Lender Protection versus Risk Compensation: Evidence from the Bilateral Repo Market[*]

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July 2016

ABSTRACT

We study secured lending contracts using a novel, loan-by-loan database of all bilateral repurchase agreements that financed a hedge fund's positions over three years. Other things equal, loans on lower-quality collateral have higher spread, higher margin and smaller loan amounts, but longer maturity. Conversely, holding loan risk constant, one point of spread substitutes approximately 9 points of margin. Using the 2005 U.S. bankruptcy reform as a positive shock to expected creditor recovery, we observe that margin alone drops, suggesting that margin has a unique role in protecting the lender from collateral illiquidity.

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

[*]The latest version of this working paper can be obtained at `http://ssrn.com/abstract=2695646`. A previous version was titled "The role of margin and spread in secured lending: evidence from the bilateral repo market." We thank Fernando Alvarez, Patrick Bolton, Dan Cao, Sebastian Infante, Mina Lee, Francis Longstaff, Iftekhar Hasan, Stefan Nagel, Carolyn Sissoko, Christian Upper, Jiang Wang, James Yae, and Michelle Zemel for helpful discussions. We also would like to thank seminar participants at Southern Methodist University, Georgetown University, Federal Reserve Board, University of Washington, University of Colorado Boulder, Hong Kong University, Peking University, and ICEF, as well as participants at the Lone Star Finance Conference, XXIV MBF Conference, ECB Money Market Workshop, 2015 International Dauphine-ESSEC-SMU Conference on Systemic Risk and the 2016 SWFA for helpful comments.

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1 Introduction

Loans secured by collateral are a central feature of financial markets. A minimum set of terms for a secured lending contract includes interest rate, loan amount, maturity, and margin, defined as the amount of collateral per dollar loaned. Given that a lender could achieve a desired risk-return profile using many possible combinations of these terms, in this paper we ask a simple yet fundamental question: how do lenders use multiple loan terms to manage loan risk? In particular, we study which risks and frictions are associated with the use of each of these terms, pointing to a rationale for their existence.

In a friction-free financial market, lender and borrower would agree on the price of risk, eliminating the need for nonprice terms. In a riskier loan, the borrower would simply pay a higher spread (interest rate), but he would not need to pledge more collateral, or accept a shorter maturity. Given the importance of collateralized lending, numerous theoretical and empirical studies have expanded our understanding of what information frictions or transaction costs motivate the need for certain contract terms, focusing on one or two terms at a time. However, there is scant evidence showing how lenders use all these terms jointly to manage their loan risk and pinning down the role of specific nonprice terms.

The goal of our study is to provide empirical facts as a first step to bridging this gap in our understanding of loan contracts, and in particular of risky loan contracts secured by collateral. We show that margin and spread increase together with loan risk, but substitute for one another when keeping loan risk constant. Conversely, maturity shortening does not appear to be lenders' primary tool to deal with loan risk. Finally, using a shock to expected creditor recovery, we show that margin also has a unique role: to protect the lender against collateral illiquidity.

Empirically linking the visible characteristics of a loan to its terms is challenging because of the hidden characteristics of the borrower and the collateral asset. For example, a comparison between two mortgage loans on similar homes is never "everything else equal" because of our inability to control for all unobserved confounding factors, such as heterogeneity of houses and borrowers. We overcome this problem using a novel, loan-level dataset, consisting of three years of bilateral repurchase agreements (repos), short-term secured loans used by a large fixed-income arbitrage fund to finance its positions.

To the best of our knowledge, we are the first to use loan-by-loan data from the bilateral repo market, a unique laboratory for the purpose of understanding contract features. Unlike in other forms of collateralized lending, the borrower enters into repeated contracts on the same well-identified collateral, as well as simultaneous contracts on collateral with a well-defined risk sorting. Moreover, unlike in the wholesale funding market, bilateral repo terms are contracted for each individual collateral security. Having multiple observations in which variation is suppressed along several dimensions enables us to eliminate any concerns about unobserved confounding factors.

We compare loans initiated on the same day between the same parties, so that the level of loan risk is univocally determined by collateral alone. Further, we restrict our analysis to sets of loans collateralized by different tranches of the same securitization. Because senior tranches are safer collateral than junior tranches by construction, we need not rely on potentially noisy inferred measures of collateral quality.

We find that, as loan risk increases, lenders require both higher risk compensation (spread) and protection (margin). Compared to the highest-quality collateral, the lowest-quality collateral has 15 basis points higher spread and almost 9 percent higher margin. Although previous literature has documented comovement of price and nonprice terms in responding to various sources of risk (Rappoport and White, 1994; Berger and Udell, 1995; Strahan, 1999; Graham et al., 2008; Benmelech and Bergman, 2009), the correlation between margin and spread that we uncover is surprisingly strong in terms of not only the direction but also the specific pattern of comovement. Moreover, there is no obvious theoretical reason why the lender should take more risk (as evidenced by the higher spread) when the collateral quality drops.

Even more surprisingly, we also find evidence of *negative* correlation between price and nonprice terms: on average, loans on lower-quality collateral have longer maturities. This finding is contrary to the common-sense expectation that riskier loans have shortened maturities. Further, the unique structure of our data enables us to observe that maturity drops only for the lowest-quality collateral, resulting overall in a hump-shaped pattern: maturity rationing does occur, but only when loan risk exceeds a threshold. This pattern is consistent with models of borrower signaling (Flannery, 1986) or borrower rollover concerns (Diamond, 1991; Brunnermeier and Yogo, 2009), suggesting that maturity rationing is not lenders' primary risk management tool.

The observation that spread and margin respond to the same risk in the same way suggests that their roles may overlap. Could a higher spread compensate at least part of the loan risk otherwise addressed by margin? To answer this question, we construct pairs of loans with essentially constant fundamental risk following two distinct approaches. First, we select consecutive loans rolled over within a very short time window (1 day to 1 week). Because these loans finance the same asset position, the lender is almost always the same. Alternatively, we select loans on the same collateral initiated at the same time with different lenders. Within these pairs, keeping loan risk constant, we should observe negative correlation between margin and spread, as increasing margin mechanically reduces loan risk. Indeed, under both approaches, we are able to observe statistically and economically significant substitution: a 1 point higher spread is associated with approximately 9 points lower margin. This finding suggests that lenders could achieve a given level of risk-adjusted return using multiple combinations of price and non-price terms.

Furthermore, we find evidence that the chosen combination of margin and spread is not random. Within the contract pairs with different lenders, we observe that the borrower obtains lower margin requirements (at the cost of higher spreads) from lenders with a better funding liquidity situation, because the value of one unit of margin to a lender depends on their availability of funding liquidity (Lee, 2015; Infante, 2015; Dang et al., 2013). We also observe that the borrower obtains lower margin requirements from less creditworthy lenders, although less creditworthy lenders are not compensated with a higher spread. Because the lender holds the collateral asset and margin is the borrower's equity in the asset, the borrower is exposed to the lender's credit for that equity amount (Ewerhart and Tapking, 2008). By reducing margin, repo borrowers reduce counterparty risk.

Although lenders manage risk using multiple combinations of margin and spread, if *all* risk can be compensated by a higher spread, it would be easier for lenders to set the spread high enough and collapse the margin to zero. Why does margin exist in the first place? Perhaps, margin also mitigates a potential loss that commands no risk premium. To investigate this possibility, we examine the effects of a bankruptcy code reform that enhanced creditor rights in certain repo contracts, including virtually all contracts that financed our fund's positions: the Bankruptcy Abuse Prevention and Consumer Protection Act of 2005 (BAPCPA). In case of borrower default, BAPCPA granted repurchase agreements an exemption from automatic stay, i.e., it enabled lenders to immediately liquidate collateral without becoming entangled in bankruptcy proceedings (Acharya and Öncü, 2013). This regulation change is unlikely to have affected the amount of priced loan risk, because it neither increased immediacy at a market-wide level, nor did it make the collateral asset inherently more liquid. Only the liquidating lender experiences enhanced immediacy and liquidity.

We track positions financed by a series of rolled-over contracts, spanning a period that includes October 17, 2005, the effective date of BAPCPA. On that date, we observe a statistically and economically significant drop in margin (approximately one percentage point) which is not accompanied by any visible change in spread or maturity. This drop in margin is driven by senior tranches of collateralized debt obligations (CDO), consistent with an adverse-selection based explanation for the existence of margin (Dang et al., 2015).

Exemption from automatic stay creates a significant advantage for the liquidation of opaque assets like CDO tranches, by reducing the time available for a prospective buyer to value the asset. If the asset is sufficiently opaque, the cost of becoming informed in a short time is prohibitively high. At the same time, if the tranche is *senior*, then the benefit of information is low because the asset is less information-sensitive. As a result, prospective buyers of opaque but senior tranches are deterred from becoming informed. The likely absence of informed buyers mitigates adverse selection, improving liquidation outcomes and reducing the need for margin ex ante. This finding suggests that margin does have a unique purpose: protecting lenders from collateral illiquidity. To the best of our knowledge, we are the first to document the effect of lenders' adverse selection concerns on debt capacity. We are able to deliver this result because the collateral in our sample, unlike most asset types, has independent and objective measures of complexity (type of securitization) and information-sensitivity (seniority).

Taken together, the results in this paper document how secured loan terms are determined and interact with each other. Margin and spread play overlapping roles in addressing loan risk. However, margin alone can mitigate the potential loss arising from liquidating illiquid collateral. Finally, maturity seems to be driven less by the lender's need to control loan risk, and more by the borrower's concerns for rollover risk.

Although we study a specific type of secured loan in this paper, repo is one of only a few loan types in which contracts frequently repeat against identifiable and non-unique collateral. This unique structure enables us to perform precise measurements and draw implications that may inform a more general theory of collateralized lending.

Our main concern about the generalizability of our results is that the dataset features a single borrower. However, the bulk of our analysis compares a cross-section of simultaneous or near-simultaneous loans, thereby sidestepping any concerns about omitted variables such as time-varying borrower risk. Moreover, this borrower entered standard contracts with more than 40 different lenders, including almost all major dealer banks. The contract terms in the sample, therefore, are unlikely to be entirely driven by borrower-specific characteristics, if at all.

The structure of the paper is as follows. Section 2 describes the data in detail, providing a discussion about repo spread estimation and its comovement with a measure of systematic risk. Section 3 analyzes the effect of collateral quality on repo terms. Section 4 presents evidence of substitution between margin and spread, showing that it is in part driven by lender characteristics. Finally, Section 5 shows that margin has a unique role using the regulation change as an instrument. Section 6 concludes.

2 Data description

Our sample covers 3 years, from 2004 up until the collapse of the subprime market in 2007. The data come from technically multiple hedge funds that actively traded fixed-income securities. 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 combined funds held on average about $9 billion in securities, making them one of the largest in their category, according to the TASS database.

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 in our exposition and we treat them as one borrower ("the fund"). However, whenever our identification strategy relies on identifying sets of loans with a common borrower, we always require that within each set the borrower be the same fund.

The fund's main portfolio holdings consisted of securitized bonds and other structured finance securities 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^2).

For further analysis, we classify the structured finance securities in the portfolio into two categories. The first one ("MBS") consists of plain-vanilla passthrough MBS whose payoff is determined by the performance of an underlying pool of mortgages. This asset class is a relatively simpler instance of structured finance. The second category ("CDO") is a more complex form of structured finance, namely, CDOs and their variations. These securities are backed by other securitized products such as passthrough MBS. Because of this additional layer of securitization, analyzing the value of such securities is substantially more difficult. For the rest of the paper, we use the labels "MBS" and "CDO" as defined here.

Our data consists of a daily panel of all the fund's repo contracts. 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 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 a given day during a contract's 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, 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 × Par Value × Current Factor), and the security's accrued coupon interest (as it is customary, book and market value are reported "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, the repo loan's accrued interest, rate, haircut/required margin, cash margin (i.e., the actual cash in the hands of the lender), and current margin (the security value as percentage of the loan principal). In the repo market, the convention is to express required margin as "haircut". If a loan has a 5 percent haircut, the borrower is required to provide $100 of collateral for a loan of $95.

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 (less than 1 percent) and 9 lenders that had a special 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 CUSIP-level information from the FISD database (bond rating for corporate and government bonds) and from Bloomberg (market sector, name, ticker, description, asset class, mortgage type, collateral type, issue amount, issue date, and maturity date). We also obtain macro-level information from Bloomberg (VIX, LOIS) 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 the expected default frequency (EDF) of lenders (those with public equity or those whose parent companies are public firms) for each day in the sample. In order to analyze the covariation of a dealer bank's funding condition and the terms of its lending contracts, we hand-collect the quarterly SEC filings of money market mutual funds (MMFs). In these filings, MMFs report all their investments, including wholesale repo loans made by the funds. 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.[1]

Haircuts vary between 0 and 50 percent; approximately 16 percent of the contracts have zero haircut. The median haircut is 5 percent, and about 11 percent of contracts have a haircut in the double digits. Rates vary from 0.80 percent to 6.88 percent.[2] Expressed as a spread to the relevant LIBOR rate (discussed in the following Subsection 2.2), 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. Throughout the paper, one contract is one observation, unless otherwise specified.

[Insert Table 1 about here]

2.1 Summary statistics by asset class

Repo spread, haircut and loan amount covary across assets classes (Table 1). The covariation between haircut and spread is particularly strong. 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 (-19 basis points and 0 percent). In fact, the haircut on Treasury bonds is identically 0 percent throughout the sample. On the other hand, maturity does not show any obvious pattern in the cross-section of asset quality.

