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

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ABSTRACT

We study secured lending contracts using a novel, loan-by-loan database of bilateral repurchase agreements in which borrower quality is fixed and collateral quality is known. Other things equal, lower-quality loans have longer maturities, indicating that borrowers' concerns with refinancing risk override lenders' incentives to engage in maturity rationing. Lower-quality loans also have higher spreads and margins, indicating that margin is lenders' main risk management tool. As collateral quality drops, lenders take more risk and earn higher spread. Holding loan quality constant, one point of spread substitutes for approximately 9 points of margin.

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

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1 Introduction

The 2007 financial crisis put a spotlight on nonprice loan terms such as collateral requirements and maturity, as lenders' active adjustment of these terms to reduce their credit exposure had systemic consequences. Recent literature has put forward several dynamic models to rationalize credit market breakdowns. In these models, lenders' actions reinforce one another leading to runs and maturity "rat races," while borrowers who anticipate similar outcomes insist on longer maturities to minimize rollover risk, and endogenously limit their leverage to avoid fire sales.[1] However, there is scant evidence on the relative importance of the mechanisms underlying each of these models, and therefore we do not know which ones will prove crucial in preventing or managing the next credit crunch. In this paper, we ask the following questions: In practice, how do lenders protect themselves in the face of heightened risk? What models of maturity and collateral best explain the cross-section of equilibrium contracts?

Existing theories of maturity and collateral requirements are able to explain almost any equilibrium outcome. Higher risk can be associated with looser contract terms (e.g., if contract terms serve a screening function) or stricter contract terms (e.g., in the presence of agency problems). Strikingly, all these predictions have empirical support: lower loan quality is associated with both shorter maturity (Graham et al., 2008; Bharath et al., 2011) and longer maturity (Berger et al., 2005; Hertzberg et al., 2016), stricter collateral requirements (Strahan, 1999; Benmelech et al., 2005) and looser collateral requirements (Jiménez et al., 2006). Some of these studies focus on local treatment effects by design, to provide sharp tests of a specific theory. In part, however, mixed evidence might be the consequence of data limitations. Existing studies feature a multiplicity of heterogeneous borrowers, and focus on loans that are either unsecured or secured by one-of-a-kind, indivisible collateral such as real estate or physical equipment (e.g., Benmelech and Bergman, 2009; Stroebel, 2016). Loan quality is usually inferred from those characteristics of borrower and collateral asset that happen to be observable, potentially ignoring unobserved risk factors.

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[1]For instance, on collateral requirements, see Fostel and Geanakoplos (2008); Brunnermeier and Pedersen (2009); Gârleanu and Pedersen (2011); Jurek and Stafford (2011); Gorton and Metrick (2012); Martin et al. (2014); Krishnamurthy et al. (2014); Gorton and Ordoñez (2014); Geanakoplos and Zame (2014); Copeland et al. (2014); Li et al. (2016). On maturity, see Brunnermeier and Yogo (2009); Acharya et al. (2011); He and Xiong (2012); Cheng and Milbradt (2012); Brunnermeier and Oehmke (2013); He and Milbradt (2016).

We overcome the problem of unobserved risk factors using a novel, loan-level dataset in which borrower quality is fixed and collateral quality does not need to be inferred. First, we keep all risk factors constant except collateral. We show that, as collateral quality drops, margin (the amount of collateral per dollar loaned) increases; spread (price) also increases, implying that loans backed by lower-quality collateral remain riskier despite a higher margin; and maturity increases, indicating that borrowers' concerns with refinancing risk override lenders' incentives to engage in maturity rationing. Next, keeping all risk factors constant (including collateral), we show that margin and spread can substitute for one another. We estimate that one point of spread substitutes for approximately 9 points of margin.

Our dataset consists of all the repurchase agreements (repos) entered by a large fixed-income arbitrage fund over the space of three years. Although repo shares important features with other forms of collateralized lending, it is interesting in and of itself because of its central role in financing the balance sheets of financial intermediaries and leveraged investors.[2] To the best of our knowledge, we are the first to use loan-by-loan data from the bilateral repo market.

Repo is also a unique laboratory for the purpose of understanding contract features. First, repo terms are standardized across different contracts, featuring only the most basic contractual components (i.e., price, margin and maturity) without complex covenants or options.[3] Second, unlike in the wholesale funding market, bilateral repo terms are customized for each individual collateral security. Third, critically for our empirical design, repo is one of only a few loan types with a high frequency of contracting and identifiable, non-unique collateral. The same borrower enters into repeated contracts on identical collateral, as well as simultaneous contracts on collateral with known risk sorting. The existence of sets of contracts in which variation is suppressed along multiple dimensions enables us to eliminate any concerns about unobserved confounding factors.

Specifically, we compare loans initiated on the same day between the same parties, so that loan

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[2]Repurchase agreements are one of the most important forms of short-term collateralized lending. Funding statistics published by the Securities Industry and Financial Markets Association (SIFMA) put the size of primary dealers' repo and reverse repo gross financing at around $4.2 trillion. According to the Office of Financial Research, the U.S. repo market provides more than $3 trillion in funding every day.

[3]Following a practice that is relatively standard in the literature on collateralized loans (see, e.g., Muth, 1962; Stiglitz and Weiss, 1981; Benmelech et al., 2005; Jurek and Stafford, 2011) we do not treat loan amount as a separate term. For a given amount of borrower capital available for investment, the margin requirement pins down the loan amount. Unreported results on loan amount closely mirror our results for margin.

quality is determined by collateral alone. Within these loans, we focus on 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 quality drops, lenders require both higher risk compensation (spread) and protection (margin). Although this may seem intuitive, there is no obvious theoretical reason why the lender should take more risk (as evidenced by the higher spread) when the collateral quality drops. For instance, a lender could simply adjust the margin to make all contracts risk-free or nearly risk-free (Brunnermeier and Pedersen, 2009; Arora et al., 2012) or, more generally, to equalize risk across loans. In reality, compared to the highest-quality collateral, the lowest-quality collateral has roughly 30 basis points higher spread over maturity-matched LIBOR, and 16 percent higher margin. Although previous literature has documented positive correlation of spread and margin in responding to various sources of risk (Rappoport and White, 1994; Berger and Udell, 1995; Strahan, 1999; Benmelech et al., 2005; Graham et al., 2008), the correlation that we uncover is surprisingly strong in terms of not only the direction but also the specific pattern of dependence on loan risk.

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. The lowest-quality collateral is typically financed with loans that are one month longer than the highest-quality collateral. For reference, the median loan maturity in our dataset is one month. This evidence is contrary to the common-sense expectation that riskier loans have shortened maturities—an expectation supported by a substantial body of evidence (Graham et al., 2008; Magri, 2010; Bharath et al., 2011; Custódio et al., 2013). On the other hand, our result is consistent with models of borrower rollover concerns (Flannery, 1986; Diamond, 1991; Brunnermeier and Yogo, 2009). In particular, we find evidence that the negative correlation between quality and maturity is mainly driven by relatively more opaque collateral (CDO tranches), consistent with an asymmetric information explanation as in Diamond (1991).

Taken together, the results on margin and maturity indicate that margin is lenders' primary risk management tool, whereas maturity seems to be mainly driven by borrower concerns about rollover risk. For a given maturity, lenders tweak loan risk by adjusting margin, and receive compensation

commensurate to the residual risk in the form of spread. To characterize this risk-return relationship more precisely, we ask a closely related question: what is the price of one unit of margin? Answering this question, i.e., pinning down the rate of substitution between margin and spread, requires fully controlling for loan quality, a daunting empirical challenge.

We overcome this measurement problem by constructing pairs of loans with essentially constant quality. We follow 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 sets of contracts we should observe negative correlation between margin and spread: keeping borrower and collateral constant, increasing margin mechanically reduces loan risk, and therefore spread should also fall. 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.

Our empirical setting differs markedly from existing studies of collateralized loans, which almost exclusively focus on loans to firms. As discussed above, to the extent that repo is different from other forms of collateralized lending, these differences are strengths because they enable us to conduct a cleaner, more thorough analysis. Moreover, even the longest repurchase agreements are short-term loans. The resulting maturity mismatch between the asset being financed and the loan that finances it implies that rollover concerns are an important determinant of contract features. Thus, the evidence we uncover is especially relevant in the context of dynamic models created to rationalize credit market breakdowns.

