. When banks grow more constrained ($h_t \uparrow$), boxed Treasuries have lower returns than unboxed Treasuries—this is pushes the collateral spread to be larger.

Comparative Statics I plot the key comparative statics and features of the model in Figure A1 using the estimated parameters from Table A1. The top-left figure shows the geometric risk premiums for both types of Treasuries over varying equilibrium values of $\mathcal{M}_t$ (equation 5). As $\mathcal{M}_t$ goes to 0, the money premium grows, pulling down expected returns; as $\mathcal{M}_t$ increases, expected returns grow at a slowing pace: households do not bid up the Treasury's price to purchase a safe asset because there are more safe assets in the economy. The bottom-left panel shows the money premium, $\omega'(\mathcal{M}_t)$, which is large when $\mathcal{M}_t$ is smaller and falls as it increases.

The top-right panel shows the collateral spread, the difference between boxed and unboxed Treasuries expected returns from equation 6. The collateral spread is positive for all values of $\mathcal{M}_t$ and increases as $\mathcal{M}_t$ falls because the two bonds have different money weights. The bottom-right panel is the convenience yield of equation A1 estimated using the boxed Treasury's covariances, where the convenience yield with the bank leverage risk adjustment excludes the σ_{h,θ_b} term. As $\mathcal{M}_t$ decreases, the convenience yield increases because safe assets are scarcer when the bank cannot produce as many B per unit of collateral, so agents are willing to pay more for a safe asset compared to the Lucas tree.

A.3 Basis Details

There are three types of basis trades included: covered interest parity, CDS-bond, and CDS-CDX.

1. Covered-Interest Parity: The trade is long a bond paying the foreign interest rate, shorts a forward exchange swap, and shorts a bond paying domestic U.S. interest rates. I measure foreign and domestic interest rates using 1-month OIS rates. Before December 2017 CHF OIS fixings were based on TOIS and then switched to SARON fixings; I splice these two different OIS rates for CHF together to create a single time series. Similarly, EUR OIS rates were based on EONIA until January 2022 when it switched to ESTR, although the ECB provided backward looking estimates. I use the ESTR-based OIS rate when they are available, otherwise I use the EONIA-based OIS rate.

2. CDS-Bond Basis: The trade is the spread between a portfolio of 5-year North America investment grade bonds and a replicating portfolio formed from their credit default swaps. The CDS-bond basis is provided by JP Morgan Markets. See Bai and Collin-Dufresne (2019) for more details.

3. CDS-CDX basis: The trade is the spread between a portfolio of 125 5-year North America firm credit default swaps (from the CDX.NA.IG) and the spread on the corresponding CDX.NA.IG index. The CDS-CDX basis is provided by JP Morgan Markets. See Boyarchenko et al. (2020) for more details.

A.4 N-MFP Equity Data Cleaning Details

The money fund data reports collateral principally by a description of the collateral, and the data cleaning is centered on cleaning the text descriptions to fuzzy match with company names in the CRSP stock dataset.

I first identify which collateral are equities in the data. Before 2016, there is no collateral investment category for equities, and instead firms described the collateral in the collateral description field. For the period before 2016, I identify equity collateral if the description field includes any of the following keywords: stock, share, equity, equities. There is one filer that appears to have persistent transposition errors in early 2016, so I drop the handful of individual equity collateral observations with fair value above $600 million.

I identify common stocks by excluding other equity-like instruments. I do this in several steps. I exclude collateral securities with nonzero yields, stocks that are likely preferred or warrants (those with % symbol in their description, “pfd”, “preferred”, “warrant”). I exclude ETFs and ETNs by excluding collateral securities with “etn”, “etf” in its description, as well as those with the names of ETF issuers, including powershare, proshare, spdr, ishare, vanguard, wisdomtree, investco, x-trackers, and direxion.

I then clean the remaining collateral string descriptions to make the strings lower case, stripping leading and trailing spaces, extra spaces, and I remove generic phrases that might cause errant fuzzy matches. There are several patterns I remove that are clearly unrelated to the name of the stock (e.g., many descriptions end with "usd"). I remove generic terms like new, co, com, inc, corp, corporation, plc, group, financial, bancorp, therapeutic, pharmaceutical, technology, technologies, industries, holdings, services, communications, group, solutions, acquisitions, systems, and similar variants.

To merge these equities to CRSP, I select all common stocks in the CRSP dataset (sharecode 10 or 11) and I clean the CRSP company names to exclude inc, corp, co, pharmaceutical, and therapeutics. When there are multiple share classes for an individual PERMCO, I match with the largest sharecode in terms of trading volume. I calculate market capitalization by aggregating across all share classes for companies with multiple share classes.