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 2 shows the median loan terms

[1] We thank Stefan Nagel and coauthors for providing the data used in Krishnamurthy et al. (2014b), so that we could check the consistency of our data collection from two overlapping quarters in 2007.

[2] 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.

by tranche for each type of structured finance securities (MBS and CDO).

In order to obtain the tranche ratings used in Table 2, we hand-classify each security as either *A*, *B*, *C*, *Junk* or *Other*, based on the text description from our data. For most securities, an additional security description available from Bloomberg is used as a cross-check. *A* includes tranches named A or M (Mezzanine).[3] *Junk* encompasses lower-seniority 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. Even though the "A, B, C" nomenclature is relatively standard, there is no official manual that structured finance issuers use to name the tranches. 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 CDO. Moreover, in our analysis of Section 3, this classification is especially accurate because we only compare tranches of the same securitization.

[Insert Table 2 about here]

2.2 Estimating the repo spread

The interest rate on a loan (repo rate) is composed of a reference rate plus a spread. The reference rate varies over time as macroeconomic interest rates vary, and even within the same day, it varies naturally for loans of different maturity: typically, longer-term loans have higher rates than short-term loans, even when they are risk-free. The focus of our study is on the loan price component that is under the control of the contracting parties, i.e., the spread, but what we actually observe is the interest rate. Therefore, it is necessary to define and measure the spread carefully.

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 base rate and of macro interest rate variation. Due to institutional practices, the interest rate of most contracts was specified as some spread over LIBOR during our sample period. 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. We use LIBOR as the benchmark rate for the rest of

[3]Including M tranches as a standalone category between *A* and *B* does not change any of our results meaningfully. Empirically, A tranches are treated by lenders only marginally better than M tranches.

our analysis.[4]

Empirically, we can only observe 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 1 shows the dynamics of the repo spread. The dark solid line is the average repo spread over LIBOR for contracts initiated on a given day. The gray confidence bands show the interquartile range. Note that in Figure 1, as in the rest of the paper, the baseline unit of 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 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.

Figure 1 provides preliminary evidence that repurchase agreements are priced as if they are risky, contrary to a widespread belief that they are nearly risk-free.[5] Although our sample is not representative of the market at large, its existence alone demonstrates that repurchase agreements can be used, and were used as early as 2004, to finance very risky collateral. 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. For reference, the spread over the U.S. federal funds rate is 33 basis points.

In the time series, the spread displays considerable variation. Such time-series variation is correlated with systematic risk factors. To show this, we run a time-series regression of daily-average repo spread on LIBOR over the Overnight Indexed Swap (LIBOR-OIS Spread, or LOIS) and the VIX index. Both variables are considered to be indicators of systemic financial risk (e.g., Gorton and Metrick, 2012).

Further, the spread displays large cross-sectional variation, as demonstrated by the width of the

[4]Our results hold with other reasonable reference rates (e.g., U.S. federal funds rate).

[5]For instance, the appendix to Brunnermeier and Pedersen (2009) states 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. 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."

interquartile range depicted in Figure 1. As is the case for time series variation, the cross-sectional variation also appears to be strongly correlated to loan risk. In order to demonstrate this, we run the same time-series regressions on five subsamples of contracts on MBS and ABS sorted by tranche rating, a measure of collateral quality (A, B, C, Junk).

Specifically, we run the following regression for the whole sample and the five tranche subsamples:

$$\overline{Spread_t} = \alpha^{AC} + \beta \cdot Risk_t + \varepsilon_t, \tag{1}$$

where $\overline{Spread_t}$ is the daily average of repo spread across all contracts initiated on that day that are included in the whole sample or a subsample. α^{AC} is an asset class fixed effect, to account for the fact that our sample contains two types of securitized tranches—both mortgage-backed securities and collateralized debt obligations, whose average spread level could be different. (The results are qualitatively unvaried with or without these fixed effects). *Risk* is one of the above-mentioned indicators of systemic financial risk (LOIS or VIX). As in Figure 1, the baseline unit of observation is a contract, but contracts are aggregated into daily averages.

[Insert Figure 1 about here]

The top panel of Table 5 displays regression results for LOIS. Column 1 of the table uses the whole sample, and shows that the β coefficient on LOIS is positive and significant, indicating that there is a comovement between repo spread and money market distress.

Columns 2–6 report the subsample regression results within each tranche category. They show that, as the collateral quality declines (from A to Junk), the sensitivity of repo spread to the macro risk increases. The pattern is monotonic except for the Junk category. The determination of risk compensation for the Junk category seems to be dominated by other factors. However, in general, this result implies that collateral of different quality has a different sensitivity to market-wide funding risk. This finding supports 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 compensation for services or monopoly rent extraction.

It is also interesting that the coefficient on VIX (bottom panel) is positive but insignificant, suggesting that the risk in question is particularly related to money market distress rather than overall volatility. The two different results between LOIS and VIX also mitigate a potential concern of spurious regression typically occurring in time-series regressions. The next section examines in detail how spread and other contract terms vary in the cross-section of collateral.

[Insert Table 5 about here]

3 Collateral quality and contract terms

When faced with a risky loan, lenders may use several nonprice contract terms to simply reduce risk or to ameliorate problems stemming from agency or asymmetric information. In a repurchase agreement, lenders can reduce their exposure by reducing principal (i.e., the absolute loan amount) or by increasing haircut (i.e. reducing the loan amount per dollar of collateral). Lenders can also engage in maturity rationing by shortening the loan term.

In this section, we show that both haircut and spread covary strongly with one another in the cross-section of collateral; both rise as collateral quality drops. We also show that principal covaries with collateral quality (better assets get larger loans). This finding holds true even after controlling for the collateral security's original issue amount, which is clearly exogenous to the loan contract being studied: higher-quality securities are typically issued in larger amounts (consistent with credit rationing at the source) and later our borrower merely happens to own larger amounts.

Finally, we show that loan maturity increases as collateral quality drops, consistent with models in which the borrower has private information and is concerned about rollover risk. Overall, the pattern of coefficients suggests that for hard-to-liquidate assets the borrower demands a longer maturity, and is willing to make concessions on other loan terms (e.g., higher spread and haircut). In other words, the borrower's concern with rollover risk overrides the lender's incentive to engage in maturity rationing in the presence of lower-quality collateral.

Collateral "quality" could be defined as low risk. If value at risk is what matters, low-quality collateral is an asset with high price volatility, and the source of volatility is not important. However, "quality" could also be defined as liquidity. In this case, low-quality collateral is an asset 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. In this section, we use a comprehensive measure of asset quality (tranche rating) without drawing a clear distinction between pure price risk and illiquidity. We also use separate proxies for price risk (volatility) and for illiquidity (issue size). Our results indicate that lenders are concerned with both price risk and illiquidity. In Section 5, we further analyze how the illiquidity concern alone is reflected in contract terms.

3.1 Simultaneous contracts on different tranches of the same securitization

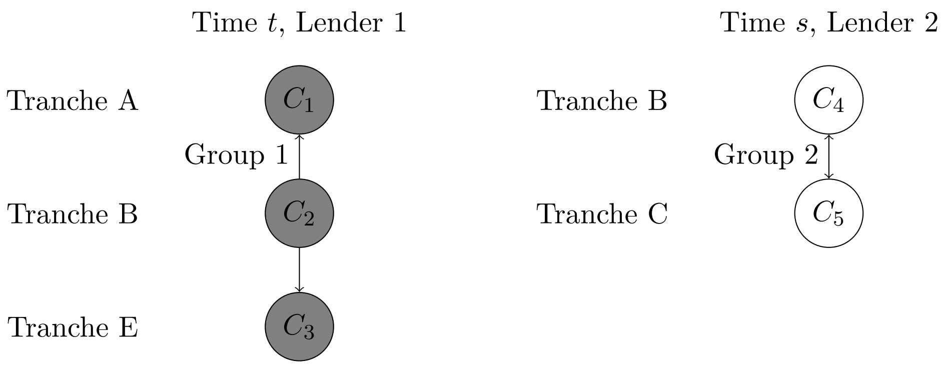
Although the summary statistics of Section 2 show a general pattern of contract terms with respect to collateral quality, there can be significant heterogeneity in asset quality within each category. For example, two "A" tranches may be associated with different levels of payoff risk, depending on the 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 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 four samples of repurchase agreement collateralized by four different tranches of the same CDO. All loans were initiated with the same lender on the same day and had the same duration. The following is the result:

Tranche	**Haircut**	Rate	Start	End	Maturity	Principal	**Spread**
A	**5%**	2.77%	1/5/05	4/25/05	110 days	25.0m	**0.11%**
B	**10%**	2.95%	1/5/05	4/25/05	110 days	9.0m	**0.28%**
C	**15%**	3.15%	1/5/05	4/25/05	110 days	3.6m	**0.48%**
D	**20%**	3.33%	1/5/05	4/25/05	110 days	8.1m	**0.66%**

Within this controlled group, spread and haircut increase much more dramatically than in Table 1 and Table 2. Those tables suffer from attenuation bias because of all the factors we cannot control for in a summary table.

The situation exemplified here is not rare in our sample. In fact, we have 3,249 instances in which each of multiple securities issued by the same issuer is pledged as collateral for a loan initiated on the same day with the same lender. Most instances of multiple securities from the same issuer are typically multiple tranches of the same CDO. This affords us a particularly clean measurement of the effect of collateral quality on loan terms, as exemplified in the following diagram:



In the diagram, five contracts are represented. One contract is one observation. Although each contract is observed on multiple days, we keep only the initiation day for each contract. The first three contracts (C_1, C_2, C_3) regard three tranches of a CDO (A, B, E) whose purchase is financed by a loan initiated at time t from Lender 1. The last two contracts (C_4, C_5) regard two tranches of another CDO (B, C) whose purchase is financed by a loan initiated at time s with Lender 2. In each case, our estimation is based on variation within each of the two groups of contracts, allowing us to measure the effect of collateral quality on spread and haircut, keeping everything else constant.

For an individual repo contract i, the regression specification takes the following form:

$$\begin{array}{r} Spread_i \\ Haircut_i \\ Maturity_i \\ Principal_i \end{array} = \alpha^{L,I,t} + \underbrace{\beta \cdot Tranche_i}_{\text{Tranche indicators}} + \underbrace{\boldsymbol{\theta} \cdot \mathbf{Quality}_i}_{\text{Direct quality measures}} + \underbrace{\boldsymbol{\gamma} \cdot \mathbf{C}_i}_{\text{Controls}} + \varepsilon_i. \tag{2}$$

where $\alpha^{L,I,t}$ is a (Lender $\times$ Issuer $\times$ Initiation Day) fixed effect.[6] The issuer is identified by the first six digits of the CUSIP number. As described above, this fixed-effect specification enables us to identify the effect of collateral quality on contract terms while keeping constant the lender, the borrower, the issuer, and the environmental conditions. $Tranche$ is a vector of tranche indicator variables (the omitted category is "A"), **Quality** is an optional vector of direct measures of collateral quality, and **C** is an additional optional vector of control variables.

[6] In the context of fixed-effect specification, the Cartesian product "$\times$" signifies that we use a separate fixed effect for each unique combination of lender, issuer, and initiation day. This notation is followed throughout the paper.

Quality consists of two direct measures of collateral quality, *Volatility* and *Issue Size*. These variables are included as controls, but also because they are interesting per se. Unlike the tranche indicator variables, these variables have a more direct interpretation as, respectively, price risk and liquidity risk.

Volatility, a proxy for price risk, is the asset price volatility as measured by the hedge fund itself over the past month. 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. 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. Note that volatility may arise without any illiquidity, and vice versa.

Issue Size, a proxy for liquidity, is 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.

As additional control variables, we use all the contract terms that are not the dependent variable. For example, if the dependent variable is *Spread*, then $\mathbf{C} = (Haircut,\ Maturity,\ Principal)$.

[Insert Table 7 and Figure 2 about here]

Table 7 contains four sets of regressions based on Eq. (2), each with a different contract term (*Spread*, *Haircut*, *Maturity* and *Principal*) as dependent variable. For each set, we run two versions of the specification. The first version (Specification 1) includes only tranche indicator variables ($\mathbf{C} = \mathbf{Quality} = \varnothing$). In the second version (Specification 2), we include the quality variables ($\mathbf{C} = \varnothing$; $\mathbf{Quality} = \{Volatility, Issue\ Size\}$). Appendix A reports an additional specification including the full set of variables, showing that the results for each term are robust to the inclusion of other terms as control variables.

For easier interpretation, Figure 2 plots the coefficients on the tranche indicators from the baseline Specification 1. The vertical axis is labeled to indicate the direction in which contract terms become stricter. For *Spread*, *Haircut* this direction is up, because a higher spread and a higher margin requirement are stricter contract terms. For *Maturity* and *Principal* this direction is down, because a shorter maturity and a smaller loan are stricter contract terms. From Figure 2, it is immediately evident that the coefficients on the tranche indicators for the haircut and spread equations follow a highly symmetric pattern. This pattern indicates that, as collateral risk grows, lenders do not raise the haircut to fully compensate, but rather they choose to bear a proportionally increasing amount of risk.