A potential concern about the generalizability of our results is that the dataset features a single borrower. However, this borrower entered standard contracts with more than 40 different lenders, including almost all major lenders in the bilateral repo market. The contract terms in the sample, therefore, are unlikely to be entirely driven by borrower-specific characteristics, if at all. Regardless, our empirical setup sidesteps any concerns about omitted variables such as time-varying borrower risk. The unique characteristics of our data enable us to take precise measurements and draw implications that may inform a more general theory of collateralized lending.

The structure of the paper is as follows. Section 2 describes the data in detail. Section 3

analyzes the effect of collateral quality on repo terms. Section 4 presents evidence of substitution between margin and spread. Section 5 concludes.

2 Data description

Our data consists of the complete portfolio of multiple hedge funds that actively traded fixed-income securities over a period of 3 years, from 2004 up until the collapse of the subprime market in 2007. The hedge funds were under the same management and earned carry by taking leveraged positions in the same structured finance securities. The combined funds held on average about $9 billion in securities, making them among 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. Some funds operated at higher leverage, 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 were securitized bonds and other structured finance securities backed by various types of collateral and featuring various degrees of complexity. Simple securities included bonds backed by pools of real-world loans, such as residential mortgages (mortgage-backed securities or MBS) or commercial loans (collateralized loan obligations or CLO). In the rest of the paper, we refer to these simple securities collectively as "MBS." Complex securities included collateralized debt obligations (CDOs) and their variations. These securities are backed by other securitized products such as passthrough MBS and even other CDOs (CDO^2). Because of the additional layer(s) of securitization, analyzing the value of such securities is substantially more difficult. For the rest of the paper we refer to complex securities collectively as "CDOs." Finally, the fund also held a few government bonds, corporate bonds, and preferred securities. These are excluded from the analysis except when explicitly stated.

2.1 Construction of the data set

For each repurchase agreement, the dataset contains 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.

Information about the collateral includes the CUSIP identifier, the current factor, and the current price (per $100 par value). The current factor is the fraction of the initial par value that is still outstanding. For instance, if 30 percent of the principal of a mortgage-backed security had been prepaid, the current factor would be 0.7. The most common reported price 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. Even with missing prices, when a new agreement is initiated, the market value of the security is implied by the loan amount and the haircut. 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.

Finally, information about the position includes par value, market value (equal to current 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).

One unique and very useful feature of our data is the presence of securities whose relative seniority is well-defined. The pooled assets in a securitization conduit are cut into multiple tranches, and therefore their relative seniority is determined by construction. Within the same conduit, a higher tranche is *always* safer than a lower tranche.

However, it is difficult to compare loan terms by tranche across different conduits. To overcome this challenge, we augment our data with contemporaneous credit rating information for each asset. Credit ratings are comparable across securitization vehicles and reflect the time-varying credit quality of the assets. Because ratings are also comparable across rating agencies, we use the

worst of three (Moody's, S&P, and Fitch) to maximize the number of complete observations. (Using the best of three does not qualitatively affect our results). We obtain the credit rating history and other CUSIP-level information (e.g., issue amount, asset class) from multiple sources—from the FISD database, for corporate and government bonds, and from Bloomberg, for structured finance securities.

Furthermore, for structured finance assets, we supplement our data with conduit-level information from Bloomberg. Specifically, we hand-collect the complete securitization structure of every conduit in our sample, including the 1,397 tranches that appear in our raw dataset and another 10,916 ones that do not. For each tranche we collect all available information including the full credit history. We use this information to calculate the level of subordination within the conduit for each tranche in our dataset, pinning down the precise degree of relative seniority.

We obtain LIBOR and U.S. risk-free interest rates at various short-term maturities from FRED. This information is necessary for the calculation of the spread, as explained in the following subsection. Finally, we obtain the fund investors' capital flow and fund returns, as well as general info about the fund, from the TASS database.

2.2   Data description

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).

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.[4] Expressed as a spread to the relevant LIBOR rate (discussed in the following Subsection 2.3), the spread varies between -285 basis points

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[4]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.

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.

These summary statistics and most other statistics in the paper are calculated by counting each contract as one observation. 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.

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. Repo spread, haircut and loan amount covary across assets classes (Table 1). The covariation between haircut and spread is particularly strong and appears related to asset quality. 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.

[Insert Table 1 about here]

Haircut and spread also covary *within* each asset class, and once again, securities of lower quality tend to have both a higher haircut and a higher rate. As an example, Table 2 reports selected variables for five repurchase agreements initiated on the same day with the same lender, and secured by five different tranches of the same conduit. Within this controlled group, spread and haircut increase dramatically as asset quality drops. Moreover, in this controlled setting it is also possible to see that lower-quality assets are financed with longer-term loans—something that is not obvious from Table 1. Our formal analysis in Section 3 expands on this example.

[Insert Table 2 about here]

Table 2 shows multiple, simultaneous contracts between the same parties. In these cases,

it is customary for repo parties to stipulate a netting agreement such that in case of borrower bankruptcy, the entire collateral would be applied to satisfy all of the lender's claims. For instance, suppose that on the day of default the D tranche is wiped out, and therefore the lender is owed the entire principal ($3.4m). At the same time, the A1 tranche drops by only 1%. After liquidating it, the lender has $113.7/(1-4\%) \times (1-1\%) = \$117.3$m cash, i.e., $3.6m more than necessary to pay the debt. Pursuant to the netting agreement, the lender would net the two positions and return $0.2m to the borrower's estate.

In light of this custom, the fact that the parties agreed upon (and therefore we are able to observe) separate terms for each security may appear puzzling. Why can't all loans have the same terms? One important reason is that the borrower retains the option to sell any one security individually and prepay the respective loan. If there were cross-subsidization in the terms of simultaneous contracts, every time the borrower sells one of the positions, all contracts would have to be renegotiated. In practice, we see no obvious difference between the margins and spread of standalone loans compared to loans that are parts of sets. If any cross-subsidization existed, however, it would bias our estimates towards zero.

Another puzzling aspect of these sets of loans is their very existence, i.e., the fact that one investors would want to hold most of the tranches of a securitization. Carving a pool of relatively homogeneous collateral into high-risk and low-risk securities adds value in the presence of market segmentation, i.e., if low-risk securities appeal to certain investors and high-risk securities are attractive to others. However, our hedge fund engaged in a form of capital structure arbitrage, which required it to hold multiple (possibly all) tranches of the same securitization at the same time.

2.3 Estimating the repo spread

The interest rate on a repurchase agreement (the repo rate) is composed of a reference rate plus a spread. The focus of our study is the spread, i.e., the loan price component that is under the control of the contracting parties. However, what we actually observe is the interest rate. Thus, to infer the spread from the interest rate, we must carefully choose a reference rate.

We define the spread as the difference between the repo rate and LIBOR with matching maturity,

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consistent with institutional practices during our sample period. The resulting spread is therefore already net of the term structure of the base rate and of macro interest rate variation. 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. Our results hold with other reasonable reference rates (e.g., the U.S. federal funds rate).

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 estimated repo spread. The dark solid line is the average spread of contracts initiated on a given day. The gray confidence bands show the interquartile range. The dashed line is the unconditional average spread over the whole sample.

On an average day, the spread of the repo rate over LIBOR is positive (6 basis points, t-statistic $= 19.5$), 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. This is evidence that repurchase agreements are priced as if they are risky, contrary to a widespread belief that they are nearly risk-free.[5] The collateral in our sample is not representative of the market at large, which is dominated by Treasury and other safe collateral. However, the existence of our sample in and of itself demonstrates that repurchase agreements can be used, and were used as early as 2004, to finance very risky collateral.

[Insert Figure 1 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

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[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."

agreement, lenders can reduce their exposure by increasing margin, thereby reducing the borrower's leverage and increasing its "skin in the game." In turn, borrowers can choose to limit their own leverage to avoid fire sales due to unmet margin calls.

Consistent with intuition, we show that haircuts (i.e., margins) rise as collateral credit rating drops. Less intuitively, we find that spread rises in a very similar pattern as haircut, suggesting margins do not increase enough to completely offset the increase in collateral risk. Rather, lenders retain an increasing amount of risk as collateral quality drops, and receive a higher spread as compensation.

We also show that haircuts and spreads on MBS and CDO collateral rise much faster as credit rating drops, compared to a reference sample of corporate bond collateral. Thus, in the three years before the subprime financial crisis, intermediaries already perceived structured finance securities as much riskier than corporate bonds of the same rating. However, within structured finance, lenders seemed to perceive no difference between MBS and CDO of the same rating.

