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Clustered Pricing in the Corporate Loan Market: Theory and Empirical Evidence *

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Abstract

Existing theories explaining security price clustering as well as clustering in the retail deposit and mortgage markets are incompatible with the clustering in the corporate loan market. We develop a new theoretical model that the attitude of the lender toward the uncertainty about the quality of the borrower leads to the clustering of spreads. Our empirical results support our theoretical model and we find that clustering increases with the degree of uncertainty between the lender and the borrower. In contrast, clustering is less likely when the uncertainty about the quality of the borrower has been reduced through repeated access and through prior interactions of the lender and the borrower.

Keywords: corporate loans, interest rate clustering, information asymmetry, uncertainty
JEL Classification: D49, D82, G12, G21

1 Introduction

Empirical evidence on the clustering of security prices is abundant. This strand of literature shows that the security prices tend to cluster around integers more frequently than half integers and half integers are more frequent than quarter integers and quarter integers are more frequent than one-eighth (Niederhoffer, 1966; Harris, 1991; Christie and Schulz, 1994; Ikenberry and Weston, 2007; Ishii, 2014). A couple of studies, both theoretically and empirically, also look at the clustering of interest rates in the retail banking markets (Kahn et al., 1999; Ashton and Hudson, 2008). There

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is hardly any study looking at the clustering of spreads in the corporate loan market.[1] In this paper, we develop a theory on the clustering of interest rate spreads in the corporate loan market because existing theories like negotiation hypothesis, tacit collusion hypothesis and limited recall model fail to answer clustering of spreads in this market. Our empirical data provide support to our theoretical argument that corporate loan spreads offered to corporate borrowers are clustered. This phenomenon is evident from Figure 1.

We specifically answer the following question in this paper: Why do corporate loan spreads cluster? The above mentioned facts clearly show that the clustering is an imperfection in the lending market. Given this friction, the interesting question is to disentangle whether the lender is: Extracting rents from the imperfection or being compensated for risk and/or uncertainty. To answer these questions, we provide a new theoretical argument by introducing decision making under uncertainty into the model given by Chatterjee and Lee (1998). We reckon, in the corporate loan market, lenders offer rounded spreads to borrowers who are unable to fully reveal their information to the lenders. Under such circumstances, instead of exerting extra efforts to exactly know their affairs, the lenders offer a single rate to a group of such borrowers. These rates are rounded more frequently at a multiple of 25 basis points.

Chatterjee and Lee (1998) study a bargaining model where there is one seller and one buyer with an outside option. They consider a two-period game theoretic model. In the first period the seller offers a price, then the buyer can either accept, reject or search in the market to find another price. If the buyer accepts the first offer, the game ends, otherwise it continues to the next period. In the second period, the buyer may search in the market for a new price while the outside option cannot be credibly communicated. Chatterjee and Lee (1998) derive the equilibrium by backward induction for buyers with different search costs. Their results show that when the search cost is high enough, the game ends immediately, otherwise they continue to the second period. We base our argument on Chatterjee and Lee (1998) and adapt it to the lender and borrower setting with two main differences. First, in our model the borrowers vary not only in the search cost, but also in the probability of getting an outside offer. This probability reflects the quality (which is referred as 'type' in our model) of the borrower. If two borrowers are from the same quality they are classified as from the same type. Second, we assume that the lender may not have full information on the quality of the borrower, which causes uncertainty in the model. To study this model, we resort to the literature on decision making under uncertainty.

We argue that the lender's attitude toward uncertainty about the quality of the borrower leads to clustering of interest rate spreads. We show that it is best for the lender to offer search-deterring rate to high quality borrowers[2]. Since the type of such borrowers is known to the lender, it is possible for the lender to derive the rate that stops the borrowers from searching in the market so that they accept the offer immediately. In other words, for every type of high quality borrower, there is an optimal rate that can be offered. Therefore, the rate offered to the high quality borrower is not clustered. On the other hand, for the low quality borrowers due to information asymmetry,

[1] Except a working paper by Kleimeier and Chaudhry (2013), which shows empirically that corporate loan spreads are clustered most frequently at a multiple of 25 basis points. While this paper explain clustering via negotiation, we argue that negotiation cannot explain clustering in the corporate loan market and we develop a new theoretical model to explain clustering.

[2] In this paper, we use AAA rated borrowers as a proxy for high quality borrowers.

the lender does not know the exact type of the borrower and categorizes these borrowers in certain groups. Since the lender cannot differentiate the exact type of the borrower in one group, she decides to offer a single rate to all of them. This is the main reason of clustered pricing for low quality borrowers.

Our empirical findings confirm the theoretical argument and that we find most corporate loans in the corporate loan market are priced at rounded spreads. First, consistent with our theoretical argument, we find that clustering increases with the degree of uncertainty between the lender (or lead arranger)[3] and the borrower. Moreover, empirical evidences show that these rounded spreads are a multiple of 25 basis points and these spreads are rounded upward. Second, a previous relationship between lead arranger and borrower reduces uncertainty and hence persuades lead arrangers to provide loans at exact spreads, because lead arrangers are able to derive search-deterring rate that can be offered to the borrowers. Finally, the most reputable lead arrangers offer loans at competitive non-rounded spreads providing evidence against tacit collusion hypothesis.

The empirical studies that first discussed negotiation cost hypothesis include Ball et al. (1985) and Harris (1991). They discussed clustering in the context of gold and stock prices. Negotiation cost hypothesis argues that the custom of clustering at rounded prices is a mechanism of reducing the negotiation cost. If the value of an asset is uncertain, rounded prices can help traders reach an agreement quickly. It can further be explained that it may also reduce the monitoring cost attached to less errors associated with rounded prices. The empirical research on financial markets is not scant that has documented that prices tend to cluster around rounded integers more than the non-rounded ones. For example, (Niederhoffer, 1966; Harris, 1991; Christie and Schulz, 1994; Ikenberry and Weston, 2007) discuss clustering in the stock market, (Ishii, 2014) in the auctions market, (Liu and Witte, 2013) in the swap market, (Goodhart and Curcio, 1990; Sopranzetti and Datar, 2002) in the foreign exchange market, (Colwell et al., 1990; Ball et al., 1985; Ibbotson and Jaffe, 1975; Ibbotson et al., 1994; Kandel et al., 2001) in the real estate market, in the gold market and in the IPO market. Furthermore, there is a literature on the effect of market regulation on price discreteness (Blau et al., 2012; Chung et al., 2002; French and Foster III, 2002) and on the role of trader's identity on pricing strategy (Chiao and Wang, 2009; Eun and Sabherwal, 2002; Liu and Witte, 2013).

We reckon that negotiation is not the cause of clustering in corporate loan market. Why? If negotiation were the cause of clustering then the borrowers having more negotiation power would have been getting the clustered spreads. The borrowers on the high spectrum of the quality (AAA rated borrowers) have more negotiation power as compared to the low quality ones, because the lenders compete on high quality borrowers and are willing to give them as competitive rates as possible. Therefore, one would expect to observe clustered (truncated) prices for high quality borrowers. However, we observe that these borrowers get the exact non-rounded spreads while low quality borrower get rounded spreads. This phenomenon gives an initial support to our argument that negotiation is not the cause of clustering, but there are some other factors causing clustering. The corporate loan market is a wholesale market and negotiating to obtain the best possible price

[3] We use the terms lenders and lead arrangers interchangeably throughout this paper. We consider lead arrangers as main lenders in a syndicated loan deal because they are the ones who are actively involve in writing a contract with the borrower.

is a huge concern for the wholesale borrowers. To give an example of the financial stake involved, the mean (median) loan size in the corporate loan market is $923 ($424) million. A one basis point increase in the spread can lead to a loss of $92,300 ($42,400) to a borrower. Therefore, the borrowers are expected to care about the rate they get.