In all specifications, all contract terms show a strong pattern as a function of collateral quality. Low-quality collateral is associated with higher spreads, higher haircuts, and smaller principal amounts. Although previous literature has documented that price and nonprice terms become stricter as collateral quality worsens (Rappoport and White, 1994; Benmelech and Bergman, 2009), the correlation between margin and spread that we uncover is surprisingly strong. In addition, our empirical setup permits us to show that margin and spread react to loan quality in a similar way in terms of not only the direction but also the specific pattern of comovement.

Existing studies report that a positive comovement patterns extends to loan maturity (Benmelech et al., 2005; Benmelech, 2009). However, the pattern that we uncover is more nuanced. In general, worse collateral is associated with *longer* loan maturity; we only observe evidence of maturity rationing for the worst collateral. The overall form of the relation between collateral quality and loan maturity is hump-shaped (C tranches have longer maturity than both B and Junk). The pattern we uncover remains qualitatively identical in version (2), controlling for other contract terms. This indicates that the longer maturity for lower-quality tranches is not a byproduct of substitution between different contract terms. For instance, suppose that lower-quality tranches have higher haircuts; further suppose that in order to accept the higher haircut, the borrower would ask for a longer maturity in exchange. In this case, the result would disappear once we control for haircut. Instead, the result remains, indicating that the increase in maturity is directly associated with a decrease in collateral quality.

This finding is counterintuitive, because when the collateral quality is bad, keeping the rest of loan terms (haircut, spread, and principal) constant, lenders are better off requiring shorter maturity and maintaining the option of not renewing the loan. However, a similar pattern is approximately compatible with theories of lending based on asymmetric information.[7] In Flannery (1986), a borrowing firm with good quality assets may want to accept a shorter maturity to signal the true asset quality to lenders. In Diamond (1991), a borrower with private information seeks longer-term financing to avoid roll-over events and the resulting possibility of inefficient liquidation. In both models, accepting a short maturity allows the borrower to enhance the other loan terms. Maturity rationing emerges because the weakest borrowers have no choice but to use short-term debt.

It is important to note that both models' results are driven by private information about true asset quality known only to the borrower. Our pattern is based on tranche seniority—a very public piece of information. We interpret our finding as an indication that, as tranche rating drops, not only does the public information reflect a lower expected asset quality, but the scope for private information about true asset quality also increases because junior tranches are more information-sensitive. This interpretation informs further analysis in Section 6, where more discussion is provided.

The coefficients on $Volatility$ and $IssueSize$ in the full specification are also interesting. $Haircut$ is strongly affected by both proxies of quality, even after controlling for tranche seniority and other contract terms. $Volatility$ also affects $Principal$, and $IssueSize$ also affects $Spread$, although the coefficient is only marginally significant. All these coefficients go in the usual direction, i.e., better collateral gets better contract terms. As is the case for the tranche indicator variables, $Volatility$ also affects time to maturity in the direction consistent with tranche variations, i.e., more volatile collateral is associated with a *longer* time to maturity. Moreover, upon adding $IssueSize$ to the $Principal$ regression, the tranche coefficients are substantially reduced. This suggests that, at least in part, the credit rationing happens at the source: lower-quality securities are issued in smaller amounts at the source, and later bought in smaller amounts by the fund. However, even after controlling for $IssueSize$, there is evidence of actual credit rationing with respect to asset quality.

[7]Typically, these models analyze the choice of maturity structure in the context of loans secured by all of the borrowing firm's assets. In our case, each loan is backed by a specific asset and therefore the existence of asymmetric information does not apply to the borrower's prospects, but to the asset itself; cross-sectional differences in collateral drive differences in loan risk and asymmetric information, and ultimately in contract terms. However, we believe that the insight from this class of models transfers naturally to our situation.

Finally, the coefficients on the **C** vector of other contract terms highlight once again that *Haircut* and *Spread* are strongly related to one another unlike any other pair of contract terms. *Haircut* and *Spread* strongly predict one another; when used as control variables, they considerably reduce the magnitude and significance of the tranche coefficients. The coefficients of each is positive, indicating that a high spread predicts a high haircut better than any available measure of collateral quality.

As noted above, other contract terms (*Maturity* and *Principal*) do not seem to respond to changes in *Haircut* and *Spread* or to one another. This pattern can also be explained based on common sense. The typical borrower is usually less flexible in terms of maturity and loan amount, compared to haircut and spread. In our specific case, the fund has a certain asset in mind. The desire for a loan of a certain maturity will be primarily driven by rollover risk considerations—more illiquid assets will necessitate less frequent rollovers. Loan size will be roughly fixed based on the fund's target asset allocation. Then, to satisfy these requirements, the fund may be willing to pay a higher spread or incur a higher haircut. The exact mix of these two remaining terms will be determined by negotiations with the lender. For this reason, the next section focuses on the trade-off between haircut and spread, using the other contract terms as control variables.

4 Substitution in contract terms

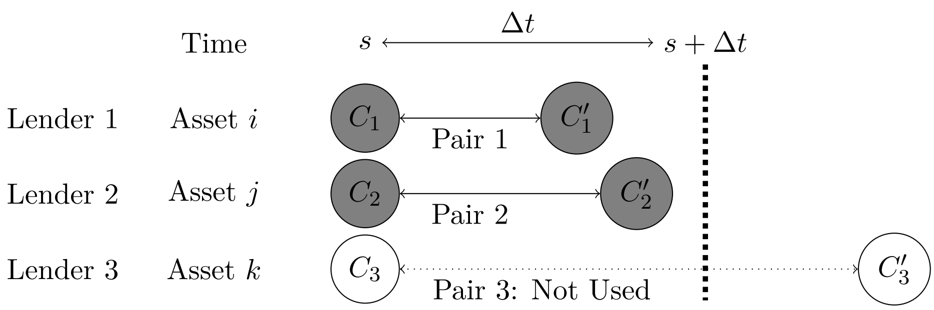
In this section, we explore the trade-off between different contract terms. In particular, we focus on the relationship between haircut and spread, motivated by the strong comovement between these two terms uncovered in the previous section. Among other things, our empirical design allows us to isolate the effect of lender-specific variables and how they drive this trade-off, while fully controlling for borrower and collateral-related risks.

4.1 Haircut and spread trade-off within lender

The results of Section 3 show that collateral quality strongly influences contract terms, suggesting that spread and haircut are driven largely by a common set of risks. However, that analysis does not reveal the relation between spread and haircut when fundamental loan risk is held constant.

Controlling for loan risk is challenging. First, loan risk is jointly determined by collateral asset risk and borrower credit risk. Most of the borrower's leveraged portfolio is invested in assets similar to the collateral itself, making it impossible to disentangle asset value and borrower creditworthiness. Second, our observables may not capture all the necessary information: 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 bond's duration; however, we do not have enough information to calculate duration, because most of the bonds in the sample have complex embedded options.

To solve these problems, we observe pairs of distinct contracts that finance the same asset position, such that the second contract is a roll-over of the first one (i.e., the initiation date of the second contract immediately follows the *maturity date* of the first). We additionally require the second contract to follow the first one in rapid succession: given a time window of Δt days, we only use the pairs in which the initiation date of the second contract is Δt or fewer days after the *initiation date* of the first. Because of this construction, almost all pairs (more than 95 percent) consist of two loans from the same lender. Moreover, since we have a single borrowing entity, the fundamental loan risk among contracts within any of these pairs is reasonably identical because the asset risk, the borrower's credit quality, and the correlation between these two are likely to stay constant within a narrow time window. The illustration below exemplifies our setup.



In the illustration, there are three contracts (C_1, C_2, C_3) initiated at time s. Each contract rolls over to a subsequent contract (C_1', C_2', C_3'). We use Pairs 1 and 2 because the time gap between the first and the second contract is less than Δt. We discard Pair 3 because the two contracts are too far apart in time.

Within each pair, we regress changes in haircut on changes in spread. We additionally control for changes in loan maturity and loan amount. All changes are simply calculated as the second contract minus the first. The following is our regression specification for pair i:

$$\Delta Haircut_i = \alpha^{T,A} + \beta^S \cdot \Delta Spread_i + \beta^M \cdot \Delta Maturity_i + \beta^P \cdot \Delta Principal_i + \varepsilon_i, \tag{3}$$

where $\alpha^{T,A}$ is a Month$\times$Asset fixed effect (one for each unique combination of calendar month and 9-digit CUSIP) to control for long-term trends in macro and asset-specific risk. Asset-level fixed effects are necessary because, although new information arrives to the market unpredictably, for fixed-income securities risk changes predictably over time, e.g., as maturity becomes closer, and principal is paid down. As a consequence, all contract terms also become more lenient, regardless of the size of the time window we use. This effect is security-specific, depending on maturity, rate of prepayment, etc.. Time fixed effects are also necessary because macro risk factors can be serially correlated. Thus, if the current rollover involves a spread increase, the next rollover is likely to involve the same. We choose one month as the time unit for fixed effects to match the typical contract length. As seen in Table 5, even the sensitivity to macro factors is asset-specific, and therefore we use Month $\times$ Asset fixed effects. The result holds regardless of whether we add a time dimension or not.

We run the regression of Eq. 3 for different values of Δt, the maximum number of days in the window between two contracts in each pair. β^S is our coefficient of interest. Table 8 displays the estimated coefficients for $\Delta t \in \{1, 2, \ldots 7\}$. Column 1 uses contracts that reset only in 1 day; Column 2 uses contracts whose start date is 2 or fewer days apart, and so forth. Across all columns, up to a 7-day window, the results show a negative relationship between haircut and spread, suggesting that haircut increases (decreases) merely because spread decreases (increases). The result is most pronounced when we use a 1-day window, and the magnitude and statistical significance fade away as we widen the window gap. This pattern is consistent with our earlier explanation: the substitution between haircut and spread becomes apparent only when the fundamental loan risk is sufficiently invariant within pairs.

Figure 3 displays the estimated coefficient β^S and 90% confidence interval $\Delta t \in \{1, 2, \ldots 30\}$. It shows that contracts more than 4 days apart (roughly 1 calendar week) have sufficiently different loan risks that we are unable to observe a substitution effect.

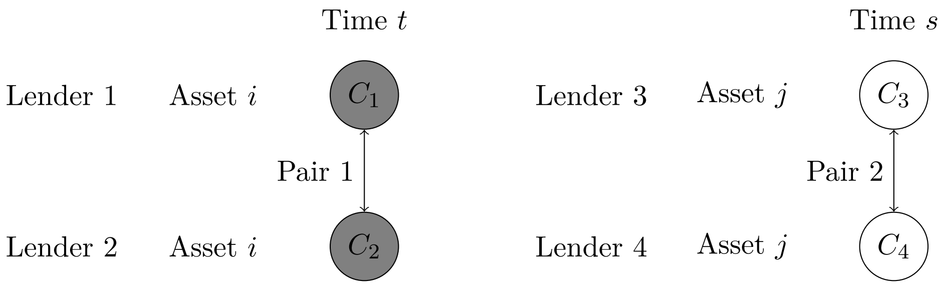
[Insert Table 8 and Figure 3 about here]

4.2 Haircut and spread trade-off across lenders

In the previous subsection, we provide large-sample evidence of substitution between margin and spread within pairs of successive loans secured by the same collateral. By constructions, the vast majority of such pairs consisted of two loans from the same lender. In this subsection we establish the existence of the same trade-off relationship within pairs of *contemporaneous* loans secured by the same collateral and made by *different* lenders. As in the previous subsection, this "pairs" setup controls for any observable and unobservable factors that may affect contract terms. Such factors may include collateral quality, time-varying macroeconomic dynamics, and borrower credit risk.

For a given match of lender and borrower, both parties have an indifference schedule between haircut and spread. The equilibrium contract is the point of tangency between these indifference curves. Note that each lender may have a differently shaped indifference schedule for the borrower. Moreover, the borrower need not have equal indifference curves vis-à-vis all lenders, because repurchase agreements expose the borrower to counterparty risk. In the previous subsection, the substitution we measure is simply a move along the borrower's indifference curve. The trade-off we are measuring in this subsection is the combined effect of a potential shift in the indifference curves of both parties. By restricting our analysis to pairs with one borrower and different lenders, we ensure that this shift is the result of lender heterogeneity. In the next subsection we provide evidence of how specific lender-related factors drive this trade-off.

Formally, we define contemporaneous contracts as loans secured by the same collateral, made by different lenders, and starting within the same time window. Such pairs are rare; based on the results from Table 8, we choose 4-day window to maximize the number of observations while keeping loan risk reasonably constant. We find 115 such contract pairs displaying within-pair haircut variation. To reduce confounding factors further, we restrict our analysis to 56 pairs of brand-new contracts, i.e., pairs in which 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 Pair 1. Both contracts are initiated at time t and have the same collateral, Asset i. Pair 2 is formed in a similar way.



For each contract i in a pair k, we run the following regression:[8]

$$Haircut_i = \alpha^k + \beta^S \cdot Spread_i + \beta^M \cdot Maturity_i + \beta^P \cdot Principal_i + \varepsilon_i \tag{4}$$

[Insert Table 9 about here]

Column 1 of Table 9 reports the results of regression Eq. 4 with only the pair fixed effect α^k (restricting $\beta^S = \beta^M = \beta^P = 0$). The R^2 of this regression (66.7 percent) represents the amount of haircut variation that is explained by asset risk and time-varying borrower risk.