Another obvious step that lenders can take to reduce risk or asymmetric information is to engage in maturity rationing by shortening the loan term, thereby increasing the frequency of monitoring. However, borrowers that anticipate difficulties in refinancing can simply insist on a longer maturity. Thus, in the case of maturity, intuition does not lead to a clear prediction.

We show that loan maturity increases as collateral quality drops. This finding is consistent with models of maturity choice in which rollover (i.e., obtaining new financing) is risky or costly (Flannery, 1986; Brunnermeier and Yogo, 2009; Diamond, 1991). Our results further show that this pattern is much stronger for collateral with a higher potential for information asymmetry, consistent in particular with Diamond (1991). Thus, the borrower's concern with rollover risk is strong enough to override the lender's incentive to engage in maturity rationing in the presence of lower-quality collateral.

Finally, our analysis also reveals that after controlling for credit quality, easier-to-sell collateral is awarded with lower margins and longer maturity, consistent with existing models of collateral liquidation values (Shleifer and Vishny, 1992) and related evidence (Benmelech et al., 2005; Benmelech and Bergman, 2009; Benmelech, 2009).

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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 loan terms to differences in asset quality.

Table 2 in the previous section shows five repurchase agreements initiated on the same day with the same lender, and collateralized by five different tranches of the same securitization conduit. Situations like the example of Table 2 are not rare in our sample. In fact, we have 3,249 instances in which multiple securities issued by the same issuer are pledged as collateral for multiple loans initiated on the same day with the same lender. Most instances are tranches of the same securitization (MBS or CDO). This setup enables us to take a particularly clean measurement of the effect of collateral quality on loan terms, as shown in the following diagram:

Time t, Lender 1		Time s, Lender 2	
Tranche A	C_1	Tranche A	C_4
Group 1		Group 2	
Tranche B	C_2	Tranche C	C_5
Tranche E	C_3		
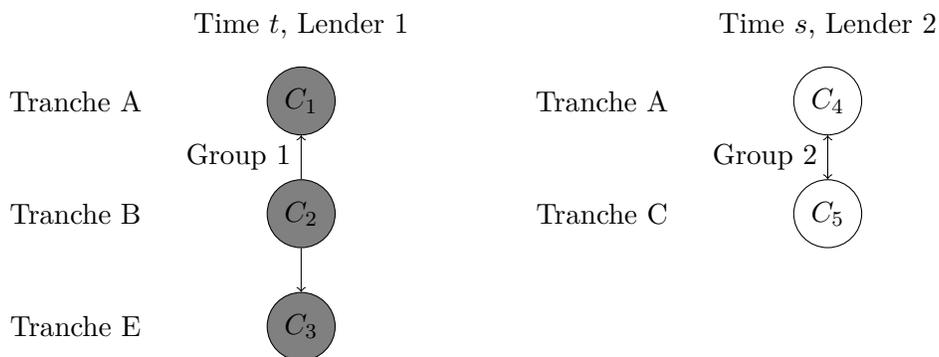
Five contracts are represented in the diagram ($C_1, \dots C_5$). The first three contracts (C_1, C_2, C_3) are secured by three tranches (A, B, E) of a conduit; their purchase is financed by loans initiated at time t with Lender 1. The last two contracts (C_4, C_5) are secured by two tranches (A, C) of another conduit; their purchase is financed by loans 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 loan terms, keeping everything else constant.

In our empirical estimates, as in the diagram, one contract is one observation. Although each

contract is observed on multiple days, we keep only the initiation day for each contract because contract terms are time-invariant until renewed. For an individual repo contract i, the regression specification takes the following form:

$$\begin{array}{c} Haircut_i \\ Spread_i \\ Maturity_i \end{array} = \alpha^{L,I,t} + \underbrace{\beta \cdot \mathbf{Rating}_i}_{\substack{\text{Rating} \\ \text{indicators}}} + \underbrace{\boldsymbol{\theta} \cdot \mathbf{Quality}_i}_{\substack{\text{Quality} \\ \text{proxies}}} + \varepsilon_i, \qquad (1)$$

where $\alpha^{L,I,t}$ is a (Lender $\times$ Conduit $\times$ Initiation Day) fixed effect.[6] In what follows, we call this a "tranche set fixed effect" because each group is a set of tranches from the same securitization conduit. Thanks to this fixed-effects specification, the lender, the borrower, and the environmental conditions are kept constant. Therefore, loan quality is directly determined by collateral quality, enabling us to obtain a clean measurement of the effect of loan quality on contract terms.

Rating is a vector of coarse credit rating indicator variables: AA, A, BBB and $<BBB$ (below BBB). AAA is the omitted category. These indicator variables are constructed using the least favorable current rating as of the contract's initiation date by either S&P, Moody's, or Fitch. For instance, AA is equal to 1 if the worst rating across the three agencies is AA+/Aa1, AA/Aa2, or AA–/Aa3, and equal to 0 otherwise.[7] The regression only uses contracts for which at least one rating exists.

Quality is an optional vector of proxies for aspects of collateral quality that are not necessarily captured by credit ratings: $Volatility$, $Issue\ Size$ and $\%\ Subordinated$. These variables are included as controls, but also because they are interesting per se.

$Volatility$, a proxy for price risk, is the asset price volatility as measured by the hedge fund itself over the past month. As volatility is persistent, past volatility should contain information about future volatility. Higher price volatility implies a higher probability that the collateral asset

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[6]Throughout the paper, we use "$\times$" to indicate the Cartesian product when specifying fixed effects. In this case, (Lender $\times$ Conduit $\times$ Initiation Day) means that we use a separate intercept for each distinct combination of lender, conduit, and initiation day.

[7]The choice of using coarse credit ratings does not destroy a significant amount of information for structured finance securities. "Round" ratings such as AA are much more common than modified ratings such as AA+ or AA–. This is true even for Moody's, i.e., Aa2 is more common than Aa1 and Aa3. The relative rarity of modified ratings is evident in the example of Table 2. Using indicator variables for the exact credit rating makes the pattern considerably harder to see, because two-thirds of the coefficients are estimated using few observations and therefore are very noisy.

value will not be sufficient to make the lender whole in case of borrower default.

Issue Size, a proxy for ease of liquidation, is the security's initial issue amount, as reported by Bloomberg. Because in our sample this value ranges from less than $1 million to more than $1 billion, we use the natural logarithm. Securities with large initial issue amounts are likely to be held or at least known by a larger number of investors and to be traded more often. Therefore, they can be liquidated with less search costs and price impact. A similar reasoning underlies the redeployability measure used in Benmelech and Bergman (2009), who point out that assets more widely held can also be sold more easily. More direct measures of liquidity such as bid-ask spread or trading volume were not available. Moreover, such measures are not necessarily better proxies for ease of liquidating the asset conditional on borrower default.

% Subordinated, a proxy for seniority of the collateral tranche, is calculated as the value of tranches subordinated to the tranche in question as a fraction of the total value of all tranches combined. For example, suppose the total value of a conduit is 100 and there are A and B tranches with value of 80 and 20 respectively. In this case, *% Subordinated* is 20% because the conduit has to lose 20% of its value before the A tranche suffers. Ratings may not fully reflect this information— because they are discrete, and because subordination is just one of several factors rating agencies take into account.

Tables 3, 4 and 5 contain three sets of regressions based on Eq. (1), each with a different contract term (*Spread*, *Haircut*, and *Maturity*) as dependent variable. For each table, we run five versions of the specification. Columns (1) and (2) include only tranche indicator variables (**Quality** $= \varnothing$). Column (1) is a pooled OLS and Column (2) uses tranche set fixed effects. Columns (3–5) include the quality variables (**Quality** $= \{Volatility, Issue\ Size, \%\ Subordinated\}$). Columns (4) and (5) are restricted to two subsamples, MBS and CDO respectively. CDO tranches are much more opaque and hard to value than MBS tranches, and thus for a given credit rating they have a greater potential for information asymmetry between borrower and lender. Finally, the sixth column (titled "Corporate") reports the results from estimating the pooled OLS specification of Column (1) on a sample of corporate bonds. Given the small sample size, the corporate bonds results are reported only for reference. The following subsections describe the results for each term.