Next to negotiation hypothesis, tacit collusion of financiers might result in clustering of prices. Tacit collusion happens when the dealers set rounded prices in order to maintain wider non-competitive bid-ask spreads. Christie and Schulz (1994) and Christie et al. (1994) find evidence for tacit collusion of NASDAQ dealers and Chen and Ritter (2000), in the IPO market, use tacit collusion among investment bankers as an explanation of seven percent average spread. Intuitively, tacit collusion can occur in the corporate loan market because this market is highly concentrated and only a few top lead arrangers capture substantial market share. Our initial observation proves that the lead arrangers offer clustered spreads to the borrowers whose quality is uncertain, which might support tacit collusion hypothesis that lead arrangers collude tacitly for the borrowers who are of lower quality. However, our empirical findings will indicate that lead arrangers with the highest market share are actually less likely to offer rounded spreads. We thus conclude that the tacit collusion hypothesis is also not the cause of clustering in the corporate loan market.

For the retail deposit market, Kahn et al. (1999) propose limited recall model where a depositor truncates components of deposit interest rate when memorizing that rate. Truncation as an encoding strategy involves cutting off digits on the right, to leave the most important digits on the left, i.e., a spread of 199 basis points would be truncated to 190 or 100 basis points. The model postulates that two extreme types of depositors exist - sophisticated depositors with full recall and naive depositors who remember only the integer of the deposit rate. In practice, however, the amount of recall may differ across depositors and depositors recall may be heterogeneous and complex. Ashton and Hudson (2008) extend the truncated price theory of Kahn et al. (1999) to rounding in the UK retail deposit and mortgage markets. Rounding is an encoding strategy where each digit of the price considered sequentially. If a number is not already a round number then an individual will round the number to the closest reference number, where the degree of rounding depends on the distance to a reference number. For example, sophisticated consumers recall a spread of 199 basis point as the nearest rounded spread of 200 basis point rather than a truncated 190 or 100 basis point. Ashton and Hudson (2008) furthermore argue that price clustering can be seen as an action undertaken by price setters to maximize returns from consumers with limited ability to recall and process number information.

The limited recall model is not able to explain clustering in the corporate loan market because of the two differences. First, in the corporate loan market, the spreads are clustered at whole, half or quarters of a percent rather than just above, in case of retail deposit market, or just below in case of retail mortgage market. Second, in the retail deposit and retail mortgage market, the lender offers one single rate and she maximizes the profit by offering lower rate to naive depositors and higher rate to naive borrowers who either truncate or round the offered rates. On the contrary, in the corporate loan market, there is no single rate to be be offered to all the borrowers rather there is one to one contract for every borrower. Also the loan amount is big and there is a huge stake involved for both the lender and the borrower. Even a fraction of lower or higher rate can earn or save reasonable amount to the borrower or the lender. We therefore explore an alternative theoretical explanation based on the uncertainty about the quality of the borrower.

A discussion with a practitioner confirmed that it is a convention to use spread of 25 basis points for borrowers having ratings lower than BBB and the clustering of spreads increase with increase in the absolute level of spreads. However, the competition is high for AAA rated borrowers. The lenders compete for these borrowers and sometimes offer rate lower than the cost. This confirms our theoretical argument that the lenders offer search deterring rate, instead of profit maximizing rate to the borrowers.

The remainder of the paper is organized as follows. Section 2 provides the model of interest rate clustering, section 3 explains data and methodology and section 4 presents empirical evidence regarding the price clustering in the US corporate loan market. Section 5 provides robustness checks and section 6 concludes the paper.

2 Model of Interest Rate Clustering

This section gives a model of interest rate clustering in the corporate loan market. Most corporate loans are priced at rounded spreads, e.g. spreads that are a multiple of 25 basis points. We believe that the attitude of the lender toward the uncertainty about the quality of the borrower leads to the clustering of spreads. To study this, we introduce decision making under uncertainty into the model given by Chatterjee and Lee (1998). We differ from Chatterjee and Lee (1998) in two ways. First, the borrowers vary not only in the search cost, but also in the probability of getting an outside offer. This probability reflects the quality of the borrower. Second, we assume that the lender may not have full information on the quality of the borrowers and their search cost, which causes uncertainty in the model. To this aim, we resort to the literature on decision making under uncertainty. Chateauneuf et al. (2007) generalize the subjective expected utility theory by taking into account the optimism and pessimism of the decision maker (worst and best in mind) toward uncertainty. They evaluate an act (a function from states of the nature to the outcomes) by considering a convex combination of the payoffs that can be derived from the worst possible outcome, the best possible outcome, and the subjective probabilities. We take the same approach in this paper for the lender who has a subjective probability on the type of the borrower, but she also considers the best and the worst possible outcome to determine the optimal rate to offer to the borrower. Olszweski (2007) also takes a similar approach to study a model of decision making under uncertainty. He develops a model where the individual first chooses a set of lotteries, then the nature selects a lottery from the chosen set. Therefore, the individual needs to evaluate different sets of lotteries and he does this by considering a convex combination of the best and the worst possible outcome.

We have a model with one lender and one borrower, who will be referred to as "she" and "he" respectively throughout this section. Let r be the LIBOR and R be the spread. We consider a game with two rounds. In the first round, the lender makes an offer $R \in [0, 1]$. In the second round, the borrower either accepts the offer or searches in the market for another offer, while keeping the offer R on hold.

We assume the probability that the borrower finds any offer below R is given by the cumulative

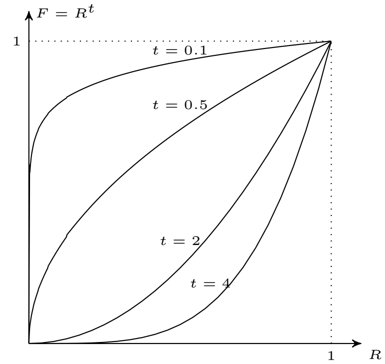


Figure 2: Distribution $F = R^t$ for $t = 4$, $t = 2$, $t = 0.5$, and $t = 0.1$.

distribution $F(R) = R^t$. The value of t in the distribution represents the quality of the borrower in terms of the likelihood of getting an offer in the market. We say that the borrower is from type $t \in (0, \infty)$. Clearly the smaller the value of t, the better chance the borrower has in getting the offer R. Namely, the smaller the value of t, the higher is the quality of the borrower. Although technically t can be a very large number, we believe that borrowers with very high values of t carry high credit risk and are not eligible for credit. On the other hand, we think that having borrowers with very small values of t is realistic, because lenders compete on lending to very high quality borrowers, hence these borrowers are able to find an outside offer with a very high probability even at very low rates.

We believe our choice for cumulative distribution functions better suits our model. What we need is a set of continuous and increasing functions such that $F(0) = 0$ and $F(1) = 1$. Also, we want to be able to order these functions, as we need a range of high quality and low quality borrowers. We can generalize Proposition 1 with a set of cumulative distributions that satisfies the first order stochastic dominance property with respect to t. Note that our class of functions satisfies this property. For Proposition 2 we have maintained the specific functional form for tractability, although it could be generalized with further specifications on the class of distribution functions.[4]

Figure 2 illustrates the distribution $F = R^t$ for borrowers with types $t = 4$, $t = 2$, $t = 0.5$, and $t = 0.1$. As this Figure shows the borrower with $t = 0.1$ has reasonably high probability of finding outside offer for even low rates. The borrower with type $t = 4$ has low probability of finding outside offer for low rates, but for rates close to 1 this probability gets large. Also, from this figure we can see that the value of t can be very small, as in this market the borrowers who are very well reputed can easily find low rates. However, the borrowers with very high value of t are extremely risky and do not have much chance of getting any offer.

