# The Role of Margin and Spread in Secured Lending: Evidence from the Bilateral Repo Market*


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**ABSTRACT**

We study secured lending contracts using a novel, loan-by-loan database of all bilateral repurchase agreements (repos) that financed a hedge fund's speculative positions over three years. A repo has two main contract terms: loan price (spread) and excess collateral (margin). By observing multiple loans originated on the same day by the same lender on different collateral, we show that margins and spreads increase together, with the lender retaining more risk as collateral quality declines. We compare contemporaneous contracts on identical collateral by different lenders, estimating that one point of spread substitutes for nine points of margin. The borrower trades off higher spread for lower margin when facing (i) less creditworthy lenders, and (ii) lenders with greater access to wholesale funding. As borrower default risk increases, margins (but not spreads) rise faster when the collateral value is more opaque. This suggests that margin has a unique role in protecting the lender from collateral illiquidity.



Keywords: Secured lending, Collateral, Margin, Interest rate, Repo
JEL: G21, G23, G32, D86, D82



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# 1 Introduction

A large fraction of all lending is guaranteed by collateral.[1] While the typical example of collateralized loan is a mortgage guaranteed by real property, short-term loans called repurchase agreements, or repos, are at the heart of modern financial markets. Every week, trillions of dollars of dealers' inventories and hedge funds' leveraged bets are financed this way.[2] The repo market has risen to prominence for its role in mediating systemic risk throughout the 2007 financial crisis, generating a wave of academic interest. Thanks to the mandatory disclosures of money market mutual funds, the main category of wholesale lenders, there is some research on the wholesale, or *tri-party*, market. However, little detailed data has been available so far for analysis, especially for *bilateral* repurchase agreements – private agreements directly negotiated and cleared between lenders such as broker-dealers and borrowers such as hedge funds, other broker-dealers, and other institutions. For the purpose of understanding contract features, data from the bilateral market is more useful, because bilateral agreements are negotiated at the individual security level, while tri-party repos are negotiated for broad pools of collateral. More in general, compared to other forms of collateralized lending, bilateral repos provide a unique setup to study contract terms because a given borrower enters multiple and repeated contracts on well-identified, non-unique collateral.

In this paper, we try to fill the gap with a unique loan-level dataset, consisting of three years of repurchase agreements between a large fixed-income arbitrage fund and essentially all major lenders in the bilateral repo market. On each business day in the sample period, we observe detailed features of every outstanding repo contract, such as interest rate, margin requirement, maturity date, specific security used as a collateral, and posted cash margin. Thanks to the multi-dimensional structure of our data, our empirical analysis is often robust to the presence

[1]Beside all mortgages and repurchase agreements, at least two studies (Avery et al. (1998); La Porta et al. (2003)) find that collateral secures also about 80 percent of bank loans.

[2]Fed Governor Daniel K. Tarullo in a 11/22/2013 speech said "Banks and broker-dealers currently borrow about \$1.6 trillion, much of this from money market funds and securities lenders, through tri-party repos, leaving aside additional funds sourced from asset managers and other investors through other channels. The banks and broker dealers, in turn, use reverse repo to provide more than \$1 trillion in financing to prime brokerage and other clients." Sifma statistics on funding put the size of primary dealer's repo and reverse repo gross financing at around \$4.2 trillion. According to the Office of Financial Research, the U.S. repo market provides more than \$3 trillion in funding every day.

of environmental variables that were available to a lender and the borrower at the time the loan contract was written, but are unobservable to us. Our findings cast light on this opaque but systemically important market, while providing insight into the economics of general secured contracts, a category including repos, mortgages, and even derivatives such as futures and swaps.

The margin requirement in a repurchase agreement takes the form of a "haircut". The haircut is akin to a downpayment in a mortgage: with a haircut of 5 percent, a borrower needs $5 of its own capital to buy $100 worth of securities. A higher haircut provides a higher level of protection to the lender. For example, with a 50 percent haircut, the lender does not suffer losses even if the borrower defaults, as long as it can sell the collateral for more than half of the value at the time of lending.[3] If the haircut goes from 50 percent to 49 percent, the lender must recover at least 51 cents on the dollar to avoid losses.

In a perfect economy with no frictions, the borrower can always compensate the lender for a marginal increase in risk with a marginally higher rate. Lender and borrower agree on the price of risk and they are indifferent among the infinite possible contracts, including one with no margin at all, rendering margin – in fact, collateral – unnecessary.

By contrast, in the real-world repo market, margin is ubiquitous. Understanding how margin is set in secured contract has important policy implications. For instance, Hardouvelis (1990) and Hardouvelis and Peristiani (1992) argue that increases in margin requirements reduce destabilizing speculation in financial markets. The prevalent common-sense view is that the haircut is chosen to offset collateral risk. For instance, Comotto (2012) claims that haircuts/initial margins are usually intended to hedge the risk on collateral. More specifically, Brunnermeier and Pedersen (2009) argue that a borrowing hedge fund's margin requirement is typically set to make the loan almost risk-free for the counterparty, so that it covers the largest possible price drop with a certain degree of confidence.

However, the repurchase agreements we observe in our data set are priced as if they were all but risk-free. We find that the spreads of the repo rate over a set of standard benchmark rates, typically used to represent risk-free or near risk-free returns, are significantly positive.

[3]Typically, collateral is marked to market periodically, and cash is exchanged between the parties to keep the lender's margin close to the initially agreed-upon margin. If the collateral is marked to market, what matters is not the price at the time of lending, but the price as of the latest mark.

Specifically, the spread over LIBOR is about 6 basis points on average, even though LIBOR is not entirely risk-free.[4] The spread also displays considerable variation, even within the same day, lender, borrower, loan duration, and collateral asset class, overall ranging from as low as -30 basis points and as high as 50 basis points. This variation is not random but is strongly correlated with collateral quality. With only one borrower in the sample and a median loan duration of 30 days, a range of 80 basis points is large.[5]

Thus, not only does spread vary considerably, but also spread and haircut covary strongly with one another. In fact, in the cross-section of collateral, we fail to establish even one source of contract risk that clearly affects spreads but not haircuts, nor one that affects haircuts but not spreads.

Further, consistent with Comotto (2012) and Gorton and Metrick (2012), we find that haircut is affected by borrower creditworthiness, and not only by collateral quality. This is not immediately obvious: if the haircut is sufficient, a lender's expected loss on liquidating the collateral upon borrower default should be independent of borrower's default probability.[6]

All these observations suggest that the haircut does not exist solely as a nonprice defense against some market failure; the haircut seems to be meant to reduce – not eliminate – lender risk exposure. The lender chooses to retain a nonnegligible amount of risk, which increases with the risk of the underlying collateral. Because the loan is not risk-free, a higher haircut reduces risk, and it is increasingly valuable as the borrower becomes riskier.

Without detailed data on the bilateral repo market, following the 2007–08 financial crisis, several authors proposed theoretical models of repo contracting (e.g., Gorton and Metrick (2009); Gorton and Ordoñez (2014)). Although the focus of these models is typically not on the contract

[4] Due to institutional practices, the interest rate of most contracts was specified as some spread over LIBOR during our sample period. We use LIBOR as the benchmark rate for the rest of our analysis. When we use safer rates such as the Fed Funds rate or the 1-month T-bill rate, we obtain an average spread of 33 basis points and our other results are consistent.

[5] By comparison, 300 basis points separate the best from the worst borrowers of 30-year conventional home mortgages. With regard to collateral in particular, Stroebel (JF, *Forthcoming*) indicates that the presence of adverse selection on home quality increases the mortgage rate on average by about 10-15 basis points.

[6] Accounting for correlation between collateral value and borrower default would make this argument stronger, i.e., worse borrowers deserve a lower haircut. A good borrower defaults only in very bad states of the world, when the asset is also likely to be worth less. A bad borrower defaults in not-so-bad states of the world, when the asset is more likely to hold its value. Thus, the distribution of asset returns conditional on default of a bad borrower is better.

terms themselves, all introduce one or more departures from the frictionless model to justify the existence of margin. To the best of our knowledge, none of the mechanisms assumed in the literature result in the lender taking on any risk, and the role of haircut and spread in these models is typically orthogonal.[7]

However, we observe that lenders take on risk and they care about both collateral price volatility and illiquidity. Our data contain thousands of instances in which multiple tranches of the same collateralized debt obligation are funded with the same lender at the same time. Within these sets of tranches, spread and haircut increase together as the tranche risk increases. Even controlling for tranche risk, both haircut and spread are affected by volatility (proxied by 1-month realized volatility) and liquidity (proxied by the tranche's total issue size).

If haircut and spread react to a common set of risks in a similar way, they might be substitutable for a given risk. The empirical challenge when testing the relationship between haircut and spread lies in the difficulty of controlling for collateral and borrower risk in a repo contract. Observable measures of risk are typically limited when the collateral is illiquid and the borrower is not a public entity. Even with all the relevant information that can be observable, finding that haircut and spread covary in a certain way does not rule out the possibility that some latent risk factor drives variation in both. To address this concern, we identify pairs or triples of brand-new contracts (i.e., not renewals of existing contracts) written in the same time period, on the exact same collateral, by the same borrower with different lenders. By comparing contracts within a pair (or a triple), we are able to control fully for any collateral and borrower risks.

Within this subsample, we directly observe substitution between haircut and spread: within a pair, when one contract's haircut is higher than the other's, its spread tends to be lower than the other's: different lenders meet the borrower at different points on the indifference curve. Our results show that, on average, a 1 percentage point increase in spread is associated with a roughly 9 percentage points drop in haircut.

Controlling for collateral, we can also identify other factors that affect the choice of a haircut.

[7]For instance, in Brunnermeier and Pedersen (2009), demand for collateral is created by the combination of (i) search frictions, and (ii) a special class of investors, "speculators," that unlike lenders are able to take advantage of order imbalances created by the search frictions. Dang et al. (2012) justify the need for margin based on some form of illiquidity of the asset.

We find that lender identity matters because of lender credit risk. Unlike unsecured lending and most secured lending, repo contracts entail two-way credit risk. If the lender undergoes bankruptcy, the borrower stands to lose the initial haircut and all the intervening appreciation in asset value. Consistent with this, allowing the haircut-spread schedule to differ across lenders, we observe that the borrower in our sample obtains lower haircuts (at the cost of higher spreads) when borrowing from lenders with a higher probability of default. Further, we find that lender identity matters because of funding liquidity: the borrower also obtains lower haircuts (again, at the cost of higher spreads) from lenders that were able to expand their funding from the wholesale funding market.

In general, within contract pairs, we observe a substantial amount of variation that cannot be attributed to any fundamental characteristics of the asset or of the borrower, and therefore has to be attributed to lender-specific factors. These factors, together with substitution between haircut and spread, explain about 23 percent of the total variation in haircuts.

Finally, along with evidence of substitution, we do find evidence of a unique role of haircuts, implying only partial substitutability. As the borrower's default probability increases, haircut rises more for more illiquid collateral, suggesting that the haircut protects lenders from a joint event of borrower failure and incurring loss because of collateral illiquidity. This appears even when using only the borrower default risk component that is orthogonal to collateral asset risk. A similar pattern does not appear for spreads, suggesting that a higher spread cannot substitute a higher haircut in this instance.

Our paper contributes broadly to the literature on secured contracts, and two strands in particular. The first strand consists of papers on the design of collateralized contracts in general. Within this literature, our results relate most closely to Benmelech and Bergman (2009) and Benmelech et al. (2005), who analyze respectively secured loans issued by U.S. airlines and real property loans. These authors find that more redeployable collateral is associated both with lower credit spreads and with higher borrower debt capacity. In addition, our finding that margin and spread are correlated in the cross-section of collateral complements Rappoport and White (1994)'s finding that in the run-up to the 1929 crisis, loan spreads and margin requirements on broker margin loans rose together. The second strand, about repo markets in particular, has come into the spotlight in the wake of the financial crisis (Gorton and Metrick (2009); Brunnermeier and Pedersen (2009); Geanakoplos and Zame (2014)). Between these two strands, to the best of our knowledge, ours is the first paper that uses loan-level data on bilateral repo markets and provides systematic evidence powerful enough to put restrictions on theory.

Within the latter literature, several mechanisms have been employed to justify the need for collateral in general and margin in particular. In one set of models, collateral requirements exist because borrowers are more optimistic (Fostel and Geanakoplos (2014); Geanakoplos and Zame (2014)) or more risk tolerant (Gârleanu and Pedersen (2011)) than lenders. Because borrowers have a comparative advantage in bearing risk, they offer to take the first loss by posting collateral.

In a second set of models, lenders require a "haircut" because the assets are illiquid (Gorton and Metrick (2009); Dang et al. (2012); Gorton and Ordoñez (2014)). In these models, if the lender has to liquidate the collateral, value will be lost; therefore, the lender requires an amount of collateral larger than the size of the loan itself.

Finally, a third set of models focuses on two-sided counterparty risk, noting that usually the borrower is more exposed to counterparty risk than the lender is for the reasons explained above. Ewerhart and Tapking (2008) point out that lender credit risk is a well-known issue, and they show that it can cause market breakdown. Lee (2015) analyzes the relationship between collateral circulation and financial stability. In Infante (2015), bank runs on dealers with higher credit risk are created by collateral providers rather than by cash lenders, because the latter are not exposed to a dealer's credit risk. In Eren (2014), the focus is on the lender's liquidity needs, as opposed to the counterparty risk itself. This last class of models, therefore, predicts that haircuts in the bilateral market would be decreasing with the dealer's credit risk and increasing with the dealer's funding liquidity status. With empirical measures of lenders' creditworthiness and funding condition, our results support these predictions.

The empirical literature has focused on how the repo market propagated negative economic shocks during the 2007 financial crisis (Copeland et al. (2014); Martin et al. (2014); Gorton and Metrick (2012); Krishnamurthy et al. (2014b)). Martin et al. (2014) argue that the bilateral repo market is less fragile in part because of the ability of haircuts to adjust to provide protection to investors ("some funding is better than none"). In contrast, Mancini et al. (2015) argue that a centralized clearing system promotes market resiliency, by studying the Euro interbank repo market during a series of crises. Hu et al. (2014) conduct a study of the tri-party repo market, where money market mutual funds are the lenders, and dealer banks (our lenders) are the borrowers. In the tri-party market, haircuts are usually constant within a given asset class and fund family.

Our findings support a view that the bilateral repo market proved more resilient because participants are more sophisticated, and therefore more likely to adjust to a new economic environment, instead of walking away. In contrast to Hu et al. (2014), every one of our lenders determines the haircut based on the detailed features of each loan, such as loan duration and fine collateral quality. However, our findings also cannot rule out Infante's (2015) theory that the lenders in the bilateral market (the dealers) are less creditworthy than the lenders in the tri-party market (the super-liquid, all-equity money market mutual funds). This theory can explain the different ways in which transaction volume and haircut levels reacted across the two markets during the financial crisis.

Overall, our findings provide evidence in favor of illiquidity theories of collateral, as well as two-sided counterparty risk theories, but fail to conform to any theory in particular. The strong covariation that we observe between spread and haircut is not explicitly predicted by any theory. Moreover, haircut and spread seem to respond to collateral price volatility in a very similar way. These findings call for both more theory development and more data.