By way of preview, Figure 2 plots the coefficients on the tranche indicators from the baseline

fixed-effects specification (Column 2). For *Spread* and *Haircut* a higher value on the vertical axis corresponds to stricter contract terms. Conversely, for *Maturity*, a higher value means more generous contract terms. From Figure 2, it is immediately evident that the coefficients on the rating 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 for the increase in risk, but rather they choose to bear an increasing amount of risk.

[Insert Figure 2 about here]

3.1.1 Spread (Loan price)

Table 3 shows the results of the regression specified in Eq. (1) with spread as the dependent variable. Columns (1–3) use the whole sample of structured finance securities, whereas Columns (4) and (5) are restricted to the MBS and CDO subsamples, respectively. The last column uses a sample of corporate bonds for reference.

Loan spread, or price, appears to be a function of collateral credit rating alone, increasing monotonically in credit risk of the underlying asset. The spread on tranches rated below BBB is 21 basis points above that of AAA-rated tranches in the pooled OLS regression (Column 1). Using tranche set fixed effects this number rises to 31–35 basis points, indicating that ignoring unobserved heterogeneity leads to a significant underestimate of the coefficient (Columns 2–3). Controlling for credit rating, the coefficients on other quality variables are small and statistically insignificant.

The fact that loans backed by lower-quality collateral have higher interest rates may sound intuitive. However, a loan with lower-quality collateral is not necessarily a higher-risk loan. For instance, the lender can adjust margin to target a constant risk level throughout its loan portfolio (Brunnermeier and Pedersen, 2009). This does not seem to be the case: lenders take more risk and receive more compensation when collateral quality is lower.

Comparing Columns (4) and (5) (MBS and CDO), the pricing is remarkably consistent across different types of structured finance securities.[8] Interestingly, the biggest jump in price is between A

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[8]The coefficient for securities rated less than BBB cannot be estimated for the MBS subsample because there are none. Similarly, the coefficient for AA corporate bonds cannot be reliably estimated because there are only four loans backed by AA corporate bonds.

and BBB (a 17-19 basis points difference), both for MBS tranches and CDO tranches. This pattern is not consistent with the pricing of loans backed by corporate bonds, for which the AAA/BBB difference is estimated as zero and is insignificant. Corporate bonds show a small 3 basis points jump at the traditional investment grade boundary (BBB/<BBB). It is well-known that credit rating agencies use the same scale inconsistently for different asset classes (Frank, 2008; Cornaggia et al., 2016). This evidence suggests that before 2007 the lenders in our dataset (i.e., dealer banks) were well aware of the quality difference between structured finance ratings and corporate ratings.

[Insert Table 3 about here]

3.1.2   Haircut (Margin)

Table 4 shows the results of the regression specified in Eq. (1) with margin as the dependent variable. Columns (1–3) use the whole sample of structured finance securities, whereas Columns (4) and (5) are restricted to the MBS and CDO subsamples, respectively. The last column uses a sample of corporate bonds for reference.

Like spread, margin is a monotonically increasing function of collateral credit risk across all structured finance specifications (Columns 1–5). Although previous literature has documented that margin and spread both rise as collateral quality worsens (Rappoport and White, 1994; Strahan, 1999; Benmelech and Bergman, 2009), the correlation between margin and spread that we uncover is surprisingly strong. The response of margin and spread to a drop in collateral quality is similar in terms of not only the direction, but also the functional shape. As is the case for spreads, there is a large jump in haircuts between A and BBB for structured finance securities, but only a small increase (at the investment grade boundary) for corporate bonds. The haircut on tranches rated below BBB is roughly 16 percentage points above the haircut on AAA-rated tranches, compared to only 4 percentage points for corporate bonds.

Unlike spread, margin is also affected by the quality variables. Although not all coefficients are statistically significant in all specifications, the coefficients have the expected sign and they are economically meaningful. Higher haircuts are associated with collateral that is more volatile, has smaller issue size, and has a less-senior position within the securitization. A 1 percentage point

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increase in realized volatility is associated with a 0.13–0.47 percentage points increase in haircut. A 1 percent decrease in issue size is associated with 0.03–0.23 percentage point increase in haircut.

Finally, the coefficient on % *Subordinated* in Columns (3)–(5) shows that tranche seniority has significant impact on margin. For example, Column (3) reports that a 1 percentage point increase in % *Subordinated* leads to an almost 1 percentage point decrease in haircut. This result indicates that the relative seniority within a conduit acts as implicit margin, together with the haircut explicitly set by the loan contract.

[Insert Table 4 about here]

3.1.3 Maturity

Table 5 shows the results of the regression specified in Eq. (1) with maturity as the dependent variable. Columns (1–3) use the whole sample of structured finance securities, whereas Columns (4) and (5) are restricted to the MBS and CDO subsamples, respectively. The last column uses a sample of corporate bonds for reference.

Existing empirical evidence on maturity choice is mixed. Higher risk or asymmetric information are associated with both shorter maturity (Graham et al., 2008; Magri, 2010; Custódio et al., 2013) and longer maturity (Berger et al., 2005; Hertzberg et al., 2016).[9] In addition, Benmelech et al. (2005) and Benmelech (2009) find that loans backed by easier-to-sell collateral have longer maturity.

In our case, the evidence is clear-cut: riskier loans have longer maturity. Lower credit ratings are associated with longer loan maturity in a statistically significant way, even controlling for other quality variables (Columns 1–5). The coefficients on *Volatility* and % *Subordinated* are not statistically significant, but their sign goes in the same direction in all specifications: loans backed by more volatile and less senior collateral have longer maturities. This finding is also robust to controlling for other contract terms, as reported in Appendix A. Thus, the longer maturity for lower-quality tranches is not a byproduct of substitution between different contract terms.[10]

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[9]In their detailed review, Berger et al. (2005) find equally mixed results in prior literature.

[10]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.

The finding that riskier loans have longer maturities may at first appear counterintuitive. Keeping the other loan terms constant, when the collateral quality is low, lenders are better off requiring a shorter maturity and maintaining the option of not renewing the loan. A similar result can only be predicted by a class of theoretical models (Flannery, 1986; Brunnermeier and Yogo, 2009; Diamond, 1991) in which rollover is undesirable, because it is risky or costly for borrowers.[11]

Further, the results in Columns (4) and (5) suggest that asymmetric information plays an important role in determining maturity choice. The effect of collateral quality on loan maturity is much larger for CDO tranches than for MBS tranches, which are much more transparent and easy to value. Within the class of models driven by rollover concerns or liquidity risk, this evidence is most compatible with Diamond (1991). In Diamond (1991), a borrower with good private information about a project's prospects borrows short-term to preserve the option to refinance at a lower cost when the good news arrive. In our dataset, the borrower is a hedge fund, and therefore it ought to be expecting good news about the collateral—i.e., about its portfolio holdings.

Further, in Diamond's model, short-term debt entails a tradeoff between the option value and the possibility of inefficient liquidation. This tradeoff is more likely to favor short-term debt for higher-rated borrowers (or, in our case, for loans backed by higher-rated collateral). If the scope for private information is reduced, as is the case with MBS tranches, Diamond's model predicts a weaker relationship between credit quality and maturity.

Other models of maturity choice that generate a negative correlation between collateral quality and maturity are not obviously applicable. Brunnermeier and Yogo (2009) explicitly investigate the dynamic consequences of borrower rollover concerns. However, in this model there is no private information and therefore there is no scope for explaining the difference between MBS and CDO. In Flannery (1986), borrowers use maturity to signal credit quality. This signaling model is unlikely to apply to our situation, in which loan risk is based on the credit rating *of the collateral*—something neither the borrower nor the lender control.

Taken together, our findings on maturity are in broad agreement with Berger et al. (2005), who show that good borrowers tend to choose shorter maturities, and more so in the presence of

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[11]The nature of our data forces us to discard many possible models of maturity. For instance, models of maturity choice based on taxes or agency problems do not apply here, because we have only one borrower.

asymmetric information.

The one estimate that appears to be different from the others is the coefficient on *Issue Size*, which we use as a proxy for ease of liquidation (Columns 3–5). The estimated coefficient is positive and significant. Thus, although collateral with lower credit quality is associated with longer maturity, *controlling for credit quality*, harder-to-sell collateral is associated with *shorter* maturity. This result suggests that liquidity-related information is not necessarily captured by credit quality measures. This result is consistent with Benmelech et al. (2005) and Benmelech (2009), who claim that collateral with high level of redeployability obtains longer maturity, in agreement with models of collateral liquidation values (Shleifer and Vishny, 1992).