In corporate loan market, the lender knows the type of the borrower if the borrower is from very high quality while she may have partial information on the low quality borrowers. Because for low quality borrowers, there is more information asymmetry on the quality of their investment and their willingness to put efforts after the investment has been financed.

[4]Proofs are available upon request.

Now let R be any rate offered by the bank. The borrower would reject the offer if he can find an outside offer x, such that $x < R$. But to find an outside offer he needs to incur the search cost of c. We assume that $c = c(t)$, as it might vary for borrowers from different types. Further, we assume that $c = c(t)$ is a non-decreasing function. Suppose that the value of the loan for the borrower is 1. If the borrower accepts the offer immediately, his payoff is $1 - R$. If he searches in the market while sitting on the offer R, his expected payoff is

$$\phi(R) = -c(t) + \int_0^R (1-x)f(x)dx + \int_R^1 (1-R)f(x)dx. \tag{1}$$

The first term in the function $\phi(R)$ is the cost of search. The second term is the borrowers' expected payoff if the outcome of the search in the market is x, while $x < R$. In this case he will reject R and accept x. The third term is the borrowers' expected payoff if the outcome of the search in the market is x, while $x > R$. In this case he will accept R. Now, the borrower would be indifferent between accepting the offer R immediately and searching to get a better offer if

$$1 - R = \phi(R) \tag{2}$$

From equation above for $F(R) = R^t$ we find the solution $R^* = \sqrt[t+1]{(t+1)c(t)}$. The calculations can be found in the Appendix 7.1. One can check that $R^* = R^*(t)$ is an increasing function of t. If the borrower gets any offer R such that $1 - R > \phi(R)$, then he would accept the offer immediately and if $1 - R < \phi(R)$ he would rather prefer search in the market and bear the search cost. This is equivalent to the statement that the borrower would accept offer R immediately, if $R < R^*$ and search in the market if $R > R^*$.[5] Hence, the rate R^* is called the maximum search deterring rate. Furthermore, we assume that $c(t) \leq \frac{1}{1+t}$ to avoid the cases where the value of R^* gets larger than 1. Note that for very large values of t, i.e. for very risky borrowers, the condition $c(t) \leq \frac{1}{1+t}$ may not hold. This intuitively means that for very risky borrowers it is not possible to find a search deterring rate.

Now, as the probability that the offer gets accepted after search is $1 - F(R)$, one can write the lenders' expected payoff function as

$$\mathbb{E}\Pi(R) = \begin{cases} R & \text{if } R \leq R^* \\ R(1-F(R)) & \text{if } R > R^* \end{cases} \tag{3}$$

Let $\pi(R) = R(1-F(R))$. To maximize $\mathbb{E}\Pi(R)$, we need to find the maximum point for the function $\pi(R)$. Therefore, we have

$$\frac{d\pi(R)}{dR} = (1 - F(R)) - Rf(R) = 0 \tag{4}$$

$$\Rightarrow \quad \bar{R} = \frac{(1 - F(\bar{R}))}{f(\bar{R})}. \tag{5}$$

Moreover, for $F(R) = R^t$ we have $\bar{R} = \sqrt[t]{\frac{1}{t+1}}$. It is easy to see that depending on t, the function

[5]This result is shown by Chatterjee and Lee (1998).

$\mathbb{E}\Pi(R)$ is maximized either in R^* or $\bar{R}$.

The lender is better off by offering R^* than $\bar{R}$, if $R^* > \pi(\bar{R})$. Chatterjee and Lee (1998) discuss that how a seller's pricing strategy depends on the search cost of a buyer. However, in corporate loan market, the borrowers differ from one another not only in the search cost, but also in the the distribution F.

If the lender knows the type t of the borrower (and consequently the distribution $F = R^t$ and search cost $c(t)$), then she knows the values of R^* and $\bar{R}$ for this borrower. Therefore, she needs to make a choice between these two pricing strategies: to offer R^*, that is the maximum search deterring rate with the payoff of R^* or to offer $\bar{R}$, with the expected payoff of $\pi(\bar{R})$. The following proposition shows the conditions under which $R^* > \pi(\bar{R})$. The proof of this result can be found in the appendix.

Proposition 1. *Let $\bar{R} = \arg\max_R \pi(R)$, where $\pi(R) = R(1 - R^t)$ and R^* be such that $1 - R^* = \phi(R^*)$. Then, there is a function $c_0(t)$ such that for every $t > 0$, when $c(t) > c_0(t)$ we have $R^* > \pi(\bar{R})$ and when $c(t) \le c_0(t)$ we have $R^* \le \pi(\bar{R})$. Moreover, $c_0(t) \longrightarrow 0$ as $t \to 0$.*

The first part of the proposition states that for every type t of the borrower, there is a threshold $c_0(t)$ such that for every search cost higher than $c_0(t)$, the lender prefers search deterring strategy to payoff maximization strategy. The second part of the proposition shows that in the case t is very small (the borrower is from very high quality), the threshold $c_0(t)$ that makes $R^* > \pi(\bar{R})$ is also very small. Intuitively, it says that for the very high quality borrowers, the lender prefers to offer the search deterring rate. This makes sense because the very hight quality borrowers not only have very small search cost but also they have very steep distribution F, and the lender's pricing strategy for such borrowers would be to offer a rate that prevents them to search in the market. There is no doubt that this rate would be very small, but still the lender prefers reaching agreement with very high quality borrowers as quickly as possible. Moreover, as the lender knows the exact value of t for such borrowers, she can derive the exact value of R^* to offer. Therefore the rate for very high quality borrowers are not clustered. This result also justifies our empirical evidence at the lower end of the distribution in Figure 1.

On the other hand, the lender may not have full information on the type of the low quality borrowers, in other words she may not know the exact value of t if t is large enough. Therefore, she needs to make decision under imprecise information or uncertainty. For this, as we explain above, we resort to the literature on decision making under uncertainty. Chateauneuf et al. (2007) generalize the subjective expected utility theory by taking into account the optimism and pessimism of the decision maker (worst and best in mind) toward uncertainty. They evaluate an act (a function from states of the nature to the outcomes) by considering a convex combination of the payoff that can be derived from the worst possible outcome, the best possible outcome, and subjective probabilities. We take the same approach in this paper for the lender who has some subjective probability on the type of the borrower, but she also considers the best and worst possible outcomes to determine the optimal rate to offer to the borrower.

The lender does not know the exact value of t for low quality borrowers. However, based on her partial information she knows that t is within a subinterval of $(0, \infty)$, say $T_i = [t_{i-1}, t_i]$, and she decides to offer a single rate to any borrower belonging to this subinterval. Let R_i be the rate to be offered to a borrower of the type $t \in T_i$. We first show that under a mild condition for cost function we have $R_i \in [R^*(t_{i-1}), R^*(t_i)]$ (Proposition 2). This condition is $c(0) < \frac{1}{e} \simeq 0.37$, which is not very restrictive because the highest quality borrower has very low search cost. The proof can be found in the appendix.

Proposition 2. *Assume for the search cost function $c(t)$ we have $c(0) < \frac{1}{e}$. Then, there is a type $\tilde{t}$ such that for every $t_i > \tilde{t}$ we have $R_i \in [R^*(t_{i-1}), R^*(t_i)]$.*

Note we assume that the lender has enough information on each borrower to identify exactly a subinterval of types within which the borrower can be placed. Moreover, the lender offers same rate to any borrowers with types within this interval. Therefore, we do not have an adverse selection problem as the borrower is not offered a menu of contracts.