I then merge the collateral text strings to the CRSP company names using two fuzzy matching techniques: I keep matches where the Levenshtein distance is greater than or equal to 85 or where the Levenshtein distance is greater than or equal to 50 and the token set ratio is greater than or equal to 95. I chose these thresholds to balance the number of matches while keeping a very high accuracy, possibly at the cost of not matching other strings that would have been matched at lower thresholds.

A.5 Appendix Figures

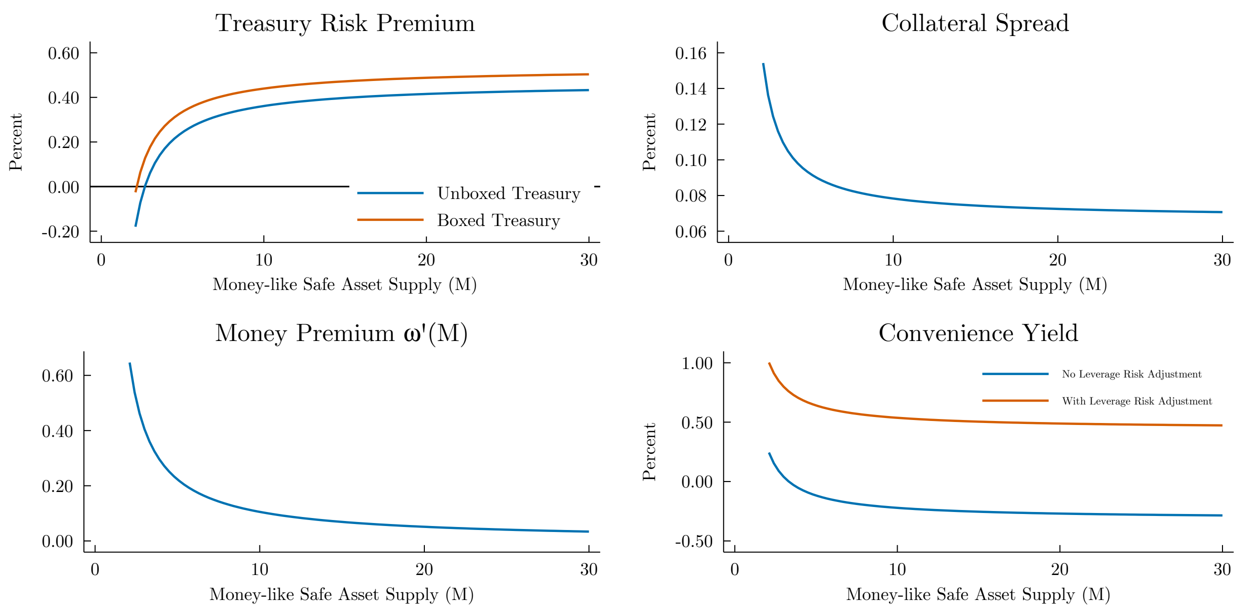

Figure A1: Comparative Statics. The top-left figure shows the geometric risk premiums for both types of Treasuries over differing equilibrium values of money-like safe assets $\mathcal{M}_t$ as given in equation 5. The bottom-left panel shows the money premium, the last term in equation 5. The top-right panel shows the collateral spread, which is the difference between the two Treasuries' expected returns as given in equation 6. The bottom-right panel is the convenience yield of equation A1 estimated using the boxed Treasury's covariances where the convenience yield with the leverage risk adjustment excludes the σ_{h,θ_b} term. I use covariances estimated in Table A1. Parameter values are $\pi_{\theta_b} = 0.9$, $\pi_{\theta_{ub}} = 1$, and $\gamma = 10$.