Unlike in the haircut and spread regressions, the magnitude of the coefficients on ratings indicator variables depends on the specification. In Column (1), the pooled OLS specification, loans backed by tranches rated below BBB have maturity about 4 weeks longer than loans backed by AAA tranches. However, in Column (2), the difference is only 1 week. In this case, the OLS regression is more reliable. The difference is due to the fact that in many cases, when multiple tranches of the same securitization are pledged as collateral on the same day with the same lender, all loans are constrained to have the same maturity for operational convenience. This friction artificially suppresses variation and biases the coefficient towards zero. In unreported results, we estimate the same specifications as in Columns (2)–(5) using only the tranche sets in which maturity is not constant, and we recover a coefficient similar to the OLS estimate.

[Insert Table 5 about here]

3.2   Borrower rollover concerns: contract maturity and propensity to sell

The results in the previous subsections show that as collateral gets worse, loan price and collateral requirements become stricter, but one key term (maturity) becomes longer. This is in line with theories of rollover concerns: rolling over is costlier and riskier if the collateral is harder to value.

We provide additional evidence consistent with this hypothesis. We show that a short contract maturity is associated with a higher probability of selling the asset and terminating the position at the end of the contract. The basic intuition is that, when the borrower intends to liquidate an

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asset, it is free to choose any maturity because rollover concerns are no longer relevant.

More formally, suppose that the borrower expects to hold the asset, and therefore needs financing, for T days. The lender is willing to lend with a maturity up to τ. Rolling over has a nonzero fixed cost, which could represent risk or actual transaction costs. Also suppose for simplicity that T is exogenous and that the cost of borrowing is the same regardless of maturity. Then, if $\tau >= T$, the borrower will choose maturity $M = T$ and sell at the end of the contract. Conversely, if $\tau < T$, the borrower will choose maturity $M = \tau$ and rollover to the subsequent contract with maturity $M = T - \tau$. Thus, our prediction is that a short M signals an intent to sell, i.e. $\partial Pr(Sale)/\partial M < 0$.

To test this prediction, we measure how the probability of selling a position depends on contract maturity. Each one of the borrower's asset positions is sequentially financed by a set of loan contracts. For contract i that finances asset position j, we run a logit regression of sale outcome (Sale $= 1$, No Sale $= 0$) on loan maturity (expressed in weeks):

$$Sale_i = \Phi\left(\alpha^j + \beta Maturity_i + \varepsilon_i\right). \tag{2}$$

Even though we do not have a record of the funds' trading, we can infer the dependent variable from the panel of asset positions. We infer a sale when the par amount of the position drops, or when the position disappears altogether. The results are robust to alternative definitions of sale.

Column (1) of Table 6 displays the results of the regression specified in Eq. (2). Column (2) reports the results of a conditional logit regression with position-level fixed effects. This regression is identical to the simple pooled regression specified in Eq. (2), except that β is measured within the series of successive contracts that finance a position. The regression results confirm the prediction, as β is negative in both specifications.

A possible confounding factor is time-varying asset quality. Suppose that a bond becomes distressed and the lender refuses to accept it as collateral for anything other than a short-term loan. At the same time, the bond is likely to be sold by the borrower, inducing negative correlation between observed maturity and probability of selling. To show that the negative coefficient is not the result of time-varying bond quality, we run a logit regression in which the β coefficient is allowed

to be different for assets of different quality specified by credit rating:

$$Sale_i = \Phi \left(\alpha + \sum_{k=AAA}^{<BBB} \beta_k \cdot \mathbb{I} \left(\text{Rating} = k \right) \cdot Maturity_i + \varepsilon_i \right). \tag{3}$$

Columns (3–4) of Table 6 display the results of the logit regression specified in Eq. (3). As above, Column (3) reports the results of the simple pooled specification and Column (4) reports the results of the corresponding fixed-effects specification. In the fixed-effects specification, the β_k coefficients are all consistently negative. Furthermore, for loans against A-quality collateral, shorter maturity is a significant predictor of propensity to sell.

[Insert Table 6 about here]

4 Substitution in contract terms

In the previous section, we show that margin is the primary risk management tool that lenders actively use to adjust loan risk. Moreover, we also show that as collateral quality drops, both margin and spread rise. This suggest that lenders do not raise margin to fully compensate for an increase in loan risk. Rather, they choose to take more risk and earn more risk compensation. Given these premises, it is natural to further investigate the trade-off between spread and margin. Specifically, in this section we attempt to measure the price of one unit of haircut.

Observing the trade-off is difficult. Even with observationally equivalent loans, our analysis may still suffer from latent confounding factors such as borrower and collateral related risk, or macroeconomic variation. Without controlling for these factors, the substitution between loan terms cannot be properly identified. Our empirical design allows us to fully control for such factors, and compare contracts with the same fundamental loan risk.

4.1 Haircut and spread trade-off within lender

Controlling for loan quality is challenging. First, loan quality is jointly determined by collateral asset quality and borrower creditworthiness. In our specific case, 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 sequential 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. Two loans in rapid succession could exist because the first one has a short maturity, but also because the first one is renegotiated prior to maturity. Regardless, because of this construction, almost all pairs (more than 95 percent) consist of two loans from the same lender. Thus, any loan contract variations from lender-specific characteristics are controlled for. Moreover, since we have a single borrowing entity, the fundamental loan risk among contracts within any of these pairs is nearly 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 diagram below illustrates our setup.
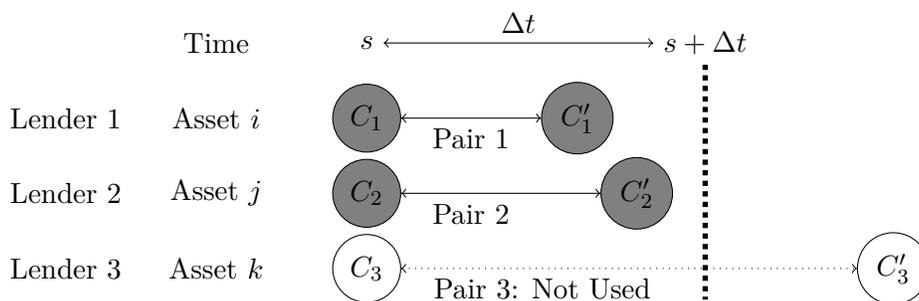
In the illustration, there are three contracts (C_1, C_2, C_3) initiated at time s. Each contract rolls over to a subsequent contract (C_1', C_2', C_3'). We use Pairs 1 and 2 because the time gap between the

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:

$$\Delta Haircut_i = \alpha^{T,A} + \beta^S \cdot \Delta Spread_i + \beta^M \cdot \Delta Maturity_i + \beta^P \cdot \Delta Principal_i + \varepsilon_i, \qquad (4)$$

where $\alpha^{T,A}$ is a Month×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. Furthermore, the sensitivity to macro factors could be 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. 4 for different values of Δt, the maximum number of days in the window between two contracts in each pair. β^S estimates the trade-off, and hence 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.[12] This pattern is consistent with

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[12]The result holds for loans that are 1 or 2 days apart taken individually, while it does not hold for loans 6 and 7 days apart. The coefficient could not be individually estimated for loans 3, 4, or 5 days apart: because of the low number of observations, the asset fixed effects absorbe all variation.

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 construction, the vast majority of such pairs consisted of two loans from the same lender. In general, loan risk is independent of lender identity. However, in our case, lenders may matter to loan contracts because they hold the collateral until the repo loans mature. Therefore, investigating if heterogeneity of lenders drives different substitution between loan terms is the natural extension of the question.

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.

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.

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Time t Time s

Lender 1   Asset i C_1 Lender 3   Asset j C_3

Pair 1   Pair 2

Lender 2   Asset i C_2 Lender 4   Asset j C_4

For each contract i in a pair k, we run the following regression:[13]

$$Haircut_i = \alpha^k + \beta^S \cdot Spread_i + \beta^M \cdot Maturity_i + \beta^P \cdot Principal_i + \varepsilon_i. \tag{5}$$

[Insert Table 9 about here]

Column (1) of Table 9 reports the results of regression Eq. 5 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, controlling for loan maturity and principal (Columns 3 and 4) and both (Column 5) does not change the result meaningfully. The coefficient 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. Taken together, the estimates in this section give a quantitative sense of the rate at which lenders trade off protection and risk compensation.