Now we discuss how the rate R_i, to be offered to any borrower whose type is within the interval T_i, can be derived. From Proposition 2, we conclude that there is a $t_i^* \in T_i$ such that $R_i = R^*(t_i^*)$ because $R^*(t)$ is a continuous function. For every $t \geq t_i^*$, as R^* is an increasing function, we have $R^*(t) \geq R^*(t_i^*) = R_i$. Therefore R_i will be accepted immediately. Similarly for every $t < t_i^*$, we have $R^*(t) \leq R^*(t_i^*) = R_i$, which leads to a search in the market by the borrower and R_i will be accepted with the probability of $(1 - F(R_i))$. Hence, the lenders' expected payoff is:

$$\mathbb{E}\Pi(R_i)(t) = \begin{cases} R_i & \text{if } t \geq t_i^* \\ R_i(1 - F(R_i)) & \text{if } t < t_i^* \end{cases} \tag{6}$$

Let μ_i be the lender's subjective probability for the type of borrower on the subinterval T_i, then her expected payoff is

$$\mathbb{E}\Pi^s(R_i) = \int_{t_{i-1}}^{t_i^*} R_i(1 - F(R_i))d\mu_i(t) + \int_{t_i^*}^{t_i} R_i d\mu_i(t) \tag{7}$$

However, the lender's payoff based on the best possible outcome (that is every type in T_i accepts the offer immediately) and the worst possible outcome (that is every type in T_i searches in the market) as well as the subjective probability is

$$\mathbb{E}\Pi^b(R_i) = \alpha_i R_i + (1 - \alpha_i - \beta_i)\, \mathbb{E}\Pi^s(R_i) + \beta_i R_i(1 - F(R_i)) \tag{8}$$

The parameters α_i and β_i represent the decision maker's attitude toward imprecise information for borrowers from the type belonging to T_i, where α_i is called the degree of the decision maker's optimism and β_i is called the degree of decision maker's pessimism toward imprecise information. The rate R_i can be found by maximizing $\mathbb{E}\Pi^b(R_i)$ over T_i. One can see that the rate R_i is a function of t, μ_i, α_i, and β_i. We predict that in such situations decision makers' underlying behavior is such that they choose α_i and β_i in a way that R_i is a rounded number. We confirm this behavioral prediction in our empirical analysis in section 4 that most of the interest rate spreads are clustered.

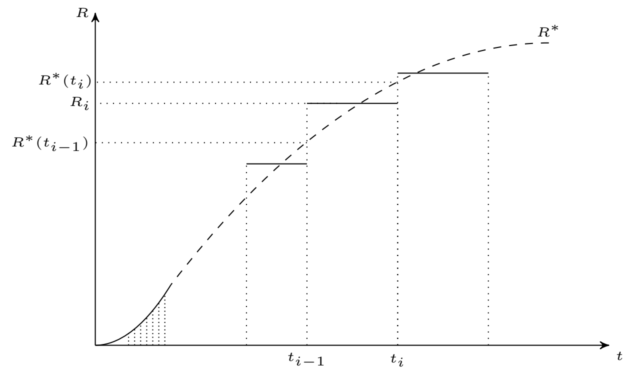


Figure 3: This figure shows the optimal rate that the lender offers to the borrower with type t.

The argument above shows how imprecise information on the borrowers' quality can cause spikes in the distribution of spreads in Figure 1.

Overall, for the borrowers with type t small enough, where there is no uncertainty, the exact rate of R^* would be offered. When t gets larger, the uncertainty on the value of t causes jumps in the offered rate to the borrower. Basically, for t large enough, the lender offers a rate $R_i \in [R^*(t_{i-1}), R^*(t_i)]$ to any borrower with type in the interval $[t_{i-1}, t_i]$. This argument is illustrated in Figure 3.

Note that our model is a static model (it has only one period of time) in two rounds; in the first round the lender offers a rate to the borrower, and in the second round the borrower either accepts the offer or decides to search in the market for another rate. One natural extension of this model is to consider a dynamic model. We give a brief discussion on this extension. Assume that in period two, the lender intends to offer a rate to a borrower of low quality. We have two cases: (1) If the borrower is new to the lender, then we are back to the first period model. In this case, the lender does not know the exact type of the borrower, but she knows that his type lies within a certain interval. (2) If the borrower was in relationship with the lender in the first period (the lender has given the loan to the borrower in the first period), then the lender can refine the interval from the first period relationship. As an extreme case we can assume that she knows the type of the borrower in this case. Consequently, in this extreme case the lender knows the value of t for this borrower and she can calculate the exact (non-clustered) optimal rate to offer to the borrower. By the above discussion, we have a more complete picture for our model, as now we can justify the high non-clustered rates in Figure 1.

We would like to emphasize here that the bargaining in this market does not cause the clustering phenomenon. We argue that bargaining only helps the low quality borrower to move from a larger rounded number to a smaller rounded number. To make this argument clearer, without loss of generality, assume (i) the borrower does not need to reject the offer to search in the market, (ii) the borrower can only bargain based on an outside offer. Let R_0 be the rate offered by the lender and R^* be the maximum search deterring rate for the borrower, known to the borrower . Note that because of the uncertainty we explained above, R_0 is a rounded number. If $R_0 \leq R^*$, the borrower accepts the offer immediately and if $R_0 > R^*$, the borrower searches in the market, incurs the search cost c and finds the rate R_1. In the latter case, if $R_1 \leq R^*$, the borrower would accept the offer R_1. Also, in this case the borrower can bargain with the first lender over the rate R_0 to be reduced to R_1 due to some other features in the contract. Note that R_1 is a rounded number too by a similar argument as for R_0. Therefore, we see that the borrower eventually either gets the rate R_0 or the rate R_1, where both of them are rounded numbers and bargaining might only help to move from R_0 to R_1.

3 Data Description and Methodology

To examine the interest rate clustering in the corporate loan market, we obtain syndicated loans data from Thomson One, which contains detailed information of syndicated lenders, borrowers and pricing of loans. The sample we use includes the whole population of 21,855 loan tranches to 4,718 U.S. firms issued anytime from January 2000 to December 2015. We include loans for which the data on industry of the borrower, maturity of the loan, loan amount, loan signing date and pricing of loan as spread over LIBOR are available. We include only syndicated loans and exclude all club syndicates and bilateral loans. We also exclude tranches for which the spread is not based on LIBOR, they were only 636 such loan tranches. We use "initialpricing" field in the Thomson One database for extracting spread over LIBOR.

We conduct our analysis at the tranche level because interest rates are decided at tranche level. In our sample 70% of the loans have a single tranche. Summary statistics for the full sample are given in Table 1. We start with the loan characteristics because our primary variable of interest is spread over LIBOR. Mean spread over LIBOR for a typical loan is 207.31 basis points and the mean loan size is $923.13 million. The size of loans have increased greatly in recent years. For example, healthcare is the top sector for global $10bn plus loans since 2010, with 20 deals totaling $313.3bn. Finance is second with 15 deals, totaling $264.4bn followed by Telecoms with 13 deals totaling $220.1bn as reported by Dealogic market insights[6]. Other loan characteristics include: The mean maturity of a loan is about 4 years, 30% of the loans are multiple tranches loans, 30% are term loans and 22% carry a covenant with them. About 59% of the borrowers have S&P long term rating and 6% do not have a ticker meaning they are not listed on either stock market or bond market. 68% of the borrowers have accessed syndicated loan market in the past and only 31% acquired loan from the same lender when they accessed the syndicated loan market in the past. Top 5 lead arrangers[7] lend 47% of the loans in our sample. The syndicated loan market is very concentrated and only a few players control a huge percentage of the total loan market.