## 2 Data description

Our data come from multiple hedge funds that actively traded fixed-income securities (mostly structured finance securities). The sample covers 3 years, from 2004 up until the collapse of the subprime market in 2007. The funds' main strategy was to invest in asset-backed securities (ABS) backed by various types of collateral: pools of residential mortgages (mortgage-backed securities or MBS), commercial loans (collateralized loan obligations or CLO), mortgage-backed securities (collateralized debt obligations or CDO), and even CDOs backed by CDOs (CDO-squared or $CDO^2$). The funds combined held on average about $9 billion in securities, making them one of the largest in their category.

The hedge funds were under the same management, and they shared a common strategy to earn carry by taking leveraged positions in structured finance securities. The funds operated at a time-varying leverage of between 5:1 and 15:1, achieved by borrowing money from the bilateral repo market. All funds invested in the same securities, but some operated at higher leverage. The additional leverage was obtained with unsecured lines of credit that were junior to the repo lenders and senior only to the fund investors, making the funds even more similar to each other from the perspective of a repo lender. Therefore, we do not distinguish these funds explicitly and we treat them as one borrower ("the fund"), unless otherwise specified.

The fund reported profits until the end of 2006. However, at the beginning of 2007 the assets underlying the securities in their portfolio, including subprime mortgage loans, started suffering from unusual defaults. Thus, the fund experienced losses and was eventually shut down in that year.

Our data consists of a daily panel of repo contracts for the fund. For each contract, we have the security's CUSIP number and a 36-character description. The description usually contains information about the issuer (for structured securities, this is often a special purpose vehicle, or SPV), tranche (for structured securities), and coupon rate. Information about the security also includes the current price (per $100 par value), together with an indication of the source; the most common sources are Bloomberg quotes, trader quotes, a model, and cost basis; but for a little less than half of the contracts, the price is just missing. Having a missing price does not mean that a repo contract can be made without knowing the valuation of the collateral. Even with missing prices, when a brand-new repo was made, the market value of the security is implied in the contract. However, on every day during a contract term or when a loan is rolled over, we do not always observe the market price of the collateral.

Information about the position includes the par value and the current factor (for instance, if 30 percent of the principal of a mortgage-backed security had been prepaid, the current factor would be 0.7; the prepayment could not be inferred by simply looking at the par value), the market value (equal to $Security\ Price \times Par\ Value \times\ Current\ Factor$), and the accrued coupon interest (as it is common in the bond market, all other quantities are "clean," i.e., they exclude the interest accrued since the last coupon was paid).

Finally, information about the repurchase agreement itself includes the name of the lender, start date, end date (which can be "open" occasionally), principal amount, interest accrued on the loan, rate, haircut/required margin, cash margin (i.e., the actual cash in the hands of the lender), current margin (the security value as percentage of the loan principal).

The raw data consists of 297,606 daily observations of 16,807 repurchase agreements with 54 lenders, financing 1,590 unique securities (CUSIPs). Among other things, we drop 1,797 observations pertaining to reverse repurchase agreements and 9 lenders that had some relationship to the fund (e.g., the parent company). The cleaned data consists of 269,212 daily observations of 13,688 repurchase agreements with 45 lenders, financing 1,496 unique securities (CUSIPs).

We augment the data using information from Bloomberg (market sector, name, ticker, description, asset class, mortgage type, collateral type, issue amount, issue date, and maturity date) and from the FISD database (bond rating for corporate and government bonds) at the CUSIP level and macro-level (VIX, LOIS, ABX returns, and other time-series variables of interest), and from FRED (LIBOR and U.S. risk-free interest rates at various short-term maturities). We obtain the fund investors' capital flow and fund returns, as well as general info about the fund, from the TASS database. Further, to have a high-frequency measure of credit risk for lenders, we merge expected default frequency (EDF) of lenders with public equity or those whose parent companies are public firms, on each day in the sample. In order to analyze the covariation of a dealer bank's funding condition and its lending contracts, we hand-collect the money market mutual funds (MMFs)' quarterly SEC filings. In these filings, MMFs report all their investments, and wholesale repo loan contracts are investments from the point of view of the funds, and therefore are reported too. The filings report information about rate, margin, principal amount and type of collateral (e.g. "Treasury obligations" or "Mortgage-backed securities") with some level of aggregation. Following Krishnamurthy et al. (2014a), we select the major money market mutual fund families for the period that coincides with our dataset, i.e., mid-2004 to mid-2007.[8]

[8]We thank Stefan Nagel and coauthors for providing the data used in Krishnamurthy et al. (2014b), so that

Haircuts vary between 0 and 50 percent. Slightly less than 20 percent of the contracts have zero haircut; the median haircut is 5 percent; and slightly more than 10 percent of contracts have a haircut in the double digits. Rates vary from 0.80 percent to 6.88 percent.[9] Expressed as a spread to the relevant LIBOR rate, the spread varies between -285 basis points and 157 basis points, with a median of just 4 basis points and a standard deviation of 17 basis points. Principal amounts of the loans (gross of the posted cash margin) vary between $30,885 and over *$700 million* with a median of $10,463,300. Loans larger than $300 million occur only for Treasury bonds, but loans between $100 million and $300 million dollars are not exceptional.

Table 1 shows the asset class composition of the securities in the data, together with median values for the contract terms for each asset class. Because the contract terms are fixed for the duration of the contract, this table is made by counting each unique contract only once (more on this below).

[Insert Table 1 about here]

Figure 1 visualizes the relationship between our two key variables of interest, haircut and spread, in the whole sample. We group contracts into seven haircut bins from 0 percent to 30 percent, and calculate mean and median of spread in each bin. This first glimpse of the data presents a monotonically increasing pattern of spreads with respect to haircuts, suggesting that they are positively correlated.

[Insert Figure 1 about here]

## 3 Estimating the repo spread

While we focus on the respective roles of margin requirements (haircut) and risk compensation (spread), what we observe in a repurchase agreement is the interest rate, not the spread. The rate varies over time as macroeconomic interest rates vary, and even within the same day, it

we could check the consistency of our data collection from two overlapping quarters in 2007.

[9]We do observe one exception to this upper limit: two contracts done on the same date with the same lender with a rate of 48 percent, corresponding to a total cost of 0.4 percent over the 3-day life of the contract. We do not have an explanation for these.

varies naturally for loans of different maturity: typically, longer-term loans have higher rates than short-term loans, even when they are risk-free. Therefore, it is necessary to define and measure the spread carefully before proceeding further.

We define the spread as the difference between the repo rate and a reference rate with matching maturity. The resulting spread is therefore already net of the term structure of the loan rate and of macro interest rate variation. As reference rates, we consider both LIBOR and the U.S. risk-free rate (Fed Funds for overnight and Treasury bill yields for longer maturities). LIBOR is the required return on short-term unsecured loans (Eurodollar deposits) to creditworthy international banks. Therefore, it is a low-risk rate, but not a risk-free one.

Empirically, we can only have the reference rate at several points in the term structure (overnight, 1-month, etc.) as opposed to the repo contract term, which can be any number of days. We address this issue by interpolating the term structure using a cubic spline. Our results do not depend on the choice of an interpolating function.

Figure 2 shows that the interest rate on repo contracts tracks LIBOR much better than it tracks the risk-free rate. The risk-free rate is still a useful reference rate in order to form an idea of the magnitude of the risk premium included in the repo rate. On an average day, the spread of the repo rate over LIBOR is positive (6 basis points, $t$-statistics = 19.5), even though repo is secured, whereas LIBOR itself represents the rate that creditworthy banks charge one another on unsecured loans. The spread over the risk-free rate is 33 basis points.

Figure 3 depicts the distribution of the spread using LIBOR as a reference rate. Although common beliefs, as well as certain theoretical models, imply that repo lending should happen at or close to the risk-free rate, we observe large variation in repo rates.[10] Both in the time series and in the cross-section, this variation appears to be strongly correlated to risk.

In both figures, as well as in the rest of the paper except where indicated, one observation is one contract, not one contract day. For instance, in our sample a 7-day loan is typically observed five times (excluding weekends). For most purposes, counting repeated observations of the same

[10] Former chairman of the Federal Reserve Board Ben Bernanke said in a May 13, 2008 speech: "Until recently, short-term repos had always been regarded as virtually risk-free instruments and thus largely immune to the type of rollover or withdrawal risks associated with short-term unsecured obligations." As we can see here, repos were not risk-free as early as 2004, at least in the bilateral market.

contract as distinct observations would not be appropriate, because the contract terms are fixed for the duration of the loan and can no longer react to new information.

[Insert Figures 2 and 3 about here]

In the time series, the spread is correlated with systematic risk factors. Table 2 shows two simple regressions of the daily-average spread of repo contracts on, respectively, the VIX index and the LOIS spread, both of which are considered to be indicators of systemic financial risk (e.g., Gorton and Metrick (2012)).[11] The coefficient on LOIS is positive and significant, whereas the coefficient on VIX is positive but insignificant. In these regressions, one observation is one day. While the results of a simple time series regression should not be taken as conclusive evidence, this finding provides additional evidence in favor of our conjecture that the lender charges a spread over the risk-free rate as a form of risk compensation, and not as a form of rent extraction. Moreover, the fact that LOIS is significant but VIX is not suggests that the risk in question is particularly related to funding liquidity of the the financial market rather than overall volatility.

[Insert Table 2 about here]

## 4 Contract terms, collateral quality, and risk

In this section, we show that both haircut and spread covary strongly with collateral quality. “Quality” could be defined as low risk. If value at risk is what matters, low-quality collateral is collateral with high price volatility, and the source of volatility is not important. However, “quality” could also be defined as liquidity. Low-quality collateral is collateral that is difficult to liquidate, because of physical search costs, or because an uninformed lender would risk being at the mercy of an informed trader when trying to dispose of it. Empirically, it is difficult to tell apart risky collateral from illiquid collateral. To the extent that it is possible, in this section we provide suggestive evidence indicating that lenders are concerned with both risk and liquidity.

[11] “LOIS” is LIBOR over the Overnight Indexed Swap.

### 4.1 Both haircuts and spreads increase with collateral asset quality

Repo spread and haircut covary across assets classes (Table 1). For instance, repos collateralized by preferred shares have both the highest median spread (24 basis points) and haircut (15 percent), whereas Treasury repos have the lowest (-20 basis points and 0 percent). We also find considerable variation *within* each asset class, and once again, securities of lower quality tend to have both a higher haircut and a higher rate (Table 3). Compared with Treasury bonds, AAA corporate bonds have higher spreads (-6 basis points) and haircuts (0 percent; note that the haircut on Treasury bonds is identically 0 percent throughout the sample, whereas the haircut on AAA bonds is often 2 percent and sometimes higher).

One notable exception that is not explained by a low number of observations is that repos collateralized by BBB bonds have lower spreads than those with A bonds (2 basis points versus 3 basis points). However, haircuts of BBB bonds are also lower (4 percent versus 5 percent): even in this case, spread and haircut both conform their relative behavior.

For structured finance securities, we hand-classify each security as either A, Mezzanine, B, C, Junk or Other, based on the text description from our data and, when available, from Bloomberg. Junk encompasses lower-rated tranches (D, E, all the way to I), notes (N), and special tranches such as servicing rights (X), while Other is a catch-all for everything that we could not classify.[12] While this text-based classification is approximate, it does seem to be informative: Junk tranches always have the highest haircut and spread both for MBS and for ABS.

[Insert Table 1 about here]

Although we show that there is a general pattern of haircut and spread with respect to rating or tranche, there can be significant heterogeneity in asset quality within each category. For example, two "A" tranches may be associated with different levels of payoff risk, depending on the credit quality of the issuer. Moreover, lender and borrower characteristics could vary through time and across lenders. Only after controlling all these sources of variation can we

[12] Even though the "A, B, C" nomenclature is relatively standard, there is no official manual that structured finance issuers use to name the tranches, so it should be considered an approximation. The actual seniority of a tranche can only be understood by reading the prospectus of the issuing entity.

observe the true response of haircut and spread to differences in asset quality. As an illustration of our approach to address this issue, we report three repurchase agreements collateralized by three different tranches of the same CDO. Tranches A and B were funded on the same day, with tranche C joining 16 days later. All tranches were funded with the same lender. The following is the result:

| **Tranche** | **Haircut** | Loan Rate | Start | End | Term | LIBOR | **Spread** |
|---|---|---|---|---|---|---|---|
| **A** | **5.00%** | 1.813% | 6/13/04 | 10/26/04 | 135 days | 1.721% | **0.09%** |
| **B** | **10.00%** | 1.988% | 6/13/04 | 10/26/04 | 135 days | 1.721% | **0.27%** |
| **C** | **15.00%** | 2.053% | 6/29/04 | 10/26/04 | 119 days | 1.643% | **0.41%** |

Within this controlled set, spread and haircut increase much more dramatically than in Table 1. Table 1 suffers from attenuation bias because of all the factors we cannot control for in a summary table. The next sections examine this setup more formally.

### 4.2 Illiquidity vs. price risk: evidence from structured finance securities

Illiquid assets and risky assets are often the same assets. Moreover, there is more than one kind of illiquidity. Illiquidity models of repo (Gorton and Metrick (2009); Dang et al. (2012); Gorton and Ordoñez (2014)) ascribe illiquidity to a specific cause – asymmetric information. In practice, it is difficult to tell apart assets that are illiquid because of asymmetric information (with unpredictable adverse price impact when trading) from assets that are illiquid because of physical search costs (with a high bid-ask spread but still a predictable sale price for the seller). Highly rated municipal securities are a rare example of security suffering only from the second kind of illiquidity.

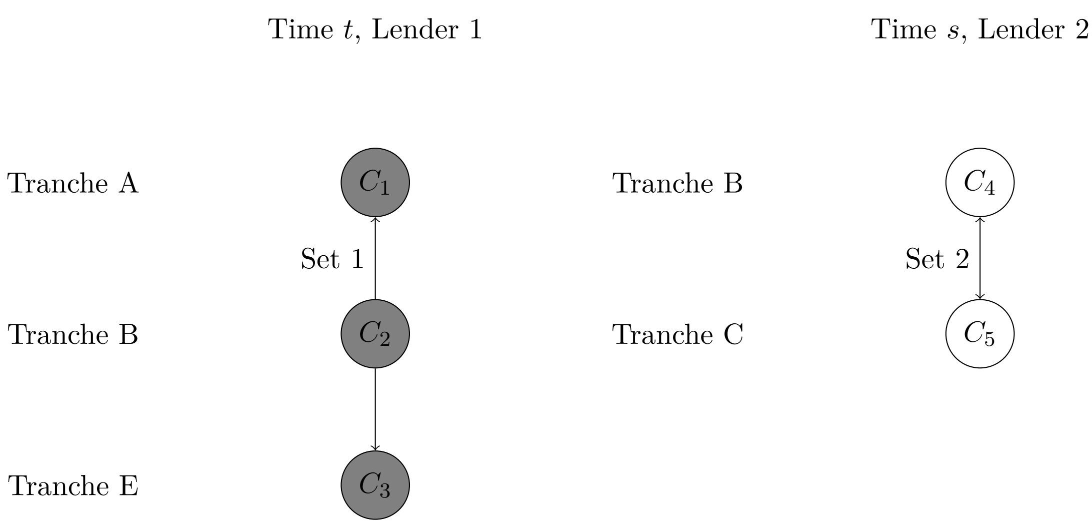
As an illustration, the highest haircut in the entire sample (50 percent) applies to the equity tranche of a CDO-squared created by the hedge fund managers themselves as part of a capital structure arbitrage deal.[13] This is clearly a very risky security (it is the residual tranche), but

[13] Capital structure arbitrage consists of acquiring the equity tranche of a structured finance vehicle (e.g., a CDO), prepaying the principal of the higher tranches, and repackaging the CDO's collateral into more marketable tranches, which can be sold for a higher price.

it is also a textbook example of a security subject to asymmetric information (a “homemade” security), as well as a thinly traded security (no one has traded this security yet, and no one will, until and unless the lender has to seize it and liquidate it).

