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The Collateral Premium and Levered Safe-Asset Production*

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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 present a model to describe private safe-asset production when intermediaries face leverage constraints. I measure bank leverage constraints using bank-intermediated basis trades. The collateral premium—a strategy long Treasuries used more often as repo collateral and short Treasuries used less often—has a positive expected return of 22 basis points per year because the collateral premium compensates for bank leverage risk.

JEL Codes: E40, E51, G12, G20

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1 Introduction

Banks produce money-like safe assets using leverage and collateral. But banks' ability to do so changes because they may become more or less leverage constrained over time. 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 develop 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 that are used as collateral.

I look within U.S. Treasury collateral backing a type of short-term safe asset—repurchase agreements (repos)—and document a collateral premium. Treasuries used as collateral have higher average returns than Treasuries not used as collateral, even after controlling for observables. I show that banks prefer to use the least money-like Treasuries as collateral, consistent with Greenwood et al. (2015)'s finding that long-term Treasuries are less money-like because of their high interest rate risk. With costly short-term equity issuance, Treasuries' collateral value depends on bank leverage constraints, leading to an implicit inefficiency: Banks use longer-term safe assets as collateral, but using them as collateral makes them riskier because their collateral value becomes linked to bank leverage constraints.

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 has low consumption covariance and is therefore information-insensitive. There are two types of safe assets: short-term safe assets that are money-like, liquid transaction media, and long-term safe assets that store value because they have minimal credit risk. Safe assets require either a government guarantee, like a Treasury bond, or collateral, like a repo backed by a security. By design, investors have little incentive to produce private information on a safe asset, and agents can use them as payment or as a store of value without fear of adverse selection. Safe assets earn the convenience yield, the non-pecuniary return on assets that provide safety or liquidity.

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 cannot produce safe assets without incremental leverage or costly balance sheet adjustments because they do not issue equity regularly. Variation in the banking system's leverage constraint leads to variation in the banking system's ability to produce private safe assets—a source of risk for collateral. Banks may be leverage constrained because of regulatory limits or market discipline, when private lenders avoid providing additional funding to risky banks.

I build 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 predicts that the collateral premium—the difference in expected returns for Treasuries used as collateral and those that are not—is positive because it compensates investors for bank leverage risk. The expected return on Treasuries used as collateral compensates the holder for the risk that bank leverage constraints might increase, reducing its value as collateral. All Treasuries hedge contractions in the safe-asset supply, but Treasuries used as collateral are worse hedges than Treasuries not used as collateral.

I use CUSIP-specific collateral data collected from money market mutual fund investments in the tri-party repo market to explore the model's asset pricing implications. The data are monthly and run from 2011 to 2018, providing more than one million CUSIP-month observations. I observe both sides of the repo—the money market mutual fund lender and the borrowing financial institution—which provides variation in both the time series and cross section. The data allow me to identify which Treasury CUSIPs banks used as collateral. For each Treasury CUSIP, I calculate their collateral ratio (CR), the share of a CUSIP's total market value used as repo collateral. In my sample, banks use 2.4 percent of each Treasury CUSIP, on average, as collateral provided to money funds.

I document that Treasuries commonly used as collateral have higher expected returns than Treasuries not used as collateral, even after controlling for observables. After I sort Treasury CUSIPs into terciles based on their collateral ratio, the collateral premium is a strategy long Treasuries in the top tercile and short Treasuries in the bottom tercile. The collateral premium has an annualized average return of 22 basis points after controlling for liquidity.

Banks deliberately choose which CUSIPs to use as collateral, and they spend considerable time and resources forecasting which Treasury CUSIPs have the lowest opportunity cost to pledge as collateral. They want to keep the highest-quality Treasuries for themselves or to use in more profitable ways. I confirm this intuition and show that banks use less liquid and longer-dated bonds as collateral more often.

The model shows that expected returns for different types of safe assets depend on their covariance with bank leverage constraints. I measure bank leverage constraints using data from Ross and Ross (2022) that calculate dozens of bank-intermediated basis trades and aggregate the returns to estimate bank leverage constraints. When banks are not leverage constrained, they can lever up and push the bank-intermediated arbitrage returns toward zero. Arbitrage returns are high in absolute value when banks cannot lever up and arbitrage the basis toward zero.

I argue that the collateral premium is positive and economically large because it compensates for bank leverage risk. Treasuries are useful as collateral if intermediaries can pledge them, which mechanically requires the bank to take on incremental leverage. I show that the collateral premium is positive because it compensates for bank leverage risk in several ways.

First, I show that the collateral premium covaries with innovations to bank leverage constraints. Second, I show that low-CR Treasuries' yields fall by more than high-CR Treasuries' yields when banks become more leverage constrained. Third, bonds used as collateral must have worse returns when leverage constraints increase if the collateral premium is compensation for bank leverage risk; otherwise, there is no risk that requires compensation. I show that Treasuries used as collateral by leverage-constrained banks had lower returns than Treasuries held by other banks in the earliest stages of the European sovereign debt crisis. Fourth, I perform an event study and show that Treasuries have negative abnormal returns after dealers begin using that CUSIP more intensively as collateral. I reject the hypothesis that the Treasuries have lower realized returns because of other risk-compensated characteristics. Fifth, I show that an individual bank's performance in the Federal Reserve's stress tests is tightly linked to the abnormal returns of the Treasury CUSIPs that the bank uses as collateral.

Relation to the Literature This paper contributes to the literature by documenting Treasuries' collateral premium, its relationship with bank leverage, and providing details about the collateral allocation process in tri-party repo. Hu et al. (2019) use similar repo 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. 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 re-use. 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. He et al. (2021) study the Treasury market's dysfunction during the COVID-19 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 in the form of 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. In the U.S., primary dealers had $4 trillion of repo outstanding in 2018. Duffie (1996) describes repo mechanics in detail.

Intermediaries provide deposit account equivalents to institutional cash pools with repo. Repos-as-deposit-accounts 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 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—always short term liabilities—without incremental leverage. 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 the bilateral market, Counterparties interact directly. Few data exist for the bilateral market despite its apparent size. 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. For example, 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: Most often, investors want that specific Treasury because the bond is on the run or is the 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. Because my data come from money market fund filings, I have data on only tri-party repo collateral.

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 to select which CUSIPs to use as collateral and decide 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, as the custodian holds both box accounts on its balance sheet.

Dealers prefer to place collateral with the lowest outside option in the box. Banks can often finance a Treasury trading special at lower rates outside the box in security-specific bilateral repos.[1] 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 frictions involved in moving collateral in and out of the box mean 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

[1]Dealers often use on-the-run Treasuries as general collateral—which is not a mistake. 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.

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—my focus—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

Setup I build 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.

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 premium 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 $\mu_h = 0$ and $\gamma\sigma_c\sigma_h = 0$, 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 $\log\left(1 + \Omega'(\mathcal{M}_{t+1})\pi_{\theta_{ub}}\right) = \mu_h + \sigma_h\varepsilon_{t+1}$, $r_{\theta_{ub},t+1} = \log(1 + R_{\theta_{ub},t+1})$, 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. The risk-free rate is $r_{f,t+1} = -\log(\beta) + \gamma\mu_c - {}^1\!/_2\gamma^2\sigma_c^2$. An analogous result holds for the boxed Treasury. The online appendix provides additional discussion of the expected return of Treasuries in the model.

The collateral premium 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 premium 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 premium 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.

□

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.

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 premium on the convenience yield.

4 Data

I use two data sets to test the model's implications and measure the collateral premium. The first data set includes collateral data from tri-party repos with money market funds. The second data set measures bank leverage constraints using bank-intermediated basis trades.

4.1 Collateral

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. I use N-MFP/2 data that is collected by the Office of Financial Research as part of its U.S. Money Market Monitor.[2]

[2]See `https://www.financialresearch.gov/money-market-funds`.

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 do 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 text collateral descriptions.

I focus on Treasury note and bond collateral in repos. Given the coupon rate and the maturity, I match Treasuries to their CUSIPs. My data include roughly 9.6 million collateral-month observations across all collateral types. I match about 1 million of these observations to Treasury CUSIPs, which I merge to the daily CRSP (Center for Research in Security Prices) Treasury data set. 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 also hand-clean the repo counterparty data because the same firm may conduct repos using different legal entities. I manually identify 70 unique cash borrowers of the roughly 2,800 different names used as repo counterparties in the data, including banks, broker-dealers, government entities (the Federal Reserve, Freddie Mac, and the Federal Farm Credit Banks), mortgage real-estate investment trusts, and others.

Table 2 presents summary statistics for the repo deals in my sample, focusing on Treasury collateral repos. There are about 302,000 repo transactions in the sample, and those repos have about 1 million collateral observations, implying the average repo has about three different CUSIPs as collateral. For Treasury repos, there are 238 cash lenders (money market mutual funds) and 1,819 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 maturity, remaining maturity, and duration than the full Treasury universe.

Collateral Use Persistence 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. 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 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 as collateral in a month with values of \$90 and \$10, 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 for most at the 12-month horizon. The average point estimate at the 1-month horizon is 0.34 and at the 12-month horizon is 0.16.

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 box. Almost all dealers with an average of more than \$5 billion of pledged Treasury collateral have significant collateral share correlations.

Measuring the Collateral Premium I calculate the collateral ratio (CR) for each Treasury CUSIP i to measure the intensity of that Treasury's use as collateral in month t:

$$CR_{i,t} = \left(\frac{\text{Market Value of Treasury CUSIP } i \text{ used as Repo Collateral}}{\text{Market Value of Treasury CUSIP } i} \right)_t . \tag{8}$$

I exclude Treasury CUSIPs pledged by the Federal Reserve when calculating a CUSIP's collateral ratio. 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 2.4 percent, with a cross-sectional standard deviation across CUSIPs of 2.3 percent and a time-series standard deviation of 1.3 percent (i.e., a CUSIP's own collateral ratio volatility over time). Figure 3 provides a box plot of the equal-weighted collateral ratios across CUSIPs by year; the average and variance of CR grow through the sample, the latter shown by the growing interquartile range.

Table 3 correlates Treasury collateral ratios on bond observables. Treasury CUSIPs with higher collateral ratios are less liquid, older, have longer maturity remaining, and have higher duration. The last column shows that Treasury CUSIPs have lower collateral ratios when they are lent by riskier banks, which I measure using CDS spreads. I calculate the CUSIP-specific CDS spread of banks using that CUSIP as collateral, and I weight by the amount of collateral pledged by the dealer. For example, if two dealers both pledge \$100 of a CUSIP as collateral and the dealers have CDS spreads of 0 and 100 bps, then the average CDS spread for that CUSIP is 50 bps. I provide additional details on the CDS data in the online appendix.