[Insert Table 1 about here]

Figure 1 gives the actual frequency distribution of the clustering of interest rate spreads over LIBOR in basis points in the US syndicated loan market. The histogram shows the number of observations at each basis point that spreads are multiples of 25 basis points above LIBOR. This clustering tendency increases at higher spread levels and also the interval of rounding increase as

[6]See http://www.dealogic.com/media/market-insights/loans-statshot/

[7]The arrangers who get a mandate to lead a syndicated loan deal are called lead arrangers. They are responsible for due diligence of the borrower and agree on the terms and conditions of the loan with the borrower.

the level of spreads increase.

[Insert Figure 1 about here]

According to our theoretical argument, the lender's attitude toward uncertainty about the quality of the borrower leads to rounding of spreads. This uncertainty comes from information asymmetry between the lender and the borrower. The higher the information asymmetry, the higher the occurrence of clustered spreads. The borrowers who are able to reveal more information about their affairs get non-rounded spreads. To test these theoretical arguments, we estimate a logit model. A logit model is a regression model where the dependent variable is categorical and in our case it is a binary dependent variable, which is the spread over LIBOR defined as 1 if the spread is a multiple of 25 basis points and 0 otherwise. Other methods to test a binary response models are linear probability model (LPM) and probit model. A logit model has advantages over LPM and probit model. One of the shortcomings of LPM is that it can produce estimated probabilities that are lower than 0 or greater than 1. The logit model produces fitted values that are confined within the interval [0,1]. A probability by definition falls within the interval [0,1] and the predicted probability outside the interval [0,1] is meaningless. Furthermore, LPM is a linear model and it is not plausible to claim that a probability is linearly related to a continuous explanatory variable for all possible values. If it were, then continually increasing this explanatory variable would eventually drive $P(y = 1|x)$ above 1 or below 0 (Greene, 2008; Wooldridge, 2010; Brooks, 2014).[8] The logit model has advantage of interpretability over the probit model.[9] The transformation for the logit model is directly interpretable as a log-odds. Thus, we estimate the logit model as follows:

$$\begin{aligned} &P_i(y_i = 1) = G(z_i) \\ &\quad \text{with} \;\; z_i = \beta_0 + \beta_1 x_{1i} + ... + \beta_k x_{ki} \\ &\quad \text{and} \;\; 0 \leq G(z_i) \leq 1 \end{aligned}$$

Using the cumulative standard logistic distribution function

$$F(z_i) = \frac{1}{1 + \exp^{-z_i}}$$

evaluated at $z_i = \beta_0 + \beta_1 X_{1i} + ... + \beta_k X_{ki}$.

Where y_i is an indicator variable that equals 1 if the spread is a multiple of 25 basis points and 0 otherwise and x_i is a vector of explanatory variables. The corresponding log-likelihood function that is maximized is:

$$\ln \mathcal{L} = -\sum_{i=1}^{N} [y_i \ln(1 + \exp^{-z_i}) + (1 - y_i) \ln(1 + \exp^{-z_i}].$$

[8] Another issue is that the LPM produce heteroskedastic residual but this issue can be resolved by using robust standard errors while estimating the LPM.

[9] Although logit model is simple compared to the probit as the equation of the logistic cumulative distribution function (CDF) is simple, whereas the normal CDF has an unevaluated integral yet this difference is not acute under dichotomous data.

Where N is the total number of observations.

Since the form of the function is $P_i = F(z_i)$, instead of $P_i = \beta_0 + \beta_1 x_{1i} + ... + \beta_k x_{ki}$, the direct interpretation of β_k will be incorrect. Therefore, we report marginal effects of the estimates and differentiate F, where F is the logistic function, with respect to z_i to interpret the coefficients and the derivative is $\beta_k F(z_i)$.

4 Empirical Evidence

4.1 Evidence of Clustering

We use the following dependent and explanatory variables to explain clustering of interest rate spreads in the corporate loan market. Our dependent variable is the spread over LIBOR, which is defined as 1 if the spread is a multiple of 25 basis points and 0 otherwise. It is important to highlight at this point that 25 basis points is merely some integer point where spreads are clustered more frequently. If the spreads are at the lower end of the distribution, say from 0 to 10, they tend to cluster more frequently at 5 basis points and if the spreads are at the higher end of the distribution, they tend to cluster more frequently at 50 or 100 basis points. Since Figure 1 shows that the spreads are clustered more frequently at 25 basis, we find it more plausible to use spread at a multiple of 25 basis points as our baseline dependent variable.

Our primary variables of interest are unrated borrower and private borrower. As the uncertainty stems from the degree of information asymmetry, our first proxy for uncertainty is the rating of the borrower. As it is well established in the literature that the information about the borrower is more likely to be opaque when the borrower does not have a credit rating (see for example, Dennis and Mullineaux, 2000; Sufi, 2007; Chaudhry and Kleimeier, 2015). The borrowers reveal less information which increases the uncertainty about their affairs if they have not been rated by a rating agency. The lenders are more likely to offer rounded spreads to such borrowers as it has been shown in our theory in section 2 above. Based on the information about the borrowers rating in the Thomson One database, we classify borrowers as unrated borrowers if they do not have an S&P long term debt rating. We measure it with a dummy = 1 if they have an S&P long term debt rating or 0 otherwise. The borrowers not listed on the financial markets with either equity or bond issues reveal a very little public information and hence increase uncertainty about their affairs. Therefore, we consider our second proxy for uncertainty is the dummy = 1 if the borrowers have no ticker available in the Thomson One database or 0 otherwise. Since both these borrowers reflect similar characteristics, we group them into one category as ("opaque"), which is defined as the dummy = 1 if the borrowers have either S&P long term debt rating or a ticker available in the Thomson One database. From Table 2 onward, we perform our analysis only on "opaque" borrowers.

Next we employ two proxies that reduce the information asymmetry. One is the existing borrower and the second is former lender. Existing borrower is defined as a dummy = 1 if the borrower has accessed the syndicated loan market within past five years or 0 otherwise. Chaudhry and Kleimeier (2015) find stronger effects of information asymmetry reduction; the more recent the borrowers have accessed the syndicated loan market. We therefore follow them and devise our proxy, existing borrowers, as a dummy = 1 if a borrower raised loans during the previous five years. With repeated access, the borrowers should have become known to the potential lenders and exhibit less uncertainty thus the theory predicts that the lenders should not give rounded spread to such borrowers. Former lender is the lender who has previous relationship with the borrower and is defined as a dummy = 1 if one of the lead arrangers has relationship within past five years or 0 otherwise. With previous interactions with a borrower, the lenders should have known more about the affairs of the borrower and hence information asymmetry should be less (Sufi, 2007; Chaudhry and Kleimeier, 2015). Our theory also predicts a non-rounded spread for such borrowers.

The control variables include year and industry dummies, the natural log of loan size as a proxy for borrower size, loan to sales ratio as a proxy for relative loan size, a dummy = 1 if the loan has more than one tranche, a dummy = 1 if a loan deal contains a term loan, the natural log of maturity of the loan in days and an indicator variable for whether a loan carries a covenant. Finally, all standard errors are heteroskedasticity robust, and clustered at the borrower as well as at the lender level.

