The Treasury Collateral Spread and Levered Safe-Asset Production[1]

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A Online Appendix

A.1 Repo Market Institutional Details

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

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

Cash lenders in the tri-party market include money market funds, corporate treasuries, municipalities, and insurance companies.[2] Cash borrowers include hedge funds and other levered investors, like mortgage real-estate investment trusts. The bank intermediates between cash lenders and cash borrowers to provide leverage to the bank's levered prime-brokerage clients. In return, cash lenders receive a set of high-quality collateral securities but not a specific security.

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

A.2 Collateral Optimization

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

[1] The views expressed in this paper are those of the authors and do not necessarily represent those of Federal Reserve Board of Governors, or anyone in the Federal Reserve System.

[2] With the introduction and expansion of the Fixed Income Clearing Corporation's sponsored service, money funds have also started lending in the cleared bilateral market (FICC DVP), mostly after 2018.

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

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

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.

In the tri-party repo market, lenders cannot control which specific collateral they receive. Lenders can specify more granular cuts or make manual adjustments for both equity and fixed-income collateral. 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 Model Details

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

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

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

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

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

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

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

The covariance of Treasury returns and consumption growth, after rounding to two decimal points, are small and equal across the unboxed and boxed Treasuries (-0.02 and -0.02), but the covariance of their returns and bank leverage constraints are different: -0.72 and -0.78, respectively. When banks grow more constrained ($h_t \uparrow$), boxed Treasuries have lower returns than unboxed Treasuries—this pushes the collateral spread to be larger.

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

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

A.4 Collateral Data Details

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

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

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

A.5 Repo Measure Robustness

An advantage to calculating leverage constraints by aggregating repo exposures across banks is that the measure will naturally weight changes by the relative size of each bank's repo business. Variation in banks' business models mean that repo borrowing matters more for some banks than others. Banks with large broker-dealers or fewer deposits tend to rely more heavily on repo borrowing. Public bank data confirms this intuition: Goldman Sachs, a legacy investment bank, had repo borrowing equal to 19 percent of its total assets in December 2023, while Wells Fargo, a bank with a large deposit base, had repo borrowing equal to only 4 percent.

I normalize repos by Treasuries outstanding to control for growth in the economy and financial system, which I proxy with the level of Treasuries outstanding. Treasuries are a useful normalization because the data is available at a daily frequency. To confirm the robustness of this normalization, Table A2 shows the measure is highly correlated if the denominator is replaced with total commercial banks assets (available at a weekly frequency from the Federal Reserve's H.8 report) or total unencumbered assets plus reserves from FR2052a. I prefer to normalize using Treasuries outstanding rather than total commercial bank assets because many repo market participants, like broker-dealers, are not commercial banks and are not captured by the H.8 data. The H.8 data is also available as weekly snapshots, which may miss important higher-frequency variation. I also prefer to normalize using Treasuries outstanding rather than the FR2052a unencumbered asset variable since a large share of repo market participants' assets are encumbered.[3]

One concern for using repos outstanding to proxy leverage constraints is that banks might be shifting their liability composition while keeping their total liabilities flat. In Table A3, I regress repo liabilities on non-repo liabilities and show that they are positively related in both levels and changes, indicating banks are broadly increasing all types of liabilities simultaneously on average rather than shifting from one type to another.[4] Moreover, banks do not issue equity at a high frequency, so it is highly unlikely that banks pair increases in repo with equity issuance to keep

[3] FR2052a data does not include a total asset variable. Conceptually, it is the sum of unencumbered assets, encumbered assets, and reserves, but FR2052a includes data on encumbered assets only beginning in the middle of 2022, which severely limits the sample.

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

their leverage ratios flat.

A.6 Basis Details and Discussion

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

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

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

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

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

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

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

A.7 Borrower CDS Details

I measure the riskiness of the cash borrowers (the repo issuer) pledging a Treasury CUSIP by manually matching the money fund data to Markit CDS entities. I use 5-year CDS on senior unsecured debt. I include contracts that Markit denotes as the primary curve and coupon. For dates when no primary curve is indicated (namely, before September 22, 2014), I use the pre-2014 contract and coupon corresponding to the contract that is later identified as the primary contract. For example, if the primary curve for an entity is identified as MM14 after September 2014, I identify the primary curve for that entity as the MM contract for observations before Markit begins indicating a primary curve and coupon for that entity.