Column 2 of the table displays the regression result with *Spread* as an explanatory variable, without any controls. In this basic specification, the negative coefficient on *Spread* shows the direct substitution effect. Going from Column 1 to Column 2 (adding *Spread*), the adjusted R^2 rises to 69.0 percent: substitution explains an additional 2.4 percentage points of unknown variation, or 7.1 percent of the residual variation. Within a pair, loan maturity and principal loan amount may vary. However, similar to the results of Section 3, controlling for loan maturity and principal (Columns 3 and 4) and both (Column 5) does not change the result meaningfully. The coefficient

[8]In this specification, as well as in the specification from the previous subsection, the coefficient of interest (β^S) is measured with attenuation bias. Appendix B explains the reasons and also argues that the bias is likely more important for the present specification compared to the previous one. However, in both specifications the bias works against us finding a significant result and does not change the sign of the coefficient. Moreover, there is no obvious solution to this bias given our observables.

on *Spread* remains negative and strongly significant. 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 approximately 9 percentage points lower. In spite of the much smaller number of observations, the estimate is remarkably similar to the coefficient measured in Table 8 using a 3-day window.

As discussed above, the effect 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 obtain if the borrower's indifference curve varies when facing 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 specific sources of lender heterogeneity in Subsection 4.3.

4.3 Lender characteristics and the choice of lending contract features

In Subsections 4.1 and 4.2, we show that there is substitution between haircuts and spreads in equilibrium: lender and borrower may agree on different combinations of contract terms, even when loan risk is constant. Thanks to the presence of multiple lenders in our sample, we are able to observe how the variation of lender characteristics plays a role in determining contractual terms. In this subsection, we focus on two of the most relevant lender variables: funding liquidity, and creditworthiness.

In this context, we define funding liquidity as the lender's ability to generate liquidity from a given piece of collateral. The bank can do so by rehypothecating the collateral to different institutions (Lee, 2015; Infante, 2015). For example, suppose a lending bank makes a loan of $80 while receiving $100's worth of collateral (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). A lender seeking to maximize the total amount of liquidity generated via this mechanism may be willing to lend at lower haircuts (e.g., 18 percent) in order to obtain more collateral, as long as that type of collateral can be easily repledged.[9]

Lenders' credit quality should also be one of the most important characteristics of lender hetero-

[9]Alternative mechanisms are also possible. For instance, a lender may be willing to accept a lower *spread* in exchange for collateral that can be repledged in large quantities. Ultimately, what lenders actually do is an empirical question.

geneity. 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 (Ewerhart and Tapking, 2008).[10] Moreover, this exposure is directly determined by the margin requirement. If the lender undergoes bankruptcy, the borrower loses access to the collateral asset, becoming an unsecured creditor. Assuming zero recovery, the borrower would lose the equity in the asset (i.e., the haircut) and all the intervening appreciation in asset value. Therefore, as lender default becomes more likely, the borrower would prefer lowering the haircut, possibly (but not necessarily) at the cost of a higher rate. In other words, the borrower's marginal rate of substitution of spread for haircut rises, resulting in a shift of the trade-off relationship.

Our results, discussed in detail later in this subsection, show evidence that high funding liquidity is associated with lower haircuts and higher spreads, suggesting that lenders with good funding liquidity can lend more liberally and earn higher compensation. Lower creditworthiness, on the other hand, is associated with lower haircuts, suggesting that borrowers are concerned with counterparty risk. This finding is not in contrast with the previous one because our measure of funding liquidity simply captures cross-sectional changes in lenders' ability to rehypothecate the particular type of assets that the fund holds. Therefore, our measure of funding liquidity is unrelated to credit quality during our sample period. Finally, we find no statistically significant evidence that borrowers need to pay higher spreads in order to obtain lower haircuts from lenders with lower credit quality.

Our analysis relies on a small number of data points. Pairs of loans initiated within the same 4-day window with the same exact collateral with two different lenders are rare; in addition to that, we must have tri-party borrowing information about *both* lenders in the pair. We are able to match mutual fund filings to the majority of lenders but not all, resulting in a sample of 52 observations (26 pairs), even fewer than in the previous subsection. These observations are few but they allow for a very clean measurement of the effects of interest. In spite of the low power, we are still able to obtain significant coefficients, and their sign and magnitude are robust to reasonable variations in specification. The lack of significance of certain coefficients, however, may be due to the low power.

[10] However, 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.

Finally, one could argue that the results in this section might be driven by omitted variables correlated with lender condition. However, by construction, we are keeping the borrower, the environmental conditions, and the collateral asset constant. Thus, any omitted variables have to be either attributes of the lender, or of the contract itself. We explicitly control for all the attributes of the contract. In order to argue that any lender-related omitted variables drive the results, then one would have to argue that these variables are correlated with lender condition, but have no actual economic relation to the condition itself.

4.3.1 Funding liquidity

We obtain a measure of lender funding liquidity using information from the tri-party repo market, in which most of our lenders are borrowers. Presumably, 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). Therefore, changes in a lender's tri-party borrowing against MBS collateral capture tri-party lenders' relative changes in demand for that asset type. We expect such changes to be linked to the terms offered by that lender to our fund. For most of our lenders, hand-collected mutual fund filings allow us to calculate total repo borrowing using mortgage-backed securities as collateral.[11]

To examine whether the lender's ability to rehypothecate collateral explains haircut or spread variation within our pairs, we run the following regression specification. For contract i in pair k,

$$\begin{array}{r} Haircut_i \\ Spread_i \end{array} = \alpha^k + \beta_1 \cdot \Delta P_i^{MBS} + \beta_2 \cdot Maturity_i + \beta_3 \cdot Principal_i + \varepsilon_i, \tag{5}$$

where ΔP^{MBS} is the quarter-on-quarter change in total borrowing using mortgage-backed securi-

[11] For the period in question, money market mutual fund filings provide coarse information about collateral type such as "MBS," "ABS," "Corporate Bonds," "Government Bonds," etc.. CDOs are more likely to be classified as "ABS" rather than "MBS", but in the case of the CDOs held by our fund, the main exposure is to mortgage collateral. From the filings it is usually not possible to tell whether ABS collateral is backed by mortgages or, as is often the case, other assets. Further, within MBS collateral type, it is not always possible to have more precise collateral type, e.g., private MBS or agency MBS. Therefore, broadly defined MBS collateral is our best proxy for the demand for collateral like the one held by our fund.

ties as collateral.[12] The results are reported in Table 10 with two dependent variables, *Haircut* (Columns 1–4) and *Spread* (Columns 5–8). Each regression is estimated with and without controls for loan maturity (*Maturity*) and loan amount (*Principal*).

The coefficient of interest is β_1. Our specification is agnostic. The sign of β_1 in the *Haircut* regression is not affected by the sign of the same coefficient in the *Spread* regression. If the lender's ability to rehypothecate collateral is driving substitution between haircut and spread within a pair, then we expect β_1 to be negative in the *Haircut* regression (Columns 1–4) while positive in the *Spread* regression (Columns 5–8).

[Insert Table 10 about here]

Columns 1–4 of the table show that, as a lender faces a favorable funding situation (positive ΔP^{MBS}), the haircut goes down, consistent with the mechanism described above. Columns 5–8 of the same table indicate that a favorable funding situation is associated with a higher spread, once again consistent with the substitution mechanism: the lender is willing to lend more liberally in order to earn a higher spread[13].

Our analysis establishes a linkage between the funding condition of a lender with respect to a certain asset class and its lending behavior with the same collateral asset class, but it cannot pin down the direction of causality. However, a reverse causality argument in which conditions in the bilateral market drive funding in the tri-party market is less plausible. Although large, our fund is quite small compared to both its lenders, and to money market mutual funds (the lenders to its lenders). Under a reverse causality argument, our fund and many other similar independent funds would have some unobservable reason to reduce their borrowing from one specific lender, thereby reducing that lender's ability to repledge mortgage-related collateral in the tri-party market. In particular, if borrowers were to avoid a lender because of concerns about its creditworthiness, we would observe lower, not higher, haircuts, as detailed next.

[12] Although there is a general tendency for all lenders to comove in terms of funding amounts against MBS securities, there is meaningful variation 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.

[13] We do not impose any restriction on the sign of β_1 of each regression in Eq. 10. In fact, if a lender's incentive to create the liquidity always dominates any profit-related objectives, we could observe the opposite sign, i.e., making haircut even higher in exchange for lower spread when rehypothecation is more probable. However, our result indicates that this is not the case: lenders manage between liquidity and profitability. Therefore, the marginal value of one unit of haircut decreases with a better funding situation, which drives the equilibrium we discover.

Finally, one could suspect that our results are driven by a market-wide change in the demand for structured finance assets 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 a given time. Given the fact that each dealer bank could transact with all MMFs, the difference in funding amount against structured finance collateral is due to differential characteristics across dealer banks. A more plausible explanation is that some dealer banks preferred and used this type of assets more to finance themselves, *relative to other banks.*

4.3.2 Lender creditworthiness

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

$$\begin{matrix} Haircut_i \\ Spread_i \end{matrix} = \alpha^k + \beta_1 \cdot ProbDef_i + \beta_2 \cdot Maturity_i + \beta_3 \cdot Principal_i + \varepsilon_i, \qquad (6)$$

where $ProbDef_i$ is the default probability of the lender of contract i. Because the default probability is not directly observable, we use 1-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).[14]

[Insert Table 11 about here]

Table 11 presents the results for Eq. 6, and it is structured symmetrically to Table 10. The coefficient on the default probability of the lender ($ProbDef$) in the haircut regression is consistently

[14]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 1-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.

negative. Controlling for fundamental loan risk, the borrower prefers a lower haircut when facing a lender with higher default probability. The magnitude of the coefficient is economically significant: 1 percentage point of lender's default probability is associated with a 17 percentage points decrease in haircut.

Columns 5–8 of Table 11 show that, when a lender's default probability is higher, the spread is positively affected, although the result is not statistically significant. Therefore, unlike in the case of the funding liquidity regression, the results do not support a view that lender creditworthiness drives substitution between haircut and spread. In this case, the lender grants the borrower a lower haircut as compensation for the heightened counterparty risk; there is no evidence of extra compensation for the lower haircut in the form of a higher spread.

5 The 2005 bankruptcy Act and the role of haircuts

In the previous sections, we show evidence that haircut and spread play overlapping roles. Both react to collateral asset risk in a very similar way. When we keep loan risk constant, they move in opposite directions. These findings raise questions: why do different contracts have different margin requirements (e.g., \$1.05 of collateral versus \$1.02 of collateral for a \$1 loan)? Can't lenders simply impose no haircut and earn a little more risk compensation? In this section, we look for a unique rationale for the existence of haircuts.

Dang et al. (2013) propose one such rationale: the haircut protects lenders not from price risk, but from the effect of adverse selection vis-à-vis better-informed traders when liquidating collateral. Informed traders would only buy the asset when it is priced at or below fair value, and steer clear of it otherwise, causing the lender to incur a loss in expectation. This potential loss does not command a risk premium, and therefore the lender is not compensated for it, providing a justification for the haircut. An adverse selection based theory explains some otherwise inexplicable observations, such as the fact that in our sample repos collateralized by long-term Treasury bonds have zero haircuts, although long-term Treasury bonds have volatile prices.

To empirically test the implications of this theory, we investigate how haircut and spread react to a regulation change that has a direct impact on expected loss upon liquidation: the Bankruptcy

Abuse Prevention and Consumer Protection Act of 2005 (BAPCPA). If the proposed rationale is correct, then the haircut alone, and not the spread, should respond to such a shock.

Among several important changes to the U.S. bankruptcy code, the Act strengthened the rights of a repo creditor upon a borrower's bankruptcy. Since repo contracts became widespread in the 1970s, the market had been unsure about the legal nature of such contracts. In a bankruptcy proceeding, the court could treat a repurchase agreement as an outright sale of the asset, or as a secured loan. If treated as an outright sale, the lender would be free to sell the asset immediately upon the borrower's default. If treated as a secured loan, the collateral would be subject to "automatic stay" and could not be sold without the court's authorization.

In several default cases in the early 1980s, the court ruled in favor of the secured loan view, forcing the repo collateral to stay. In 1984, a safe harbor provision was introduced granting an exemption from automatic stay to repo contracts on very liquid and safe assets (e.g., Treasury securities). The exemption allows a creditor to seize and liquidate collateral without becoming entangled in bankruptcy proceedings. The creditor, therefore, could avoid delays or the loss of proceeds from the collateral sale in favor of other creditors (Garbade, 2006).

In 2005, BAPCPA extended the exemption to cover repurchase agreements on all collateral types which did not qualify before (Acharya and Öncü, 2013). Ganduri (2015) argues that the extension of automatic stay facilitated the issuance of subprime loans by independent mortgage companies, as the ability to use repurchase agreements instead of standard warehouse lines of credit relaxed their credit constraints.

In the following subsections, we show that the enhancement of creditors' rights reduces the required haircut, but not the spread. By doing so, we highlight another channel through which the Act may have promoted the issuance of subprime mortgages: by increasing the borrowing capacity of the ultimate buyers of opaque structured finance securities, thereby boosting the demand for the low-quality mortgages that are likely to underlie such securities.

5.1 BAPCPA and the demand for complex structured finance

If the Act increased the fund's borrowing capacity using opaque structured finance securities as collateral, an increase in demand for such securities should be reflected in the fund's asset class composition. In this subsection we provide suggestive evidence that this was indeed the case.