The riskiness of dealers pledging collateral varies considerably over time, leading to differential exposures to bank leverage risk across Treasuries. Figure 4 shows the average and range of the CUSIP-specific CDS spreads each month. During the euro crisis, the variation in CUSIP-specific CDS spreads increased dramatically. Some Treasury CUSIPs were pledged by dealers with an average CDS spread below 100 bps, and other CUSIPs were pledged by dealers with an average CDS spread above 400 bps.

I construct the collateral premium strategy by sorting Treasuries by their collateral ratios and liquidity. The collateral premium is the return an investor would earn by holding a portfolio long Treasuries used as collateral often and short Treasuries used as collateral less often. I double-sort Treasuries by their liquidity and collateral ratio to control for liquidity differences:

$$\begin{aligned}\text{Collateral Premium} =& \frac{\text{Hi CR/Low Liq} + \text{Hi CR/Mid Liq} + \text{Hi CR/High Liq}}{3} \\ &- \frac{\text{Lo CR/Low Liq} + \text{Lo CR/Mid Liq} + \text{Lo CR/High Liq}}{3}.\end{aligned} \tag{9}$$

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. I measure liquidity using the monthly average of daily bid-ask spreads for each Treasury CUSIP, also lagged by one month. Following the sorting procedure in Asness et al. (2013), I independently sort each Treasury CUSIP into a CR tercile and a liquidity tercile using the lagged data.

Table 4 gives the annualized average return for the sorts. The annualized average collateral premium, controlling for liquidity, is 22 bps per year with a standard deviation of 1.66 percent. A portfolio long Treasuries in the high-CR tercile and short Treasuries in the low-CR tercile without controlling for liquidity has an average annualized return of 30 bps with a standard deviation of 2.52 percent. Table 5 reports the average returns and standard deviations for the tercile sorts. Averaging across the bottom High−Low row gives the collateral premium of 22 bps per year.

Figure 5 plots the cumulative return over the full sample. Average annual returns of two-year and five-year Treasury notes between 2011 and 2018 were 0.83 percent and 2.34 percent, so the collateral premium is economically large by comparison, 27 percent of a two-year note's return and 9 percent of a five-year note's return. As expected, the collateral premium is most volatile during the European sovereign debt crisis in 2011 and 2012, as waves of good and bad news led to large swings. Notably, in the fall of 2011 the collateral premium had large net gains as markets digested news about central bank support for FX swaps and political progress on broader recapitalization plans for European banks.

Tercile sorts are useful because they provide tractable ways to mimic investable strategies, but they collapse information along other dimensions. I use nearest-neighbor matching to estimate the collateral premium more precisely. I match Treasuries used often as collateral to their nearest-neighbor Treasury not used often as collateral. I sort Treasuries into two equal-sized buckets: high- or low-CR, where the latter has many Treasuries with $CR = 0$. I match Treasuries to their nearest neighbor in the other bucket using duration, liquidity, and maturity remaining each month. Table 6 shows the matching results. Each column shows the annualized average difference in monthly returns between Treasuries in the high- and low-CR halves using different distance metrics. The nearest-neighbor match shows the collateral premium is between 13 and 16 bps, lower than the tercile-sorted collateral premium, as expected, but not far from the tercile-sorted 22 bps estimate and always positive.

4.2 Bank Leverage Constraints

I use data from Ross and Ross (2022) to estimate bank leverage constraints using bank-intermediated basis trades identified in Boyarchenko et al. (2020). I proxy bank leverage constraints using bank-intermediated arbitrage returns across two products: interest rates and foreign exchange. The rates trades include cash U.S. Treasury versus swaps (2y, 5y, 10y, 20y, 30y) and the cheapest-to-deliver cash Treasury versus Treasury futures (2y, 5y, 10y, 20y, 30y). The foreign exchange trades are covered interest parity trades in the spirit of Du et al. (2018) for AUD, CAD, CHF, DKK, EUR, GBP, JPY, NOK, NZD versus USD, at one-week, one-month, and three-month maturities, using overnight indexed swap (OIS) or interbank offered rates. The online appendix describes the assumptions for secured and unsecured funding costs, initial margin, and variation margin to calculate the bases.

There are many advantages to using market data to estimate bank leverage constraints. 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. Ross and Ross (2022) focus on arbitrages that are bank-intermediated and aggregate them together to minimize idiosyncrasies in any given market. There is good reason to believe that bank balance sheet measures do not fully reflect intermediaries' true economic leverage due to window dressing, netting across contracts, and risk weights.[3] Balance sheet data are often unavailable for non-public or foreign intermediaries. Moreover, the arbitrages are not exotic; intermediaries can trade them easily. Because banks from many countries participate in these markets, the measure captures the marginal value of global intermediaries' wealth at a daily frequency.

The measure is not without drawbacks. First, it is limited to public data. When possible, Ross and Ross (2022) approximate the costs with public data but cannot include institution specific funding costs, haircuts, or capital charges. 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. Second, none of the basis trades are true arbitrages. They are exposed to noise-trader risk, horizon risk, and model risk. Perhaps most important, the measure of the annualized basis trade returns assumes no change in funding costs. The assumption is reasonable in normal times but likely underestimates distortions in bad times.

Ross and Ross (2022) provide a daily approximation of bank leverage constraints by aggregating the basis trades to a single measure called *ArbConstraint*. They also estimate daily innovations to bank leverage constraints, *ArbFac*, following the method of He et al. (2017). The online appendix describes the aggregation and daily innovation methodology.

5 Empirical Results

I show that the collateral premium is positive because it is compensation for bank leverage risk. Treasuries are useful as collateral when intermediaries can pledge them, which mechanically requires the bank to use leverage. There are fewer money-like safe assets available when banks become constrained because banks produce fewer private safe assets. Investors then bid up the prices of the remaining safe assets, like Treasuries, which is equivalent to pushing their yields down. When banks become leverage constrained, unboxed Treasuries' prices increase more than boxed Treasuries' prices because banks are less willing to buy and hold boxed Treasuries when they are less useful as collateral.

[3] 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.

I show that the collateral premium is positive because it loads on bank leverage risk in five ways. First, I show that the collateral premium covaries with innovations to bank leverage constraints. Second, I show that low-*CR* Treasuries' yields fall by more than high-*CR* Treasuries' yields when banks are leverage constrained. Third, I show that bonds used as collateral by leverage-constrained banks—which I define as European banks in the earliest stages of the European sovereign debt crisis—had lower returns than Treasuries held by other banks. Fourth, I perform an event study and show that Treasuries have negative abnormal returns after banks begin using that specific CUSIP as collateral. I reject the hypothesis that the CUSIP has lower returns because of other risk-compensated characteristics. Fifth, I use the Federal Reserve's annual stress tests as an exogenous shock to bank leverage constraints to show abnormal Treasury returns are linked to the specific banks that are using that Treasury as collateral. I find that when banks' leverage constraints ease, the Treasury CUSIPs they hold as collateral have higher returns.

The Collateral Premium and Innovations to Bank Leverage Constraints Table 7 shows that daily innovations to bank leverage constraints covary with the collateral premium, even after controlling for changes in the riskiness of the banking system and changes in Treasuries' liquidity. The first column shows the results from regressing the collateral premium on *ArbFac* with no controls or fixed effects. A two standard deviation increase in *ArbFac* corresponds to a concurrent collateral premium return of 0.9 bps (column 3). When not sorted to control for liquidity, the collateral premium is positively correlated with *ArbFac* but not significantly, as shown in the last three columns.

Yields by Bank Constraint State If the collateral premium is compensation for bank leverage risk, then boxed bonds should have relatively lower prices—and higher yields—than unboxed bonds in bad states when marginal utility over money-like safe assets is high. I show that yields for boxed and unboxed Treasuries fall—equivalent to prices increasing—when banks are constrained, but unboxed Treasuries' yields fall more than boxed Treasuries' yields. In other words, both boxed and unboxed Treasuries hedge contractions in the safe-asset supply, but boxed Treasuries are worse hedges than unboxed Treasuries. I calculate the value-weighted yield to maturity for each leg of the collateral premium analogous to equation 9. I define high and low bank constraint states by sorting *ArbConstraint* into buckets based on the median level of *ArbConstraint*.

Table 8 shows the difference in high- and low-*CR* portfolios' yields, less the one-month T-bill rate. The table shows the *CR* and liquidity double-sorted portfolios' yields. The low-*CR* portfolio has lower yields than the high-*CR* portfolio. Consistent with the model intuition, yields fall when moving from the unconstrained to the constrained bank leverage state. The effect is equivalent to their prices increasing. Bank leverage risk shows up in the table's last row. The low-*CR* portfolios' yields fall by more than those of the high-*CR* portfolios when banks become constrained. The yield spread for the double-sorted portfolios grows 9 bps.

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 the collateral premium's primary driver. Bonds used as collateral must have worse returns in bad states if the collateral premium 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 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:

$$r_{i,t} = \alpha + \gamma_1 \mathbb{I}(\text{Post}) + \gamma_2 \mathbb{I}(\text{Treated}) + \gamma_3 \mathbb{I}(\text{Post}) \times \mathbb{I}(\text{Treated}) + \beta' X_t + \varepsilon_{i,t}, \tag{10}$$

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 a on-the-run indicator variable. I weigh the regression with the market value of each CUSIP. I define $\mathbb{I}(\text{Post}) = 1$ if the date is after 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 9 presents the regression results. The first two columns use high-CR bonds, and the last two columns use low-CR bonds. The main result is shown in the $\mathbb{I}(\text{Post}) \times \mathbb{I}(\text{Treated})$ row in the first two 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 57 bps lower average monthly returns, as shown in column (2). Bonds not used as collateral—low-CR bonds—should not have as large of a return differential depending on whether European or non-European banks pledged them. I confirm this logic in columns (3) and (4), where the interaction term coefficient is weakly negative and not different from zero.

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 and significant for all specifications. Figure 6 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.