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[13]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.

5   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.

We analyze how three main contract terms vary as a function of collateral quality. These contract terms are loan spread (price), haircut (required margin), and maturity. We find that low-quality collateral is associated with higher spreads and higher required margins but *longer* maturities. This evidence is consistent with theoretical models in which 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 although margin is their primary tool for risk management, lenders choose to take on significant amounts of risk when the repo collateral itself is risky.

Within this risk-return relationship, we try to quantify the price of a unit of margin. By comparing loans collateralized by the same asset using both successive contracts and contemporaneous contracts with different lenders, we estimate that one percentage point of spread substitutes for nine percentage points of margin.

Taken as a whole, our results indicate that both lender and borrower concerns play an important role in determining the nonprice terms of secured loan contracts. Lenders' concerns are more likely to be addressed through the use of margin, whereas borrower concerns via the use of maturity. 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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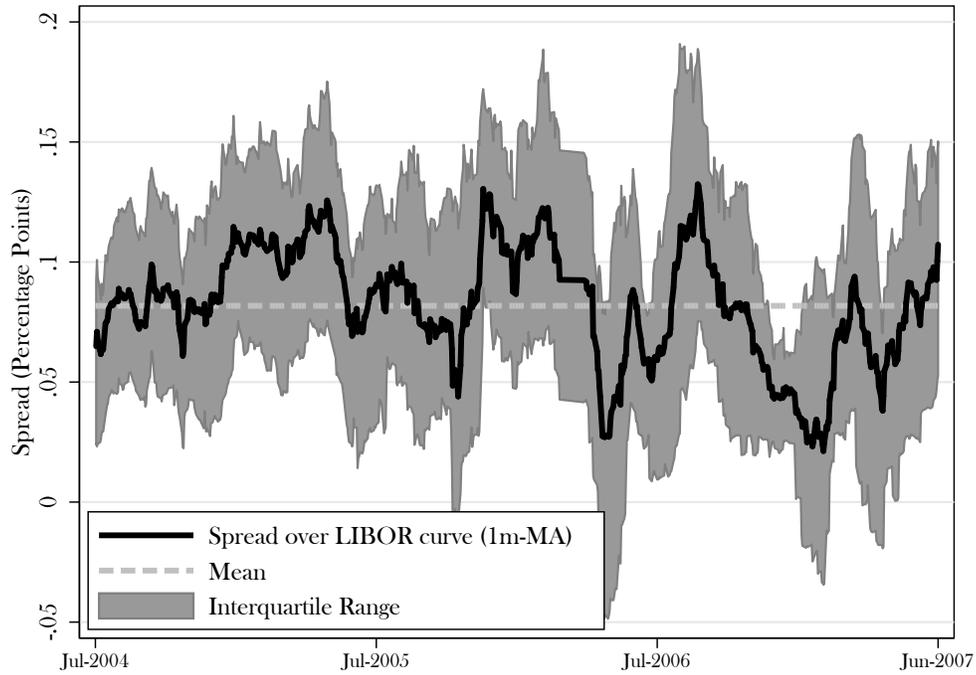
Figure 1: **Repo spread dynamics.** This figure plots a time-series of the *Spread* using LIBOR as the reference rate. *Spread* is defined as the difference between the repo rate and LIBOR at the contract start date, matching the loan maturity in days. Each day, we calculate average *Spread* for contracts 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).
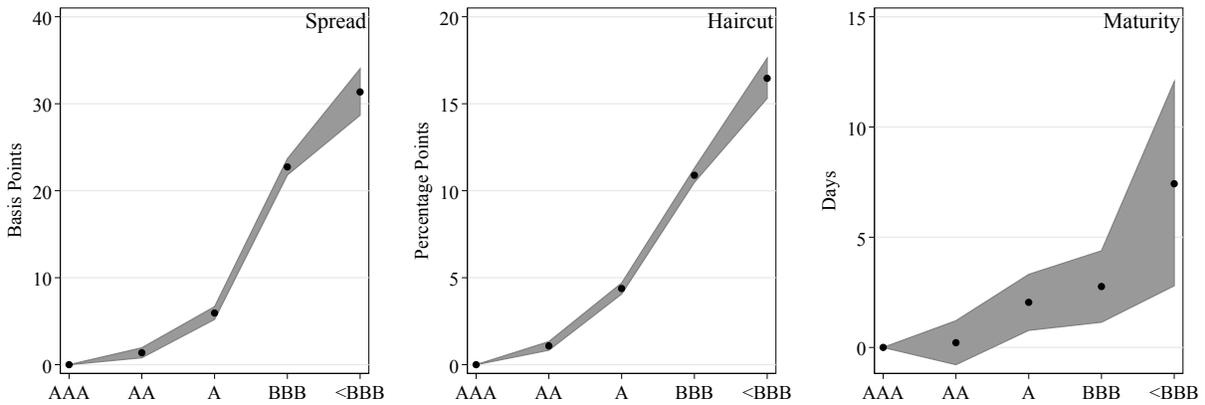
Figure 2: **Effect of tranche seniority on contract terms.** This plot displays the regression coefficients on rating indicators, estimated using Eq. 1 and presented in Tables 3, 4, and 5. The coefficients correspond to our baseline specification with tranche set fixed effects and no control variables (Column 2). Note that for *Haircut* and *Spread* a higher value on the vertical axis corresponds to a stricter contract, while for *Maturity* a lower value corresponds to a stricter contract. Tranche credit rating is on the horizontal axis. AAA 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.
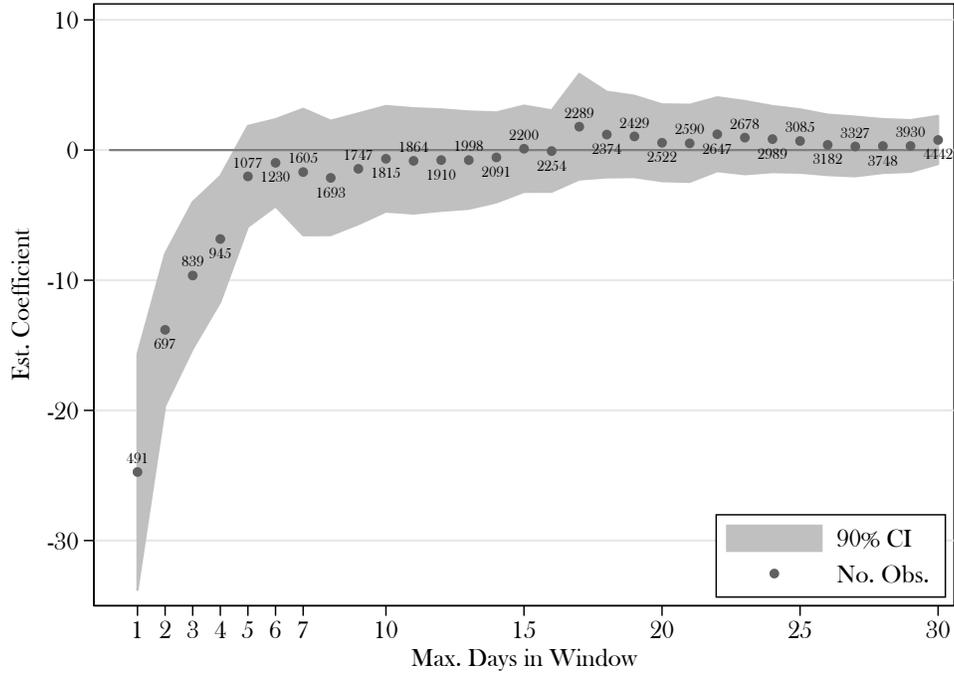
Figure 3: **Trade-off between haircut and spread in neighboring contracts.** This plot displays the coefficient β^S, estimated using Eq. 4. The subsamples used for estimation vary with respect to window size, i.e., the maximum number of days allowed for the gap between two neighboring contracts. The 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.

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 Bloomberg 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. 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 the text. One observation corresponds to one contract.