[Insert Figure 4 about here]

Figure 4 shows that up to about the point when the Act was passed, the fund held approximately similar amounts of vanilla passthrough MBS and CDOs ("MBS" and "CDO" are used consistent with their definitions in Section 2). Immediately after the Act, the fund experienced significant growth, almost entirely driven by the accumulation of structured finance securities. At the same time, the fund reduced its holdings of MBS.

Structured finance securities held by the fund consist mostly of collateralized debt obligations (CDOs) backed by various types of collateral, largely MBS or even other CDOs. Compared to vanilla MBS, CDOs are much more informationally opaque due to the additional layer(s) of securitization.[15] It is important to notice that the demand for mortgage-related securities was already on the rise long before the passage of BAPCPA. The clear bifurcation between vanilla MBSs and complex structured finance appears to be related to the ability to finance the purchase of *increasingly opaque* mortgage-related securities, at least for our funds.

5.2 The reaction of haircut and spread to the enhanced creditors' right

Our data contains securities of different levels of transparency and information sensitivity. For instance, the fund held passthrough MBSs, which are relatively transparent, and also relatively opaque securities such as CDOs. Within each asset type, there is variation in credit quality: higher-rated tranches have higher seniority on the underlying assets' cash flows.

In Dang et al. (2013), two characteristics of the collateral asset determine the degree of asymmetric information between lender and borrower. The first is information sensitivity. If a security's payoff largely depends on the quality of the underlying assets, then the security's value is very sensitive to information about such quality. For example, a junior tranche would have much higher information sensitivity than a senior one. The second characteristic is the cost of acquiring information. If a security's payoff is based on another set of complex securities, one would have to spend

[15] CDOs backed by other CDOs were initially called CDO^2. As it became undesirable to keep track of the number of nested securitizations—for instance, because a given CDO was holding both direct MBS and other CDOs as collateral—this label was generalized to CDO^N, freeing the exponent from the burden of being an integer number.

significant amount of time to value such a security. For example, valuing a CDO^2 would have a much higher cost than a passthrough vanilla MBS.

Third-party traders choose whether to pay the cost to become informed. This decision jointly depends on these two characteristics. When the security's value is sensitive to information and acquiring information is not costly, traders' incentive to become informed is greatest, and the adverse selection problem faced by the lender is worst. In the words of Gorton and Ordoñez (2014), "desirable characteristics of collateral include a high perceived quality and a high cost of information production." In this context, a haircut is simply a buffer to absorb losses due to adverse selection. Therefore the required haircut level depends on the expectation of how many traders choose to become informed.

An exemption from automatic stay in bankruptcy allows lenders to liquidate the collateral faster. As a result, traders have less time to become informed, increasing the information gathering cost. When the asset is opaque (e.g., a CDO) the cost of acquiring information becomes prohibitive. Furthermore, an increase in cost is most likely to deter information acquisition when the value of information is low (e.g., a senior tranche of a securitization). Thus, BAPCPA is most likely to discourage information acquisition for opaque, information-insensitive securities, such as senior CDO tranches, improving expected lender outcomes and reducing the need for a haircut.

Because of the structure of our data, we are able to provide detailed evidence of this phenomenon. Our data contains successive contracts between the same lender and borrower, secured by the same asset. In particular, we identify the last batch of contracts that matured before the effective date of BAPCPA, and their immediate rollovers—i.e., the last set of contracts prior to the reform, and the first batch of contracts to be directly affected by it.

On the effective date of BAPCPA (October 17, 2005), the fund had 442 open contracts. Of these, 398 had a predecessor contract. We discard 24 contracts collateralized by corporate bonds, preferred shares and unknown collateral. Including these does not change the results in a meaningful way, but it makes the interpretation of our results less straightforward. The remaining 375 contracts were collateralized by securitized tranches (MBS or CDO). By comparing these contracts with their predecessors, we estimate the magnitude of the drop in haircuts across different levels of opaqueness (asset class) and information sensitivity (tranche seniority).

We first visualize the haircut dynamics during the event window. In particular, we use a one-year window centered on the effective date of BAPCPA (from April 17, 2005 to April 17, 2006). Because most contracts have a term of 90 days or less, a one-year window contains at least one roll-over before and one after the event. In order to visualize the effect of BAPCPA on a constant portfolio of securities, we plot the average haircut for a subset of 94 individual securities that were held by the fund throughout the entire window. Although choosing a narrower time window results in a higher number of securities, it does not qualitatively affect the aspect of the figure.

[Insert Figure 5 about here]

Figure 5 shows that only the haircuts of senior CDO tranches are affected by the regulation change, dropping on average by more than 1 percentage point exactly on the effective date of the Act. On that day, several contracts expired and were rolled over with a lower haircut, suggesting that the term date of these contracts was not set randomly in the first place.

It is worth noting that the law change was fully anticipated, as the effective date was known at least since the date the Act was passed by the U.S. Congress (April 20, 2005). The new rules could not have affected directly those contracts that expired prior to the effective date. However, foreknowledge of the arrival of a more creditor-friendly regime could have affected those contracts indirectly in several ways. For instance, by increasing the value of collateral to *future* lenders, BAPCPA likely improved the odds of a successful rollover at a future period, reducing the *current* lender's risk (Acharya et al., 2011). This mechanism—and any plausible mechanisms based on anticipation of the law's effects—would bias our estimate of the law's effect *downwards*, making it harder for us to observe any meaningful change upon the Act's effective date.[16]

One may also argue that this dynamic pattern could be explained by a change in the borrower's credit quality, which happened to be perfectly correlated with the regulation change. It is true that the borrower's default probability affects the expected loss from liquidation, because liquidation

[16]Before BAPCPA, safe harbor was explicitly granted only to repos secured by Treasury, Agency securities, bank certificates of deposit and bankers' acceptances (Acharya and Öncü, 2013). For other collateral, in the absence of a clear pronouncement of Congress, the question whether repos were secured loans or outright sales was a matter of precedent. Although precedents may have weighed in favor of the secured loan interpretation, the mere passage of BAPCPA could have enhanced a creditor's argument in favor of exemption from automatic stay. If that were the case, the effect of BAPCPA would have shown over time, or even all at once on the passage date (April 20, 2005). However, Figure 5 shows no recognizable effects on this date or in the intervening period.

only happens when the borrower fails. However, a change in the borrower's default probability would have affected the haircuts for the other asset categories which remain essentially constant during the whole period. Also, the credit default swap spread and equity-based expected default frequency of the parent entity of our fund show no significant changes in default probability during the time window.

To formally estimate the effect of improved creditor rights on loan terms, we run the following regression:

$$\begin{array}{r} \Delta Haircut_i \\ \Delta Spread_i \\ \Delta Maturity_i \end{array} = \alpha + \beta_1 \cdot \mathrm{CDO}_i + \beta_2 \cdot \mathrm{CDO}_i^{\mathrm{Senior}} + \beta_3 \cdot \mathrm{MBS}_i^{\mathrm{Senior}} + \gamma \cdot Controls_i + \varepsilon_i, \tag{7}$$

where $\Delta Haircut_i$, $\Delta Spread_i$ and $\Delta Maturity_i$ are respectively the change in haircut, spread and maturity between the current contract (first contract affected by the Act) and predecessor contract (last contract before the Act is effective) on the same security. This difference specification is not applicable to *Principal* as a dependent variable, because for a given position *Principal* mechanically decreases through partial sales or prepayments of the collateral security's underlying assets. On the other hand, Figure 4—without tracking specific positions—shows that the availability of credit for CDOs as a whole increases after BAPCPA.

CDO is an indicator variable that is one if the collateral asset is a complex structured finance security, and zero otherwise (i.e., if the collateral is a passthrough mortgage-backed security). $\mathrm{CDO}^{\mathrm{Senior}}$ and $\mathrm{MBS}^{\mathrm{Senior}}$ are indicator variables that are one if the security is an A-rated tranche and zero otherwise. *Controls* is a vector of optional controls including the other contract terms. These controls are necessary because, although the contracts before and after the effective date of the Act have the same underlying collateral, they may differ with respect to the other contract terms.

[Insert Table 12 about here]

Table 12 reports the regression results. Echoing the results of Figure 5, the β_2 coefficients on CDO$^{\text{Senior}}$ in the haircut regression (Columns 1–2) are consistently negative and significant at the 1% level, while the coefficients on the indicator variables for the other security types are not significantly different from zero. This result implies that only the haircuts of contracts on opaque and senior tranche collateral fall in responding to the shock implied by the Act.

The results of Table 12 and Figure 5 complement each other. Because the regression in Eq. 7 is a difference-in-differences specification, a negative coefficient could simply be found because the haircut of senior CDO tranches is on a long-run downward trend for reasons unrelated to BAPCPA. Figure 5 shows that the different asset types share a common trend, and a true step down exists for only one asset type on the effective date of the Act. At the same time, Table 12 uses all possible contracts and shows that the change is statistically significant, controlling for other variables, confirming that the haircut drop seen in the figure is not simply an artifact of sample selection or omitted variable bias.[17]

On the other hand, Columns 3–6 of the table show that spread and maturity are unaffected. The coefficient remains insignificant across all specifications. Therefore, the results in this section identify a unique role for margin requirements, consistent with an adverse selection theory of the haircut. A haircut is required to protect the lender from expected losses due to adverse selection, and spread cannot address this potential problem.

6 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 refinancing of the same collateral (rollover events), enabling us to conduct powerful tests of theories of collateralized lending.

[17]For those contracts that begin before the effective date of BAPCPA and end afterwards, the applicable bankruptcy regime depends on the default date. As one of several robustness check, we also define $\Delta Haircut_i$, $\Delta Spread_i$ and $\Delta Maturity_i$ as the difference between the successor contract and the predecessor contract, i.e., skipping the contract that straddles across the effective date. This reduces power as the number of observations falls from 375 to 297. However, even in this case, the coefficient estimates are qualitatively unchanged and still significant at the 5% level.

We analyze how four main contract terms vary as a function of collateral quality. These contract terms are loan spread (price), required margin, amount and maturity. We find that low-quality collateral is associated with higher spreads, higher required margins and lower loan amounts, but *longer* maturities. We interpret this finding as evidence that the borrower has private information about the collateral asset, and is concerned about refinancing risk; if the collateral asset is illiquid, the borrower has an incentive to minimize the number of rollover events.

Among contract terms, spread and margin are most sensitive to collateral quality, and highly correlated with one another. In particular, this correlation between spread and collateral quality and the sheer range of spreads observed are surprising in light of the super-senior nature of repo contracts, and of a widespread perception that repo loans are nearly risk-free. 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.

The high correlation between spread and haircut suggests that they may be at least in part substitutable. We find evidence of substitution between spread and haircut by comparing loans collateralized by the same asset using both successive contracts and contemporaneous contracts with different lenders.

Finally, we provide evidence of a unique role of margin requirements. Using the effective date of the Bankruptcy Abuse Prevention and Consumer Protection Act of 2005 (BAPCPA) as a shock to expected creditor recovery, we show evidence that haircuts fell only for opaque, information-insensitive collateral, consistent with an adverse selection based theory in which the haircut protects lenders against losses to informed traders when liquidating collateral.

Summarizing, we find that loan maturity increases as collateral quality declines. We also find that haircut and spread are related differently in different dimensions. They show strong comovement across asset quality, 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 that potential losses caused by adverse selection upon liquidation can be exclusively addressed by the haircut.

Taken as a whole, our results indicate that asymmetric information plays an important role in determining the nonprice terms of secured loan contracts. Although our analysis focuses on repurchase agreements, much of the insight we provide is not specific to the repo market and may help shape a more general theory of secured lending.

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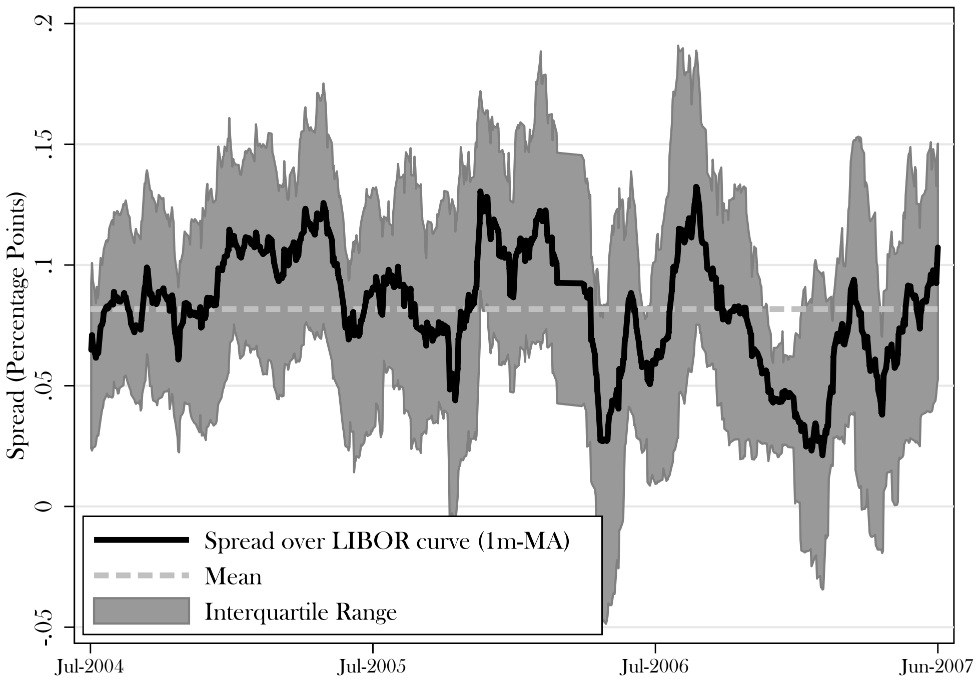

Figure 1: **Repo spread dynamics.** This figure plots a time-series of the *Spread* using LIBOR as the reference rate. *Spread* is defined as the difference between the repo rate and LIBOR at the contract start date, matching the loan maturity in days. Each day, we calculate average *Spread* for contracts initiated on that day. The thick black line depicts the 1-month moving average of the daily average *Spread*. The shaded area indicates the 75th and 25th percentiles of the *Spread* distribution (also 1-month moving average of the daily values). The dashed horizontal line displays the whole-sample average of the spread. To construct a reference rate for every maturity (in days), the LIBOR curve is interpolated by fitting a cubic spline to the available points (overnight, 1 month, 3 months, 6 months and 1 year).