Typically, as in this case, information on price impact as well as bid-ask spreads is not available precisely for those assets that are traded the least. Moreover, from the perspective of lenders in our data, identifying and decomposing the source of illiquidity carries little value. What matters to them is the expected loss because of this illiquidity, regardless of its cause. Therefore, in our analysis, we also do not attempt to discriminate formally different sources of illiquidity.

The situation exemplified in the previous subsection is not rare in our sample. In fact, we have 3,249 instances in which more than one security issued by the same issuer is funded on the same day with the same lender. Most instances of multiple securities from the same issuer are simply multiple tranches of the same CDO. This affords us a particularly clean measurement of the effect of collateral price risk and illiquidity on loan terms, as exemplified in the following diagram:




In the diagram, five contracts are represented. The first three contracts ($C_1$, $C_2$, and $C_3$) regard three tranches of a CDO (A, B, and E) whose purchase is financed by borrowing at time $t$ from Lender 1. The last two contracts ($C_4$, $C_5$) regard two tranches of another CDO (B and C) funded at time $s$ with Lender 2. In each case, our estimation is based on variation within each of the two sets of contracts, allowing us to measure the effect of asset risk on spread and haircut, keeping everything else constant.

Collateral price risk can be directly measured by the volatility of the asset price. Assuming that a price is readily available, higher price volatility implies a higher probability that the collateral asset value is not sufficient to make the lender whole in case of borrower default.[14]

[Insert Table 4 about here]

Table 4 contains several regressions, each run for both haircut and spread, using a set of $(Lender \times Issuer \times Day)$-fixed effects $(\alpha_{L,I,t})$. $Issuer$ is identified by the first six digits of the CUSIP number. For a repo contract $i$, the regression specification takes the following form:

$$\begin{matrix} Haircut_i \\ Spread_i \end{matrix} = \alpha_{L,I,t} + \underbrace{\beta_1 \cdot Volatility_i}_{\substack{\text{Collateral} \\ \text{price risk}}} + \underbrace{\beta_2 \cdot IssueSize_i}_{\substack{\text{Collateral} \\ \text{liquidity}}} + \underbrace{\mathbf{C}_i \cdot \boldsymbol{\gamma}}_{\text{Controls}} + \epsilon_i. \tag{1}$$

where $i$ indexes individual contracts, and $\mathbf{C}_i$ is a vector of control variables.

The first specification includes only proxies for collateral price risk and liquidity ($\mathbf{C}_i = \varnothing$). $Volatility$, a proxy for price risk, is the asset price volatility as measured by the hedge fund itself over the past month. If the price of the asset at each time can be precisely estimated, or the uncertainty on the asset value is small, then realized price volatility must be a good measure for price uncertainty. The effect of price volatility ($Volatility$) is positive for both haircut and spread, and significant for spread.

Our measure of liquidity is $IssueSize$, the natural logarithm of the security's initial issue amount (obtained from Bloomberg). Unfortunately, other popular proxies of liquidity such as bid-ask spreads were not available. Securities with large initial issue amounts are likely to be held by a larger number of investors and to be traded more often. Therefore, they can be liquidated with less search costs and price impact. The effect of liquidity is very large and negative, i.e.,

[14]This risk may arise without any illiquidity. Likewise, illiquidity can be present without a high price volatility.

liquid securities require both lower haircuts and lower spreads. Once again this suggests that lenders choose to bear some risk instead of setting the haircut so high that the loan is risk-free.

The second specification includes two loan contract parameters (other than haircut and spread) that may affect the lender's risk exposure: loan duration and the natural logarithm of loan principal only ($\mathbf{C}_i \cdot \boldsymbol{\gamma} = \gamma_1 \cdot Duration_i + \gamma_2 \cdot Principal_i$). Loan duration (measured as just the number of days to maturity of the loan) is a measure of risk for the lender. Even though we calculate the spread using maturity-matched LIBOR to account for the term structure of interest rates, borrower risk could have a term structure too. The coefficient on duration is positive and strongly significant. Loan principal, at least in principle, is a measure of lender exposure: for a given lender/borrower pair, a larger loan carries more risk. However, the coefficient on loan principal ($Principal$) is strongly negative and significant. This phenomenon arises because higher-rated tranches of structured finance securities typically have much larger principal amounts, and the loans to finance these securities are larger, but they also have better collateral. Not controlling for collateral quality, larger loans are less risky.

Similarly, the initial issue size of bond ($IssueSize$) may suffer from the same reverse causality problem as loan principal amount, because higher-rated tranches of a CDO have a larger face value. To address this issue, our third specification explicitly controls for $Tranche$, a vector of a indicator variables for various tranches, as classified previously: $Tranche_i^M$ for Mezzanine, $Tranche_i^B$ for B, $Tranche_i^C$ for C, and $Tranche_i^J$ for Junk (A is the omitted category):

$$\mathbf{C}_i \cdot \boldsymbol{\gamma} = \gamma_1 \cdot Duration_i + \gamma_2 \cdot Principal_i + \sum_{j \in \{M,B,C,J\}} \gamma_3^j \cdot Tranche_i^j \tag{2}$$

The tranche indicator variables work surprisingly well, capturing about one quarter of the remaining unexplained variation. Moreover, once controlled for otherwise unobservable collateral quality, the negative sign on loan principal ($Principal$) disappears, whereas that on issue size ($IssueSize$) does not, indicating that this is a robust finding: even across securities of the same tranche, controlling for all non-collateral factors, issue size of bonds has a strong negative effect on both haircut and spread.

Looking at the economic magnitude of the coefficients, lenders care both about the liquidity of the assets and the price risk. The coefficients are of the same order of magnitude (in absolute value), but $IssueSize$ has six times larger standard deviation, indicating that collateral liquidity is a more important factor. Furthermore, the coefficients on the tranche indicators fall in a highly symmetric pattern across the haircut and spread equations, as plotted in Figure 4. This pattern indicates that joint determination of haircut and spread may respond to the common risk of collateral quality in a proportional form.

[Insert Figure 4 about here]

### 4.3 The functional shape of the spread-haircut relation in the whole sample

So far, we have shown that haircut and spread both increase with collateral risk. We further analyze the functional shape of this relationship: is it linear, convex, or concave?

Column (1) of Table 5 reports the result of a simple specification with ($Lender \times Issuer \times Day$)-fixed effects from Section 4.2:

$$Spread_i = \alpha_{L,I,t} + \epsilon_i. \tag{3}$$

The $R$-squared of 78 percent implies that 22 percent of spread variation happens within the same lender, issuer, and time; likely, enough variation to have a well-identified answer to the question.

Columns (2) and (3) report the following specification without and with the quadratic term ($Haircut^2$):

$$Spread_i = \alpha_{L,I,t} + \beta_1 \cdot Haircut_i + \beta_2 \cdot Haircut^2 + \epsilon_i. \tag{4}$$

Column (2) shows that spread and haircut are significantly positively correlated, and Column (3) suggests that a higher-order relationship between them exists: *Spread* is an increasing and convex function of $Haircut$.

Columns (4) and (5) also report estimates of Equation (4) but without fixed effects and pooling all asset classes and all securities. These unconditional results also imply the same convex relationship. Figure 5 visually displays this relationship. Across different levels of $Haircut$, the fitted line indicates that *Spread* increases faster than *Haircut* does, as *Haircut* increases.

[Insert Table 5 and Figure 5 about here]

### 4.4 Graphical interpretation of results

The strong positive covariation between haircut and spread that we observe is not immediately obvious. To make this point, we present a graphical illustration.

For a given lender-borrower pair, we can represent each contract as an equilibrium point in an Edgeworth box with haircut ($h$) on the horizontal axis and spread ($s$) on the vertical axis. The borrower and the lender have indifference curves with respect to haircut and spread, and they maximize their respective utilities. The borrower always prefers lower haircut (higher leverage) and lower spread (higher carry); an indifference curve lying closer to the origin corresponds to higher borrower utility. However, the lender prefers higher spread (higher return) and higher haircut (higher safety); an indifference curve lying further from the origin corresponds to higher lender utility. A contract between lender and borrower is, therefore, the point of tangency of their indifference curves as in Figure 6(a). For simplicity, we assume that the borrower has limited initial capital and is risk neutral, while the lender is risk averse (in general, it is sufficient that the borrower be less risk averse than the lender). For simplicity, we also assume that riskier assets offer higher expected returns.

The indifference curves of the risk-neutral borrower are represented as concave in $(h, s)$-space, while the indifference curves of the risk-averse lender are represented as convex. The concavity of the borrower's curves is partly induced by the fact that the borrower can afford to pay a spread of at most $\bar{s} \equiv y - r$, where $y$ is the expected return on the asset, and $r$ is the risk-free rate. If the spread is higher than $\bar{s}$, the borrower will expect to lose money on the trade. Conversely, the convexity of the lender's indifference curves is a product of the nonlinear relationship between haircut and leverage. As the haircut approaches zero, the borrower's leverage $1/h$ increases progressively faster, and the lender's risk increases proportionally. Thus, the lender will require increasingly higher compensation for every additional unit of haircut conceded to the borrower.

Now compare two collateral assets of varying risk ("low risk" and "high risk") as in Figure

6(b). Because riskier assets have higher return, the risk-neutral borrower is able to afford to pay a higher spread when borrowing to invest in riskier assets. For a constant level of profit, the borrower's indifference curves move up.

Like the borrower's, the lender's indifference curves become higher: for a given haircut $h$, a riskier asset means a higher probability that upon default of the borrower, the asset value is not enough to repay the lender. Because of this higher risk, the lender will require higher spread $s$ to achieve the same utility level. However, the indifference curves of the lender become steeper too. If the lender must sell the asset, one unit of haircut is more valuable (i.e., the protection it provides is more likely to be useful to the lender) for a high-risk asset than for a low-risk asset.

Figure 6(b) shows the result of two possible lender indifference curves. In one case ($H_1$), the new equilibrium has both higher spread and higher haircut. If this is the representative case, then we will observe a positive correlation between spread and haircut, as indicated by the regression line.

However, in another case ($H_2$), the new equilibrium has a lower spread, implying a downward-sloping regression line, i.e., negative correlation between spread and haircut. In this case, too, the lender's indifference curve is steeper than the original curve, so this is also a possible outcome.

The co-movement between haircut and spread with respect to the collateral risk that we show in this section is consistent with the case $H_1$, restricting the class of possible theories. Our results also rule out a corner solution shared by several theory models, in which lender's and borrower's indifference curves touch only at the corner where the spread is zero (Figure 6(c)).

[Insert Figure 6 about here]

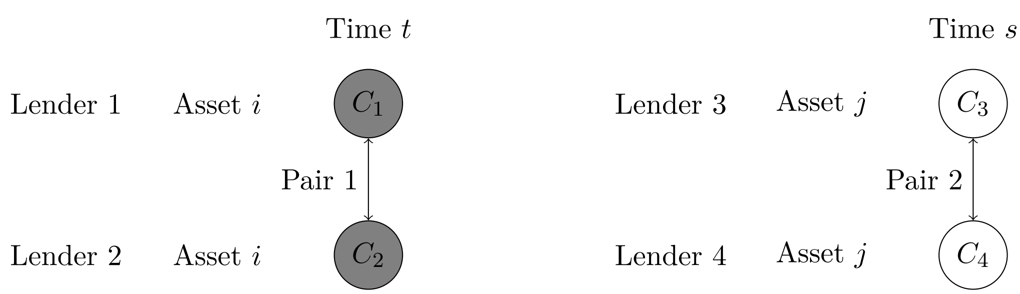
# 5 Beyond collateral: lender characteristics and contract terms

In this section, we focus on factors other than collateral that affect contract terms. In particular, our empirical design allows us to isolate the effect of lender-specific variables while fully controlling for collateral-related risks.

## 5.1 Haircut and spread trade-off

The results of the previous section suggest that spread and haircut do not appear to address mutually exclusive sets of risks. Using a set of observable collateral-specific information, the results in Table 4 show that collateral quality strongly influences contract terms. However, it is difficult to control for fundamental loan risk, which is jointly determined by the characteristics of asset risk and borrower credit risk. Our observables do not properly capture certain unobservable risks: for example, credit ratings and tranches are discrete measures of credit risk, and there can still be significant variation in credit risk *within* each rating or tranche category. Similarly, time to maturity of the collateral bond may capture the first-order sensitivity of bond prices to interest rate changes, but the sensitivity could be more precisely estimated by the duration of bonds, which we do not have enough information to calculate because most of the bonds in the sample have complex embedded options. Moreover, it is very difficult to identify the covariance of asset value and borrower's creditworthiness from what we can observe.

To control fully for variation in fundamental loan risk and focus our analysis on other factors, we compare multiple repo contracts written on *the same collateral* and starting *in the same time period* with different lenders. In our dataset, there are 115 such contract pairs, which display variation in haircuts within the pair. To reduce confounding factors further, we restrict our analysis to 56 pairs of brand-new contracts, i.e., where both contracts were started anew and were not rollovers of existing contracts. The illustration below describes the empirical design. In the figure, contracts $C_1$ and $C_2$ form a pair. Both contracts start at time $t$ and have the same collateral, Asset $i$. Pair 2 is formed in a similar way.




Within contracts in these pairs, *any* observable and unobservable risks that may affect contract terms, such as collateral price risk or time-varying macroeconomic dynamics and borrower credit risk are fully controlled, permitting us to get a sense of the fraction of variation in haircuts that is determined by a combination of lender-related factors and variation in other contract terms.

Moreover, the fact that the borrower has accepted both contracts at the same time suggests that spread and haircut are substitutable contract features. Given any acceptable contract, a borrower should be willing to consider a different, non-dominated contract featuring a higher haircut (lower leverage) and a lower spread (cheaper borrowing).