Actual versus Predicted Event Study When a CUSIP jumps from low to high collateral use, it becomes riskier as it now loads more on bank leverage risk, and it should have lower realized returns after the event. I show that Treasuries have lower realized returns after banks use them more as collateral. I also show that the lower returns are not due to other risk-compensated characteristics. I perform an event study for Treasury returns around the event of CUSIPs moving from the low-CR tercile to the high-CR tercile. I find that bonds have negative cumulative abnormal returns after making the jump. The result is consistent with the bond earning a larger risk premium once dealers use the bond as collateral more because the bond now loads on bank leverage risk.

I define a jump event as the first date a CUSIP moves from a low-CR tercile directly to the high-CR tercile. I use the 10-year Treasury return as the benchmark to estimate abnormal returns. I estimate the CUSIP's beta to the benchmark using daily data in the quarter before the event: $r_{i,t} = \alpha_i + \beta_i r_{10yr,t} + \epsilon_{i,t}$. The abnormal return, $AR_{i,t}$, is the difference between the predicted return and the actual return.

In Table 10 I test whether CUSIPs have negative abnormal returns after they make the jump to higher collateral use by regressing a CUSIP's abnormal returns on a dummy equal to 1 after the CUSIP makes the jump and 0 before. The first two columns show the average abnormal return is negative in the 3 days (10 days) after the jump in column 1 (2). Column 1 shows that the average abnormal return is 1.8 bps lower in the 3 days after the jump than in the 3 days before the jump.

The blue line in Figure 7 shows the value-weighted average cumulative abnormal return. There is no obvious pattern in the average cumulative abnormal return for Treasuries before the event. After the event, realized abnormal returns are lower.

Do Treasuries have lower realized abnormal returns because banks use them more as collateral, or do they exhibit some characteristic that makes banks more likely to use them as collateral? I compare abnormal returns around the *actual* event to a *predicted* event to answer the question.

I forecast CR_{t+1} using a Treasury CUSIP's observables available at time t. The predicted event is the first date when I predict a Treasury CUSIP will jump from the low-CR to the high-CR tercile. Suppose the cumulative abnormal return falls after the predicted event. In that case, the actual event study shows that bonds with specific characteristics have lower returns and that those same characteristics are why banks use the bonds as collateral more often.

I estimate $\mathbb{E}_t[\text{Tercile}(CR_{t+1}) = \text{High} \mid \text{Tercile}(CR_t) = \text{Low}]$ with a one-step-ahead cross-validated LASSO with candidate explanatory variables including maturity remaining, age, and dummies for whether the security is a bond or note. The LASSO also includes lagged variables: duration, the market value of the issue outstanding held by the public, yield, change in yield, monthly return, liquidity, and collateral ratio. I calculate abnormal returns by estimating the CUSIP's beta to the 10-year benchmark Treasury returns using daily data over the quarter before the event.

Table 10 columns (3) and (4) show the results from the predicted event study, and the red line in Figure 7 shows the value-weighted average cumulative abnormal return from the predicted event study. I find that abnormal returns after the predicted event are not statistically different from zero. In contrast, the abnormal returns after the actual event are different from zero and negative. I reject the hypothesis that some other risk-compensated characteristic explains why banks use the bonds more often as collateral.

Stress Tests and Collateral Returns In the post-crisis era, the Federal Reserve conducts annual stress tests for large banks. The Comprehensive Capital Analysis and Review (CCAR) test incorporates the bank's capital plans and studies whether the bank maintains post-stress capital adequacy given an adverse scenario set by regulators. The Fed can object to a bank's capital plans if the bank does not maintain capital adequacy in the CCAR. The Fed can also request that a bank resubmits its capital plans. The CCAR's results are important for banks' ability to pay dividends, lever up, or expand their balance sheets.

The Federal Reserve's annual bank stress tests provide a natural experiment to identify the effects of bank leverage constraints on collateral returns. Often, increases in bank leverage constraints coincide with a flight to safety and increased risk aversion, which boosts Treasuries' prices. Such dynamics are absent in a small window around the announcement of stress test results. The stress tests can change bank leverage constraints, but the announcements of the tests' results does not coincide with bad times and a concomitant flight to safety.

I show that a bank's performance in the stress test has a material and priced effect on the collateral that the bank pledges. First, I calculate abnormal returns for each bank in my sample and for each Treasury used as collateral. I calculate abnormal returns for banks by regressing that bank's stock excess return on the Fama–French excess market return using daily returns over the previous quarter before the results announcement. I calculate abnormal returns for each Treasury CUSIP used as collateral in a similar process using the 10-year Treasury return index from CRSP.

Treasury CUSIPs are typically used as collateral by several banks, so I calculate a Treasury CUSIP-specific value-weighted abnormal bank stock return with weights given by the bank's use of that CUSIP as collateral as a share of all banks' use of that CUSIP as collateral in each month. For example, if only three banks use a CUSIP as collateral in equal amounts, then the value-weighted abnormal bank stock return assigned to that CUSIP would be the average of the three banks' abnormal returns. I lag the value weights by one month to reflect the data lag. I provide additional details on the banks included and the dates of the tests in the online appendix.

The first three columns of Table 11 show the regression of Treasury CUSIP abnormal returns on that CUSIP's corresponding value-weighted abnormal bank stock return on the first trading day following the stress test results announcement. The table shows that Treasury CUSIPs' abnormal returns are strongly positively related to the abnormal returns of the banks that use that Treasury as collateral: good news for the bank is good news for the collateral that specific bank uses. When banks' leverage constraints ease, the Treasury CUSIPs they hold as collateral have higher returns. The test uses only the first trading day following the test because the identifying assumption is that bank leverage constraints are changing without being confounded by a flight to safety or risk-off sentiment, which is likely true over such a small time frame.

One concern is that it doesn't matter which bank uses a bond as collateral, but instead that Treasury abnormal returns could be explained by any bank's abnormal returns in the day after the stress tests. I reject this possibility with a placebo test. I calculate an equal-weighted abnormal bank stock return for each Treasury CUSIP using only the banks that do not use that CUSIP as collateral. If collateral returns covary only with a bank-wide risk factor, then a regression of abnormal Treasury returns on any combination of banks' abnormal returns would yield a positive regression coefficient. The last three columns of Table 11 shows this is not true for the day following the stress test announcements. Abnormal Treasury returns are linked to which specific banks are using that Treasury as collateral.

6 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 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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7 Figures

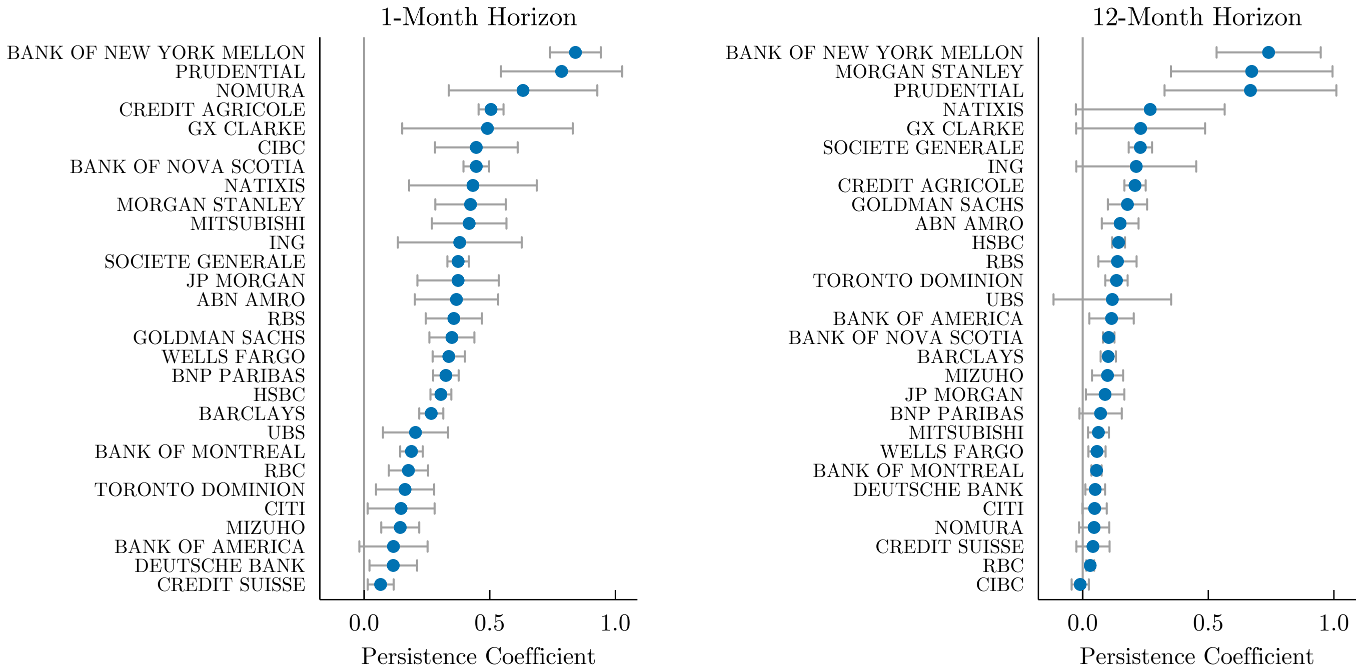

Figure 1: Time-Series Persistence of Boxed Treasuries. Plot gives the estimated beta coefficient with 95% confidence intervals from the regression Collateral $\text{Share}_{i,d,t} = \alpha + \beta\text{Collateral Share}_{i,d,t-1} + \varepsilon_{i,d,t}$, where Collateral $\text{Share}_{i,d,t}$ is the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