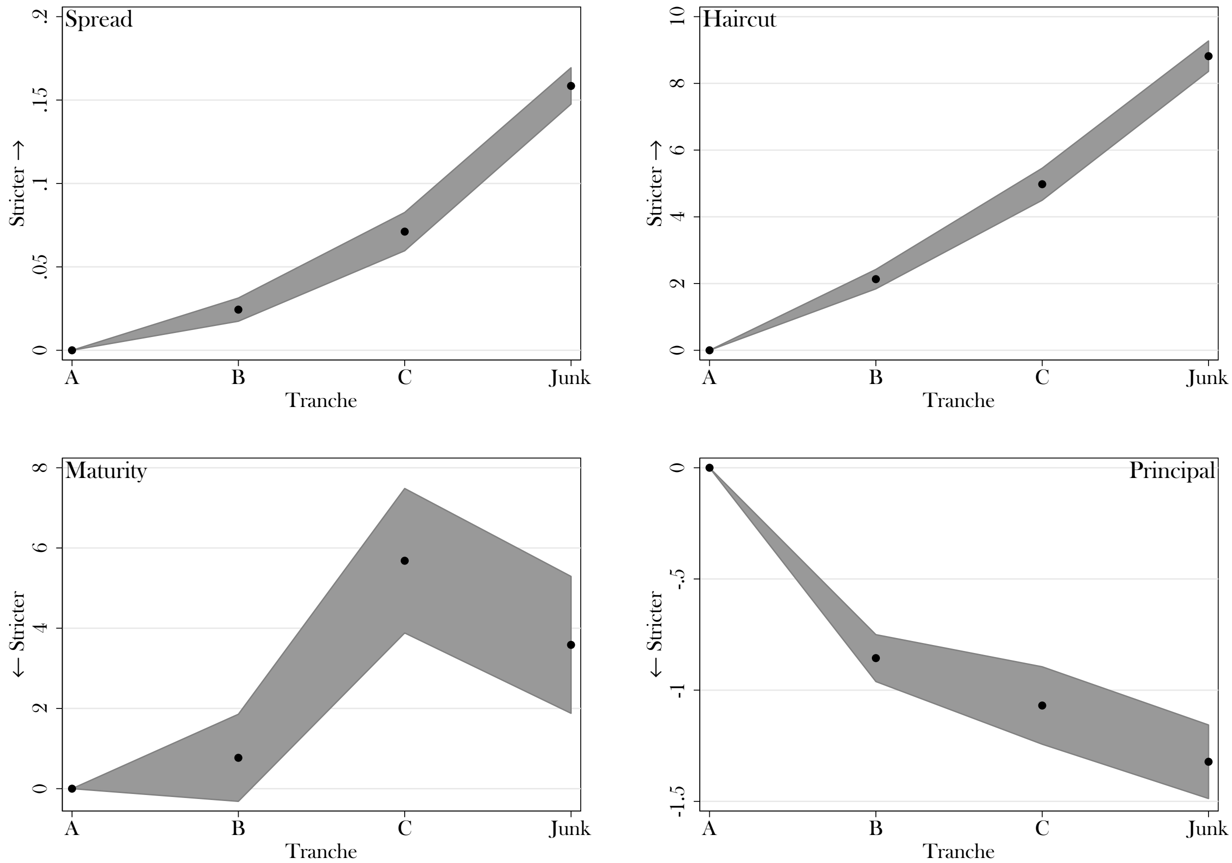

Figure 2: **Effect of tranche seniority on contract terms.** This plot displays the regression coefficients on tranche indicators, estimated using Eq. 2 and presented in Table 7 Specification (1). In each plot, the vertical axis direction is set so that a higher point on the plot signifies stricter contract terms: for $Haircut$ and *Spread* the axis is in the usual direction (higher value corresponds to a stricter contract), while for $Maturity$ and *Principal* the axis is reversed (lower value corresponds to a stricter contract). The horizontal axis displays tranche denomination from A to Junk, in descending order of seniority. The A tranche is always the omitted category, so its coefficient is always zero. The shaded area around the point estimates shows the 95% confidence interval. $Haircut$ is the contract margin as a percentage of collateral value. *Spread* is the contract interest rate minus maturity-matched LIBOR. $Maturity$ is the loan maturity in days. *Principal* is natural logarithm of the dollar loan amount.

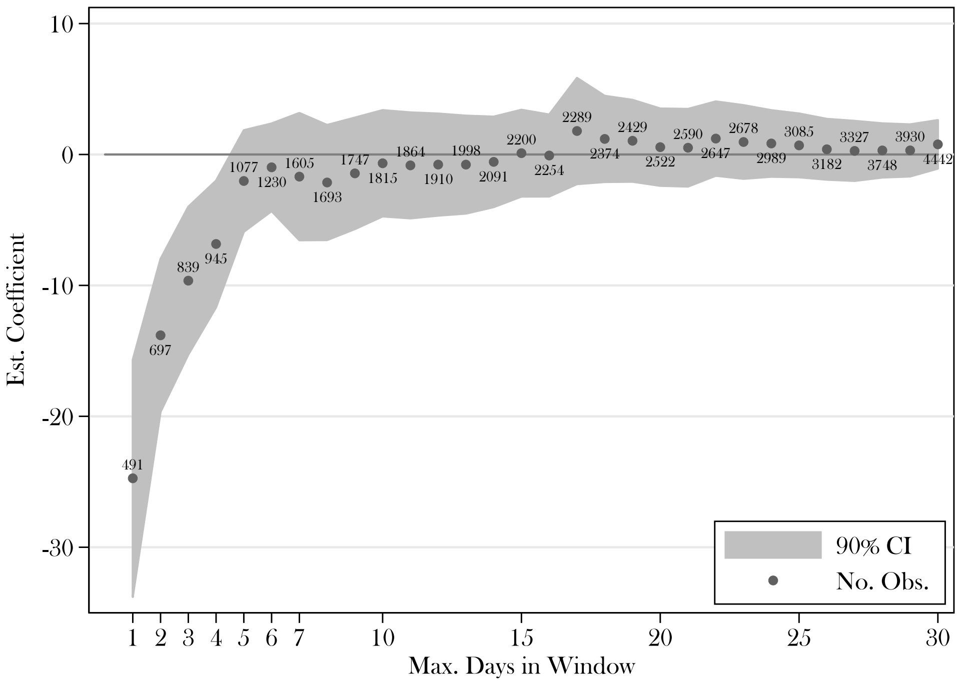

Figure 3: **Trade-off between haircut and spread in neighboring contracts.** This plot displays the coefficient β^S, estimated using Eq. 3. The subsamples used for estimation vary with respect to window size, i.e., the maximum number of days allowed for the gap between two neighboring contracts. The horizontal axis displays window size. The marker is the coefficient point estimate and the shaded area around it shows the 90% confidence interval. The numbers next to each marker represent the number of observations in each regression. The first seven points correspond to the seven columns of Table 8.

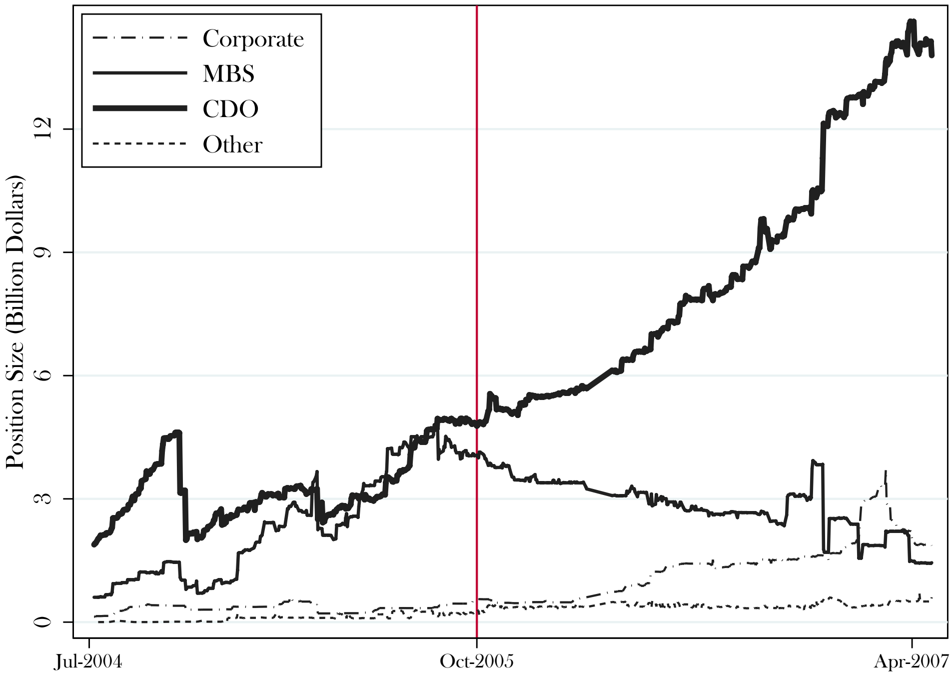

Figure 4: **Asset allocation change after BAPCPA.** This plot displays the time variation in the fund's asset class composition over the sample period. The vertical line marks October 17, 2005, the effective date of the Bankruptcy Abuse Prevention and Consumer Protection Act (BAPCPA). Four asset classes are identified to illustrate the fund's asset allocation: Corporate (dashed), MBS (thin solid), CDO (thick solid), and other (dotted). MBS consists of plain-vanilla passthrough mortgage-backed securities. CDO (collateralized debt obligations) consists of complex structured finance securities, including synthetic CDOs and CDO^2. More detail on these categories is given in Section 2. Other consists of preferred equity and securities we are not able to classify.

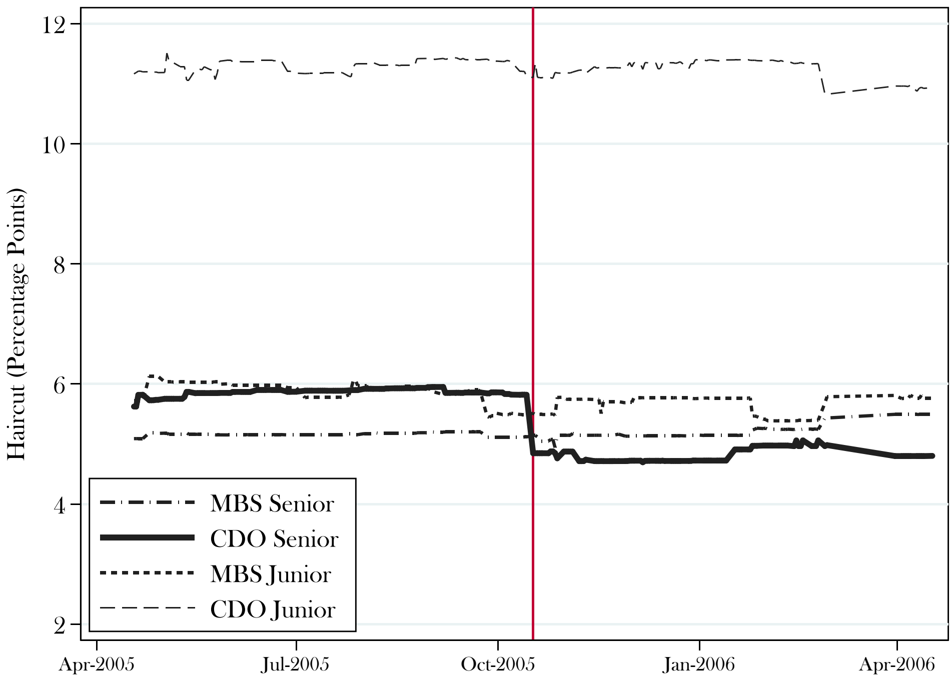

Figure 5: **Haircut dynamics around BAPCPA.** This plot presents the time-series dynamics of haircut during a one-year period centered at the effective date (October 17, 2005) of the Bankruptcy Abuse Prevention and Consumer Protection Act (BAPCPA), indicated by the vertical line. This figure uses a constant portfolio of 94 securities that were held throughout the entire event window. Each line stands for dollar-value weighted average haircut across contracts within four different asset categories: senior tranche MBS, senior tranche CDO, junior tranche MBS, and junior tranche CDO. MBS consists of plain-vanilla passthrough mortgage-backed securities. CDO (collateralized debt obligations) consists of complex structured finance securities, including synthetic CDOs and CDO^2. More detail on these categories is given in Section 2.