To account for the fact that haircut and spread are endogenously and simultaneously determined, as well as in order to measure the rate of substitution between them, we write the following model, designed to be as simple and agnostic as possible. For contract $i$ in pair $k$, haircut and spread are determined as:

$$\begin{bmatrix} Spread_i \\ Haircut_i \end{bmatrix} = \begin{bmatrix} \alpha_k^S \\ \alpha_k^H \end{bmatrix} + \begin{bmatrix} \beta^S \\ \beta^H \end{bmatrix} Duration_i + \begin{bmatrix} \lambda_i + \eta_i^S \\ s\lambda_i + \eta_i^H \end{bmatrix}, \tag{5}$$

where $\alpha_k^j$ ($j \in \{S, H\}$) is the pair fixed effect representing unobservable contract risk (i.e., collateral quality and borrower credit). Other than collateral quality and borrower credit, contract risk is also affected by an additional contract term that displays economically meaningful within-pair variation: loan maturity. Therefore, we expand our model specification to explicitly model the effect of loan maturity (*Duration*). In addition, the lender may offer the borrower to pay an extra $\lambda_i$ points of spread in exchange for $s\lambda_i$ points of haircut. Finally, there may be some random and independent error term $\eta_i^S$ for the spread and $\eta_i^H$ for the haircut.

As anticipated, the model has few restrictions. For instance, $\alpha_k^S$ and $\alpha_k^H$ could be assumed to be proportional (as implied by Figure 4), and a similar restriction could be placed on $\beta^S$ and $\beta^H$. Moreover, based on our discussion above, we expect $s$ to be negative, but we do not restrict it to be negative.

Without imposing further structure on the error term, what we can estimate from our pairs setup is:

$$\begin{bmatrix} Spread_i \\ Haircut_i \end{bmatrix} = \begin{bmatrix} \alpha_k^S \\ \alpha_k^H \end{bmatrix} + \begin{bmatrix} \beta^S \\ \beta^H \end{bmatrix} Duration_i + \begin{bmatrix} \epsilon_i^S \\ \epsilon_i^H \end{bmatrix}, \tag{6}$$

that is, by construction, the actual amount of substitution $\lambda_i$ is unidentified:

$$\begin{bmatrix} \epsilon_i^S \\ \epsilon_i^H \end{bmatrix} = \begin{bmatrix} \lambda_i + \eta_i^S \\ s\lambda_i + \eta_i^H \end{bmatrix}. \tag{7}$$

However, we can still estimate the rate of substitution $s$ by noting that

$$Var \begin{bmatrix} \epsilon_i^S \\ \epsilon_i^H \end{bmatrix} = \Sigma = \begin{bmatrix} \sigma_S^2 & \\ \sigma_{SH} & \sigma_H^2 \end{bmatrix} = \begin{bmatrix} Var(\lambda) + Var\left(\eta^S\right) & \\ sVar(\lambda) & s^2 Var(\lambda) + Var\left(\eta^H\right) \end{bmatrix}. \tag{8}$$

Since the variance-covariance matrix $\Sigma$ can be estimated, we can calculate

$$\tilde{s} = \frac{\sigma_{SH}}{\sigma_S^2} = s\left[\frac{Var(\lambda)}{Var(\lambda) + Var(\eta^S)}\right] \equiv \beta^S. \tag{9}$$

From Equation (9), two things are clear. First, $\tilde{s}$ is numerically equivalent to the regression coefficient obtained by adding $S_i$ on the right-hand side of the haircut equation:[15]

$$Haircut_i = \alpha^k + \beta^S Spread_i + \beta^D Duration_i + \epsilon_i \tag{10}$$

Second, $\beta^S$ is not a consistent estimate of $s$ because it suffers from attenuation bias, i.e., it is shrunk towards zero. However, it has the correct sign and it can be interpreted (in absolute value) as a lower bound to $s$:

$$\begin{cases} s > \beta^S & \text{if } s > 0 \\ s < \beta^S & \text{if } s < 0 \end{cases}$$

Estimating Equation (10) makes it possible to express the significance of $\tilde{s}$ as a standard $t$-statistic.

[15]The last equality in Equation (9) holds regardless of what variables are on the right-hand side, as long as the same variables are in both the haircut and the spread equations. Here, $\sigma_{SH}$ and $\sigma_S^2$ are the covariance and variance, respectively, of the residuals with respect to all the other right-hand-side variables.

Column (1) of Table 6 reports the results of regression Equation (10), restricting $\beta^S = \beta^D = 0$. The $R$-squared of this regression (66.7 percent) represents the amount of haircut variation that is explained by asset risk and time variation in borrower risk. The remainder must be explained by substitution between spread and haircut, possibly driven by lender-specific factors.

Columns (2)–(3) of Table 6 report the results of Equation (10) restricting $\beta^D = 0$ and no restrictions, respectively (that is, with and without *Duration*). Going from Column (1) to Column (2) (adding *Spread*), the adjusted $R$-squared rises to 69.0 percent: substitution explains an additional 2.4 percentage points of unknown variation, or 7.1 percent of the residual variation. Controlling for loan maturity in Column (3) does not change the result meaningfully. In spite of attenuation bias, the coefficient on *Spread* is negative and strongly significant, clearly indicating the trade-off relationship between haircut and spread. The result implies that within the average pair, if one contract's spread is 1 percentage point higher than the other, that contract's haircut is likely to be at least 9 percentage points lower.

The substitution we measure could be interpreted as different lenders choosing to meet the borrower at different points of the borrower's indifference curve. Alternatively, our results could also be obtained if the borrower's indifference curve also varies when it faces different lenders. In either case, variation in haircuts that is not explained by characteristics of the asset or the borrower must be driven by lender heterogeneity. We investigate this in Section 5.3.

[Insert Table 6 about here]

## 5.2 Sticky lending relationships

Columns (4)–(6) of Table 6 report results of the regressions specified in Equation (10) when using all pairs, including not only brand-new contracts but also rollovers of existing lending relationships. In the specification the $R$-squared is much lower (13 percent to 22 percent). Moreover, *Spread* has a positive coefficient in Column (5); i.e., we still observe the ubiquitous positive covariation between haircut and spread, although it is not statistically significant. In this larger sample, we find apparently dominated loans: within a pair, one of the loans has both higher haircut and higher spread. Even with loan duration controlled for, we fail to obtain the same statistically significant relationship between haircut and spread as we do with brand-new contracts. These results suggest that the contracts are "sticky": upon a rollover, the haircut of the renewed contract tends to inherit the one of the previous contract. This finding together with results in the previous subsection could be interpreted as evidence of some cost of renegotiating the contract, perhaps because of relationship lending or search frictions.

### 5.3 Lender characteristics and the choice of lending contract features

In Subsection 5.1, we show that there is a trade-off between haircuts and spreads in equilibrium: lenders and the borrower may agree on different combinations of haircut and spread, even when loan risk is identical. In our data with one borrower and multiple lenders, we are able to observe how the variation of lender characteristics plays a role in a contractual term determination. In this subsection, we focus on two most important characteristics of lenders in the lending contracts: their funding liquidity and creditworthiness.

When the lending bank experiences funding illiquidity, it must be willing to sacrifice more units of spread in exchange for an additional unit of haircut. There are two reasons for this mechanism: first, with low liquidity, the bank simply cannot make the size of the loan larger; second, the bank can generate liquidity by rehypothecating the collateral to different institutions. A higher haircut means a higher amount of collateral for every dollar loaned out, and ultimately increases liquidity.[16]

For this task, we obtain a direct measure of lender funding liquidity using information from the tri-party repo market, in which most of our lenders are borrowers. Hand-collected mutual fund filings allow us to calculate total repo borrowing using mortgage-backed securities for most of our lenders.

In several recent models of the repo market (Lee (2015); Infante (2015)), intermediaries lend cash in exchange for collateral in the over-the-counter bilateral market, and they borrow cash in exchange for that same collateral in the wholesale tri-party market. In some sense, therefore, intermediaries shuttle cash from cash lenders to investors, and collateral from investors to cash

[16]For example, suppose a lending bank makes a loan of \$80 while receiving an asset worth \$100 (a 20 percent haircut). Then, the bank repledges the asset to a different institution with haircut of 10 percent. Doing this, the lending bank creates \$10 of cash (liquidity).

lenders. Presumably, therefore, the availability of cash in the tri-party market for a certain type of collateral influences the availability and the terms of repo lending to investors who own that type of collateral.

Specifically, our fund owns mostly mortgage-backed collateral (direct MBS, or CDOs of MBS). In the tri-party market, this collateral can be repledged as part of pools of MBS securities. Therefore, changes in a lender's tri-party borrowing against MBS collateral should be linked to the terms offered by that lender to our fund. The equation we estimate is:

$$\begin{matrix} Haircut_i \\ Spread_i \end{matrix} = \alpha^k + \beta_1 \cdot \Delta P_i^{MBS} + \beta_2 \cdot Duration_i + \epsilon_i. \tag{11}$$

where $\Delta P^{MBS}$ is the quarter-on-quarter change in total borrowing using mortgage-backed securities as collateral.[17] The results are reported in Table 7, Panel I for haircut and Panel II for spread. We observe that, as a lender faces unfavorable funding situation (negative $\Delta P^{MBS}$), the haircut goes up. This is because the lender values haircut more, relative to a unit of spread.[18] To compensate for the higher haircut, Panel II of the same table shows that spread becomes lower, which is consistent with the substitution results. In other words, the lender is willing to give up more spread to increase haircut or contract the lending.

Although we can establish a linkage, we cannot pin down the direction of causality for the changes in the lending terms between broker-dealer banks and our fund. However, it is unlikely that our fund has caused market-wide changes in collateral demands in the tri-party repo market (regardless of reasons outside of our fund). Moreover, we do not find any evidence that our fund wished to decrease its leverage.

One could suspect that our results are driven by market-wide change of demand for structure

[17]The tri-party repo data provide us collateral type such as MBS, ABS, Corporate Bond, Government Bond, etc. Since our fund's main asset type is MBS, most relevant collateral to us is also MBS. Within MBS collateral type, it is not always possible to have more precise collateral type, e.g., private MBS or agency MBS. Similarly, it is usually not possible to tell whether ABS collateral is backed by mortgages or other assets. Therefore, broadly defined MBS collateral is our best proxy for the demand for collateral like the one held by our fund.

[18]Although there is a general tendency for all lenders to comove in terms of funding amounts against MBS securities, there is a meaningful variations across lenders. For example, in the second quarter of 2007, one lender's funding on MBS contracted by 12.6% from the previous quarter whereas another lender's had almost constant funding amount.

finance asset as collateral, i.e., MMFs collectively would not take such assets as collateral for dealer banks' funding. We consider this explanation unlikely, because our estimation identifies the effect in the cross-section of dealer banks at the same time. Thus, the difference in funding amount against structured finance collateral is due to differential characteristics across dealer banks. Given the fact that each dealer bank could transact with all MMFs, it is more plausible that some dealer banks preferred and used this type of assets more to finance themselves, *relative to other banks*. Even though we do not consider any explicit causal channel, it is clear that the funding condition of a lender against a certain asset class is correlated with its lending behavior with the same collateral asset class.

[Insert Table 7 about here]

Lenders' credit quality should also be one of the most important characteristics of lender heterogeneity. Unlike unsecured lending and most secured lending, repo contracts entail two-way credit risk, as the borrower is also exposed to the lender's default risk. If the lender undergoes bankruptcy, the borrower loses access to the collateral asset and invested equity, becoming an unsecured creditor. Assuming zero recovery, the borrower would lose the initial haircut and all the intervening appreciation in asset value. Therefore, as lender default becomes more likely, the borrower would prefer lowering the haircut, possibly at the cost of a higher rate, resulting in a shift of the trade-off relationship.

In order to empirically measure how lender's credit quality play a role in repo contracts. we run the following regression specification. For the contract $i$ in pair $k$,

$$\begin{matrix} Haircut_i \\ Spread_i \end{matrix} = \alpha^k + \beta_1 \cdot ProbDef_i + \beta_2 \cdot Duration_i + \epsilon_i. \tag{12}$$

where $ProbDef_i$ is the default probability of the lender of contract $i$. Because the default probability is not directly observable, we use 3-year EDF as a proxy. EDF is the default probability of a firm estimated from a Merton-type structural model. Using market prices of the equity and balance sheet information, the structural model provides firms' implied distance to default, and eventually a probabilistic measure of default in high frequency. Because having publicly traded equity is required for the estimation, this analysis is limited to contracts with public lending firms (or lenders whose parent company is public).[19]

Table 8 presents the results for Equation (12), which is structured symmetrically to Table 7. Each regression is estimated in two specifications: with and without loan maturity ($Duration$). In each panel, the first two columns use only brand-new contracts, whereas the last two columns use all contracts (brand-new ones, and rollovers of existing ones). The coefficient on the default probability of the lender ($ProbDef$) in the haircut regression is consistently negative. When all contracts are used, the negative effect of the lender's default probability on haircut becomes strongly significant. Controlling for fundamental loan risk, the borrower strongly prefers a lower haircut when facing a lender with higher default probability. This result suggests that, within a set of admissible contracts, the borrower's concern about losing haircut and capital gain because of lender failure dominates the lender's incentive to raise haircuts because of funding illiquidity. The magnitude of the coefficient is economically significant: 1 percentage point of lender's default probability is associated with a 2.5 to 2.9 percentage points decrease in haircut.

Panel II of Table 8 shows that, when a lender's default probability is higher, the equilibrium spread is set higher to compensate for the lower haircut. These coefficients are consistent with the trade-off relation between haircut and spread, and their magnitude is consistent with the magnitude of the haircut regression coefficients. To get a sense of the "natural" covariation of spread and haircut, typically a contract with 5 percent haircut has a 5 basis points spread; a contract with 10 percent haircut has a 10 basis points spread; and a contract with 20 percent haircut has 25–30 basis points spread. In this context, the relative magnitudes of the coefficients in the two regressions are comparable.[20]

[Insert Table 8 about here]

[19] Among lenders in the sample, 16 had public equity or a parent with public equity during the sample period. Although the sample period does not span through the financial crisis, there is a economically significant cross-sectional variation of EDF across lenders. For example, on 8/25/2005, there was 2 percentage points difference in 3-year EDF between the highest and the lowest. For a detailed explanation for EDF, see Bharath and Shumway (2008). We thank KMV-Moody's for providing these data.

[20] Arora et al. (2012) study a similar question in the CDS market by analyzing contemporaneous CDS prices on the same underlying firm across dealers with different counterparty risks, and conclude that counterparty risk is not sufficiently priced in. The magnitude of our results is economically more significant.

### 5.4 Graphical interpretation of results

We provide a graphical illustration of this section's results, using the Edgeworth box introduced in Subsection 4.4. Once again, each haircut and spread combination is represented by a point in the Edgeworth box, and each contract is a tangency point of the lender's and borrower's indifference curves. In Figure 7(a), the red (concave) curve is the borrower's indifference curve, and the green (convex) is the lender's. The equilibrium, or the tangency point, is marked by the green $G$ point.

With all loan risk fully controlled within a pair, our results in Subsection 5.1 imply that different lenders have different indifference curves, touching the borrower's indifference curve at different points. Equation (10) measures the pattern of these points, estimating the trade-off relationship of haircut and spread.