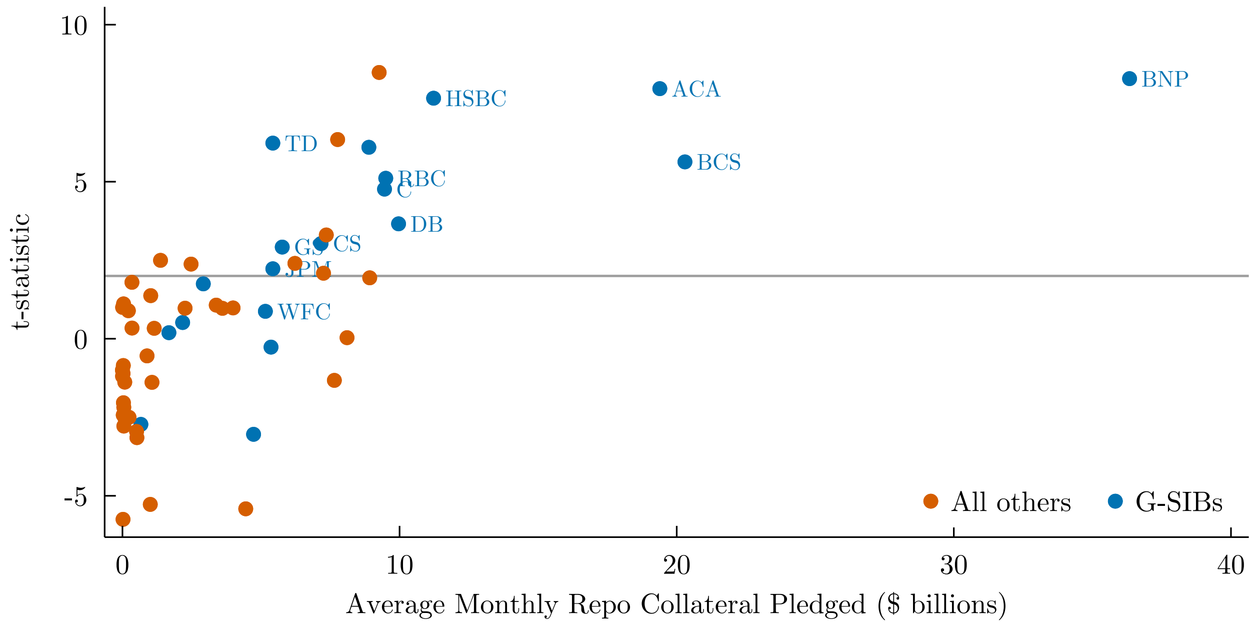

Figure 2: Cross-Sectional Persistence of Boxed Treasuries. Plot gives the t-statistics of the beta coefficient from the regression Collateral Share$_{i,d,t} = \alpha + \beta$Collateral Share$_{i,SocGen,t} + \varepsilon_{i,d,t}$, where Collateral Share$_{i,d,t}$ is the collateral share of CUSIP i for dealer d at time t across all the Treasuries used as collateral by that dealer at that time, 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.

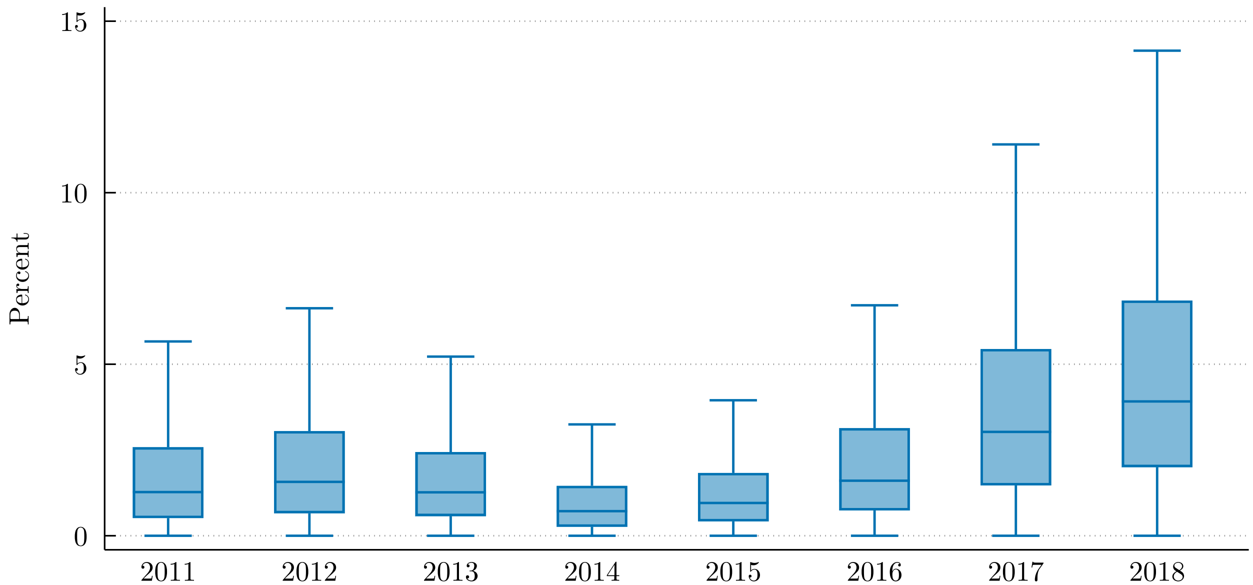

Figure 3: Time-Series Variation in Collateral Ratio. Box plot of the collateral ratio at the month-CUSIP level by year, equal-weighted across CUSIPs. The blue bar in the middle of the box is the average collateral ratio in that year, the blue box represents the interquartile range, and the lines up and down trace out the lower- and upper-adjacent values.

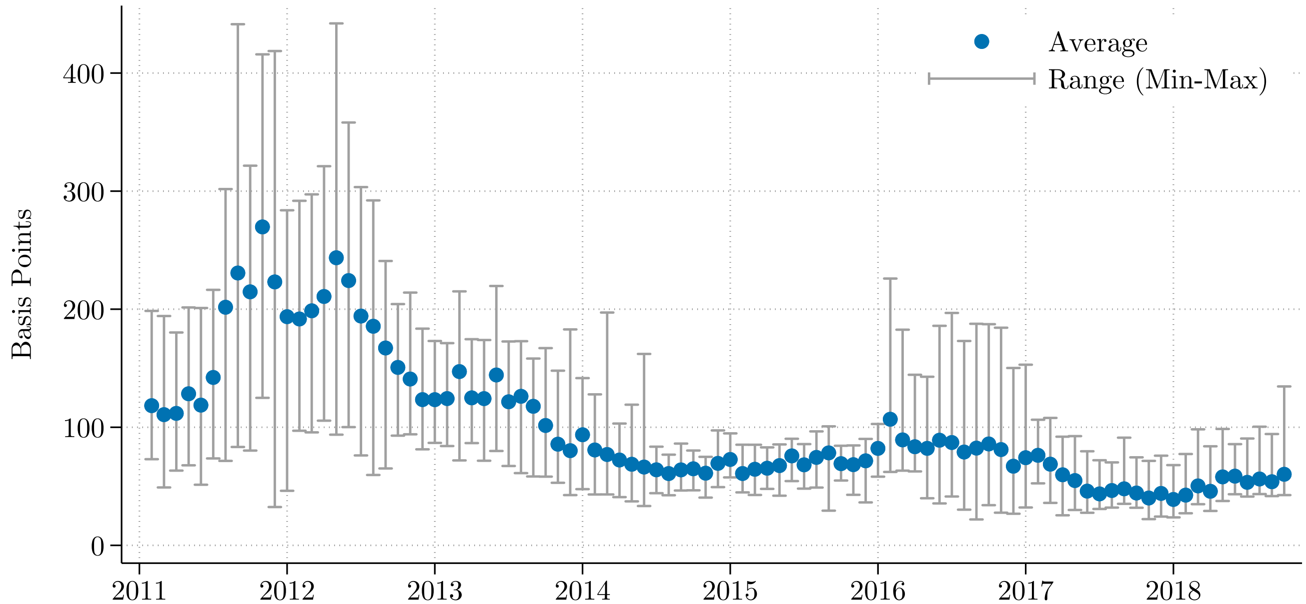

Figure 4: CDS Spread Variation Across Treasury Repo Collateral. Figure shows the range and average of CUSIP-specific CDS spreads over the full sample. The CUSIP-specific CDS spread is calculated by averaging the CDS spreads of the dealers using a specific CUSIP as collateral; only dealers with traded CDS are included. I then collapse the CDS spreads to the CUSIP-level, weighting by the dealers' use of that collateral.

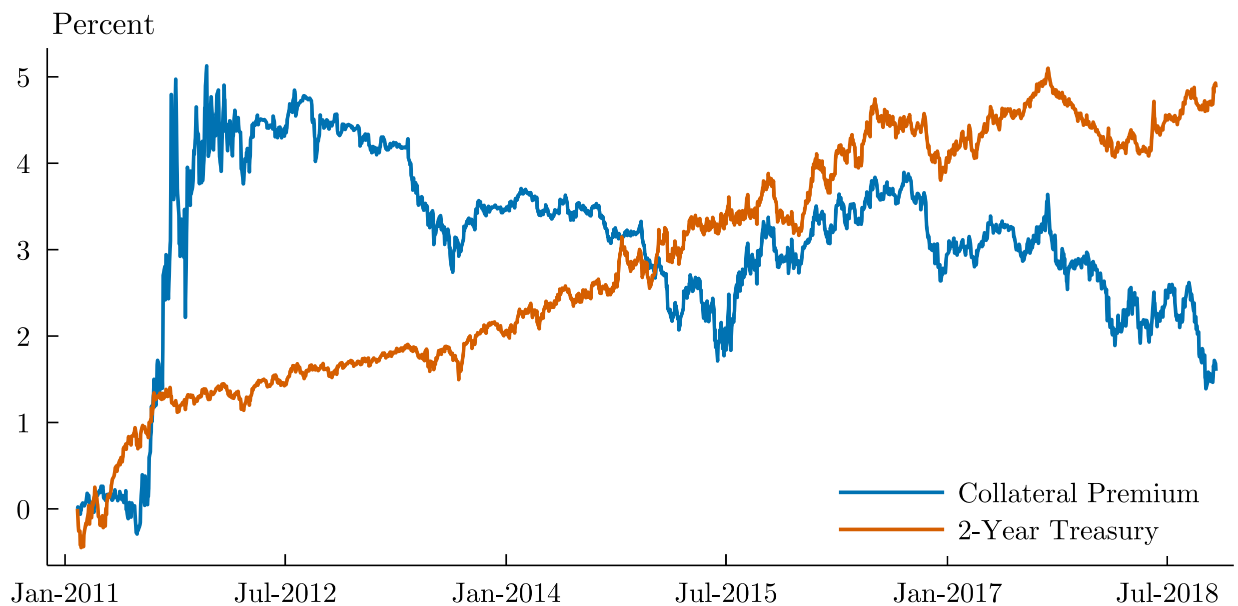

Figure 5: Collateral Premium. Figure plots the cumulative return of the collateral premium, which double sorts to control for liquidity, and the 2-year Treasury.