Tranche	Rating	% Subord.	Haircut	Rate	Spread	Maturity	Principal
A1	AAA	38.9%	**4%**	5.37%	**0.04%**	**22 days**	113.7m
A2	AA	27.8%	**5%**	5.38%	**0.05%**	**22 days**	11.2m
B	A	19.4%	**8%**	5.45%	**0.11%**	**91 days**	14.0m
C	BBB	13.0%	**15%**	5.66%	**0.31%**	**91 days**	4.4m
D	BB+	7.9%	**25%**	5.80%	**0.46%**	**91 days**	3.4m

Table 2: **Data snapshot.** Five loans initiated on the same date with the same lender, collateralized by five different tranches of the same securitization. "Rating" indicates the credit rating from S&P. "% Subord." is the value of tranches subordinated to the current one, as a fraction of the total value of all tranches. A high number indicates a safer tranche. As collateral quality drops, haircut and spread rise, but maturity also rises.

| | Dependent Variable: Spread | | | | | |
	(1)	(2)	(3)	(4)	(5)	Corporate
AA	0.01***	0.01***	0.01***	0.01	0.02***	
	(8.57)	(4.69)	(3.42)	(0.63)	(3.24)	
A	0.05***	0.06***	0.06***	0.05***	0.06***	0.01
	(28.56)	(15.94)	(9.46)	(4.32)	(7.22)	(0.44)
BBB	0.22***	0.23***	0.24***	0.24***	0.25***	-0.00
	(100.66)	(47.93)	(31.71)	(15.51)	(25.10)	(-0.18)
<BBB	0.21***	0.31***	0.34***		0.35***	0.03*
	(33.87)	(23.03)	(22.18)		(20.04)	(1.98)
Volatility			0.00	0.00	0.01	
			(0.37)	(0.18)	(0.43)	
ln(Issue Size)			0.00	0.00	0.00	
			(1.06)	(0.59)	(0.54)	
% Subordinated			-0.00	-0.01	0.00	
			(-0.44)	(-0.85)	(0.31)	
N. Obs.	11,302	3,008	2,081	846	1,235	362
Tranche Set F.E.	N	Y	Y	Y	Y	N

Table 3: **Loan spread as a function of collateral characteristics.** This table shows how *Spread* (the contract interest rate minus maturity-matched LIBOR, in percentage points) reacts to characteristics of the collateral asset. The regression specification is Eq. (1). Column (1) is a pooled ordinary least squares. Columns (2–5) use (Lender $\times$ Issuer $\times$ 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. Column (3) has additional control variables. Columns (4) and (5) are estimated on subsamples: Column (4) on MBS tranches and Column (5) on CDO tranches. *AA*, *A*, *BBB* and $< BBB$ are indicator variables for the least favorable current rating as of the contract's initiation date by either S&P, Moody's, or Fitch. For instance, *AA* is equal to 1 if the worst rating is AA+/Aa1, AA/Aa2, or AA-/Aa3, and equal to 0 otherwise. The regression only uses contracts for which at least one rating exists. *AAA* is the omitted category. The other three variables measure characteristics of the security that are not necessarily measured by ratings, such as *Volatility* (the asset's daily return volatility in the 20 trading days before the transaction), $ln(Issue\ Size)$ (the natural logarithm of the security's original issue amount) and % *Subordinated* (the value of tranches subordinated to the tranche in question as a fraction of the total value of all tranches combined). *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)	Corporate
AA	0.96***	1.08***	0.93***	0.75**	0.87***	
	(12.18)	(8.56)	(5.26)	(2.48)	(3.67)	
A	3.73***	4.38***	3.90***	4.64***	3.17***	2.55***
	(43.99)	(27.21)	(16.17)	(11.58)	(9.48)	(3.00)
BBB	11.98***	10.89***	11.25***	11.09***	11.21***	3.00**
	(113.84)	(53.15)	(35.43)	(21.47)	(26.20)	(2.43)
<BBB	13.34***	16.46***	15.61***		15.39***	4.04***
	(44.50)	(27.99)	(24.53)		(20.49)	(5.93)
Volatility			0.38	0.47**	0.13	
			(1.37)	(1.99)	(0.20)	
ln(Issue Size)			-0.12	-0.03	-0.23*	
			(-1.54)	(-0.37)	(-1.89)	
% Subordinated			-0.93***	-0.46	-1.78***	
			(-2.68)	(-1.43)	(-2.73)	
N. Obs.	11,304	3,009	2,081	846	1,235	362
Tranche Set F.E.	N	Y	Y	Y	Y	N

Table 4: **Haircut as a function of collateral characteristics.** This table shows how *Haircut* (the contract margin as a percentage of collateral value, in percentage points) reacts to characteristics of the collateral asset. The regression specification is Eq. (1). Column (1) is a pooled ordinary least squares. Columns (2–5) use (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. Column (3) has additional control variables. Columns (4) and (5) are estimated on subsamples: Column (4) on MBS tranches and Column (5) on CDO tranches. *AA*, *A*, *BBB* and $< BBB$ are indicator variables for the least favorable current rating as of the contract's initiation date by either S&P, Moody's, or Fitch. For instance, *AA* is equal to 1 if the worst rating is AA+/Aa1, AA/Aa2, or AA-/Aa3, and equal to 0 otherwise. The regression only uses contracts for which at least one rating exists. *AAA* is the omitted category. The other three variables measure characteristics of the security that are not necessarily measured by ratings, such as *Volatility* (the asset's daily return volatility in the 20 trading days before the transaction), $ln(Issue Size)$ (the natural logarithm of the security's original issue amount) and % *Subordinated* (the value of tranches subordinated to the tranche in question as a fraction of the total value of all tranches combined). *t*-statistics are reported in parentheses. The number of stars (*) represents statistical significance at 10% (*), 5% (**), and 1% (***).

	Dependent Variable: Maturity					
	(1)	(2)	(3)	(4)	(5)	Corporate
AA	-1.43**	0.21	1.10	0.87	0.58	
	(-2.17)	(0.42)	(1.28)	(1.27)	(0.45)	
A	-2.88***	2.04***	4.13***	1.41	4.53**	3.87
	(-4.07)	(3.16)	(3.56)	(1.56)	(2.52)	(0.72)
BBB	2.57***	2.76***	5.96***	2.07*	6.54***	1.74
	(2.93)	(3.34)	(3.88)	(1.77)	(2.82)	(0.16)
<BBB	18.69***	7.42***	9.76***		9.65**	3.48
	(7.48)	(3.15)	(3.20)		(2.39)	(1.00)
Volatility			0.64	0.49	0.18	
			(0.45)	(0.91)	(0.05)	
ln(Issue Size)			0.75**	0.23	1.10*	
			(2.08)	(1.16)	(1.70)	
% Subordinated			-1.75	-0.69	-5.20	
			(-1.04)	(-0.95)	(-1.47)	
N. Obs.	11,234	2,992	2,064	844	1,220	360
Tranche Set F.E.	N	Y	Y	Y	Y	N

Table 5: **Loan maturity as a function of collateral characteristics.** This table shows how *Maturity* (the loan maturity in days) reacts to characteristics of the collateral asset. The regression specification is Eq. (1). Column (1) is a pooled ordinary least squares. Columns (2–5) use (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. Column (3) has additional control variables. Columns (4) and (5) are estimated on subsamples: Column (4) on MBS tranches and Column (5) on CDO tranches. *AA*, *A*, *BBB* and *< BBB* are indicator variables for the least favorable current rating as of the contract's initiation date by either S&P, Moody's, or Fitch. For instance, *AA* is equal to 1 if the worst rating is AA+/Aa1, AA/Aa2, or AA-/Aa3, and equal to 0 otherwise. The regression only uses contracts for which at least one rating exists. *AAA* is the omitted category. The other three variables measure characteristics of the security that are not necessarily measured by ratings, such as *Volatility* (the asset's daily return volatility in the 20 trading days before the transaction), *ln (Issue Size)* (the natural logarithm of the security's original issue amount) and *% Subordinated* (the value of tranches subordinated to the tranche in question as a fraction of the total value of all tranches combined). *t*-statistics are reported in parentheses. The number of stars (*) represents statistical significance at 10% (*), 5% (**), and 1% (***).

	Dependent Variable: Sale = 1, No Sale = 0			
	(1)	(2)	(3)	(4)
Maturity	-0.04***	-0.07***		
	(-5.03)	(-7.65)		
AAA × Maturity			-0.08***	-0.07***
			(-7.35)	(-4.06)
AA × Maturity			-0.02**	-0.12***
			(-2.01)	(-4.54)
A × Maturity			-0.05***	-0.04*
			(-3.54)	(-1.65)
BBB × Maturity			0.00	-0.07***
			(0.04)	(-2.71)
<BBB × Maturity			0.01	-0.02
			(0.24)	(-0.38)
N. Obs.	12,084	10,195	10,725	9,252
Position F.E.	N	Y	N	Y

Table 6: **Loan contract terms as a function of loan maturity.** The table presents the estimation results of a Logit regression where the dependent variable is the binary outcome (Sale = 1, No Sale = 0). In certain specifications, the effect is allowed to differ across assets of different quality. In regressions with position fixed effects, the coefficient is estimated within the series of contracts financing a position. t-statistics are reported in parentheses. The number of stars (*) represents statistical significance at 10% (*), 5% (**), and 1% (***).