Table A4 provides 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 otherwise the related entity with the least sparse CDS data. The matching works well, with only a small number of entities without matches. The unmatched entities tend to have small repo borrowing activity, so the overall coverage is very high: on average, 97 percent of repo collateral is matched to an entity with a CDS spread.

In the case of sponsored DVP repo (where sponsored money funds lend into the DVP repo market), I identify the counterparty as the Fixed Income Clearing Corporation (FICC), since these trades are novated to FICC and FICC is the legal counterparty to the fund. FICC is a financial market utility and it does not have a CDS spread. Because FICC mutualizes losses across its members—large financial institutions—in cases of default when the defaulters' resources and FICC's corporate contributions are insufficient to cover losses, I estimate FICC's counterparty risk with the average CDS spread across the eight U.S. GSIBs (BAC, BK, C, JPM, MS, GS, STT, WFC, all of which are members); on some days, not all eight companies have CDS spreads, in which case I average across those with spreads reported by Markit on a given day.

I use the CDS data to calculate two control variables: (1) a measure of borrower risk embedded in the collateral spread (*Hi-Low CR Borrower* CDS_t), and (2) a measure of borrower risk across all repo borrowers, weighted by their involvement in the repo market (*Financial* CDS_t).

1. *Hi-Low CR Borrower* CDS_t: First, I estimate the weighted average CDS spread of borrowers pledging a CUSIP as collateral (since many CUSIPs are pledged by more than one repo borrower). Weights are taken from the previous month's repo collateral data, which are applied to daily CDS data. Since CDS data for some borrowers is not available every day, I rescale the weights to sum to 1 for each date. This process yields a CUSIP by date panel with the average CDS spread of repo borrowers pledging each CUSIP.

   Next, I sort bonds into their collateral ratio tercile, using the CUSIPs' previous month-end collateral ratios.

I then calculate the weighted average CDS spread for each collateral ratio tercile. Following the collateral spread estimate, I weight the average by the CUSIP's lagged market value as a share of the total market value of all CUSIPs in the same tercile. This yields two time series: the average CDS spread of borrowers pledging collateral in the high-collateral-ratio tercile, and another for those in the low-collateral-ratio tercile.

Finally, *Hi-Low CR Borrower* CDS_t is the difference between the CDS spread for bonds in the high-collateral-ratio tercile minus the CDS spread for bonds in the low-collateral-ratio tercile. If *Hi-Low CR Borrower* $CDS_t > 0$, then high-collateral-ratio tercile bonds are pledged by borrowers with higher CDS spreads.

2. *Financial* CDS_t: The variable is the average CDS spread of repo borrowers, weighted by their repo borrowing. Weights are taken from a borrower's Treasury collateral pledged as a share of all Treasury collateral pledged by borrowers with CDS data. Weights are calculated using month-end data from the previous month's repo collateral data.

A.8 Repo Maturity

I clean the maturity of the repos in several steps. First, I define the maturity of the repo as the business days between the security's legal maturity (or the next business day, if different) and the reporting date, where business days are defined using days with Treasury prices from the CRSP daily Treasury dataset. Since the reporting date is typically the last calendar date of a month, I adjust the reporting date to be the last business day of the month.

I set the repo maturity equal to 1 day when the security is denoted as an open repo or when the repo maturity date is equal to the filing date. I also set the maturity equal to 1 day in the handful of cases when the repo maturity is greater than 5 years since these are likely open repos, many of which have a maturity in 2050 or 2099, which is implausibly long for a repo tenor. Repos with reported tenors greater than 5 years are infrequent, about 0.2 percent of collateral observations. Finally, I exclude cases when the security maturity date is less than the filing date, which are infrequent (0.02 percent of observations) and appear to be data entry errors.