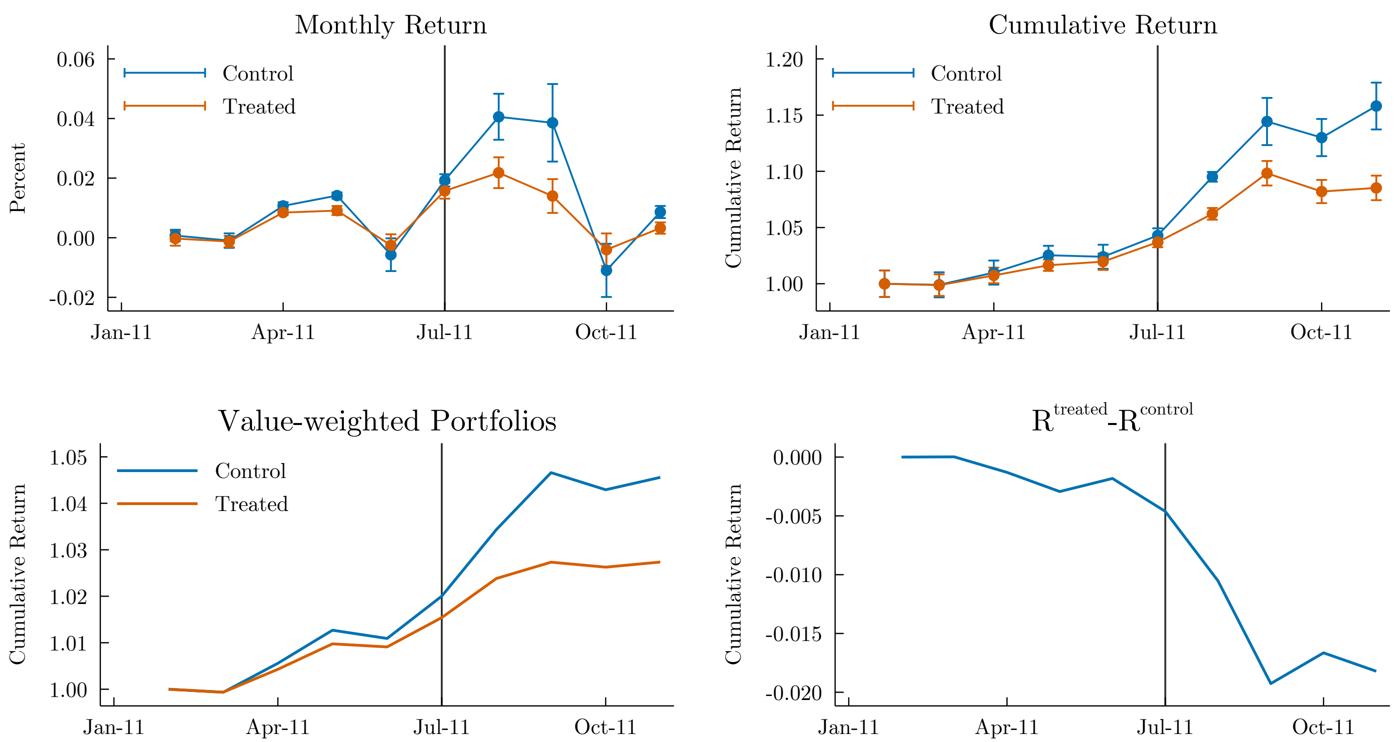

Figure 6: Parallel Trends around July 2011 Euro Sovereign Debt Crisis Event. The top-left panel shows the predictive margins of monthly returns for treated and control bonds estimated from equation 10 and shown in column (1) of Table 9, where a treated bond is a bond that is more often pledged as collateral 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 (1) 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.

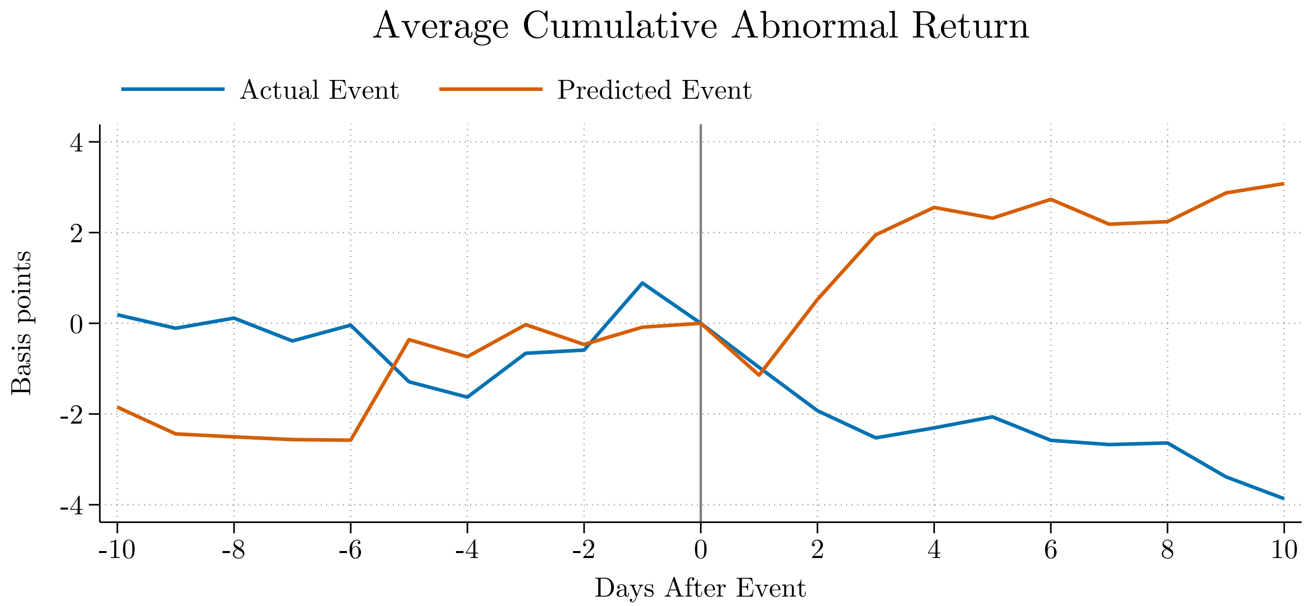

Figure 7: Collateral Use: Actual and Predicted Event Studies. Plot shows the average cumulative abnormal returns across Treasury CUSIPs on each day relative to the actual event (indexed to 0 at date 0), defined as the first date a CUSIP jumps from the low-CR tercile directly to the high-CR tercile. The predicted event is the first date when I predict a Treasury CUSIP will jump from the low-CR to high-CR terciles using a model to estimate the collateral ratio from the bond's characteristics, e.g., the predicted date is when $\mathbb{E}_t[\text{Tercile}(CR_{t+1}) = 3|\text{Tercile}(CR_t) = 1]$. I form expectations using a one-step-ahead cross-validated LASSO with candidate explanatory variables including maturity remaining, age, and dummies for whether the security is a bond or note and lags of duration, the market value of the issue outstanding held by the public, yield, change in yield, monthly return, liquidity, and collateral ratio. Abnormal returns are calculated by estimating the CUSIP's beta to the 10-year benchmark Treasury return using daily returns over the quarter before the event.

8 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	280	285
	Market Value (USD billions)	7,588	7,726
	Original Maturity (months)	11.37	11.30
	Remaining Maturity (months)	74.64	73.82
	Duration (months)	59.59	58.93
	On-the-run CUSIPs	5.42	5.47
Repo Transaction (full sample)	N (Month-Collateral level)	1,029,166	
	N (Month-Repo level)	302,434	
	# Funds (Lenders)	238	
	# Counterparties (Borrowers)	1,819	
	# Borrower-Lender Pairs	5,266	
Repo Transaction (monthly)	Collateral Value (avg, USD millions)	236	
	Repo Value (avg, USD millions)	211	
	Collateral Value (sum, USD billions)	769	
	Repo Value (sum, USD billions)	681	
	Avg. Haircut	5.87%	
	Std. Dev Haircut (time-series)	3.41%	
Collateral Ratio (monthly)	Average	2.40%	2.38%
	Max (avg, monthly)	16.72%	
	Std. Dev. (cross-section)	2.26%	
	Std. Dev. (time-series of monthly mean)	1.29%	

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 February 2011 to October 2018. Repo transaction rows include all repos, not just repos with Treasury collateral and haircuts are winsorized at the 1 and 99% level to reduce the influence of outliers.

	Iliquidity	Age	Maturity Remaining	Duration	Borrower CDS Spread
CR_{it}	0.12***	0.02***	0.13***	0.15***	−0.13***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
N	26,784	26,784	26,784	26,784	26,252

Table 3: Collateral Ratio Correlations. Table presents the correlation of CUSIP-month collateral ratio on the CUSIP's observables: illiquidity, age, maturity remaining, duration, and value-weighted borrower CDS spread. Illiquidity is measured as the bid-ask spread as a percent of the average of the bid and ask price; age is the age of the CUSIP in months relative to its dated date; maturity remaining and duration are in months; borrower CDS spread is the CUSIP-specific CDS spread of banks using that CUSIP as collateral weighted by the amount of collateral pledged by the dealer. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

		Mean	StDev	Mean/StDev
Single-Sorts	Collateral Ratio	0.30	2.52	0.12
	Liquidity	1.41	6.29	0.22
Double-Sorts	Collateral Ratio by Liquidity	0.22	1.66	0.13
	Liquidity by Collateral Ratio	1.38	6.18	0.22

Table 4: Collateral Premium. Collateral ratio defined as Collateral $\text{Ratio}_{i,t}$ = (Market Value of Treasury CUSIP i used as Repo Collateral)/(Market Value of Treasury CUSIP $i)_t$, and liquidity is the average of daily bid-ask spreads for each CUSIP in each month. Both measures are lagged by one month. Single-sort premiums are the high-tercile minus low-tercile premiums. Double-sort premiums are independent sorts based on terciles. Statistics are annualized from daily observations. Sample is 2011 to 2018.

Average Return				
	Illiqudity			
Collateral Ratio	Low	Mid	High	High−Low
Low	1.04	1.47	3.37	2.34
Mid	1.31	1.91	2.62	1.31
High	1.57	2.37	2.61	1.05
High−Low	0.53	0.90	−0.76	

Standard Deviation			
	Illiqudity		
	Low	Mid	High
Low	1.09	2.05	6.59
Mid	1.66	2.81	7.26
High	2.12	3.62	7.41

Table 5: Collateral Premium: Double-Sorted with Liquidity. Collateral ratio defined as Collateral Ratio$_i$ = (Market Value of Treasury CUSIP i used as Repo Collateral)/(Market Value of Treasury CUSIP i), and liquidity is the average of daily bid-ask spreads for each CUSIP in each month. Both measures lagged by one month and sorts are independent. The collateral premium is the average of the High−Low row. Returns and standard deviations are percent and annualized from daily observations. Sample is 2011 to 2018.