Table 2 presents evidence of rounding of spreads by using logit regressions. We report marginal effects for all of our logit regressions. In regression 1, we use only unrated borrowers and private borrowers as explanatory variables without any controls. We find that lenders give rounded spreads to both unrated and private borrowers. The unrated borrowers get rounded spread more often compared with private borrowers. In regression 2, we add borrower and lender fixed effects and find very similar results. It shows that the variation within borrowers and lenders do not have any effect on our baseline results. In regression 3, we add a few more borrower and loan characteristics and our results remain the same except that the marginal effects for private borrower are the same as that of unrated borrowers. Overall our baseline results are consistent with our theory that low quality borrowers defined by the proxies of unrated borrower as well as private borrower get rounded spreads from the lenders.

We use complete models in Table 3. Since both unrated and private borrowers show similar results, we group them into one category ("opaque") and do further analyses on opaque borrower category. In regression 1, we include all the borrower and loan characteristics together with borrower and lender fixed effects, year and industry dummies. We find that opaque borrowers are more likely to get rounded spreads. In regression 2, we add existing borrowers, the borrowers who repeatedly access the loan market. Consistent with our theory, we find that the marginal effects of existing borrowers is significantly negative. In regression 3, we use former lender proxy, the lenders who have acted as a former lender to a borrower, as another proxy of reduction in information asymmetry or uncertainty. We indeed find a negative significant marginal effects showing that the borrowers who have previous relationship with a lender get non-rounded spread.

Next to our primary proxies, we find negative significant marginal effects for borrower size. Large borrowers are usually high quality who do not exhibit greater uncertainty. This result is also in agreement with our argument that lenders offer non-rounded spread to large borrowers and clustering happens because of the uncertainty about the quality of the borrower. However, we do not find significant results for relative loan size showing that uncertainty is reduced only by large borrowers and the relative loan size cannot act as a uncertainty reduction proxy.[10] Our

[10]This is a control variable and its insignificant effect does not contradict with our theory. Our variable of interest,

other control variables of a natural log of maturity, indicator variables for a multiple tranche loan, a term loan in a deal and a loan carrying a covenant all show positive significant marginal effects showing lenders consider such loans more uncertain and offer rounded spreads. This is inline with the literature because longer maturity loans and term loans are considered to be riskier for lenders because the probability of default of a loan increases with maturity. One possible explanation for positive significant marginal effects for a multiple tranche loan is that they are complex and lenders might take them as more risky. Finally, positive significant marginal effects for a loan with covenants can be explained by the fact that covenant and collateral are associated with riskier borrowers (Berger and Udell, 1990; Jimenez and Saurina, 2004; Indersta and Mueller, 2007).

[Insert Tables 2 and 3 about here]

4.2 Unobserved credit risk is not related to rounding

In order to show rounding of spreads happens because of uncertainty about the quality of a borrower and that unobserved credit risk is not related to rounding of spreads over LIBOR, we get residuals from loan pricing regression and put them as explanatory variables in a logit regression to see if they can significantly explain rounding of spreads. Before, we do this, we first run loan pricing regressions to show the evidence of upward rounding of spreads. Kahn et al. (1999) and Ashton and Hudson (2008) also provide evidence that lenders maximize profits by rounding or truncating interest rates in their favor. We use the same model as in Tables 2 and 3 but we add borrower's risk based on its rating, which is in line with the empirical loan pricing literature (Gorton and Pennacchi, 1995; Carey and Nini, 2007; Ivashina, 2009).

Before running loan pricing regressions to show the evidence of upward rounding of spreads, we describe the summary statistics for rounded and non-rounded spreads in Table 4. Table 4 presents number, mean, median and standard deviation of loans with rounded spreads and non-rounded spreads in our sample. Out of total 21,855 loans, 15,659 (about 72%) loans are with rounded spreads and 6,196 (about 28%) are with non-rounded spreads. In our sample mean opaque borrowers are more (48%) who get rounded spreads compared with (36%) who do do get rounded spreads. However, mean existing borrowers, mean top 5 lead arrangers and mean former lender are more (74%, 54% and 33% respectively) for borrowers getting non-rounded spreads compared with (66%, 44% and 30% respectively) borrowers getting rounded spreads. These statistics provide initial support to our theory that if there is uncertainty about the quality of borrower, like opaque borrower, the borrowers get rounded spread. If the uncertainty about their quality is reduced by accessing the loan market repeatedly or by repeated interactions, then lenders feel comfortable about borrowers' quality and offer them non-rounded spreads. Mean spread over LIBOR for a typical loan with rounded spread is much higher, i.e., 254.21 basis points compared with only 88.79 basis points for a loan with non-rounded spreads. The loans with non-rounded spreads are much larger, i.e., mean $1174.52 million compared with $823.66 million for loans with rounded

the "Opaque borrower" in regression 1 of Table 3 shows that the low quality borrowers get rounded spread from the lenders. Nevertheless, this is consistent with some of the literature (Berger et al., 2005; Champagne and Coggins, 2012).

spreads. The maturity, the number of multiple tranches in a loan deal and a loan is a term loan in a deal all are higher for loans with rounded spreads.

[Insert Table 4 about here]

Now we present loan pricing regression results. Table 5 provides evidence of upward rounding of spreads over LIBOR. Our dependent variable is spread over LIBOR measured as a spread given to borrowers over LIBOR. Our primary variable of interest is a dummy = 1 if the spread is rounded at a multiple of 25 basis points or 0 otherwise. Regression 1 gives positive coefficient indicating that loans with rounded spreads are rounded upwards by an average of 125.38 basis points. The inclusion of loan characteristics in regression 2 does not change the sign and significance of rounded spread proxy. However, the average spread reduces to 104.57 basis points. This raises a question that the rounding might be related to some unobserved credit risk and not because of uncertainty about the quality of the borrower.[11]

To check whether the unobserved credit risk is related to rounding of spreads over LIBOR, we get residuals from regression 1 and 2 of Table 5 and put them as explanatory variables in a logit regression, which is shown in Table 6. The residuals are the unobserved credit risk that are not captured by the model. Our dependent variable is a dummy = 1 if the spread is rounded at a multiple of 25 basis points or 0 otherwise. We want to see if these unobserved credit risk characteristics explain the rounding of spreads over LIBOR. Both regressions 1 and 2 in Table 6 are the same as regressions 3 in Table 2 except that we do not add loan characteristics in regression 1 to see whether loan characteristics have any different impact. This makes the model similar to regression 1 of Table 5. We find that in both the regressions, residual is not statistically significant indicating that unobserved credit risk is not related to rounding of spreads.

[Insert Tables 5 and 6 about here]

4.3 Intertemporal changes and rounding over different range of spreads

In Tables 2 and 3, we gave evidence of rounding of spreads over LIBOR at a multiple of 25 basis points. However, in Table 5 we observe that lenders are rounding the spreads upward by about 125 basis points when we do not include loan characteristics and about 104 basis points when we include loan characteristics. If lenders round an interest rate spreads upward the maximum number of basis points which they round upward is 24 basis points (e.g. from 301 to 325). On average we should expect a coefficient around 10 basis points. Whereas we find that they round on average 124 and 104 basis points. We give two explanations for this. One is that it is because of the overall interest rate environment and the second is that it is because of the different range of interest rate spreads. Regarding overall interest rate environment, if a Central Bank follows a contractionary monetary policy and the interest rate levels are higher then the spread over LIBOR might be

[11] We also predict spreads from the sub-sample loan-pricing regressions of 6,196 loans that are priced at non-rounded spreads over LIBOR and compare them with actual spreads of 15,659 loans that are rounded. We find that the average actual spread is much higher than the predicted spread i.e., 122.3 and 132.4 basis points for regression 1 and regression 2 respectively. The results are available on demand.

higher on average as well. On the contrary, if a Central Bank follows an expansionary monetary policy and the interest rate levels are lower then the spread over LIBOR might be lower on average as well. This has further impact on the rounding in the sense that when spread level is higher, the rounding might occur at higher multiples. We get a figure (Figure 4) from ICE Benchmark Administration Limited (IBA) of Federal Reserve at St. Louis, which shows the 12-Month LIBOR, based on US Dollar from 1995 till 2015. We can see from the figure that the LIBOR was more than 5% on average from 1995 to 2000 and about 3% on average from 2000 to 2005 and the level dropped to about 1% from 2009 till 2015.