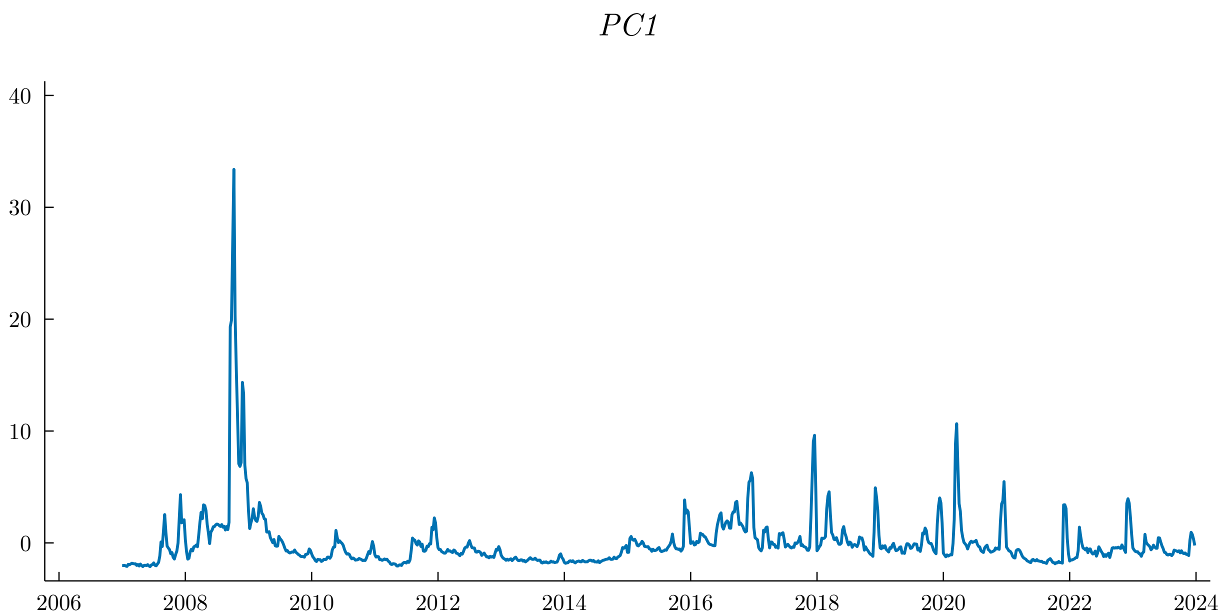

Figure A2: Bank-Intermediated Arbitrage Dislocations. Figure plots the first principal component of the absolute value of the bank-intermediated trades. The trades include 1-month covered-interest parity violations calculated following Du et al. (2018) as well as the CDS-bond and CDS-CDX basis provided by JP Morgan Markets.

A.6 Appendix Tables

Monthly Data (2011–2023)	Variable	Empirical Proxy	Mean (%)	SD (%)	Cov$(\cdot, \Delta c) \times 100$	Cov$(\cdot, h) \times 100$
Real economy	$r_K - r_f$	Fama–French Market	10.390	15.17	0.02	−4.72
Boxed Treasury	$r_{\theta_b} - r_f$	Hi Collateral Ratio Tercile	−2.702	3.63	−0.02	−0.76
Unboxed Treasury	$r_{\theta_{ub}} - r_f$	Lo Collateral Ratio Tercile	−2.697	3.62	−0.02	−0.69
Consumption	Δc_{t+1}	PCE	2.561	4.80	0.23	−1.64

Table A1: Empirical Covariances. Table presents summary statistics of real excess returns for the market and Treasury portfolios, as well as covariances with real consumption growth and innovations to bank leverage constraints. Each series is in real terms using the PCE inflation index. The risk-free rate is the 1-month T-bill rate. Summary statistics are calculated from monthly return series but reported as annualized numbers. The boxed Treasury return is calculated using the estimated yield on a 5-year Treasury when estimating the yield curve using Treasuries with collateral ratios—the share of the total Treasury CUSIP market value used as tri-party repo collateral with a money market fund—in the top tercile, lagged by one month. The return is then approximated by $-1 \times \Delta y_t \times duration_t$, where duration is 4 years. Similarly, the unboxed Treasury portfolio is calculated using Treasuries that are in the bottom tercile of collateral use. Bank leverage constraints are proxied by changes in the repo to Treasury measure used in Table 3. Sample runs from 2011 to 2023 except for the bank leverage measures which begins in 2016.

	$\Delta \ln(\text{Repo}_t)$	$\ln(\text{Repo}_t)$
	(1)	(2)
$\Delta \ln(\text{Non-Repo Liabilities}_t)$	0.36^{***}	
	(5.45)	
$\ln(\text{Non-Repo Liabilities}_t)$		0.84^{***}
		(11.01)
N	1,975	1,988
R^2	0.02	0.68

Table A2: Repo and Non-repo Liabilities. Table presents the regression of repos outstanding on non-repo liabilities outstanding. Daily data, constant omitted. First column is daily changes and second column is daily (log) levels. Data aggregated from FR2052a. t-statistics shown using heterosketastic and autocorrelation consistent standard errors using the Newey and West (1994) automatic lag selection procedure where * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

	Value-Weighted	1y	2y	3y	5y	7y	10y	20y	30y
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Constant	0.53***	0.82***	0.51***	0.15***	0.20***	0.88***	2.05***	2.22***	−1.17***
	(16.78)	(9.35)	(8.21)	(2.76)	(3.67)	(8.52)	(11.82)	(13.81)	(−6.86)
N	3,231	3,231	3,231	3,231	3,231	3,231	3,231	3,231	3,231

Table A3: Treasury Collateral Spread Significance by Tenor. Table presents the regression of the value-weighted Treasury collateral spread (column 1) or the collateral spread at various tenors on a constant. t-statistics are reported in parentheses using robust standard errors clustered by month.