One cause of lender heterogeneity is funding illiquidity. When a lender experiences funding illiquidity, its marginal rate of substitution of spread for haircut becomes larger. This shift happens because rehypothecation of the collateral in the wholesale funding market becomes less feasible, constraining the total amount available for lending. In this case, reducing the loan amount has higher priority than profiting from a higher spread. A higher marginal rate of substitution translates to a steeper (more negatively sloping) indifference curve. In this case, as Figure 7(b) illustrates, the equilibrium haircut will be higher and the spread will be lower. This illustration is consistent with our results in Table 7.

In Subsection 5.3, we further show that the joint determination of haircut and spread depends on lenders' credit risk. As discussed earlier, a borrower posting collateral with a risky lender is concerned about losing the invested equity and unrealized capital gain. Because the haircut is a direct measure of the borrower's exposure to the lender, the borrower may prefer to pay a higher interest rate for the loan in exchange for a lower haircut. In other words, the borrower's marginal rate of substitution of spread to haircut becomes larger, resulting in the steeper indifference curves depicted in Figure 7(c). This illustration indicates that the borrower's indifference curve is not unique vis-à-vis all lenders at a given time. As a consequence, Figure 7(d) illustrates that the equilibrium haircut will be lower and spread will be higher when the lender's default probability is higher for a given loan risk.[21] This prediction is consistent with our results in Table 8.

[Insert Figure 7 about here]

### 5.5 What determines variation in haircuts? A variance accounting exercise

In this section and the previous one, we have shown evidence that haircut and spread both increase with collateral risk. Conversely, in their response to lender creditworthiness, as the borrower's exposure to lender credit risk increases, haircut decreases while spread increases.

In the overall sample, the relation is increasing, reflecting that our sample contains a great variety of collateral, but it only covers a relatively short period. During the sample period, the credit conditions of all lenders are rather stable. Therefore, the whole-sample variation reflects mainly the variation in the cross-section of collateral.

To visualize this, we decompose haircut variation in our sample into its identifiable sources. Although this is a simple accounting exercise, we believe it is nonetheless insightful. We summarize the results of this accounting exercise in Figure 8.

First, we run a regression of haircut with only week fixed-effects (one dummy variable for every week). The $R$-squared of this regression (0.208) is the amount of haircut variation that can be explained by time-varying factors common to all loan contracts. That includes the borrower's default probability, systematic asset risk change, market-wide funding illiquidity change, etc.

Second, we predict haircut as the residual of the first regression, and we run our pairs fixed-effect regression in Subsection 5.1. For this regression, $(1 - R^2) = (1 - 0.707) = 0.293$ is the amount of residual variation explained by lender heterogeneity, including haircut/spread substitution. The total amount of variation explained by lender-related sources is therefore $(1 - 0.208) \times (1 - 0.707) = 0.792 \times 0.293 = 0.232$.

Finally, based on these calculations, $(0.792) \times (0.707) = 0.560$ of variation is explained by the collateral asset. In the figure, the portion corresponding to the asset risk is marked in a

[21] For simplicity of exposition, we assume that the lender's indifference curve is unchanged, even though the lender's creditworthiness changes. However, our interpretation is valid as long as the borrower's indifference curve steepens more than the lender's.

spectrum of blue colors. To break down this amount further, we run a regression on a special subsample containing 170 contracts done in the same day with the same lender. Across these contracts, everything is constant except collateral and loan duration, allowing us to measure the relative importance of the various collateral characteristics. Applying standard variance decomposition to these regression results indicates that $0.371 \times 0.560 = 0.208$ of remaining variation is explained by Tranche fixed effects, $0.116 \times 0.560 = 0.065$ by asset class fixed effects, and $0.262 \times 0.560 = 0.147$ by other variables (loan duration, an indicator variable for floating rate, and issue size). Finally, $0.251 \times 0.560 = 0.141$ remains unexplained.

[Insert Figure 8 about here]

# 6 The role of the haircut

Until now, we have shown that the roles of spread and haircut are not mutually exclusive, and they overlap substantially to the extent that they are at least partly substitutable. In light of this evidence, any theory of the determination of margin in secured lending must allow for some substitution. We extend this line of inquiry by asking whether haircut and spread are, in fact, perfect substitutes. In this section, we look for evidence of a unique role for the haircut by analyzing how price risk and illiquidity of collateral differentially affect lending terms.

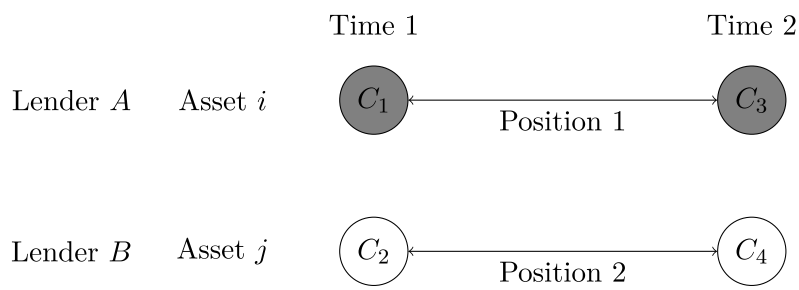
A plausible unique role for the haircut is protecting the lender from illiquidity of the collateral asset. Illiquidity may only cause a loss when the borrower fails to repurchase the collateral (i.e., pay off the loan) and the lender must sell the collateral to recover. The lender's expected loss when liquidating an illiquid asset is:

$$\text{Expected loss} = \mathbb{E}\left[f(\text{Illiquidity})|\text{Borrower failure}\right] \times \Pr\left(\text{Borrower failure}\right). \tag{13}$$

where $f(\cdot)$ is an arbitrary function, increasing in the illiquidity of the asset. Although there is only one borrower in our sample, we do observe the time-series dynamics of that borrower's probability of default. We illustrate our empirical design in the figure below. In this case, we compare contracts on the same asset with the lender at different times. For example, contracts

$C_1$ and $C_3$ (and $C_2$ and $C_4$) have the same collateral and same lender, but the borrower's default probability is different at Time 1 and Time 2.

The main empirical challenge comes from the fact that the systematic asset risk is also not constant throughout time. Therefore, it is difficult to disentangle the effect of the borrower's default risk on contractual term from dynamic changes of *systematic* asset risk profile, even within the same collateral asset. To overcome this challenge, we first seek a measure of borrower default risk that is uncorrelated with changes in asset risk. Then, we test how much such a measure explains haircut dynamics in time.




Our measure of borrower default risk relies on the fact that the funds were housed under the asset management arm of a publicly listed firm ("the parent"). Therefore, it is reasonable to assume that the parent firm's creditworthiness reflected upon the fund's own creditworthiness, i.e., that the credit default swap spread (CDS spread) of the parent was correlated with the default probability of the fund.

To disentangle default probability and collateral asset risk, we conduct the following exercise. First, we translate the CDS spread into an instantaneous hazard rate, to have an intuitive interpretation of the magnitude. This process is explained in the Appendix. Then, we regress the hazard rate on the ABX index, a performance index of structured finance.[22] Therefore, the residual of the regression is the portion of instantaneous default probability that is orthogonal to the systematic payout risk of collateral assets. We denote this stripped part of default probability

[22]The ABX index is publicly available, at daily frequency, from January 2006. Although it does not fully cover our sample period, there is not much variation in the economy before 2006 at the same time as the default probability of the borrower is tiny and essentially constant. Post-2006 is the active period of time in terms of the borrower's creditworthiness, justifying our selection of the measure. There are multiple sub-indices of ABX, depending on the aggregate credit quality of the asset (AAA, AA, A, BBB, etc.). Among them, we choose the index that has the highest correlation with the fund's return (AAA). However, our results are qualitatively immune to the choice of sub-index.

implied in the CDS spread as $Default$.

First, we show that the haircut is reacting to the metric of borrower failure, controlling for systematic asset risk ($Default$). For a contract $i$ that start at time $t$, we consider the following specification:

$$Haircut_i = \alpha^{T,AC,L} + \alpha^Y + \beta_1 \cdot Default_t + \beta_2 \cdot ABX_t + \beta_3 \cdot Duration_i + \epsilon_i. \tag{14}$$

where $ABX$ is the past 1-month return on the ABX index. To control for cross-sectional variation of contracts in each time $t$, we consider all of the dimensions found in the analysis so far: the loan duration of contract $i$ ($Duration$) and ($Tranche \times Asset\ class \times Lender\ family$)-fixed effects ($\alpha^{T,AC,L}$). In addition, to capture any long-run economic trends, we include a year fixed effect $\alpha^Y$ in some specifications. Table 9 shows the results of the regression. The first two columns show the extent to which the borrower's default risk explains the variation in haircuts within lender and controlling for all observable collateral asset characteristics, as well as systematic asset risk. As the borrower's default risk increases, haircut also increases. For example, in the second column, when the portion of instantaneous default probability uncorrelated with the asset risk increases by 1 percentage point, the haircut also increases by 12.7 percent. In more intuitive terms, if the default probability over 30 days (the typical duration of a loan in our sample) goes up by 1 percentage point, the haircut goes up by a quarter of a percentage point (assuming a constant hazard rate). Second, when the asset risk increases, the haircut also increases. For example, Column (1) shows that 1 percent of negative return on ABX corresponds to 0.8 percent of haircut increase. This coefficient may seem large, but the index we use tracks the safest class of structured finance securities (AAA), for which a 1 percent negative return per month is an extreme event.

[Insert Table 9 about here]

In Column (3) and (4), we repeat this analysis on contracts within the same asset (by 8-digit CUSIP) and lender family ($\alpha^{A,L}$ instead of $\alpha^{T,AC,L}$). Therefore, other observables such as tranche and asset class are already controlled for. The result is qualitatively the same: the haircut reacts positively to the risk of borrower's default.

The actual test of Equation (13) is to see if the haircut becomes more sensitive to collateral illiquidity as the borrower's default risk increases. As discussed in Section 4, it is difficult to obtain a clean measure of illiquidity, mainly because it is often correlated with price risk.

To address this issue, we use price type as a proxy for the illiquidity of assets. In our data, we have a current value of the asset for any given day. However, this value is not always a "fresh" mark-to-market price. There are five categories for price type: trader quote, Bloomberg quote, model estimation, cost-based estimation, and no entry.[23] The price type depends on the market price search cost, rather than on the price risk, because assets with a high degree of payoff risk need not have a transparent market price.

The first type is the actual trader's quote. If there is a trader's quote, there is at least one counterparty who is willing to make a market. Hence, this type of price should be close to the true asset value. The second and third types are at least estimates of mark-to-market prices. This means that one could estimate the value of the asset, or the cost of valuation is not prohibitively high. In other words, the illiquidity for this asset at the moment is moderate. However, when cost-based value or no value is available, this means that it would be equally difficult for a lender to estimate the current value of the asset. Hence, for assets with this price type at a given time, not much information is available to lenders. We use this information to gauge the degree of information opaqueness.

We group contracts into three categories: (1) contracts with actual market value, (2) those with estimated mark-to-market price, and (3) contracts without even market-based estimation. It is natural to argue that illiquidity becomes larger for a category with a higher number (more opaque pricing). Our indicator variables are $Type^j$ with $j \in \{1, 2, 3\}$ , and they take the value 1 when the price type falls under category $j$, and otherwise 0.

For a contract $i$ that starts at time $t$, we consider the following regressions:

$$\begin{matrix} Haircut_i \\ Spread_i \end{matrix} = \alpha^{T,AC,L} + \alpha^Y + \beta_1 \cdot ABX_t + \Sigma_{j=1}^{3} \gamma_j \cdot Type_i^j \cdot Default_t + \beta_2 \cdot Duration_i + \epsilon_i. \quad (15)$$

[23]Gorton and Metrick (2012) have "unpriced ABS" as a category of collateral, indicating that lenders use the existence and quality of a market price as information when they decide how to treat collateral.

We consider loan duration ($Duration$) as control variable and a set of fixed effects similar to regression Equation (14). The coefficients of interest are $\gamma_i$, $i \in \{1, 2, 3\}$, particularly their order of magnitude and statistical significance.

Tables 10 and 11 present the results of the estimation of Equation (15). For Column (1) and (2), we use ($Tranche \times Asset\ class \times Lender\ family$)-fixed effects ($\alpha^{T,AC,L}$). For Column (3) and (4), we use ($Asset\ (CUSIP) \times Lender\ family$)-fixed effects ($\alpha^{A,L}$); therefore, we measure the effect within contracts that share the same collateral asset and lender. Again, to capture long-run economic trends, we include year fixed effect $\alpha^Y$ in all specifications.

For the haircut, across the four different specifications, Table 10 shows that the magnitude and the significance of the fixed-effect coefficients (the $\gamma$'s) monotonically increase as asset types go from category 1 to 3. This result implies that when default risk increases, its effect on the haircut is differential with respect to the opaqueness of asset value. In particular, we have $\gamma_3 > \gamma_2 > \gamma_1$, showing that borrower risk only matters when the collateral asset value is uncertain and loss because of illiquidity becomes a concern, controlling for systematic asset risk. When collateral value is intact and there is no expected loss from illiquidity, then the borrower's counterparty risk does not affect contract terms as much, because lenders could seize the collateral and be made whole upon any credit events.

However, Table 11 indicates that a similar pattern does not emerge for the spread. When duration is controlled for, almost all $\gamma$ coefficients become insignificant, and the pattern is absent, implying that the expected loss because of illiquidity is not addressed by the price of loan.

The expected liquidation cost caused by illiquidity is at least an increasing function of the value uncertainty. Therefore, as described in Equation (13), these interaction terms proxy for the expected loss from liquidating an illiquid asset upon the borrower's default. Consistent with the predictions of Gorton and Metrick (2009) and Gorton and Ordoñez (2014), the results imply that haircut exists to protect lenders from a joint event of borrower's default and loss because of illiquidity, and only haircut covers this risk.

[Insert Tables 10 and 11 about here]

## 7 Conclusion

In this paper we have presented new evidence on collateralized lending, using a unique dataset containing over 13,000 bilateral repurchase agreements between a large hedge fund and essentially all major repo lenders in the market over a span of 3 years. Unlike other "low-frequency" forms of collateralized lending, repo is characterized by short maturities (days, weeks, or at most a few months) and repeated transactions on the same collateral (rollover events), allowing powerful tests of theories of collateralized lending.

Our findings are not fully compatible with existing empirical studies that focus on the tri-party repo market, highlighting important differences between these two repo markets. In particular, we conjecture that the presence of sophisticated lenders in the bilateral repo market explains the wide variation in haircuts that we observe, compared with the relative "flatness" of haircuts in the tri-party market.

The evidence we present is also not perfectly consistent with any of the existing theories of the repo market, or collateralized lending in general. We find that in spite of the super-senior nature of repo contracts there is considerable variation in interest rates, based on collateral quality, collateral liquidity (i.e., ease with which the lender could liquidate the collateral), loan duration, and borrower default risk. Contrary to common perception, the general picture that appears from our data is that lenders choose to take on significant amounts of risk when the repo collateral itself is risky.