Asset Class	Haircut (%)	Spread (%)	Principal (mil.)	Maturity (days)	N. Obs.	Unique CUSIPs
Government	0.00	-0.192	107.7	10	141	11
Corporate	4.00	0.035	12.6	30	1,112	99
MBS	5.00	0.056	12.4	30	4,229	365
CDO	5.00	0.063	9.6	30	7,810	991
Preferred Shares	15.00	0.243	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 terms.** This table shows median values of $Haircut$, $Spread$, loan $Principal$, and loan $Maturity$ by asset class. $Haircut$ is the contract margin as a percentage of collateral value. $Spread$ is the contract interest rate minus maturity-matched LIBOR. $Maturity$ is the loan maturity in days. $Principal$ is the loan amount in millions of dollars. We use Bloomberg information for asset class classification using each asset's CUSIP. MBS consists of plain-vanilla passthrough mortgage-backed securities. CDO (collateralized debt obligations) consists of complex structured finance securities, including synthetic CDOs and CDO^2. More detail on these categories is given in Section 2. One observation corresponds to one contract.

Panel I: Mortgage-Backed Securities

MBS Tranche	Haircut (%)	Spread (%)	Principal (mil.)	Maturity (days)	N. Obs.	Unique CUSIPs
A	5.00	0.053	15.1	29	3,603	295
B	7.00	0.071	5.4	30	365	45
C	7.00	0.083	3.2	9	3	1
Junk	10.00	0.137	5.5	30	84	6
Other	5.00	0.076	7.4	30	174	24
All Tranches	5.00	0.056	12.4	30	4,229	371

Panel II: Collateralized Debt Obligations

CDO Tranche	Haircut (%)	Spread (%)	Principal (mil.)	Maturity (days)	N. Obs.	Unique CUSIPs
A	5.00	0.052	13.4	30	5,108	713
B	7.00	0.072	6.8	31	1,098	113
C	10.00	0.103	6.8	32	589	67
Junk	15.00	0.268	5.3	30	783	85
Other	10.00	0.096	5.3	34	232	16
All Tranches	5.00	0.063	9.6	30	7,810	994

Table 2: **Loan terms by collateral quality within asset class.** These tables summarize median values of $Haircut$, *Spread*, *Principal* and $Maturity$ by tranche name or rating, within each asset class (MBS and CDO). $Haircut$ is the contract margin as a percentage of collateral value. *Spread* is the contract interest rate minus maturity-matched LIBOR. $Maturity$ is the loan maturity in days. *Principal* is the loan amount in millions of dollars. MBS consists of plain-vanilla passthrough mortgage-backed securities. CDO (collateralized debt obligations) consists of complex structured finance securities, including synthetic CDOs and CDO^2. More detail on these categories is given in Section 2. One observation corresponds to one contract.

Panel I: LIBOR-OIS (LOIS)

	Dependent Variable: Spread				
	(1) All	(2) A	(3) B	(4) C	(5) Junk
LOIS	0.431***	0.379***	0.610***	0.840**	-0.046
	(4.494)	(4.908)	(3.039)	(2.552)	(-0.133)
N. Obs.	2,938	1,270	484	291	352
Adj. R^2	0.223	0.024	0.028	0.086	0.022

Panel II: VIX

	Dependent Variable: Spread				
	(1) All	(2) A	(3) B	(4) C	(5) Junk
VIX	0.000	0.001*	0.002	0.005	-0.003
	(0.443)	(1.829)	(1.135)	(1.344)	(-0.941)
N. Obs.	2,938	1,270	484	291	352
Adj. R^2	0.217	0.008	0.012	0.071	0.024

Table 5: **Sensitivity of repo spread to systematic risk.** These tables display how average repo spread comoves with measures of systematic risk, specified in Eq. 1. For both panels, the dependent variable is daily average repo spread in the whole sample (Column 1) or in subsamples categorized by each tranche (Columns 2–5). A is the most senior tranche, followed by B, C, and Junk in terms of payoff seniority. Both panels use a measure of market-wide risk as the independent variable. The top panel uses the LIBOR-OIS spread (LOIS) and the bottom panel uses the VIX index. All regressions use asset class fixed effects. t-statistics are reported in parentheses. The number of stars (*) represents statistical significance at 10% (*), 5% (**), and 1% (***).

Dependent Variable:	Spread		Haircut		Maturity		Principal	
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
Tranche: B	0.02***	0.01	2.13***	1.45***	0.77	1.94**	-0.86***	-0.18**
	(6.85)	(1.26)	(14.35)	(8.81)	(1.39)	(3.16)	(-15.89)	(-3.29)
Tranche: C	0.07***	0.06***	4.98***	4.50***	5.68***	6.52***	-1.07***	-0.26**
	(12.13)	(8.74)	(20.31)	(16.69)	(6.18)	(6.45)	(-12.03)	(-2.94)
Tranche: Junk	0.16***	0.13***	8.82***	7.78***	3.58***	4.13***	-1.32***	-0.48***
	(28.44)	(21.59)	(37.85)	(30.66)	(4.12)	(4.35)	(-15.65)	(-5.82)
Volatility		0.02***		1.36***		1.73*		-0.18*
		(3.45)		(6.20)		(2.08)		(-2.53)
Issue Size		-0.01***		-0.54***		0.38*		0.59***
		(-8.66)		(-11.03)		(2.05)		(36.34)
All specifications have Lender × Issuer × Initiation Day fixed effects.								
N. Obs.	6,965	6,084	6,968	6,084	6,941	6,059	6,968	6,084
Adj. R^2	0.721	0.720	0.836	0.843	0.927	0.924	0.732	0.798

Table 7: **Loan contract terms as a function of collateral characteristics.** This table shows how *Spread*, *Haircut*, *Maturity* and *Principal* react to several characteristics of collateral assets. The regression specification is Eq. 2. *Haircut* is the contract margin as a percentage of collateral value. *Spread* is the contract interest rate minus maturity-matched LIBOR. *Maturity* is the loan maturity in days. *Principal* is natural logarithm of the dollar loan amount. *Tranche* is a vector of indicator variables for the different tranche seniority levels (in order: A, B, C, Junk; A is the omitted category). In Specification (2), *Volatility* is the asset's daily return volatility in the 20 trading days before the transaction, and *Issue Size* is the natural logarithm of the security's initial issue amount (obtained from Bloomberg). The regression uses (Lender × Issuer × Initiation Day) fixed effects, i.e., all coefficients are measured within different tranches of the same securitization pledged as collateral with the same lender for contracts initiated on the same calendar day. t-statistics are reported in parentheses. The number of stars (*) represents statistical significance at 10% (*), 5% (**), and 1% (***).

Dependent Variable:	Dependent Variable: ΔHaircut						
	(1) 1-Day	(2) 2-Day	(3) 3-Day	(4) 4-Day	(5) 5-Day	(6) 6-Day	(7) 7-Day
ΔSpread	-24.734***	-13.813***	-9.640***	-6.836**	-2.025	-0.980	-1.691
	(-4.524)	(-3.911)	(-2.821)	(-2.333)	(-0.862)	(-0.483)	(-0.573)
ΔMaturity	-0.021	-0.010	-0.005	-0.002	-0.005	0.003	0.003
	(-1.175)	(-0.725)	(-0.508)	(-0.193)	(-0.642)	(0.421)	(0.321)
ΔPrincipal	-0.131***	-0.038**	-0.025*	-0.019	-0.005	-0.003	-0.007
	(-3.094)	(-2.222)	(-1.669)	(-1.519)	(-0.626)	(-0.351)	(-0.619)
Fixed Effect:							
Month × Asset	Y	Y	Y	Y	Y	Y	Y
N. Obs.	491	697	839	945	1,077	1,230	1,605
Adj. R^2	0.480	0.473	0.362	0.360	0.179	0.078	-0.637

Table 8: **Relationship between haircut and spread within neighboring contracts.** This table displays the results of the regression specified in Eq. 3. Each column corresponds to a different subsample, based on the maximum number of days allowed for the gap between a pair of neighboring contracts. For example, Column 2 uses contracts whose start dates differ by 2 or fewer days. Dependent variable is $\Delta Haircut$. $Haircut$ is the contract margin as a percentage of collateral value. *Spread* is the contract interest rate minus maturity-matched LIBOR. $Maturity$ is the loan maturity in days. *Principal* is natural logarithm of the dollar loan amount. Δ indicates the change in the corresponding variable between the two successive contracts. In addition, we use fixed effects for each unique combination of calendar month and asset (9-digit CUSIP). t-statistics are reported in parentheses. The number of stars (*) represents statistical significance at 10% (*), 5% (**), and 1% (***).

	Dependent Variable: Haircut				
	(1)	(2)	(3)	(4)	(5)
Spread		-9.076**	-9.067**	-9.543**	-9.534**
		(-2.292)	(-2.269)	(-2.371)	(-2.348)
Maturity			0.003		0.003
			(0.184)		(0.179)
Principal				-0.244	-0.244
				(-0.750)	(-0.742)
Fixed Effect:					
Pair	Y	Y	Y	Y	Y
N. Obs.	112	112	112	112	112
Adj. R^2	0.667	0.690	0.685	0.688	0.682

Table 9: **Regression within contract pairs.** This table presents the estimation results for the regression specification described by Eq. 4. The dependent variable is $Haircut$. $Haircut$ is the contract margin as a percentage of collateral value. *Spread* is the contract interest rate minus maturity-matched LIBOR. $Maturity$ is the loan maturity in days. *Principal* is natural logarithm of the dollar loan amount. The sample consists of contract pairs of only brand-new contracts (excluding rollovers) made at the same time on the same collateral (9-digit CUSIP) between the borrower and different lenders. We use pair fixed effects, meaning that the regression coefficients are identified using within-pair variation, i.e., keeping borrower, asset, and initiation time constant. t-statistics are reported in parentheses. The number of stars (*) represents statistical significance at 10% (*), 5% (**), and 1% (***).

	Dependent Variable: Haircut				Dependent Variable: Spread			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ΔP^{MBS}	-2.427**	-2.860**	-2.434**	-2.862**	0.056*	0.058*	0.052*	0.054
	(-2.342)	(-2.614)	(-2.290)	(-2.552)	(1.882)	(1.785)	(1.763)	(1.696)
Maturity		-0.043		-0.043		0.000		0.000
		(-1.164)		(-1.138)		(0.148)		(0.202)
Principal			-0.044	-0.012			-0.026	-0.026
			(-0.063)	(-0.017)			(-1.322)	(-1.303)
Fixed Effect:								
Pair	Y	Y	Y	Y	Y	Y	Y	Y
N. Obs.	52	52	52	52	52	52	52	52
Adj. R^2	0.674	0.679	0.661	0.665	0.657	0.643	0.667	0.653

Table 10: **Lenders' funding liquidity and contract terms.** This table presents the estimation results for the regression specification described by Eq. 5. The dependent variable is $Haircut$ for Columns 1–4 and *Spread* for Columns 5–8. $Haircut$ is the contract margin as a percentage of collateral value. *Spread* is the contract interest rate minus maturity-matched LIBOR. $Maturity$ is the loan maturity in days. *Principal* is natural logarithm of the dollar loan amount. ΔP^{MBS} is the quarter-on-quarter change in the lender's total borrowing using mortgage-backed securities as collateral in the tri-party repo market. The sample consists of contract pairs of only brand-new contracts (excluding rollovers) made at the same time on the same collateral (9-digit CUSIP) between the borrower and different lenders. We use pair fixed effects, meaning that the regression coefficients are identified using within-pair variation, i.e., keeping borrower, asset, and initiation time constant. t-statistics are reported in parentheses. The number of stars (*) represents statistical significance at 10% (*), 5% (**), and 1% (***).

	Dependent Variable: Haircut				Dependent Variable: Spread			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ProbDef	-17.598*	-17.845*	-17.554*	-17.800*	0.179	0.208	0.162	0.191
	(-2.047)	(-2.015)	(-1.995)	(-1.963)	(1.143)	(1.335)	(1.053)	(1.256)
Maturity		0.005		0.005		-0.001		-0.001
		(0.197)		(0.194)		(-1.322)		(-1.385)
Principal			0.035	0.037			-0.013	-0.014
			(0.065)	(0.068)			(-1.453)	(-1.507)
Fixed Effect:								
Pair	Y	Y	Y	Y	Y	Y	Y	Y
N. Obs.	52	52	52	52	52	52	52	52
Adj. R^2	0.738	0.727	0.727	0.716	0.826	0.831	0.833	0.839

Table 11: **Lenders' default probability and contract terms.** This table presents the estimation results for the regression specification described by Eq. 6. The dependent variable is $Haircut$ for Columns 1–4 and *Spread* for Columns 5–8. $Haircut$ is the contract margin as a percentage of collateral value. *Spread* is the contract interest rate minus maturity-matched LIBOR. $Maturity$ is the loan maturity in days. $Principal$ is natural logarithm of the dollar loan amount. $ProbDef$ is the lender's 1-year default probability derived from the expected default frequency (EDF) measure. The sample consists of contract pairs of only brand-new contracts (excluding rollovers) made at the same time on the same collateral (9-digit CUSIP) between the borrower and different lenders. We use pair fixed effects, meaning that the regression coefficients are identified using within-pair variation, i.e., keeping borrower, asset, and initiation time constant. t-statistics are reported in parentheses. The number of stars (*) represents statistical significance at 10% (*), 5% (**), and 1% (***).