A.9 Other Collateral Types

Table A9 provides a snapshot of the assets used as collateral in the money-fund market and in the broader repo market captured by the FR2052a data. The table shows the December 2023 value for money funds and the average of daily values from the first half of December 2023 for the FR2052a data to avoid possible year-end distortions. The datasets likely have considerable overlap, but the N-MFP data includes repos with banks that are not included in the FR2052a data, while the FR2052a data spans all types of repos, not just money-fund transactions.[6]

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

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

Even though equity collateral is small in the N-MFP data, bank leverage risk should depend on collateral use across all segments of the repo market, not just the tri-party market which dominates money-funds' repo activity. In this view, the $95 billion is a lower bound since it spans only the handful of banks that file daily FR2052a reports. There is also considerable time series variation in equities posted as collateral. Figure A3 shows that equity collateral peaked at $190 billion in 2021 but has been falling since.

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

A related risk for collateral is "bundling" different types of securities together to back the same repo. For example, if a Treasury and an MBS were both used as collateral for the same repo, then that Treasury's collateral risk could be higher than for another Treasury that isn't bundled alongside risky assets. Such dynamics may be important but are likely muted for Treasuries, as the data suggests they are only infrequently bundled with other collateral. In the money-fund data, conditional on a repo having a nonzero amount of Treasury collateral, the average (median) share of Treasury collateral backing that repo is 88 percent (100 percent). In this view, money-fund repos backed by Treasuries are overwhelmingly backed by only Treasuries. Unfortunately, the FR2052a data does not present transaction-level data, so it is not possible to study collateral bundling outside of the money-fund market with these datasets.

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

$$\mathbb{E}_t[r_{p,t+1} - r_{f,t+1}] \approx \gamma\sigma_{c,p} - \sigma_{h,p}. \tag{A2}$$

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

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

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

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

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

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

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

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

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

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

Results I test whether bank leverage risk appears in firm-specific stock returns in Table A10 by running the regression

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

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

The first two columns of Table A10 run the regression on the full sample of equities, not conditioning on whether that company's stock has been used as collateral and find that repo growth is significantly positively related to firm returns. The first column uses Fama and French (1996)'s 3-factor model and finds a 1pp increase $\Delta \ln(\text{Repo}_t)$ corresponds to a 1.3 bps increase in stock returns, all else equal. The second column adds the momentum factor and finds similar results. Intuitively, the first two columns are consistent with all equities' collateral value increasing as banks increase their repo, even if those stocks are not actively being used as collateral. That the coefficient is a magnitude smaller for repo growth than for the common stock factors is consistent with the expectation that the effect of bank leverage risk is smaller for equities given their comparatively limited role as repo collateral.

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

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

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

As robustness, I also check that the results do not materially change if I require a stricter level of fuzzy matching, for example, by requiring the Levenshtein distance to be greater than or equal to 95 (compared to the base case requirement of 85 described in the appendix). This stricter fuzzy matching makes the results stronger, although at the cost of making the matched sample smaller. The results are also similar using the change in the ratio of repos to Treasuries outstanding, given its 0.99 correlation coefficient with changes in log of repos.