	High Tercile, MAPE	High Tercile, RMSE
	(1)	(2)
Low Tercile, MAPE	0.93***	
	(19.08)	
Low Tercile, RMSE		0.90***
		(16.81)
Constant	−0.00	0.00
	(−0.44)	(0.51)
N	3,231	3,231
R^2	0.92	0.89

Table A4: Collateral Spread Estimate Error Regression. Table presents the regression of two measures of pricing error from the yield curve model used to estimate the collateral spread: the mean absolute pricing error (MAPE) and the root mean squared error (RMSE) of the pricing error. The pricing error is the difference between the model's estimated yield for a CUSIP given its maturity remaining compared to the observed yield. The pricing error is in percentage points. The left hand side variable in each regression are the pricing errors from the high-collateral ratio tercile yield curve, and the right hand side is the pricing errors from the low-collateral ratio tercile yield curve. t-statistics are reported in parentheses using heterosketastic and autocorrelation consistent standard errors using the Newey and West (1994) automatic lag selection procedure.

	Mean (bps)	ρ
Benchmark Estimate		
Value-Weighted	0.53	1.00
Static Weights	0.56	0.99
Including On-the-Runs		
Value-Weighted	0.56	0.95
Static Weights	0.58	0.95
Excluding Cheapest-to-Deliver		
Value-Weighted	0.52	0.98
Static Weights	0.55	0.98
Excluding 25 Most Special CUSIPs		
Value-Weighted	0.42	0.83
Static Weights	0.44	0.81

Table A5: Treasury Collateral Spread with Alternate Assumptions. Table presents the average collateral spread when estimated using different filters: the first row is the benchmark estimate. Value-weighted indicates the weights are taken from Treasury market values by maturity bucket lagged by a month, static weights use the average monthly weight. Alternative assumptions are relative to the benchmark (e.g., excluding a variable is excluding that variable in addition to the benchmark filters). "Include on-the-runs" changes the sample to include first and second on-the-run CUSIPs. "Excluding Cheapest-to-Deliver" excludes the cheapest-to-delivery CUSIPs identified by Bloomberg for 2y, 5y, 10y, and 30y Treasury futures. "Excluding 25 Most Special CUSIPs" excludes the most special CUSIPs after ranking by their average specialness over the month, where specialness is the spread between the DTCC GCF repo index and the volume-weighted repo rate on trades between 7:30am and 10:00am using data from the interdealer broker community.

	Event			Placebo		
	(1)	(2)	(3)	(4)	(5)	(6)
	Control	Treated	Treated−Control	Control	Treated	Treated−Control
$\mathbb{I}$(Post)	−0.909***	0.977***	1.886***	0.071	−0.495**	−0.567**
	(−2.99)	(6.15)	(3.77)	(0.25)	(−2.08)	(−2.51)
Constant	0.822***	0.180**	−0.642*	0.464***	0.792***	0.327*
	(4.52)	(2.06)	(−1.72)	(2.80)	(3.81)	(1.90)
N	209	209	209	210	210	210

Table A6: Collateral Spread Estimated from Treated and Control Groups during July 2011 Euro Crisis. Table presents the regression of different Treasury collateral spreads on a post dummy: Collateral $\text{Spread}_t = \alpha + \beta\mathbb{I}(\text{Post}) + \varepsilon_t$. The collateral spread is either estimated from the "control" or "treated" sample, where treated indicates high collateral ratio bonds used more by European banks in that month, and control indicates high collateral ratio bonds used less by European banks in that month, analogous to the treated and control sample in the first three columns of Table 12. Sample is daily from February 2011 to November 2011, and post is equal to 1 for dates after or on July 11, 2011. Treated−Control column is the regression of the difference in the collateral spreads for treated and control on a post dummy. The last 3 columns repeat the regression in a placebo test with the sample and post dummy moved forward one year, running from February 2012 to November 2012 with post equal to 1 for dates after or on July 11, 2012. t-statistics shown using heterosketastic and autocorrelation consistent standard errors using the Newey and West (1994) automatic lag selection procedure where * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.