Average Treatment Effect	(1)	(2)	(3)
Collateral Premium	15.35***	13.50***	16.41***
	(3.11)	(3.21)	(3.62)
Observations	26,141	26,141	26,141
R^2	Mahalanobis	Euclidean	Inverse Variance

t statistics in parentheses

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

Table 6: Collateral Premium Estimated with Nearest-Neighbor Match. Table shows the results of nearest-neighbor matching across Treasuries sorted into one of two buckets: high- and low-CR. I then match Treasuries to their nearest neighbor using duration, liquidity and maturity remaining each month. Each column shows the annualized average difference in monthly returns between Treasuries in the high- and low-CR halves using different distance metrics. T-statistics are reported in parentheses using robust standard errors.

	Double Sort with Liquidity			Single Sort		
	(1)	(2)	(3)	(4)	(5)	(6)
Bank Leverage Constraints						
$ArbFac_t$	3.90*	3.99*	4.02**	5.32	5.19	5.32
	(1.74)	(1.69)	(1.97)	(1.30)	(1.27)	(1.43)
Controls						
ΔCDS$_t$			64.48***			112.58***
			(4.69)			(5.07)
ΔU.S. Gov't Liquidity Index$_t$			−0.07			−0.08
			(−1.44)			(−1.12)
Observations	1,940	1,940	1,939	1,940	1,940	1,939
R^2	0.00	0.04	0.06	0.00	0.04	0.07
Year/Month Fixed-Effects	No	Yes	Yes	No	Yes	Yes

t statistics in parentheses

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

Table 7: Covariance of Bank Leverage Constraints and Collateral Premium. Collateral Premium$_t = \alpha + \beta_1 ArbFac_t + \beta_2' X_t + \varepsilon_t$ where X_t is a vector of controls. Regression run at the daily level. Dependent variable is collateral premium return in basis points; the first three columns are the collateral premium double-sorted with liquidity. Independent variables are $ArbFac_t$ which measures bank constraints by calculating the returns to bank-intermediated arbitrages; see the text for additional discussion of its construction. ΔCDS$_t$ is the change in the median CDS spread for the financial sector. The U.S. Government Liquidity index is the Bloomberg U.S. Government Securities Liquidity index, which measures liquidity of Treasury notes and bonds. T-statistics are reported in parentheses using heterosketastic and autocorrelation consistent standard errors using the Newey and West (1994) automatic lag selection procedure.

Bank Constraint State	Portfolio	Months	Mean	Std. Error	T-test	p-value
Unconstrained	Low Collateral Ratio	47	1.03	0.04		
	High Collateral Ratio	47	1.26	0.05		
	High−Low Collateral Ratio	47	0.23	0.03		
Constrained	Low Collateral Ratio	46	0.81	0.03		
	High Collateral Ratio	46	1.13	0.03		
	High−Low Collateral Ratio	46	0.32	0.03		
High−Low Collateral Ratio: Constrained vs. Unconstrained		46	0.09	0.04	2.29	0.02

Table 8: Collateral Ratio-Sorted Portfolio Yields by Bank Leverage Constraint State. Table presents the value-weighted yield-to-maturity less the 1-month T-bill for high- and low-CR portfolios across bank leverage constraints. Bank leverage constraint is calculated by the median *ArbConstraint*. 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)
Diff-in-Diff				
$\mathbb{I}$(Post)	121.65***	40.39***	54.82***	73.76***
	(6.56)	(3.29)	(3.47)	(6.57)
$\mathbb{I}$(Treated)	24.56**	22.06**	3.58	3.38
	(2.31)	(2.15)	(0.49)	(0.51)
$\mathbb{I}$(Post)$\times\mathbb{I}$(Treated)	−58.05***	−57.24***	−3.74	−5.01
	(−2.71)	(−2.62)	(−0.24)	(−0.35)
Bond Characteristics				
Duration	2.62***	2.67***	2.52***	2.44***
	(5.58)	(6.57)	(5.81)	(6.75)
Liquidity	−34.43***	−22.12***	−13.00***	−1.29
	(−4.51)	(−2.84)	(−3.78)	(−0.36)
On-the-run	1.70	−15.88	−71.57***	−10.96
	(0.08)	(−1.08)	(−3.59)	(−0.68)
Maturity Remaining	−0.61**	−0.60**	−0.63*	−0.61*
	(−2.17)	(−2.52)	(−1.78)	(−1.93)
Observations	1,060	1,060	1,147	1,147
R^2	0.26	0.50	0.25	0.50
Month Fixed-Effects	No	Yes	No	Yes

t statistics in parentheses

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

Table 9: 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. Regression is weighted by the CUSIP market-value. $r_{i,t}$ is 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 specific Treasury CUSIP is intensively used by collateral by European banks. Specifically, I look at all Treasury bonds used as collateral one quarter before the July event—in April 2011—and sort 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. I set $\mathbb{I}(\text{Treated}) = 1$ for bonds above the median European share in April 2011. I examine the five months before and after the July 11 event. I limit the test to CUSIPs used as collateral in April 2011. I define a CUSIP as on-the-run if it spends more than half the month as the on-the-run security. Standard errors clustered by CUSIP. T-statistics using robust standard errors are reported in parentheses.

	Actual Event		Predicted Event	
	(1)	(2)	(3)	(4)
$\mathbb{I}$(Post)	-1.76^{***}	-0.53^{**}	0.26	-0.02
	(-3.91)	(-2.06)	(0.34)	(-0.04)
Observations	2,910	8,720	820	2,458
R^2	0.01	0.00	0.00	0.00
Year Fixed-Effects	Yes	Yes	Yes	Yes
Weighted	Yes	Yes	Yes	Yes
Window	3 Days	10 Days	3 Days	10 Days

t statistics in parentheses

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

Table 10: Average Abnormal Return after Collateral Use Changes. $r_{i,t} = \mathbb{I}(\text{Post})_{i,t} + \varepsilon_{i,t}$ where i is a Treasury CUSIP, $r_{i,t}$ is the abnormal return of a Treasury CUSIP, and $\mathbb{I}(\text{Post})_{i,t}$ dummy equal to 1 after the CUSIP moves from the low tercile of collateral ratio to high tercile (for the actual event columns) and when the CUSIP is predicted to move from the low tercile to the high (for the predicted event columns). Observations are day by CUSIP. Treasury CUSIP abnormal returns estimated using daily data and the 10-year Treasury return index from CRSP. T-statistics using robust standard errors are reported in parentheses.

	Actual			Placebo		
	(1)	(2)	(3)	(4)	(5)	(6)
Weighted Bank Abnormal Return$_{i,t}$	24.70*	62.37***	62.52***			
	(1.91)	(3.51)	(3.10)			
Placebo-Bank Abnormal Return$_{i,t}$				−6.80	−16.32	−0.62
				(−0.87)	(−1.11)	(−0.04)
Observations	1,995	1,995	1,995	1,796	1,796	1,796
R^2	0.00	0.07	0.08	0.00	0.07	0.08
Year Fixed-Effects	No	Yes	Yes	No	Yes	Yes
Weighted	No	No	Yes	No	No	Yes

t statistics in parentheses

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

Table 11: Collateral and Bank Abnormal Returns after Stress Tests. $r_{i,t} = \alpha + \beta\,\text{Weighted Bank Abnormal Return}_{i,t} + \varepsilon_{i,t}$ where t is month, i is a Treasury CUSIP, $r_{i,t}$ is the abnormal return of a Treasury CUSIP, and Weighted Bank Abnormal Return$_{i,t}$ is the value-weighted abnormal return of banks using CUSIP i as collateral. Observations are day by CUSIP, and includes only the first trading day after stress test announcements. Value-weights are calculated by aggregating across bank stock abnormal return with weights given by the bank's use of that CUSIP as collateral as a share of all the banks' use of that CUSIP as collateral in a given month. I lag the value-weights by one month to reflect the data lag on collateral use. Bank abnormal returns calculated by year and bank using daily excess returns over the previous three months and the Fama–French excess market return. Treasury CUSIP abnormal returns estimated using daily data and the 10-year Treasury return index from CRSP. Placebo-Bank Abnormal Return$_{i,t}$ is the equal-weighted return of all banks not using that CUSIP as collateral. See section A.5 for additional details. T-statistics using robust standard errors are reported in parentheses.

A Online Appendix

A.1 Model Details

The proposition in the model section uses the geometric risk premium of Treasuries given in Equation 5, which shows:

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

assuming $\mu_h = 0$ and $\gamma\sigma_c\sigma_h = 0$, 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. The risk-free rate is $r_{f,t+1} = -\log(\beta) + \gamma\mu_c - {}^1\!/_2\gamma^2\sigma_c^2$. An analogous result holds for the boxed Treasury.

Expected returns for unboxed Treasuries depend on 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 them 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 low and the bond carries a smaller risk premium than risky assets, like equities.

The second term, $\sigma_{h,\theta_{ub}}$, is the covariance of innovations to the safe-asset supply with the Treasury's returns. Suppose $h_{t+t} > h_t$, then banks are hit by a rising haircut, pushing down R_B, which in turn 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-like, safe-asset value. 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: $\lim_{\mathcal{M}\to\infty} \omega'_{\theta_{ub}}(\mathcal{M}_t) = 0$.

The effect of increasing haircuts on the money premium is

$$\frac{\partial \omega'_{\theta_{ub}}(\mathcal{M}_t)}{\partial h_t} = \pi_{\theta_{ub}}\left[(1-h_t)A'(h_t) - A(h_t)\right]\left[\frac{1}{\mathcal{M}_t} - \frac{1}{\mathcal{M}_t - \pi_{\theta_{ub}}}\right] > 0 \tag{A1}$$

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). I empirically estimate the sign and find it is negative, $A'(h_t) < 0$, consistent with Adrian et al. (2014)'s finding that broker-dealer leverage is correlated with asset growth. I give details for the empirical exercise in the parameter estimation discussion below. 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. Empirically, I find that banks shrink their balance sheets when haircuts increase so the latter channel dominates.

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

$$\mathbb{E}_t[r_{K,t+1} - r_{\theta_b,t+1}] \approx \gamma(\sigma_{c,K} - \sigma_{c,\theta_b}) + \sigma_{h,\theta_b} + \omega'(\mathcal{M}_t) \tag{A2}$$

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}. $\square$

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 1959 to 2019.