We find that haircut and spread are related differently in different dimensions: across asset quality, they show strong comovement, whereas they are at least partly substitutable when keeping loan risk constant. Although we show that the roles of haircut and spread generally overlap, we also provide evidence of unique risk that can be addressed only by the haircut. Taken as a whole, our results indicate that haircut and spread are neither perfect substitutes nor mutually exclusive.

Although our analysis focuses on repo data, we provide insight on the role of margin (haircut) and price (loan spread) that can be generally applied to any secured lending setting. The results of this paper invite a fresh theoretical challenge.

# A The hazard rate

To describe how we extract the instantaneous hazard rate (immediate default probability) implied by the credit default swap spread (CDS spread), first we define the following notation:

- $DF_t(T)$: Discount factor from $(t, T)$
- $P_t(T)$: Survival probability from $(t, T)$
- $S_t$: CDS spread at time $t$
- $\tau_i$: CDS payment dates, $i = 1, 2, \dots, N$ where, $\tau_N = T$
- $R$: Recovery rates,

where $T = t + \Delta t$ for some $\Delta t$ to be chosen later.

With this notation, the present value of the expected CDS premium received by the protection seller in a CDS with maturity $T$ at time $t$ can be expressed as:

$$S_t \cdot \Sigma_{i=1}^{N}(\tau_i - \tau_{i-1}) \cdot DF_t(\tau_i) \cdot P_t(\tau_i) - S_t \cdot \Sigma_{i=1}^{N} \int_{\tau_{i-1}}^{\tau_i} ((\theta - \tau_{i-1}) \cdot DF_t(\theta))\, dP_t(\theta). \tag{16}$$

In addition, the present value of the expected CDS payout for the protection buyer in a CDS with maturity $T$ at time $t$ is:

$$(1 - R) \cdot \int_{t}^{T} DF_t(\theta) dP_t(\theta). \tag{17}$$

Therefore, the spread $S_t$ solves the following equation:

$$S_t \cdot \Sigma_{i=1}^{N}(\tau_i - \tau_{i-1}) \cdot DF_t(\tau_i) \cdot P_t(\tau_i) - S_t \cdot \Sigma_{i=1}^{N} \int_{\tau_{i-1}}^{\tau_i} ((\theta - \tau_{i-1}) \cdot DF_t(\theta))\, dP_t(\theta) = (1-R) \cdot \int_{t}^{T} DF_t(\theta) dP_t(\theta). \tag{18}$$

Now, we define the instantaneous hazard rate $H_t$ implied at time $t$ by the spread of a CDS that matures at $T$:

$$H_t = -\frac{dP_t(T)}{P_t(T)}. \tag{19}$$

The second term of Equation 18 is of the order of $O(S^2)$. Hence, we can ignore it and obtain the approximated instantaneous hazard rate:

$$H_t = \frac{S_t \cdot \Sigma_{i=1}^{N}(\tau_i - \tau_{i-1}) \cdot DF_t(\tau_i)}{(1-R) \cdot \int_t^T DF_t(\theta)d\theta}. \tag{20}$$

We use $\Delta t = 5$ year because the 5-year CDS is the most liquid instrument. For the discount factor, we use the yields of constant maturity Treasury (1, 3, and 6 month and 1, 2, 3, and 5 year) and interpolate them each day using a cubic spline.

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# Figures

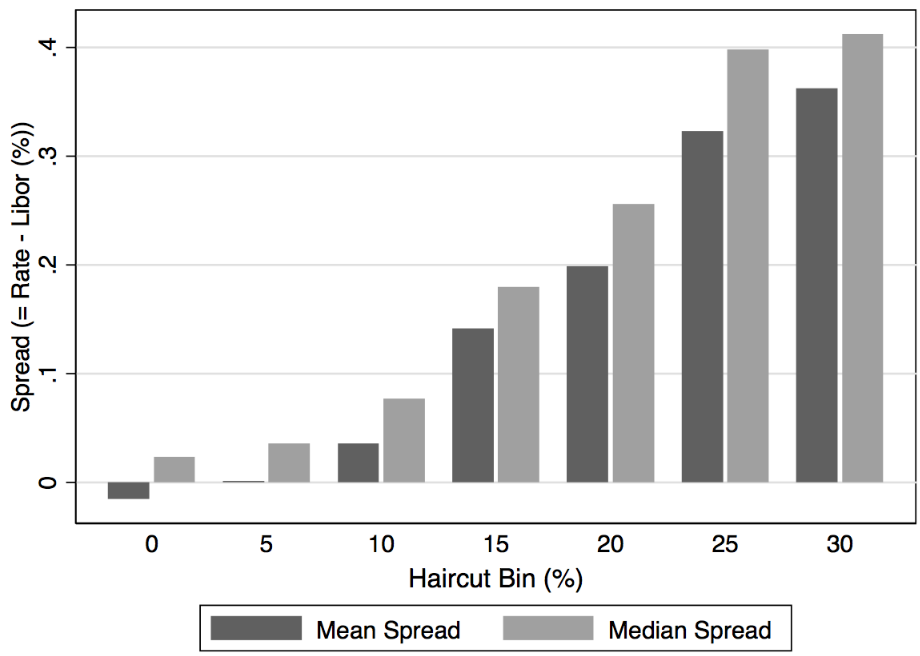


Figure 1: **Relationship between haircuts and repo spreads.** This chart presents the whole-sample relationship between haircuts and repo spreads in mean and median. Haircut is grouped into seven categories from 0% to 30% by 5% gaps. Each contract's haircut is rounded to the nearest bins. Spread is defined as contractual repo rate minus term-structure-matched LIBOR curve. Because only a few points of the LIBOR curve can be observed, the whole term structure is interpolated by cubic-spline method.

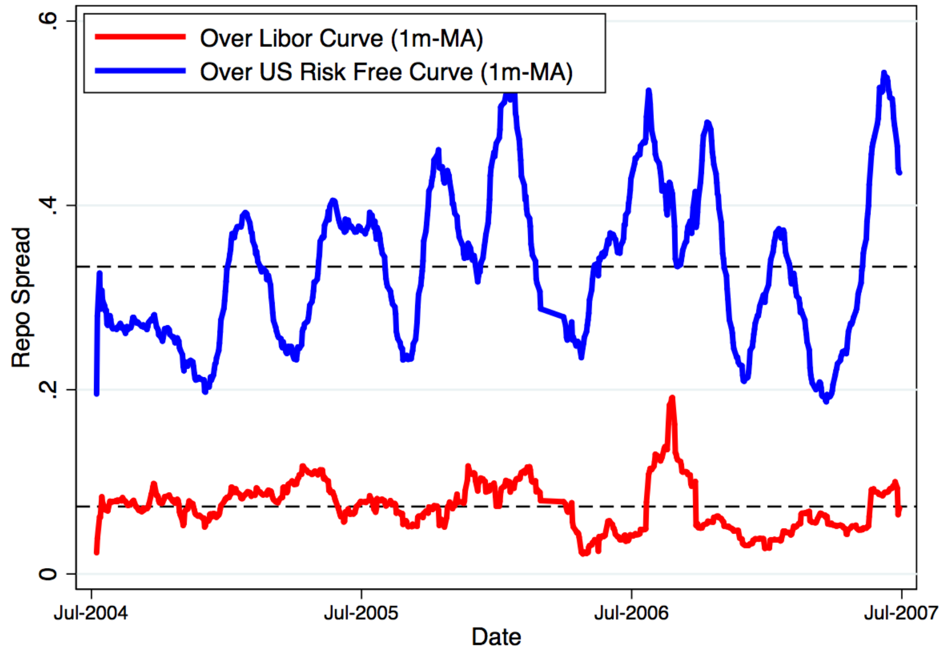


Figure 2: **Repo spread – Comparison of two reference rates.** This figure plots a time-series of the repo spread over two different reference rates: LIBOR and U.S. risk free. Spread is defined as the difference between the repo rate and the relevant reference rate for the relevant maturity. Each day, we calculate the median repo spread for contract initiated on that day. To have a reference rate for every maturity (in days), the reference rate is interpolated by fitting a cubic spline to the available points (overnight, 1 month, 3 months, 6 months and 1 year).

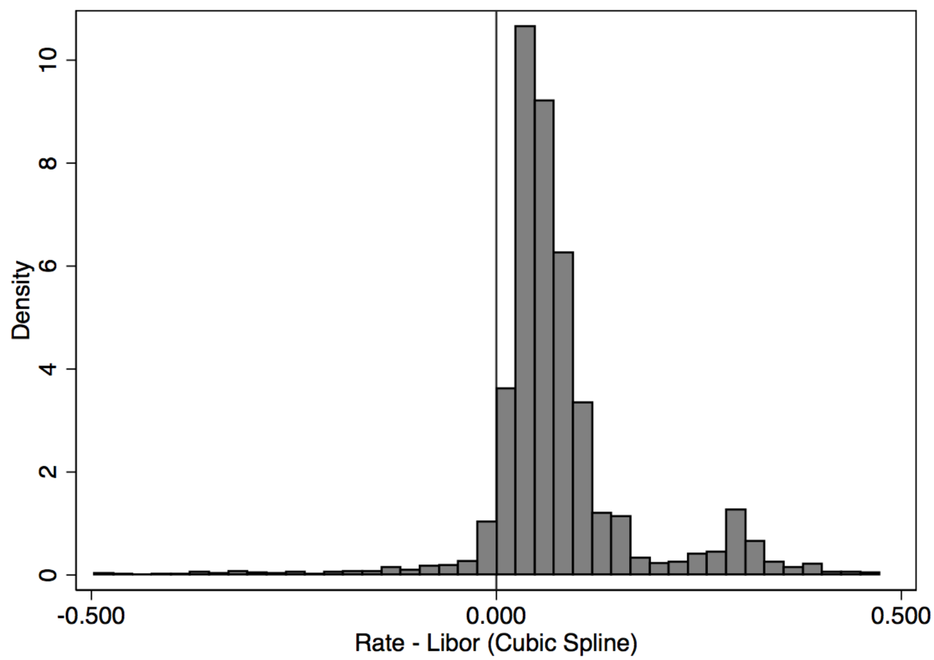


Figure 3: **Repo spread of new contracts.** This histogram presents the distribution of repo spread over matching maturity LIBOR. To have a reference rate for every maturity (in days), LIBOR is interpolated by fitting a cubic spline to the available points (overnight, 1 month, 3 months, 6 months, and 1 year). The majority of the negative spreads are from repurchase agreements collateralized by Treasury bonds; the small "bump" on the right is mostly made up of low-seniority ABS tranches.

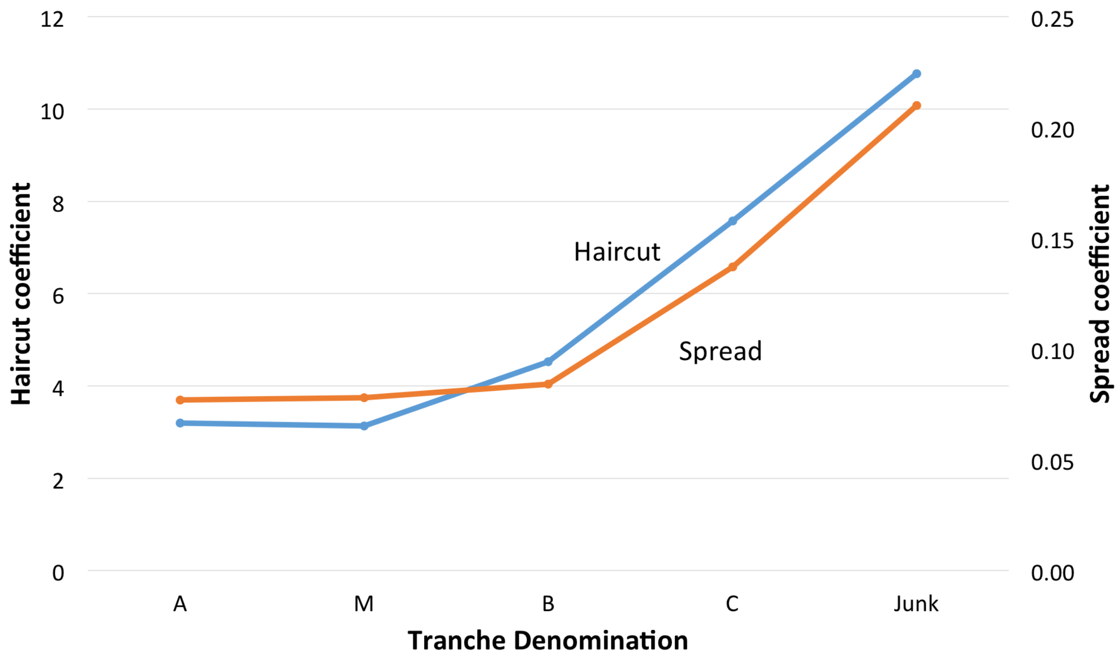


Figure 4: **The pattern of coefficients on tranche indicator.** This plot displays the pattern of regression coefficients on tranche indicator, estimated by Equations (1)–(2) and presented in Table 4. The horizontal axis displays tranche denomination from "A" to "Junk", in descending order of seniority. The coefficient in the Haircut (Spread) regression is measured on the left (right) vertical axis. Both Haircut and Spread are measured in percentage points.

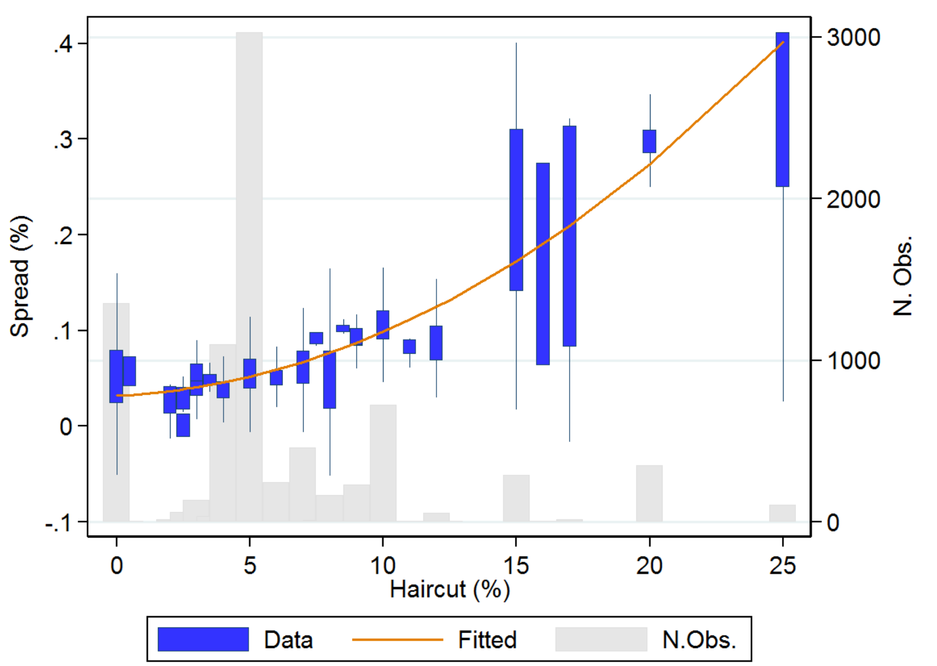


Figure 5: **The quadratic relationship of spread and haircut.** This plot displays the relationship between haircut and spread. The boxes indicate the middle 50% of the empirical distribution; the whiskers include the rest of the distribution except outliers. The "fitted" line uses the specification of Equation (4). The light gray bars on the background provide the number of observations. Most haircuts are set at salient round numbers, as can be seen from the spikes at 0, 5, 10, 15, 20, and 25 percent.