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

A.10 Appendix Figures

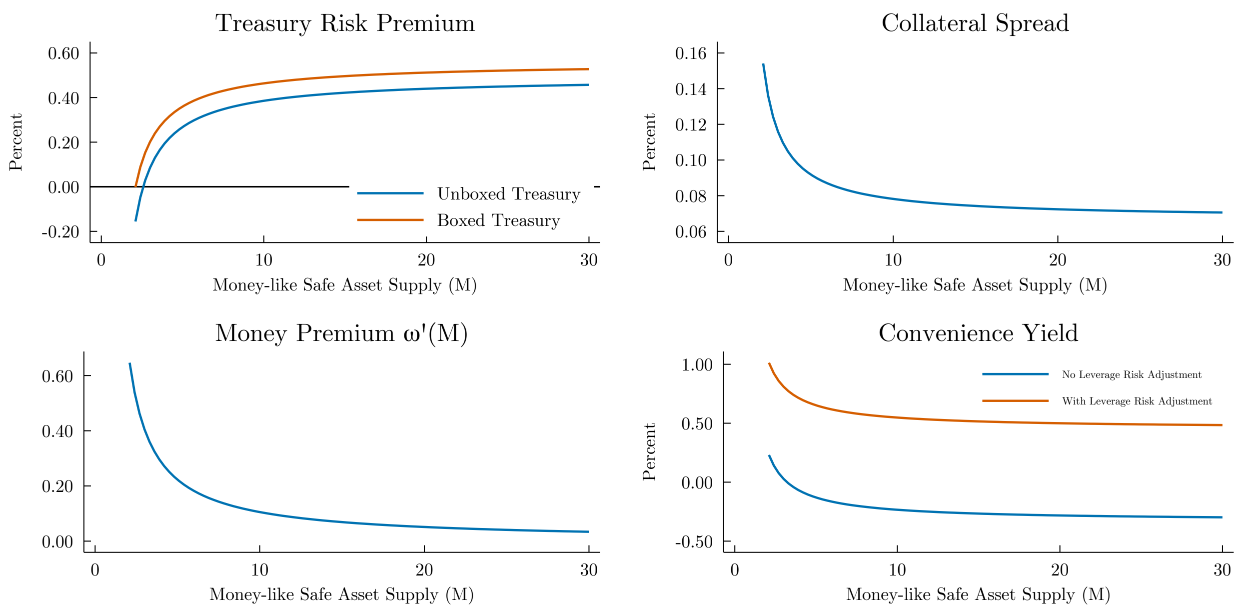

Figure A1: Comparative Statics. The top-left figure shows the geometric risk premiums for both types of Treasuries over differing equilibrium values of money-like safe assets $\mathcal{M}_t$ as given in equation 5. The bottom-left panel shows the money premium, the last term in equation 5. The top-right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

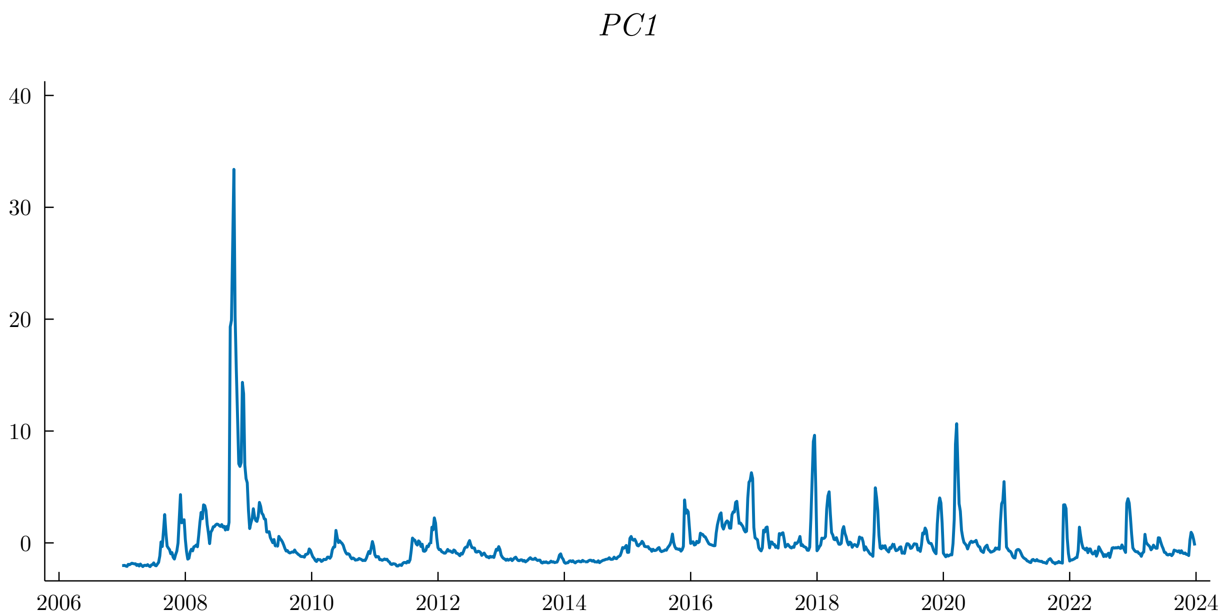

Figure A2: Bank-Intermediated Arbitrage Dislocations. Figure plots the first principal component of the absolute value of the bank-intermediated trades. The trades include 1-month covered-interest parity violations calculated following Du et al. (2018) as well as the CDS-bond and CDS-CDX basis provided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