To see whether the level of LIBOR has any bearing on the level of spread over LIBOR, we split our sample into two subsamples. One subsample is from 2000 to 2005 when the LIBOR level was about 3% and the second from 2009 to 2015 when the LIBOR level was about 1%. The results are given in Table 7. Regressions 1 and 2 are the same as regression 2 in Table 5. Regression 1 shows the results of a subsample from 2000 to 2005 and regression 2 shows results of a subsample from 2009 to 2015. We can see the spread over LIBOR was higher, i.e., 118.66 basis points when the overall LIBOR level was higher during 2000 to 2005 and the spread over LIBOR was lower , i.e., 87.12 basis points when the overall LIBOR level was lower.

The size and sign of some of the control variables vary across the two regressions. For example, the size of the indicator variable of a multiple tranche is much higher for the subsample from 2009 to 2015. One plausible explanation for this is that loans with multiple trancehs are complex and lenders consider them riskier. After the global financial crisis, the banks have become more prudent in their lending practices and they require even higher spread for loans that are complex and riskier. As we explain above the average LIBOR level dropped to about 1% during the period from 2009 to 2015. The insignificant natural log of maturity variable in regression 2 can be explained by the fact that at low levels of interest rates, the lenders do not want to lock themselves to longer maturity loans and focus only on shorter term loans with the expectation to lend at higher rates in future. Therefore, we do not find any relationship between spread above LIBOR and the natural log of maturity in regression 2. Furthermore, we note that the sign of the covenant inverses from positive to negative in regression 2. As we know the risk of borrowers increased during the global financial crisis and in order to get favorable contract terms, the higher quality borrowers are willing to provide more covenants than low quality borrowers (Stiglitz and Weiss, 1981; Besanko and Thakor, 1987). Furthermore, covenants and collateral also help to mitigate moral hazard problem after the loan is disbursed (Boot et al., 1991). Therefore, we find negative relationship between spread over LIBOR and covenant as high quality borrowers are more likely to provide covenants who get loans at lower spreads.

[Insert Figure 4 about here]

The second explanation of getting a higher upward rounding spread is the different range of interest rate spreads. To confirm this, we split our sample into three subsamples based on the level of spread over LIBOR. Our first subsample is over a range when the spread over LIBOR is from 0 to 99 basis points, second subsample is when the spread over LIBOR is from 100 to 199 basis points and the third subsample is when the spread over LIBOR is above 199 basis points. We run OLS regression as in Table 7 and present results in Table 8. In our dataset, there is no borrower with rating D that has received the loan with spread over LIBOR from 0 to 99 and spread over LIBOR from 100 to 199. This is why there is no result on "RatingD" in regressions 1 and 2. Our results in regressions 1, 2 and 3 show that at lower range of spreads, the rounding occurs lower levels and at higher range of spreads, the rounding occurs at higher levels. This confirms our argument that the rounding does not necessarily occur at a multiple of 25 basis points but varies across LIBOR levels as well as across spread over LIBOR levels.

[Insert Tables 7 and 8 about here]

4.4 Interest rate clustering across the type of industry and during the financial crisis

Although we include industry dummies as controls in all of our regressions yet we test whether the type of industry has any bearing on interest rate clustering.[12] We use our complete model of regression 1 in Table 3 and run a set of regressions on top five industries namely: Energy and Power, Industrials, Materials, Consumer Products and Services, and Technology. We indeed find that there are differences across industries with respect to interest rate clustering. For example, we find that the lenders do not provide rounded spreads to borrowers from the industry type of "Industrials". However, we do find evidence of interest rate clustering in all other top four industries. We report these results in Table 9.

Next, to investigate whether the interest rate clustering in the corporate loan market is significantly different after the global financial crisis, we split our sample into three subsamples.[13] Our first subsample is the pre crisis sample for the period from January 2000 to December 2007. As there is always a time lag between the loan approval and the loan disbursement, we consider the period till December 2007 as a pre crisis period. Our second subsample is the crisis sample for the period from January 2008 to December 2010 and our third subsample is the post crisis sample for the period from January 2011 to December 2015. The results are reported in Table 10. We use our complete model of regression 1 in Table 3. We indeed find that the risk of borrowers have increased during the global financial crisis as the low quality borrowers get more rounded spreads for the period from January 2008 to December 2010. One interesting finding is that the marginal effect of the opaque borrower variable is lower after the global financial crisis compared to the pre crisis period indicating that the borrowers get less rounded spread after the global financial crisis. This is consistent with the literature that banks received liquidity and funding during the global financial crisis and they restricted the supply of credit to firms (Cetorelli and Goldberg, 2011, 2012; De Haas and Van Lelyveld, 2014; Giannetti and Laeven, 2012; Popov and Udell, 2012). Consequently, many low quality borrowers left the market and the remaining borrowers are of high quality relatively who get exact spreads. Therefore, we find the magnitude of interest rate clustering is less after the global financial crisis.

[12] We thank an anonymous referee for this comment.
[13] We thank an anonymous referee for this comment.

4.5 Evidence against tacit collusion hypothesis

As motivated in section 1 above that a few lead arrangers might tacitly collude in the corporate loan market, which is highly concentrated, because of the substantial market share. However, we empirically test this by using a dummy = 1 if one of the lead arrangers is among top 5 who hold highest market share. If we find a positive significant coefficient, it would show that the lead arrangers who are in a position to collude because of their substantial market share, are colluding and offering higher rounded spread to borrowers. On the contrary, if we find a negative significant coefficient, it would indicate that the top lead arrangers are not tacitly colluding. We reproduce regressions 2 and 3 of Table 3 and include Top 5 lead arrangers proxy and run logit regression. The negative significant marginal effects confirm that the top 5 lead arrangers are not involved in tacit collusion and hence we reject this hypothesis that rounding of spreads is happening because of tacit collusion hypothesis. The results are reported in Table 11.

[Insert Table 11 about here]

5 Robustness checks

In all our empirical analyses, we cluster standard errors at both borrower and lender level to capture the variation across borrowers and lenders. Since most of the empirical literature cluster standard errors only at borrower level, we perform a robustness check if our results are robust if we cluster standard errors only at borrower level. We find our results are robust if we cluster standard errors only at borrower level. The results are presented in Table 12.

[Insert Table 12 about here]

Furthermore, we do analysis on all the firms. We do not excluded financial firms from our sample. We check here that whether our results are robust if we exclude financial firms from our sample and perform analysis only on non-financial firms as financial firms are more likely to be known to the lenders because of being in the same industry. Furthermore, most of the empirical literature on loan pricing exclude financial firms from their analyses (Sufi, 2007; Ivashina, 2009; Chaudhry and Kleimeier, 2015). We present our results in Table 13 and find that all of our results are robust to the exclusion of financial firms and even slightly stronger both economically and statistically.