I estimate covariances for boxed and unboxed Treasuries by sorting Treasury CUSIPs on their collateral ratio, the percent of the Treasury CUSIP's market value used as tri-party repo collateral with money market funds. The boxed Treasury portfolio consists of Treasuries with collateral ratios in the highest tercile. The unboxed Treasury portfolio consists of Treasuries in the lowest collateral ratio tercile. Both Treasury portfolios control for liquidity and are the highest or lowest tercile of collateral ratio after double sorting with liquidity. Treasury portfolios are available from 2011 to 2018.

To measure haircut covariances, I proxy innovations to h_t with innovations to bank-intermediated arbitrage returns, $h_t = -1 \times \mathit{ArbFac}$. I describe *ArbFac*'s construction in Section 4.2. The covariance of Treasury returns and consumption growth, after rounding to two decimal points, are equal across the unboxed and boxed Treasuries (0.00 and 0.00), but the covariance of their returns and bank leverage constraints are different: -0.44 and -0.57, respectively. When banks grow more constrained ($h_t \uparrow$), boxed Treasuries have lower returns than unboxed Treasuries—this is why the collateral premium is positive.

I estimate $A'(h_t)$ in Table A2, which shows correlations of the change in banks' collateral holdings, $A = \lambda K + \theta_b^B + \theta_{ub}^B$, as haircut h_t increases. I proxy for h_t using *ArbFac*, where $\mathit{ArbFac} > 0$ corresponds to bank leverage constraints falling. All four columns use quarterly balance sheet data from the Federal Reserve's Financial Accounts of the U.S. The first two columns calculate A using Table L.108, "Domestic Financial Sector" where A is the sum of loans and Treasury securities. The last two columns calculate A using Table L.110, "Private Depository Institutions." The point estimates in each regression show a positive relationship between shrinking haircuts and banks' asset growth. Since banks cannot easily adjust their loan portfolios quickly, the effect is larger and more significant at longer lags. The results support my assumption that $A'(h_t) < 0$ and are consistent with Adrian et al. (2014)'s finding that broker-dealer leverage is correlated with asset growth.

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 premium, the difference between boxed and unboxed Treasuries from equation 6. The collateral premium 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 A2 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.2 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.3 Borrower CDS Details

I measure the riskiness of the cash borrowers (the repo issuer) using a Treasury CUSIP by manually matching to Markit CDS entities to calculate a CUSIP-specific CDS spread that value weights across all the borrowers using a single CUSIP as collateral. I calculate the CUSIP-specific CDS spread of banks using that CUSIP as collateral, and I weigh by the amount of collateral pledged by the bank. I include 5-year CDS on senior secured debt and average the CDS spreads across all currencies that quotes are available for on a given day for a given entity. I include contracts with different document clauses based on the convention by geography: MR for US and Australian firms; CR for Asian firms; and MM for European firms. I use the *14* vintages of the contracts (CR14, MR14, MM14) for dates on September 22, 2014 and after.

Table A3 provide the matches between manually-identified issuers in the repo collateral data and the best Markit CDS entity match. In general, I matched to the entity at the consolidated level when possible (e.g., Merrill Lynch is matched to Bank of America's Markit redcode), otherwise matching with the broker-dealer (e.g., Natwest is matched to RBS), or the related entity with the most CDS data. Several entities have no match in the CDS data.

A.4 Basis Details

There are three types of basis trades included: covered interest parity, cash Treasuries vs. futures, and cash Treasuries vs. swaps. Long-short positions described for a negative basis. See Boyarchenko et al. (2020) for additional details.

1. Covered Interest Parity: The trade is long a bond paying the foreign interest rate, financed via repo at the overnight repo rate, with the haircut financed at 3-month OIS, shorts a forward exchange swap and finances the initial margin at 3-month OIS, and shorts a bond paying domestic U.S. interest rates, financing with overnight reverse repo. We measure foreign and domestic interest rates using with OIS rates or inter-bank offered rates. We assume the repo haircuts are 2.8 percent for both the domestic and the foreign bond, repo rates are overnight GCF repo rate, and the initial margin is 6 percent. No OIS rates are unavailable for NOK. Additionally, 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 timeseries.

2. Cash Treasury vs. Futures: The trade is long the duration-adjusted Treasury future, and the futures margin is financed via 3-month OIS. The trade shorts the cheapest-to-deliver Treasury identified by Bloomberg, financed via repo, with the haircut financed at 3-month OIS. We assume the repo haircut is 2.8 percent, the initial future margin comes from the CME and varies between 0.1 percent and 6.5 percent, and the delivery date is the last day for the futures contract. Repo rate is the overnight GCF repo rate.

3. Cash Treasury vs. Swap: The trade is long a Treasury, financed with repo and the haircut financed at 3-month OIS. The trade shorts an interest rate swap which pays a fixed rate, and the swap margin is financed at 3-month OIS. We assume the repo haircut is 2.8 percent and the initial swap margin is 3.9 percent. Repo rate is the overnight GCF repo rate.

To minimize idiosyncrasies in any one market, Ross and Ross (2022) provide a daily approximation of bank leverage constraints by aggregating the basis trades to a single measure. Ross and Ross (2022) calculate the z-score for each basis trade using that trade's moments from its first full year of data. They take the absolute value of the z-score to capture the intuition that the trades are often reversible (i.e., if the trade expected return is negative, you can often flip the long and short legs). They calculate the equal-weighted average across the individual basis trades available on that day for each category of arbitrages (e.g., 2y Treasury cash/future, 5y Treasury cash/futures, etc.). Finally, they average across the category-level averages (e.g., Treasury cash/future, Treasury cash/swap, CIP) to create *ArbConstraint*.

They estimate daily innovations to bank leverage constraints, *ArbFac*, following the method of He et al. (2017): first, they estimate innovations u_t to $ArbConstraint_t$ using an AR(1)

$$ArbConstraint_t = \rho_0 + \rho ArbConstraint_{t-1} + u_t$$

They then convert it to a growth rate by dividing with the lagged level and multiplying by -1 so the interpretation is consistent with most factors: a positive number reflects good news as the banking system becomes less leverage constrained.

$$ArbFac_t = -1 \times \frac{u_t}{ArbConstraint_{t-1}}$$

Figure A2 plots the level of the average arbitrage constraint *ArbConstraint* and the innovations as measured by the factor *ArbFac*.

A.5 Stress Test Abnormal Return Details

I create the sample of bank stock returns and Treasury collateral returns by merging two data sets. First, I manually identify the bank borrower in each repo in the Form N-MFP/MFP2 data. There are roughly 70 institutions in the data, many of which are neither banks nor included in the Federal Reserve's stress tests.

Second, I get stock prices for firms in the intersection of the banks with repo data and banks that were included in the stress tests, for a total of 22 banks. I calculate returns for each of the banks included in the stress tests between 2011 and 2019 using stock returns for the parent company's stock traded in its home country; I use Bloomberg to convert end-of-day prices to dollars when the stock's price is not quoted in dollars. The sample of banks is (with associated Bloomberg tickers): Bank of America Corporation (BAC US Equity), Barclays US LLC (BARC LN Equity), BMO Financial Corp. (BMO CN Equity), BNP Paribas USA, Inc. (BNP FP Equity), Citigroup Inc. (C US Equity), Credit Suisse Holdings (USA), Inc. (CSGN SW Equity), DB USA Corporation (DBK GR Equity), HSBC North America Holdings Inc. (HSBA LN Equity), JPMorgan Chase & Co. (JPM US Equity), Morgan Stanley (MS US Equity), MUFG Americas Holdings Corporation (8306 JT Equity), RBC US Group Holdings LLC (RY CN Equity), RBS Citizens Financial Group, Inc. (NWG LN Equity), State Street Corporation (STT US Equity), SunTrust Banks, Inc. (STI US Equity), TD Group US Holdings LLC (TD US Equity), The Bank of New York Mellon Corporation (BK US Equity), The Goldman Sachs Group, Inc. (GS US Equity), The PNC Financial Services Group, Inc. (PNC US Equity), U.S. Bancorp (USB US Equity), UBS Americas Holding LLC (UBSG SW Equity), Wells Fargo & Company (WFC US Equity). I match collateral data from the Form-NFP/2 attributed to Merrill Lynch to Bank of America, and from RBS to NatWest.

Deutsche Bank changed its legal name in the stress test from "Deutsche Bank Trust Corporation" to "DB USA Corporation." Before 2015, RBS Citizens Financial Group was a subsidiary of NatWest Group through RBS, and it was spun off into the separate Citizens Financial Group in 2015. Citizens Financial Group does not appear in the Form-NFP/2 repo data.

I use daily returns over the previous three months to estimate abnormal returns, excluding the day of the stress test result announcement, and I require all banks to have a return on a given day otherwise that date is excluded from the estimation period.

Table A4 gives the dates that the Federal Reserve announced the results of the CCAR stress tests. The announcement occurred after markets closed at 4:30pm for the tests between 2012 and 2019. No firm-specific results were released in the 2011 CCAR, and the results were released at 11:00am.