	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. 4. 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. 5. 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% (***).

Appendix A Robustness checks: collateral regressions

Tables 3, 4 and 5 in Section 3 present the estimation results for Equation (1). Table B.1 in this Section reports two extra specifications based on an expanded regression equation:

$$\begin{array}{c} Haircut_i \\ Spread_i \\ Maturity_i \end{array} = \alpha^{L,I,t} + \underbrace{\beta \cdot \mathbf{Rating}_i}_{\substack{\text{Rating} \\ \text{indicators}}} + \underbrace{\boldsymbol{\theta} \cdot \mathbf{Quality}_i}_{\substack{\text{Quality} \\ \text{proxies}}} + \underbrace{\boldsymbol{\gamma} \cdot \mathbf{C}_i}_{\text{Controls}} + \varepsilon_i. \qquad (A.6)$$

$\mathbf{C}$ is a vector of additional controls that consists of the other two contract terms as dependent variables. For example, if the dependent variable is $Spread$, then $\mathbf{C} = (Haircut, Maturity)$.

The table has six columns, grouped by dependent variable (Spread, Haircut, Maturity). For each dependent variable, Column (1) reports a pooled OLS specification in which $\alpha^{L,i,t} = \alpha$ for all contracts, and Column (2) reports a fixed-effects specification in which $\alpha^{L,i,t}$ is allowed to vary for each contract.

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 form of omitted variable bias, we add other loan terms as control variables. If this bias 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 $Haircut$ and $Maturity$ do not. By and large, such ideal sets of loans do not exist, precisely because two of the three loan terms become stricter together as loan risk increases. We do 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* in Column (2) of the Spread panel (fixed-effects regression). This coefficient is positive and highly significant, with a *t*-statistic of 19.15.[14] 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 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 information on collateral quality that was available to the lender at the time the contract was made, the omitted information will drive spurious positive correlation between spread and haircut. What is of interest in Table B.1 are the coefficients on the *Rating* indicator variables and the *Quality* variables.

The coefficient estimates in Table B.1 confirm our conclusions. In spite of the fact that the added control variables absorb a significant amount of variation because of spurious correlation, all our findings are still qualitatively present. As the tranche rating drops, *Haircut* and *Spread* rise, and *Maturity* displays an increasing pattern.

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[14]Note that the *t*-statistics of the coefficients on the control variables are pairwise identical: for instance, the *t*-statistic of the coefficient on *Spread* in the *Haircut* regression is the same as the *t*-statistic of the coefficient on *Haircut* in the *Spread* regression. It is easy to show that this has to be the case, 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:

$$
\begin{bmatrix} Spread_i \\ Haircut_i \end{bmatrix} = \begin{bmatrix} \alpha_k^S \\ \alpha_k^H \end{bmatrix} + \begin{bmatrix} \lambda_i + \eta_i^S \\ s\lambda_i + \eta_i^H \end{bmatrix},
\tag{B.7}
$$

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. 5 is:

$$
\begin{bmatrix} Spread_i \\ Haircut_i \end{bmatrix} = \begin{bmatrix} \alpha_k^S \\ \alpha_k^H \end{bmatrix} + \begin{bmatrix} \varepsilon_i^S \\ \varepsilon_i^H \end{bmatrix},
\tag{B.8}
$$

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

$$
\begin{bmatrix} \varepsilon_i^S \\ \varepsilon_i^H \end{bmatrix} = \begin{bmatrix} \lambda_i + \eta_i^S \\ s\lambda_i + \eta_i^H \end{bmatrix}.
\tag{B.9}
$$

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

$$
Var \begin{bmatrix} \varepsilon_i^S \\ \varepsilon_i^H \end{bmatrix} = \Sigma = \begin{bmatrix} \sigma_S^2 & \\ \sigma_{SH} & \sigma_H^2 \end{bmatrix} = \begin{bmatrix} Var\left(\lambda\right) + Var\left(\eta^S\right) & \\ sVar\left(\lambda\right) & s^2Var\left(\lambda\right) + Var\left(\eta^H\right) \end{bmatrix}.
\tag{B.10}
$$

Next, define

$$\tilde{s} \equiv \frac{\sigma_{SH}}{\sigma_S^2} = s \left[\frac{Var(\lambda)}{Var(\lambda) + Var(\eta^S)} \right]. \tag{B.11}$$

From Eq. B.11, 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

$$Haircut_i = \alpha^k + \beta_H^S \cdot Spread_i + \varepsilon_i, \tag{B.12}$$

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. 5 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. 4 with a minor setup adjustment.

Finally, Eq. B.11 also shows that the attenuation bias is increasing in $Var(\eta^S)$. In the case of Eq. 5, 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. 4.

	Dep. Var.: Spread		Dep. Var.: Haircut		Dep. Var.: Maturity	
	(1)	(2)	(1)	(2)	(1)	(2)
AA	0.01***	0.01***	0.92***	0.80***	1.71**	1.18
	(3.22)	(2.63)	(9.29)	(4.57)	(1.99)	(1.37)
A	0.03***	0.04***	3.17***	3.54***	2.74***	4.56***
	(11.56)	(6.27)	(27.27)	(14.37)	(2.61)	(3.49)
BBB	0.16***	0.20***	9.93***	9.74***	11.61***	6.73***
	(39.46)	(17.99)	(55.75)	(22.75)	(6.43)	(2.66)
<BBB	0.13***	0.28***	10.03***	13.55***	22.11***	10.83***
	(17.48)	(14.85)	(29.89)	(18.16)	(7.26)	(2.61)
Volatility	-0.01	0.00	1.40***	0.13	-5.17***	0.65
	(-1.51)	(0.26)	(8.57)	(0.46)	(-3.65)	(0.46)
ln(Issue Size)	-0.00*	0.00	-0.16***	-0.15**	0.51	0.72**
	(-1.92)	(1.29)	(-4.37)	(-1.98)	(1.64)	(1.97)
% Subordinated	0.00	0.00	0.26**	-1.00***	2.40**	-1.92
	(0.87)	(0.04)	(2.01)	(-2.93)	(2.13)	(-1.15)
Haircut	0.00***	0.00***			-0.43***	-0.20
	(19.14)	(5.06)			(-4.54)	(-1.35)
Maturity	-0.00	0.00	-0.01***	-0.01		
	(-0.74)	(0.98)	(-4.54)	(-1.35)		
Spread			9.87***	6.02***	-3.39	5.78
			(19.14)	(5.06)	(-0.74)	(0.98)
N. Obs.	8,135	2,064	8,135	2,064	8,135	2,064
Tranche Set F.E.	N	Y	N	Y	N	Y

Table B.1: **Spread, haircut and maturity as a function of collateral characteristics.** This table shows how *Spread*, *Haircut* and *Maturity* (defined in Section 3 react to characteristics of the collateral asset. The regression specification is Eq. (A.6). Each panel corresponds to a different dependent variable. Column (1) is a pooled ordinary least squares regression. Column (2) uses (Lender × Issuer × Initiation Day) fixed effects. *AA*, *A*, *BBB* and $< BBB$ are indicator variables for the least favorable current rating as of the contract's initiation date by either S&P, Moody's, or Fitch. For instance, *AA* is equal to 1 if the worst rating is AA+/Aa1, AA/Aa2, or AA-/Aa3, and equal to 0 otherwise. The regression only uses contracts for which at least one rating exists. *AAA* is the omitted category. The other three variables measure characteristics of the security that are not necessarily measured by ratings, such as *Volatility* (the asset's daily return volatility in the 20 trading days before the transaction), $ln(Issue\ Size)$ (the natural logarithm of the security's original issue amount) and % *Subordinated* (the value of tranches subordinated to the tranche in question as a fraction of the total value of all tranches combined). *t*-statistics are reported in parentheses. The number of stars (*) represents statistical significance at 10% (*), 5% (**), and 1% (***).