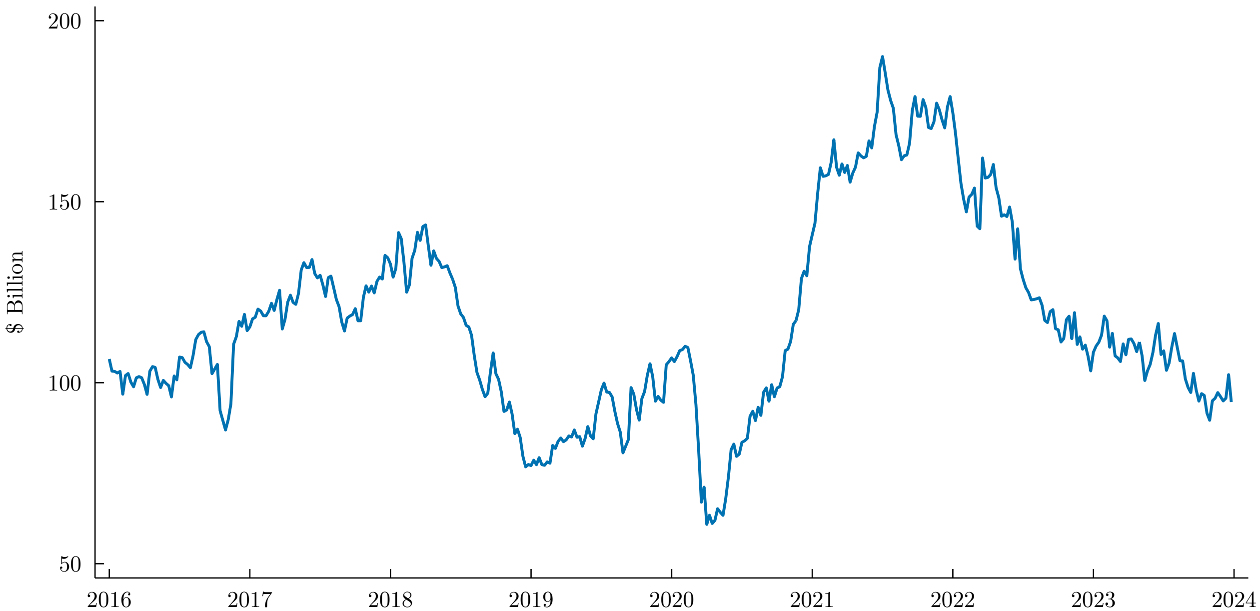

Figure A3: Equity Repo Collateral. Figure plots the volume of repos with equity collateral from FR2052a. Plot is weekly averages of daily data.

A.11 Appendix Tables

Monthly Data (2011–2023)	Variable	Empirical Proxy	Mean (%)	SD (%)	Cov$(\cdot, \Delta c) \times 100$	Cov$(\cdot, h) \times 100$
Real economy	$r_K - r_f$	Fama–French Market	10.380	15.17	0.02	−4.75
Boxed Treasury	$r_{\theta_b} - r_f$	Hi Collateral Ratio Tercile	−2.712	3.62	−0.02	−0.78
Unboxed Treasury	$r_{\theta_{ub}} - r_f$	Lo Collateral Ratio Tercile	−2.706	3.62	−0.02	−0.72
Consumption	Δc_{t+1}	PCE	2.668	4.84	0.23	−1.74

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

	$Repo_t$/Treasuries $Outstanding_t$		Δ($Repo_t$/Treasuries $Outstanding_t$)	
	(1)	(2)	(3)	(4)
$Repo_t$/H8 $Assets_t$	0.93***			
	(10.28)			
$Repo_t$/FR2052a Unencumbered $Assets_t$		0.24***		
		(27.33)		
Δ($Repo_t$/H8 $Assets_t$)			1.06***	
			(69.79)	
Δ($Repo_t$/FR2052a Unencumbered $Assets_t$)				0.25***
				(49.44)
Constant	1.37	1.93***	−0.00*	−0.00
	(1.44)	(5.57)	(−1.91)	(−0.59)
N	1,988	1,988	1,975	1,975
R^2	0.63	0.84	0.96	0.80