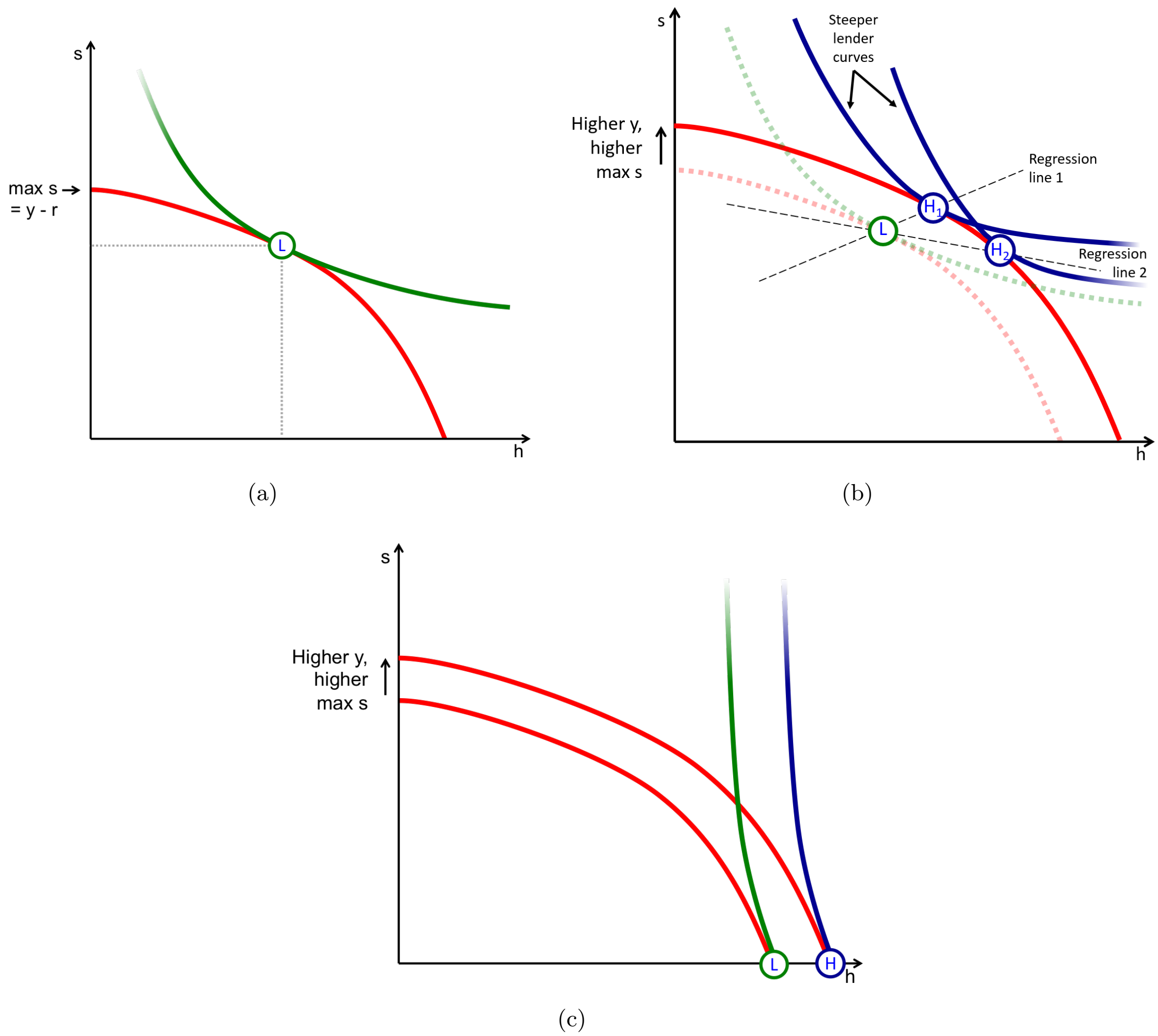


Figure 6: **Illustration of equilibrium with different quality collateral.** These plots illustrate the joint determination of haircut and spread between the borrower and a given lender with respect to collateral risk. In each plot, haircut is on the horizontal axis, and spread is on the vertical axis; "max s" stands for maximum repo spread that the borrower can accept, equal to the expected return on the asset ($y$) minus the contractual repo rate ($r$). The concave red curves represent the borrower's indifference curve. The convex green (blue) curve is the lender's indifference curve when the collateral asset has low risk (high risk). The green dot with $L$ represents an equilibrium with low-risk collateral asset. In Panel 6(b), the blue dots with $H_1$ or $H_2$ illustrate two possible equilibria when the collateral is high-risk asset. Finally, in Panel 6(c), the indifference curves only have a corner solution, and all lending happens at the risk-free rate.

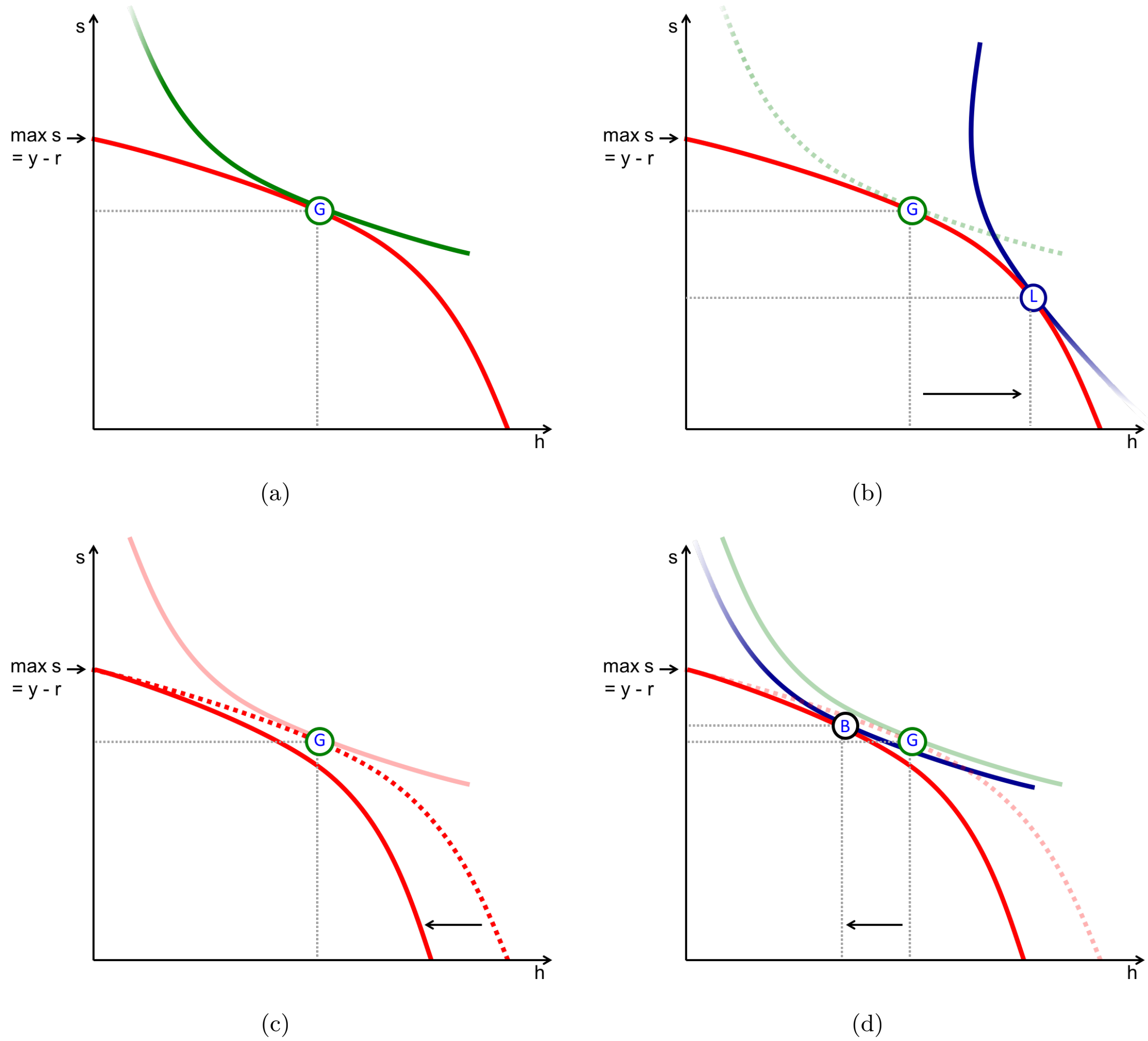


Figure 7: **Illustration of equilibrium with different lenders.** These plots illustrate the joint determination of haircut and spread between the borrower and multiple lenders. In each plot, haircut is on the horizontal axis, and spread is on the vertical axis; "max s" stands for maximum repo spread that the borrower can accept, equal to the expected return on the asset ($y$) minus the contractual repo rate ($r$). The concave red curves represent the borrower's indifference curves. The convex green curve is the indifference curve of a good lender (lower credit risk), and the convex blue curve that of a bad lender (higher credit risk). The green dot with $G$ represents an equilibrium between the borrower and a lender with high funding liquidity and good creditworthiness. The blue dot with $L$ illustrates an equilibrium when the borrower faces a lender with low funding liquidity, and $B$ illustrates another equilibrium when the borrower faces a lender with bad credit quality.

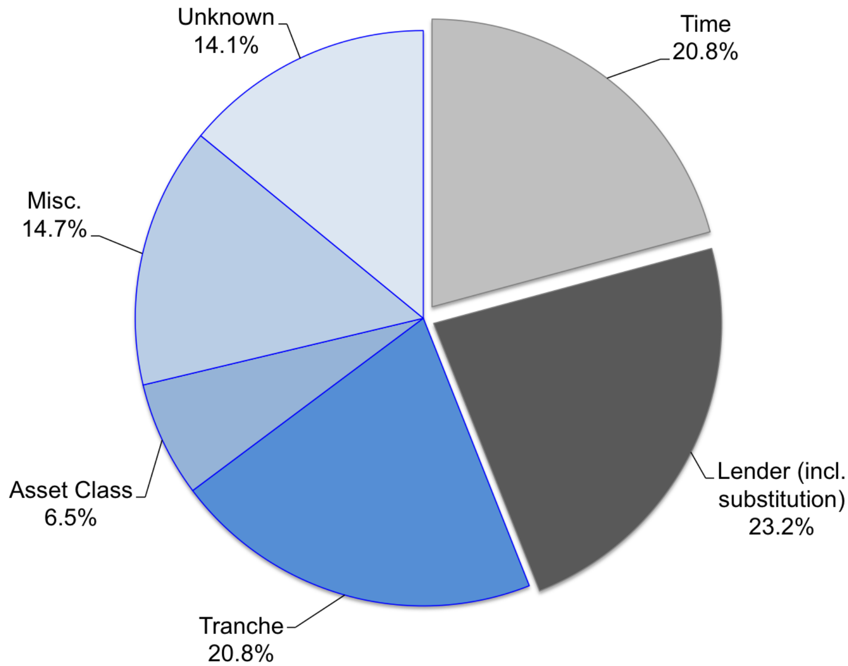


Figure 8: **Decomposition of sources of haircut variation.** This chart presents an approximation of total variation decomposition in haircuts by looking at each variable's (or group of variables') contribution to the $R$-squared of regressions. The portion in a spectrum of blue colors represents the contribution of collateral asset to the haircut variation, and it is further divided into four parts. A detailed explanation is in Subsection 5.5.

# Tables

| Asset Class | Haircut (%) | Spread (%) | Principal (1m) | Duration (days) | N. Obs. | Unique CUSIPs |
|---|---|---|---|---|---|---|
| Government | 0.00 | -0.203 | 107.7 | 10 | 141 | 11 |
| Corporate | 4.00 | 0.035 | 12.6 | 30 | 1,112 | 99 |
| MBS | 5.00 | 0.055 | 12.4 | 30 | 4,229 | 365 |
| ABS | 5.00 | 0.063 | 9.2 | 30 | 6,983 | 881 |
| Other SF | 5.00 | 0.056 | 14.4 | 36 | 827 | 110 |
| Preferred Shares | 15.00 | 0.242 | 25.8 | 30 | 48 | 1 |
| Unknown | 6.00 | 0.095 | 7.3 | 29 | 348 | 29 |
| All Asset Classes | 5.00 | 0.056 | 11.0 | 30 | 13,688 | 1,496 |

Table 1: **Collateral asset class and loan features.** This table shows median values of haircut, spread, loan principal, and loan term by Bloomberg asset class. Other SF represents structured finance securities not categorized into either MBS (mortgage-backed securities) or ABS (asset-backed securities). It includes complex CDO (collateralized debt obligations) or $CDO^2$ tranches. One observation is one contract.

| | VIX | LOIS |
|---|---|---|
| Coeff | 0.001 | 0.370*** |
| | (0.776) | (2.721) |
| N. Obs. | 703 | 703 |
| Adj. R2 | -0.001 | 0.008 |

Table 2: **Regressions of repo spread on measures of systematic risk.** This table displays regressions of spread on measures of macro credit risk. The dependent variable is the daily mean repo spread over LIBOR. The independent variables are the VIX volatility index (Column 1) and LIBOR over OIS Spread (Column 2), two indices known to proxy for systematic risk in credit markets. One observation is one day. Standard errors are White-robust. $t$-statistics are reported in parentheses. The number of stars (*) represents statistical significance at 10% (*), 5% (**), and 1% (***).