Dependent Variable:	ΔHaircut		ΔSpread		ΔMaturity	
	(1)	(2)	(3)	(4)	(5)	(6)
CDO	0.063	0.048	0.018	0.015	5.337	5.151
	(0.501)	(0.392)	(1.050)	(0.834)	(1.371)	(1.334)
$\text{CDO}^{\text{Senior}}$	-0.288***	-0.359***	0.006	0.015	-0.226	0.306
	(-2.614)	(-3.309)	(0.389)	(0.972)	(-0.066)	(0.088)
$\text{MBS}^{\text{Senior}}$	0.042	0.028	0.027	0.026	-0.047	-0.547
	(0.317)	(0.219)	(1.436)	(1.431)	(-0.011)	(-0.133)
one	-0.085	-0.102	-0.036**	-0.030**	-1.559	-1.273
	(-0.813)	(-0.988)	(-2.459)	(-2.067)	(-0.480)	(-0.391)
ΔSpread		0.486				11.130
		(1.332)				(0.961)
ΔMaturity		0.257***		0.002		
		(2.679)		(0.178)		
ΔPrincipal		-1.338***		0.135***		-14.247
		(-3.764)		(2.640)		(-1.246)
ΔHaircut				0.010		4.444***
				(1.332)		(2.719)
N. Obs.	375	375	375	375	375	375
Adj. R^2	0.026	0.079	0.018	0.030	0.004	0.027

Table 12: **Haircut, spread and maturity changes due to BAPCPA.** This table reports the results of regression specification in Eq. 7. Each group of regressions has a different dependent variable, indicated at the top. In each group, the first column is the basic specification and the second uses the other contract terms as controls. *Haircut* is the contract margin as a percentage of collateral value. *Spread* is the contract interest rate minus maturity-matched LIBOR. *Maturity* is the loan maturity in days. *Principal* is natural logarithm of the dollar loan amount. Δ indicates the change in the corresponding variable between the two successive contracts. A pair of successive contracts is formed by the first contract affected by the adoption of Bankruptcy Abuse Prevention and Consumer Protection Act (BAPCPA) and the immediately preceding contract (i.e., the last contracts before BAPCPA is effective) on the same security. The sample includes only CDO and MBS tranches. CDO is an indicator variable that is one if the tranche is a CDO tranche. $\text{CDO}^{\text{Senior}}$ and $\text{MBS}^{\text{Senior}}$ are indicator variables whose value is 1 if the asset is an A-rated tranche and zero otherwise. The constant term is omitted. t-statistics are reported in parentheses. The number of stars (*) represents statistical significance at 10% (*), 5% (**), and 1% (***).

Appendix A Robustness checks: collateral regressions

Table 7 in Section 3 presents the results of Equation (2), which we report here for convenience:

$$\begin{array}{r} Spread_i \\ Haircut_i \\ Maturity_i \\ Principal_i \end{array} = \alpha^{L,I,t} + \underbrace{\beta \cdot Tranche_i}_{\substack{\text{Tranche} \\ \text{indicators}}} + \underbrace{\boldsymbol{\theta} \cdot \mathbf{Quality}_i}_{\substack{\text{Direct qua-} \\ \text{lity measures}}} + \underbrace{\gamma \cdot \mathbf{C}_i}_{\text{Controls}} + \varepsilon_i. \tag{A.8}$$

Table B.2 in this Section reports one extra specification (Specification 3), which includes the other three contract terms as dependent variables. For example, if the dependent variable is *Spread*, then $\mathbf{C} = (Haircut, Maturity, Principal)$.

Controlling for the other contract terms is necessary to guarantee the robustness of our conclusions. To see this, consider the following example. Suppose that for a given asset the Fund requires a lower haircut, and offers to pay a higher spread in exchange. In that case, our estimate of all coefficients in the Spread regression would be an overestimate, and that in the Haircut regression would be an underestimate. To show that our estimates are robust to this concern, we add other loan terms as control variables. If this concern had a first-order magnitude, the coefficient on Spread as a control variable would be negative.

Adding the other contract terms as control variables is not our preferred method of controlling for the other contract terms, but it is the result of a necessary trade-off. In our setup we already keep most variables constant: borrower, lender, initiation day, and issuer of the securities, obtaining a clean measure of the effect of collateral quality on contract terms. The one thing we cannot keep constant are the other contract terms. For instance, suppose that the dependent variable is *Spread*. Ideally, we would like to find sets of loans with collateral of different quality for which *Spread* varies and $Haircut$, $Maturity$ and *Principal* do not. *By and large, such ideal sets of loans do not exist*, precisely because three of the four loan terms become stricter together as loan risk increases. As seen in the anecdotal example at the beginning of in Section 3, it is possible to find sets of contracts with constant $Maturity$. Conditioning on constant $Maturity$ does not change the other results, but it reduces sample size.

It is important to note that the coefficients on these control variables do not identify the effect of one term on another, and therefore they should not be interpreted. For instance, consider the coefficient of *Haircut* on *Spread* (third column of the table). This coefficient is positive and highly significant, with a t-statistic of 49.01.[18] Clearly this cannot be the effect of *Haircut* on *Spread*, because such effect should be negative: a contract with a higher haircut is safer for the lender, who in turn should be willing to accept a lower spread, and vice versa.

In reality, for each contract, the four terms are determined simultaneously and endogenously. As we have seen, as the collateral quality gets worse, both haircut and spread rise in a very similar way. If our right-hand side variables do not capture 100 percent of the variation in collateral quality, it is likely that haircut and spread will be spuriously correlated. What is of interest in Specification 3 (as in the other specifications) are the coefficients on the *Tranche* indicator variables and the *Quality* variables.

The coefficient estimates of Specification 3 confirm our conclusions. In spite of the fact that the added control variables absorb a significant amount of variation because of the spurious correlation, all our findings are still qualitatively present. As the tranche rating drops, *Haircut* and *Spread* rise, *Principal* shrinks, and *Maturity* displays a hump shape.

[18]It is easy to show that the t-statistics of the coefficients on the control variables have to be pairwise identical: for instance, the t-statistic of the coefficient on *Spread* in the *Haircut* regression has to be the same as the t-statistic of the coefficient on *Haircut* in the *Spread* regression, regardless of the absolute magnitude of the coefficients.

Appendix B Attenuation bias in pairs regressions

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:

$$\begin{bmatrix} Spread_i \\ Haircut_i \end{bmatrix} = \begin{bmatrix} \alpha_k^S \\ \alpha_k^H \end{bmatrix} + \begin{bmatrix} \lambda_i + \eta_i^S \\ s\lambda_i + \eta_i^H \end{bmatrix}, \tag{B.9}$$

where α_k^j $(j \in \{S, H\})$ is the pair fixed effect representing unobservable contract risk (i.e., collateral quality and borrower credit). In addition, the lender may offer the borrower to pay an extra λ_i points of spread in exchange for $s\lambda_i$ points of haircut. s is the rate of substitution that we aim to measure. Finally, there may be some random and independent error term η_i^S for the spread and η_i^H for the haircut.

As anticipated, the model has few restrictions. For instance, α_k^S and α_k^H could be assumed to be proportional (as implied by Figure 2), and a similar restriction could be placed on β^S and β^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 of Eq. 4 is:

$$\begin{bmatrix} Spread_i \\ Haircut_i \end{bmatrix} = \begin{bmatrix} \alpha_k^S \\ \alpha_k^H \end{bmatrix} + \begin{bmatrix} \varepsilon_i^S \\ \varepsilon_i^H \end{bmatrix}, \tag{B.10}$$

that is, by construction, the actual amount of substitution λ_i is unidentified:

$$\begin{bmatrix} \varepsilon_i^S \\ \varepsilon_i^H \end{bmatrix} = \begin{bmatrix} \lambda_i + \eta_i^S \\ s\lambda_i + \eta_i^H \end{bmatrix}. \tag{B.11}$$

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

$$Var \begin{bmatrix} \varepsilon_i^S \\ \varepsilon_i^H \end{bmatrix} = \Sigma = \begin{bmatrix} \sigma_S^2 & \\ \sigma_{SH} & \sigma_H^2 \end{bmatrix} = \begin{bmatrix} Var(\lambda) + Var\left(\eta^S\right) & \\ sVar(\lambda) & s^2 Var(\lambda) + Var\left(\eta^H\right) \end{bmatrix}. \tag{B.12}$$

Next, define

$$\tilde{s} \equiv \frac{\sigma_{SH}}{\sigma_S^2} = s\left[\frac{Var\left(\lambda\right)}{Var\left(\lambda\right) + Var\left(\eta^S\right)}\right]. \tag{B.13}$$

From Eq. B.13, two things are clear. The first equivalence shows that $\tilde{s} \equiv \sigma_{SH}/\sigma_S^2$ is numerically equivalent to the regression coefficient β_H^S obtained by adding $Spread_i$ on the right-hand side of the haircut equation

$$Haircut_i = \alpha^k + \beta_H^S \cdot Spread_i + \varepsilon_i, \tag{B.14}$$

and therefore it can be easily estimated. We are going to call the actual estimator $\hat{\beta_H^S}$. The second equality shows that $\hat{\beta_H^S}$ suffers from attenuation bias, because $\tilde{s}$ is not equal to s—it is shrunk towards zero. However, $\tilde{s}$ has the correct sign and it can be interpreted (in absolute value) as a lower bound to s:

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

Therefore, estimating Eq. 4 allows us to express the significance of $\tilde{s}$ as a standard t-statistic with the potential bias that makes it more difficult for us to find anything. A similar argument can be made for Eq. 3 with a minor setup adjustment.

Finally, Eq. B.13 also shows that the attenuation bias is increasing in $Var\left(\eta^S\right)$. In the case of Eq. 4, the presence of heterogeneous lenders may introduce more noise in the process by which the contract terms are set, increasing the variance of η_S and η_H. Thus, the attenuation bias is more likely to be serious for the heterogeneous lender setup, compared to the same-lender setup of Eq. 3.

Dependent Variable:	Spread			Haircut			Maturity			Principal		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
Tranche: B	0.02***	0.01	-0.02***	2.13***	1.45***	1.29***	0.77	1.94**	1.79**	-0.86***	-0.18**	-0.18**
	(6.85)	(1.26)	(-5.42)	(14.35)	(8.81)	(9.98)	(1.39)	(3.16)	(2.87)	(-15.89)	(-3.29)	(-3.26)
Tranche: C	0.07***	0.06***	-0.01*	4.98***	4.50***	3.00***	5.68***	6.52***	6.00***	-1.07***	-0.26**	-0.26**
	(12.13)	(8.74)	(-1.98)	(20.31)	(16.69)	(13.95)	(6.18)	(6.45)	(5.72)	(-12.03)	(-2.94)	(-2.83)
Tranche: Junk	0.16***	0.13***	0.01*	8.82***	7.78***	4.32***	3.58***	4.13***	3.26**	-1.32***	-0.48***	-0.46***
	(28.44)	(21.59)	(2.52)	(37.85)	(30.66)	(20.49)	(4.12)	(4.35)	(3.07)	(-15.65)	(-5.82)	(-4.94)
Volatility		0.02***	-0.00		1.36***	0.78***		1.73*	1.60		-0.18*	-0.17*
		(3.45)	(-0.26)		(6.20)	(4.49)		(2.08)	(1.91)		(-2.53)	(-2.36)
Issue Size		-0.01***	-0.00		-0.54***	-0.29***		0.38*	0.38		0.59***	0.58***
		(-8.66)	(-1.48)		(-11.03)	(-6.58)		(2.05)	(1.78)		(36.34)	(35.56)
Spread						25.49***			-0.11			-0.19
						(49.01)			(-0.03)			(-0.66)
Haircut			0.02***						0.12			0.00
			(49.01)						(1.55)			(0.27)
Maturity			-0.00			0.01						0.00
			(-0.03)			(1.55)						(0.53)
Principal			-0.00			0.01			0.10			
			(-0.66)			(0.27)			(0.53)			
All specifications have Lender × Issuer × Initiation Day fixed effects.												
N. Obs.	6,965	6,084	6,059	6,968	6,084	6,059	6,941	6,059	6,059	6,968	6,084	6,059
Adj. R^2	0.721	0.720	0.828	0.836	0.843	0.905	0.927	0.924	0.924	0.732	0.798	0.798

Table B.2: **Loan contract terms as a function of collateral characteristics.** This table shows how *Spread*, $Haircut$, $Maturity$ and *Principal* react to several characteristics of collateral assets. The regression specification is Eq. 2. *Haircut* is the contract margin as a percentage of collateral value. *Spread* is the contract interest rate minus maturity-matched LIBOR. $Maturity$ is the loan maturity in days. *Principal* is natural logarithm of the dollar loan amount. $Tranche$ is a vector of indicator variables for the different tranche seniority levels (in order: A, B, C, Junk; A is the omitted category). In Specifications (2) and (3), $Volatility$ is the asset's daily return volatility in the 20 trading days before the transaction, and $Issue\ Size$ is the natural logarithm of the security's initial issue amount (obtained from Bloomberg). In Specification (3), *Spread*, $Haircut$, $Maturity$ and *Principal* are also included as control variables in each other's regression. See text for a discussion of the coefficients. The regression uses (Lender × Issuer × Initiation Day) fixed effects, i.e., all coefficients are measured within different tranches of the same securitization pledged as collateral with the same lender for contracts initiated on the same calendar day. t-statistics are reported in parentheses. The number of stars (*) represents statistical significance at 10% (*), 5% (**), and 1% (***).