Table A2: Repo/UST Correlations. Table presents the regression of repos outstanding divided by Treasuries outstanding on (1) repos outstanding divided by total commercial bank assets (non-seasonally adjusted) from the Federal Reserve H.8 and (2) repos outstanding divided by total unencumbered assets from FR2052a. First two columns are levels, and second two columns are first differences. Total commercial bank asset data is available weekly, which I forward fill to a daily basis (using the most recently available value for a given date). Total unencumbered assets are defined as the sum of unencumbered assets, assets pre-positioned at central banks or GSEs, restricted reserves, and unrestricted reserves. The FR2052a data was modestly updated in several ways in April 2022, and I limit the data to the business lines and portfolio classifications that the banks consistently reported over the period 2016 to 2023 to create a panel that is directly comparable over the sample. Daily data. t-statistics shown using heterosketastic and autocorrelation consistent standard errors using the Newey and West (1994) automatic lag selection procedure where * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

	$\Delta \ln(\text{Repo}_t)$	$\ln(\text{Repo}_t)$
	(1)	(2)
$\Delta \ln(\text{Non-Repo Liabilities}_t)$	0.36***	
	(4.14)	
$\ln(\text{Non-Repo Liabilities}_t)$		0.84***
		(10.35)
N	1,975	1,988
R^2	0.02	0.68

Table A3: Repo and Non-repo Liabilities. Table presents the regression of repos outstanding on non-repo liabilities outstanding. Daily data, constant omitted. First column is daily changes and second column is daily (log) levels. Data aggregated from FR2052a. t-statistics shown using heterosketastic and autocorrelation consistent standard errors using the Newey and West (1994) automatic lag selection procedure where * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

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.*
BANCO SANTANDER	Bco SANTANDER SA
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	BPCE
CALYON	Societe Generale
CANTOR FITZGERALD	*n.a.*
CIBC	Cdn Imperial Bk Comm
CIT GROUP	CIT Gp Inc
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	Fed Farm Cr Bks Fdg Corp
FHLMC	Fed Home Ln Mtg Corp (new)
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

Name	Matched Markit Entity
JEFFERIES	Jefferies Group LLC
JP MORGAN	JPMorgan Chase & Co
LEHMAN	*n.a.*
LLOYDS	LLOYDS BK PLC
LOOP	*n.a.*
MERRILL LYNCH	Bk of America Corp
METLIFE	MetLife Inc
MITSUBISHI	Mitsui & Co Ltd
MIZUHO	Mizuho Bk Ltd
MORGAN STANLEY	Morgan Stanley
NATIONAL AUSTRALIA BANK	Natl Aust Bk Ltd
NATIONAL BANK OF CANADA	Natl Bk Cda
NATIXIS	Natixis
NATWEST	Royal Bk Scotland Gp PLC
NOMURA	Nomura Hldgs Inc
NORINCHUKIN BANK	Norinchukin Bk
NORTHERN TRUST	*n.a.*
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
TEACHER RETIREMENT SYSTEM OF TEXAS	*n.a.*
TORONTO DOMINION	Toronto Dominion Bk
TRUIST	Truist Finl Corp
UBS	UBS AG
UMB	*n.a.*
UNITED OF OMAHA LIFE INSURANCE CO.	*n.a.*
US BANK	U S Bancorp
WELLS FARGO	Wells Fargo & Co

Table A4: 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.

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

Table A5: Treasury Collateral Spread Significance by Tenor. Table presents the regression of the value-weighted Treasury collateral spread (column 1) or the collateral spread at various tenors on a constant. t-statistics are reported in parentheses using robust standard errors clustered by month where * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

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

Table A6: Collateral Spread Estimate Error Regression. Table presents the regression of two measures of pricing error from the yield curve model used to estimate the collateral spread: the mean absolute pricing error (MAPE) and the root mean squared error (RMSE) of the pricing error. The pricing error is the difference between the model's estimated yield for a CUSIP given its maturity remaining compared to the observed yield. The pricing error is in percentage points. The left-hand side variable in each regression are the pricing errors from the high-collateral ratio tercile yield curve, and the right-hand side is the pricing errors from the low-collateral ratio tercile yield curve. t-statistics are reported in parentheses using heterosketastic and autocorrelation consistent standard errors using the Newey and West (1994) automatic lag selection procedure where * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