Panel I: Government and Corporate Bonds

| Bond Rating | Haircut (%) | Spread (%) | N. Obs. | Unique CUSIPs |
|---|---|---|---|---|
| Treasury | 0.00 | -0.203 | 141 | 11 |
| AAA | 0.00 | -0.060 | 19 | 6 |
| AA | 5.00 | 0.034 | 4 | 1 |
| A | 5.00 | 0.028 | 288 | 16 |
| BBB | 4.00 | 0.024 | 169 | 11 |
| BB | 2.50 | 0.040 | 27 | 3 |
| Other | 4.00 | 0.043 | 605 | 66 |
| All Ratings | 4.00 | 0.032 | 1,253 | 114 |

Panel II: Mortgage-Backed Securities

| MBS Tranche | Haircut (%) | Spread (%) | N. Obs. | Unique CUSIPs |
|---|---|---|---|---|
| A | 5.00 | 0.050 | 2,701 | 187 |
| M | 5.00 | 0.065 | 866 | 107 |
| B | 7.00 | 0.070 | 365 | 45 |
| C | 5.00 | 0.045 | 39 | 2 |
| Junk | 10.00 | 0.137 | 84 | 6 |
| Other | 5.00 | 0.076 | 174 | 24 |
| All Tranches | 5.00 | 0.055 | 4,229 | 371 |

Panel III: Asset-Backed Securities

| ABS Tranche | Haircut (%) | Spread (%) | N. Obs. | Unique CUSIPs |
|---|---|---|---|---|
| A | 4.00 | 0.048 | 3,039 | 301 |
| M | 5.00 | 0.073 | 1,604 | 357 |
| B | 7.00 | 0.071 | 915 | 91 |
| C | 10.00 | 0.103 | 531 | 58 |
| Junk | 15.00 | 0.255 | 702 | 65 |
| Other | 10.00 | 0.093 | 192 | 12 |
| All Tranches | 5.00 | 0.063 | 6,983 | 884 |

Table 3: **Spread and haircut by asset quality within class.** These tables summarize median values of haircut and spread by tranche name or rating, within each asset class (Treasury or corporate bonds, MBS, or ABS). One observation is one contract.

| | (1) | | (2) | | (3) | |
|---|---|---|---|---|---|---|
| | Haircut | Spread | Haircut | Spread | Haircut | Spread |
| Volatility | 0.278 | 0.010** | 0.187 | 0.011** | 0.860*** | 0.022*** |
| | (1.268) | (2.021) | (0.845) | (2.043) | (4.342) | (4.489) |
| Issue Size | -0.774*** | -0.009*** | -0.691*** | -0.007*** | -0.640*** | -0.007*** |
| | (-18.633) | (-9.178) | (-15.149) | (-6.478) | (-13.794) | (-6.536) |
| Duration | | | 0.017*** | 0.000** | 0.009** | 0.000 |
| | | | (3.539) | (2.200) | (2.019) | (1.254) |
| Principal | | | -0.238*** | -0.006*** | 0.012 | -0.002 |
| | | | (-4.695) | (-5.012) | (0.249) | (-1.326) |
| Tranche: A | | | | | 3.198*** | 0.077*** |
| | | | | | (5.279) | (5.169) |
| Tranche: M | | | | | 3.130*** | 0.078*** |
| | | | | | (5.139) | (5.227) |
| Tranche: B | | | | | 4.524*** | 0.084*** |
| | | | | | (7.540) | (5.676) |
| Tranche: C | | | | | 7.581*** | 0.137*** |
| | | | | | (11.954) | (8.797) |
| Tranche: Junk | | | | | 10.769*** | 0.210*** |
| | | | | | (17.524) | (13.886) |
| Fixed Effects: | | | | | | |
| Lender | Y | Y | Y | Y | Y | Y |
| Issuer | Y | Y | Y | Y | Y | Y |
| Day | Y | Y | Y | Y | Y | Y |
| N. Obs. | 6,296 | 6,292 | 6,266 | 6,266 | 6,266 | 6,266 |
| Adj. R2 | 0.803 | 0.676 | 0.806 | 0.675 | 0.848 | 0.718 |

Table 4: **Margin and spread as a function of collateral characteristics.** This table shows how haircut and spread react to several characteristics of collateral assets. *Volatility* is the past 1-month (20 trading days) return volatility measured at 1 previous day of each transaction. *Issue Size* and *Principal* are the natural logarithms of the respective quantities. All coefficients are measured within different securities of the same issuer (usually, different tranches of the same CDO) pledged as collateral with the same lender on the same calendar day. $t$-statistics are reported in parentheses. The number of stars (*) represents statistical significance at 10% (*), 5% (**), and 1% (***).

| | Spread | | | | |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| Haircut | | 0.015*** | 0.001 | 0.012*** | -0.000 |
| | | (57.847) | (0.892) | (79.860) | (-0.102) |
| $\text{Haircut}^2$ | | | 0.001*** | | 0.001*** |
| | | | (17.752) | | (31.561) |
| Fixed Effects: | | | | | |
| Lender | Y | Y | Y | N | N |
| Issuer | Y | Y | Y | N | N |
| Day | Y | Y | Y | N | N |
| N. Obs. | 8,382 | 8,382 | 8,382 | 13,617 | 13,617 |
| Adj. R2 | 0.779 | 0.866 | 0.874 | 0.319 | 0.365 |

Table 5: **The quadratic relationship between spread and haircut.** This table studies the shape of spread as a function of haircut. All coefficients are measured within different securities of the same issuer (usually, different tranches of the same CDO) used as collateral with the same lender on the same calendar day, thus measuring the sole effect of collateral features. $t$-statistics are reported in parentheses. The number of stars (*) represents statistical significance at 10% (*), 5% (**), and 1% (***).

| | At Inception Only | | | At Rollover and Inception | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Spread | | -9.076** | -9.067** | | 2.677 | -0.286 |
| | | (-2.292) | (-2.269) | | (0.841) | (-0.092) |
| Duration | | | 0.003 | | | 0.047*** |
| | | | (0.184) | | | (3.837) |
| N. Obs. | 112 | 112 | 112 | 230 | 230 | 230 |
| Adj. R2 | 0.667 | 0.690 | 0.685 | 0.128 | 0.126 | 0.220 |

Table 6: **Regression within contract pairs or triples.** This table presents the regression results for contract pairs or triples of only brand-new contracts (Columns (1)–(3)) or all reset points of contracts including rollovers (Columns (4)–(6)) made at the same time on the same collateral (8-digit CUSIP). The dependent variable is $Haircut$. Using pair fixed effects means that the regression coefficients are identified using within-pair variation. The regression specification for this table is described by Equation (10). (The full specification is estimated in columns (3) and (6); the other columns restrict some coefficients to zero). Standard errors are clustered at position level. $t$-statistics are reported in parentheses. The number of stars (*) represents statistical significance at 10% (*), 5% (**), and 1% (***).

Panel I: Haircut

| | At Inception Only | | At Rollover and Inception | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| dPMBS | -2.427** | -2.860** | -0.819 | -0.414 |
| | (-2.342) | (-2.614) | (-1.167) | (-0.605) |
| Duration | | -0.043 | | 0.055*** |
| | | (-1.164) | | (2.780) |
| N. Obs. | 81 | 81 | 172 | 172 |
| Adj. R2 | 0.607 | 0.612 | -0.099 | 0.003 |

Panel II: Spread

| | At Inception Only | | At Rollover and Inception | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| dPMBS | 0.056* | 0.058* | 0.010 | 0.023 |
| | (1.882) | (1.785) | (0.629) | (1.546) |
| Duration | | 0.000 | | 0.002*** |
| | | (0.148) | | (4.056) |
| N. Obs. | 81 | 81 | 172 | 172 |
| Adj. R2 | 0.511 | 0.491 | 0.313 | 0.443 |

Table 7: **Lenders' default probability and contract terms.** This table presents the regression results for contract pairs or triples of only brand-new contracts (Columns (1)–(2) of each panel) or all reset points of contracts including rollovers (Columns (3)–(4)) made at the same time on the same collateral (8-digit CUSIP). The dependent variable for Panel I is $Haircut$ and Panel II is *Spread*. Using pair fixed effects means that the regression coefficients are identified using within-pair variation. Regression specifications for this table can be found in Equation (11). $\Delta P^{MBS}$ is the quarter-on-quarter change in total borrowing using mortgage-backed securities as collateral in the tri-party repo market. Standard errors are clustered at position level. $t$-statistics are reported in parentheses. The number of stars (*) represents statistical significance at 10% (*), 5% (**), and 1% (***).

Panel I: Haircut

| | At Inception Only | | At Rollover and Inception | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| ProbDef | -2.982 | -2.995 | -2.687** | -2.530** |
| | (-1.625) | (-1.592) | (-2.539) | (-2.555) |
| Duration | | 0.002 | | 0.058*** |
| | | (0.067) | | (3.366) |
| N. Obs. | 81 | 81 | 186 | 186 |
| Adj. R2 | 0.643 | 0.628 | 0.017 | 0.142 |

Panel II: Spread

| | At Inception Only | | At Rollover and Inception | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| ProbDef | 0.062* | 0.066** | 0.034* | 0.038** |
| | (1.994) | (2.159) | (1.683) | (2.281) |
| Duration | | -0.001 | | 0.002*** |
| | | (-1.409) | | (5.645) |
| N. Obs. | 81 | 81 | 186 | 186 |
| Adj. R2 | 0.779 | 0.788 | 0.484 | 0.640 |

Table 8: **Lenders' default probability and contract terms.** This table presents the regression results for contract pairs or triples of only brand-new contracts (Columns (1)–(2) of each panel) or all reset points of contracts including rollovers (Columns (3)–(4)) made at the same time on the same collateral (8-digit CUSIP). The dependent variable for Panel I is $Haircut$ and Panel II is *Spread*. Using pair fixed effects means that the regression coefficients are identified using within-pair variation. Regression specifications for this table can be found in Equation (12). $ProbDef$ is 3-year default probability derived from an expected default frequency (EDF) measure. Standard errors are clustered at position level. $t$-statistics are reported in parentheses. The number of stars (*) represents statistical significance at 10% (*), 5% (**), and 1% (***).

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Default | 10.515*** | 12.724*** | 7.260*** | 8.104*** |
| | (8.541) | (8.639) | (7.774) | (7.530) |
| ABX | -0.867** | -0.346 | -1.154*** | -1.007*** |
| | (-2.225) | (-0.803) | (-4.874) | (-4.223) |
| Duration | | -0.010*** | | -0.008*** |
| | | (-2.749) | | (-4.125) |
| Fixed Effects: | | | | |
| Lender | Y | Y | Y | Y |
| Tranche | Y | Y | N | N |
| Asset Class | Y | Y | N | N |
| Year | Y | Y | Y | Y |
| Asset | N | N | Y | Y |
| N. Obs. | 6,551 | 6,480 | 8,003 | 7,833 |
| Adj. R2 | 0.615 | 0.623 | 0.814 | 0.815 |

Table 9: **Reaction of haircuts to borrower's risk of failure.** This table shows how haircut reacts to dynamic changes of borrower's default probability. ABX is the 1-month average return of the AAA-ABX index, which proxies for the systematic asset risk of structured finance securities. $Default$ is the instantaneous hazard rate implied in the decomposed CDS spread of the fund's parent firm. The decomposed spread is orthogonalized with respect to ABX returns to separate pure borrower risk from exposure to the collateral assets. *Duration* is the length of repo contracts in days. $Lender\ family$ fixed-effects capture the lender's identity, $Tranche$ and $Asset\ Class$ information is from the funds' books and Bloomberg. *Asset* is the fixed effect of the exact asset using 8-digit CUSIP. Standard errors are clustered at the position level. $t$-statistics are reported in parentheses. The number of stars (*) represents statistical significance at 10% (*), 5% (**), and 1% (***).

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| ABX | -0.470 | -0.294 | -0.827*** | -0.901*** |
| | (-1.200) | (-0.681) | (-3.861) | (-3.951) |
| $Type^1 \times$ Default | 7.853* | 7.877 | -2.381 | 3.482*** |
| | (1.708) | (1.561) | (-0.408) | (2.999) |
| $Type^2 \times$ Default | 5.636*** | 6.647*** | 4.673*** | 3.845*** |
| | (3.923) | (2.938) | (5.374) | (3.049) |
| $Type^3 \times$ Default | 14.229*** | 14.843*** | 10.792*** | 10.783*** |
| | (9.456) | (9.449) | (8.907) | (8.489) |
| Duration | | -0.010*** | | -0.007*** |
| | | (-2.781) | | (-4.000) |
| Fixed Effects: | | | | |
| Lender | Y | Y | Y | Y |
| Tranche | Y | Y | N | N |
| Asset Class | Y | Y | N | N |
| Year | Y | Y | Y | Y |
| Asset | N | N | Y | Y |
| N. Obs. | 6,551 | 6,480 | 8,003 | 7,833 |
| Adj. R2 | 0.618 | 0.624 | 0.817 | 0.817 |

Table 10: **Reaction of haircuts to borrower's risk of failure using price type.** This table displays how haircut reacts to dynamic changes of borrower's default probability. ABX is the 1-month average return of the AAA-ABX index, which proxies for the systematic asset risk of structured finance securities. $Default$ is the instantaneous hazard rate implied in the decomposed CDS spread of the fund's parent firm. The decomposed spread is orthogonalized with respect to ABX returns to separate exposure to the collateral assets from pure borrower risk. The $Type^j$ indicator variables represent different levels of price information quality: $Type^1$ is a trader quote; $Type^2$ is a Bloomberg quote of a model price; and $Type^3$ is cost basis or no price information. The omitted category consists of entries for which there is no information about the price type. *Duration* is the length of repo contracts in days. *Lender* fixed-effects capture the lender's identity at their family level, $Tranche$ and $Asset\ Class$ information is from the funds' books and Bloomberg. *Asset* is the fixed effect of the exact asset using 8-digit CUSIP. Standard errors are clustered at position level. $t$-statistics are reported in parentheses. The number of stars (*) represents statistical significance at 10% (*), 5% (**), and 1% (***).

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| ABX | 0.003 | -0.005 | 0.010** | -0.003 |
| | (0.512) | (-0.905) | (2.288) | (-0.946) |
| $Type^1 \times$ Default | -0.082 | -0.143 | -0.049 | -0.083 |
| | (-0.830) | (-1.397) | (-1.134) | (-1.572) |
| $Type^2 \times$ Default | 0.086*** | -0.003 | 0.093*** | 0.014 |
| | (5.007) | (-0.165) | (9.396) | (1.227) |
| $Type^3 \times$ Default | 0.020 | 0.002 | 0.005 | -0.028* |
| | (1.223) | (0.129) | (0.365) | (-1.847) |
| Duration | | -0.000 | | 0.000** |
| | | (-0.083) | | (2.041) |
| Fixed Effects: | | | | |
| Lender | Y | Y | Y | Y |
| Tranche | Y | Y | N | N |
| Asset Class | Y | Y | N | N |
| Year | Y | Y | Y | Y |
| Asset | N | N | Y | Y |
| N. Obs. | 6,541 | 6,477 | 7,993 | 7,830 |
| Adj. R2 | 0.521 | 0.518 | 0.787 | 0.792 |

Table 11: **Reaction of spread to borrower's risk of failure using price type.** This table reports how spread reacts to dynamic changes of borrower's default probability. ABX is the 1-month average return of the AAA-ABX index, which proxies for the systematic asset risk of structured finance securities. *Default* is the instantaneous hazard rate implied in the decomposed CDS spread of the fund's parent firm. The decomposed spread is orthogonalized with respect to ABX returns to separate exposure to the collateral assets from pure borrower risk. The $Type^j$ indicator variables represent different levels of price information quality: $Type^1$ is a trader quote; $Type^2$ is a Bloomberg quote of a model price; and $Type^3$ is cost basis or no price information. The omitted category consists of entries for which there is no information about the price type. *Duration* is length of repo contracts in days. *Lender* fixed-effects capture the lender's identity at their family level, *Tranche* and *Asset Class* information is from the funds' books and Bloomberg. *Asset* is the fixed effect of the exact asset using 8-digit CUSIP. Standard errors are clustered at position level. $t$-statistics are reported in parentheses. The number of stars (*) represents statistical significance at 10% (*), 5% (**), and 1% (***).