A.6 Appendix Figures

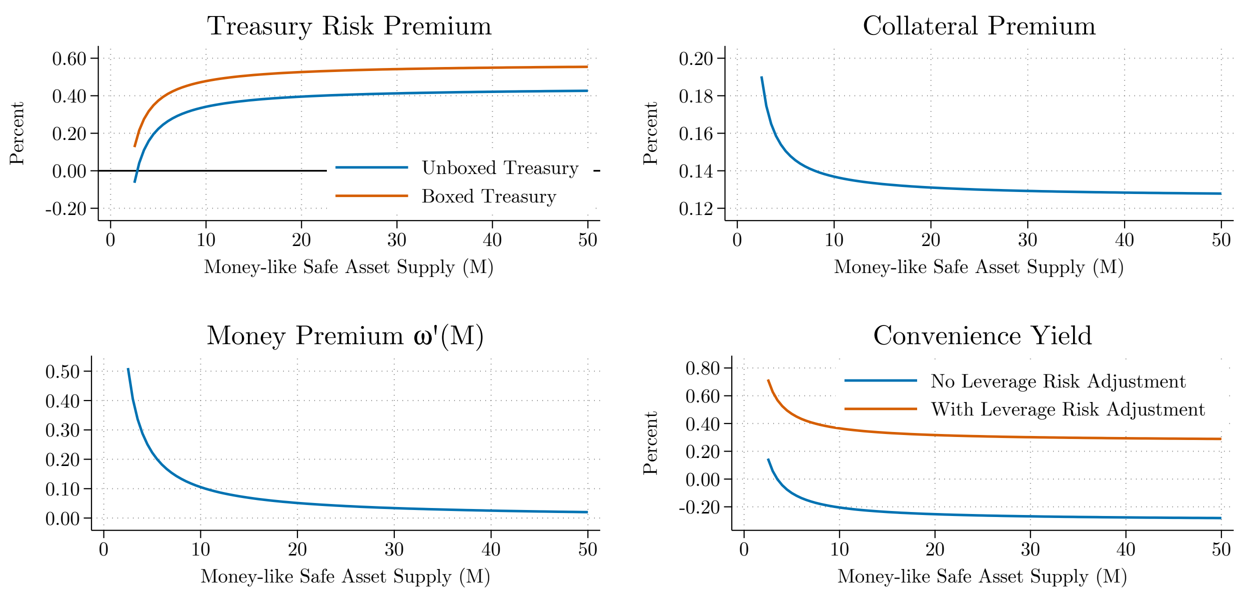

Figure A1: Comparative Statics. The top-left figure shows the geometric risk premiums for both types of Treasuries over differing equilibrium values of money-like safe assets $\mathcal{M}_t$ as given in equation 5. The bottom-left panel shows the money premium, the last term in equation 5. The top-right panel shows the collateral premium, 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 A2 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 $\gamma = 10$.

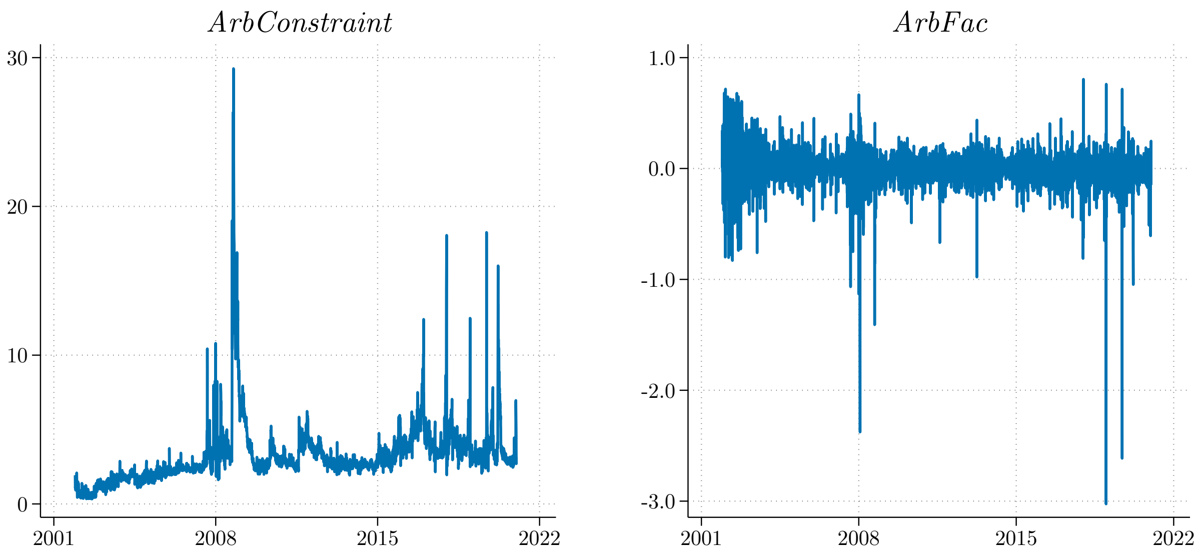

Figure A2: *ArbConstraint* and *ArbFac*. Left panel is *ArbConstraint*, which is the average z-score of the basis trades available on that date. Right panel shows *ArbFac*, estimated as the AR(1) innovations from *ArbConstraint* multiplied by -1 so the interpretation is the same as normal factors: a positive number reflects banks growing less leverage constrained.

A.7 Appendix Tables

Monthly Data (2011–2018)	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	3.37	15.17	0.03	-0.85
Boxed Treasury	$r_{\theta_b} - r_f$	Hi Collateral Ratio Tercile	0.32	3.72	0.00	-0.57
Unboxed Treasury	$r_{\theta_{ub}} - r_f$	Lo Collateral Ratio Tercile	0.13	2.84	0.00	-0.44
Consumption	Δc_{t+1}	PCE	3.26	1.81	0.03	-0.50

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 portfolios is a portfolio long 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 and controlling for liquidity. Similarly, the unboxed Treasury portfolio is long Treasuries that are in the bottom tercile of collateral use, and controls for liquidity. Sample for Treasuries runs from 2011 to 2018, and sample for consumption and market return are 1959 to 2020.

	Domestic Financial Sector		Depository Institutions	
	$\Delta\log(A)$	$\Delta\log(A)$	$\Delta\log(A)$	$\Delta\log(A)$
$ArbFac_{t-1}$	0.19^{***}	-0.06	0.13	-0.01
	(3.24)	(-0.66)	(1.47)	(-0.16)
$ArbFac_{t-2}$		0.42^{***}		0.08
		(3.34)		(0.49)
$ArbFac_{t-3}$		0.04		0.14
		(0.23)		(1.09)
$ArbFac_{t-4}$		0.17		0.25^{*}
		(1.23)		(1.95)
Observations	123	120	124	121
R^2	0.02	0.16	0.01	0.06

t statistics in parentheses

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

Table A2: Empirical Estimate of $\partial A(h_t)/\partial h_t$. Table presents empirical results for the sign of the change in banks' collateral holdings, A, as haircut h increase, where $A = \lambda K + \theta^B$, with bank loans λK and bank-owned Treasuries θ^B. Innovations to h_t are proxied by *ArbFac*, which is the innovations to bank-intermediated arbitrage returns. I discuss *ArbFac*'s construction in Section 4.2; $ArbFac > 0$ when banks are less constrained. All four columns use quarterly balance sheet data from the Federal Reserve Financial Accounts of the United States. The first two columns calculate A using Table L.108, "Domestic Financial Sector" where A is the sum of loans and Treasury securities. The last two columns calculate A using Table L.110, "Private Depository Institutions." T-statistics are reported in parentheses using heterosketastic and autocorrelation consistent standard errors using the Newey and West (1994) automatic lag selection procedure.

Name	Matched Markit Entity
ABN AMRO	ABN AMRO Bk NV
AMERICAN HONDA FINANCE	Amern Honda Fin Corp
AMHERST PIERPONT	*n.a.*
ANNALY	*n.a.*
ANZ	Aust & New Zld Bkg Gp Ltd
ASL	*n.a.*
BANK OF AMERICA	Bk of America Corp
BANK OF MONTREAL	Bk Montreal
BANK OF NEW YORK MELLON	Bk of NY Mellon Corp
BANK OF NOVA SCOTIA	Bk Nova Scotia
BARCLAYS	Barclays Bk plc
BNP PARIBAS	BNP Paribas
BPCE	*n.a.*
CALYON	Societe Generale
CANTOR FITZGERALD	*n.a.*
CIBC	Cdn Imperial Bk Comm
CITI	Citigroup Inc
COMMERZBANK	Commerzbank AG
CREDIT AGRICOLE	Cr Agricole SA
CREDIT SUISSE	Credit Suisse Gp AG
CURVATURE SECURITIES	*n.a.*
DAIWA	Daiwa Secs Gp Inc
DEUTSCHE BANK	Deutsche Bk AG
DNB ASA	DNB Bk ASA
FCSTONE	*n.a.*
FEDERAL RESERVE	*n.a.*
FFCB	*n.a.*
FHLMC	*n.a.*
FIRST UNION CORP	Wells Fargo & Co
FIXED INCOME CLEARING CORP	*n.a.*
GOLDMAN SACHS	Goldman Sachs Gp Inc
GREENWICH	*n.a.*
GUGGENHEIM	*n.a.*
GX CLARKE	*n.a.*
HARVARD	*n.a.*
HSBC	HSBC Hldgs plc
ING	ING Groep NV
JP MORGAN	JPMorgan Chase & Co
LEHMAN	*n.a.*
LLOYDS	LLOYDS BK PLC
MERRILL LYNCH	Bk of America Corp
METLIFE	MetLife Inc
MITSUBISHI	Bk of Tokyo Mitsubishi UFJ Ltd
MIZUHO	Mizuho Bk Ltd
MORGAN STANLEY	Morgan Stanley
NATIONAL AUSTRALIA BANK	Natl Aust Bk Ltd
NATIONAL BANK OF CANADA	*n.a.*
NATIXIS	Natixis
NATWEST	Royal Bk Scotland Gp PLC
NESBITT BURNS	Bk Montreal
NOMURA	Nomura Hldgs Inc
NORINCHUKIN BANK	Norinchukin Bk
NORTHWESTERN MUTUAL	*n.a.*
PNC	PNC Finl SERVICES GROUP INC
PRUDENTIAL	Prudential Finl Inc
RBC	Royal Bk Cda
RBS	Royal Bk Scotland Gp PLC
SBCW MORTGAGE	*n.a.*
SCOTIA	Bk Nova Scotia
SOCIETE GENERALE	Societe Generale
SOUTH STREET	*n.a.*
STANDARD CHARTERED	STANDARD CHARTERED PLC
STATE STREET	St Str Corp
SUMITOMO MITSUI	Sumitomo Mitsui Bkg Corp
SUNTRUST	SunTrust Bks Inc
TORONTO DOMINION	Toronto Dominion Bk
UBS	UBS AG
UMB	*n.a.*
US BANK	U S Bancorp
WELLS FARGO	Wells Fargo & Co

Table A3: CDS Matches. Table provides the links used to calculate an repo issuer (cash borrower) CDS spread by matching consolidated entities in the repo collateral data to an entity in the Markit CDS data set. *n.a.* denotes no match is available.

Year	Date
2011	Friday, March 18, 2011
2012	Tuesday, March 13, 2012
2013	Thursday, March 14, 2013
2014	Wednesday, March 26, 2014
2015	Wednesday, March 11, 2015
2016	Wednesday, June 29, 2016
2017	Wednesday, June 28, 2017
2018	Thursday, June 28, 2018
2019	Thursday, June 27, 2019

Table A4: CCAR Stress Test Announcement Dates.