	Mean (bps)	ρ
Benchmark Estimate		
Value-Weighted	0.53	1.00
Fixed Weights	0.56	0.99
Including On-the-Runs		
Value-Weighted	0.56	0.95
Fixed Weights	0.58	0.95
Excluding Cheapest-to-Deliver		
Value-Weighted	0.52	0.98
Fixed Weights	0.55	0.97
Excluding 25 Most Special CUSIPs		
Value-Weighted	0.42	0.83
Fixed Weights	0.44	0.81

Table A7: Treasury Collateral Spread with Alternate Assumptions. Table presents the average collateral spread when estimated using different filters and the second column shows its correlation with the benchmark collateral spread estimate: the first row is the benchmark estimate. Value-weighted indicates the weights are taken from Treasury market values by maturity bucket lagged by a month, Fixed Weights use the average monthly weight. Alternative assumptions are relative to the benchmark (e.g., excluding a variable is excluding that variable in addition to the benchmark filters). "Include on-the-runs" changes the sample to include first and second on-the-run CUSIPs. "Excluding Cheapest-to-Deliver" excludes the cheapest-to-delivery CUSIPs identified by Bloomberg for 2y, 5y, 10y, and 30y Treasury futures. "Excluding 25 Most Special CUSIPs" excludes the most special CUSIPs after ranking by their average specialness over the month, where specialness is the spread between the DTCC GCF repo index and the volume-weighted repo rate on trades between 7:30am and 10:00am using data from the interdealer broker community.

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

Table A8: Collateral Spread Estimated from Treated and Control Groups during July 2011 Euro Crisis. Table presents the regression of different Treasury collateral spreads on a post dummy: Collateral Spread$_t = \alpha + \beta\mathbb{I}(\text{Post}) + \varepsilon_t$. The collateral spread is either estimated from the "control" or "treated" sample, where treated indicates high collateral ratio bonds used more by European banks in that month, and control indicates high collateral ratio bonds used less by European banks in that month, analogous to the treated and control sample in the first three columns of Table 12. Sample is daily from February 2011 to November 2011, and post is equal to 1 for dates after or on July 11, 2011. Treated−Control column is the regression of the difference in the collateral spreads for treated and control on a post dummy. The last 3 columns repeat the regression in a placebo test with the sample and post dummy moved forward one year, running from February 2012 to November 2012 with post equal to 1 for dates after or on July 11, 2012. t-statistics shown using heterosketastic and autocorrelation consistent standard errors using the Newey and West (1994) automatic lag selection procedure where * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

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

Table A9: Repo Collateral Composition. Table presents the collateral composition for repos reported in the money fund N-MFP data and in the FR2052a data. N-MFP data is for December 2023, and FR2052a data is average of daily values in the first half of December 2023. I classify collateral classes in the FR2052a data into buckets that are similar to the categories provided in the N-MFP.

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

Table A10: Spanning Tests of Repo and Common Equity Risk Factors. Table presents the regression of excess stock returns on repo growth and asset pricing factors: $r_{i,t} - r_{f,t} = \alpha + \beta_1 \Delta \ln(\text{Repo}_t) + \beta_2(Mkt_t - r_{f,t}) + \beta_3(SMB_t) + \beta_4(HML_t) + \beta_5(MOM_t) + \varepsilon_{i,t}$. Regression run at the day by company level from January 2016 to December 2023 (the period that repo data is available from FR2502a). The first two columns run the regression on the full sample of equities, not conditioning on whether that company's stock has been used as collateral. Column (3) limits the sample to stocks have been used as collateral at some point before the current month, reflecting the set of information available to investors, denoted "rolling." Alternatively, Column (4) instead limits to stocks that are used at least once in the entire sample, denoted "full." Column (5) uses the rolling sample approach to identify stocks never used as collateral (like column 3) up to the current month. Column (6), analogous to column (4), limits the sample to stocks that are never used as collateral at any point in the full sample. t-statistics shown using robust standard errors clustered by company and date where * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.