[Insert Table 13 about here]

6 Summary and conclusions

Given the friction that spreads in the US corporate loan market cluster at certain levels, we set out to answer the following question: Why do corporate loan spreads cluster? We argue that the existing theories like negotiation hypothesis, tacit collusion hypothesis and limited recall model cannot answer these questions. We develop a theoretical argument and test it empirically that the attitude of the lender toward the uncertainty about the quality of the borrower leads to clustering of spreads over LIBOR. In the corporate loan market, clustering increases with the degree of uncertainty, e.g. information asymmetry between the lender and the borrower. However, a previous lending relationship between lender and borrower reduces this uncertainty and hence persuades lenders to provide loans at non-rounded spreads. We also show empirically that the unobserved credit risk do not explain rounding of spreads over LIBOR in the US corporate loan market. As loans are generally priced at upwardly rounded spreads, we provide evidence against tacit collusion hypothesis that the most reputable lead arrangers offer loans at competitive non-rounded spreads.

Our study highlights an important loan market friction that loans are clustered at certain levels and provides argument for this friction. Corporate borrowers are sophisticated and you do not expect that loans are not offered at exact spreads rather at some rounded spread and more so are rounded upwards. Furthermore, corporate loans are big in volume and one basis point can have high costs for the borrowers especially if they are rounded upwards. The identification of such a friction has a great impact on proper functioning of the loan market that can contribute toward its development. The relationship between developed financial markets and economic growth is well established in the literature (see Levine, 2005; Beck, 2012 among others). This study also has policy implications because it brings this friction to the attention of policy makers who can influence lenders to properly price the loans and eliminate this friction from the corporate loan market.

7 Appendix

7.1 Derivation of $R^* = \sqrt[t+1]{(t+1)c(t)}$

From equations (1) and (2) we have

$$1 - R = \phi(R) = -c(t) + \int_0^R (1-x)f(x)dx + \int_R^1 (1-R)f(x)dx.$$

Also, we know the cumulative distribution is $F(R) = R^t$. Therefore, the density distribution is $f(R) = tR^{t-1}$. Now, we have

$$1 - R = -c(t) + \int_0^R (1-x)tx^{t-1}dx + \int_R^1 (1-R)tx^{t-1}dx.$$

By taking the integrals we calculate

$$\begin{aligned} 1 - R &= -c(t) + \left[x^t - \frac{t}{t+1}x^{t+1}\right]_0^R + (1-R)\left[x^t\right]_R^1 \\ &\Rightarrow 1 - R = -c(t) + R^t - \frac{t}{t+1}R^{t+1} + (1-R)(1-R^t) \\ &\Rightarrow 1 - R = -c(t) + R^t\left(1 - \frac{t}{t+1}R - (1-R)\right) + 1 - R \\ &\Rightarrow 0 = -c(t) + R^t\left(\frac{1}{t+1}\right) \\ &\Rightarrow R = \sqrt[t+1]{(t+1)c(t)} \end{aligned}$$

Therefore, the maximum search deterring rate R^* is $\sqrt[t+1]{(t+1)c(t)}$. □

7.2 Proof of Proposition 1

We know that $R^* = \sqrt[t+1]{(t+1)c(t)}$, where $c(t) \leq \frac{1}{t+1}$ for every t. We show that if $c(t) > c_0(t)$ where $c_0(t) = t^{t+1}(\frac{1}{t+1})^{t+\frac{1}{t}+3}$, we have $R^* > \pi(\bar{R})$. We know

$$\pi(R) = R(1 - F(R)) = R(1 - R^t)$$

To find $\bar{R}$, we need to maximize $\pi(R)$:

$$\frac{d\pi}{dR} = 1 - (t+1)R^t = 0$$

Therefore,

$$\bar{R} = \sqrt[t]{\frac{1}{t+1}}$$

Thus, $\pi(\bar{R}) = \bar{R}(1-\bar{R}^t) = \sqrt[t]{\frac{1}{t+1}}(1-\frac{1}{t+1})$. We get $R^* > \pi(\bar{R})$ if and only if

$$\begin{aligned}
\sqrt[t+1]{(t+1)c(t)} > \sqrt[t]{\frac{1}{t+1}}(1-\frac{1}{t+1}) &\iff (t+1)c(t) > (\frac{1}{t+1})^{\frac{t+1}{t}}(\frac{t}{t+1})^{t+1} \\
&\iff c(t) > \frac{1}{t+1}(\frac{1}{t+1})^{\frac{t+1}{t}}(\frac{t}{t+1})^{t+1} \\
&\iff c(t) > t^{t+1}(\frac{1}{t+1})^{t+\frac{1}{t}+3}
\end{aligned}$$

Let $c_0(t) = t^{t+1}(\frac{1}{t+1})^{t+\frac{1}{t}+3}$. Then, the proof of the first part of the proposition is complete. For the second part of the proposition, we show that $\lim_{t\to 0} c_0(t) = 0$. In the function $c_0(t)$, clearly, $\lim_{t\to 0} t^{t+1} = 0$. To find $\lim_{t\to 0}(\frac{1}{t+1})^{t+\frac{1}{t}+3}$, we use L' Hospital's Rule for this purpose. Let $y = (\frac{1}{t+1})^{t+\frac{1}{t}+3}$. We first find $\lim_{t\to 0} \ln y$:

$$\begin{aligned}
\lim_{t\to 0} \ln y &= \lim_{t\to 0}(t+\frac{1}{t}+3)\ln(\frac{1}{t+1}) \\
&= \lim_{t\to 0} \frac{\ln(\frac{1}{t+1})}{\frac{t}{t^2+3t+1}}
\end{aligned}$$

By L' Hospital's Rule we have

$$\lim_{t\to 0} \ln y = \lim_{t\to 0} \frac{\frac{-1}{t+1}}{\frac{1-t^2}{(t^2+3t+1)^2}} = -1$$

Therefore, $\lim_{t\to 0} y = e^{-1}$. This implies that $\lim_{t\to 0} c_0(t) = 0 \cdot e^{-1} = 0$. □

7.3 Proof of Proposition 2

First we argue that $R_i \geq R^*(t_{i-1})$. As $R^*(t_{i-1})$ is the maximum rate that will be accepted by all the types in T_i, there is no need for the lender to offer below that. Now, to prove that there is a type $\tilde{t}$ such that if $t_i \geq \tilde{t}$, then $R_i \leq R^*(t_i)$, we show that there is a type $\tilde{t}$ such that if $t_i \geq \tilde{t}$, then the expected payoff $\int_{t_{i-1}}^{t_i} R(1-R^t)\mu(t)dt$ is decreasing for every $R \geq R^*(t_i)$. For this aim, by taking the first derivative of the expected payoff with respect to R we have

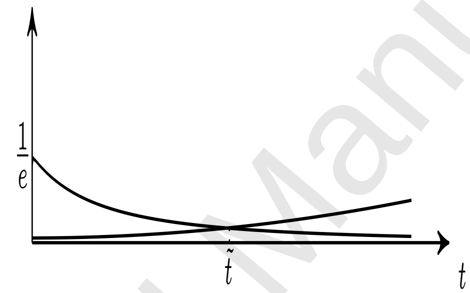
$$\begin{aligned}
\frac{d}{dR}\int_{t_{i-1}}^{t_i} R(1-R^t)\mu(t)dt &= \int_{t_{i-1}}^{t_i} \frac{d}{dR}R(1-R^t)\mu(t)dt \\
&= \int_{t_{i-1}}^{t_i} (1-(t+1)R^t)\mu(t)dt
\end{aligned}$$

If we show that $1-(t+1)R^t \leq 0$ for every $t \in [t_{i-1}, t_i]$, then the above first derivative is negative too. It is easy to see that the inequality $1-(t+1)R^t \leq 0$ is equivalent to the inequality $R \geq \sqrt[t]{\frac{1}{t+1}}$. Now if we show that $R^*(t_i) \geq \sqrt[t_i]{\frac{1}{t_i+1}}$, then we have $R \geq \sqrt[t]{\frac{1}{t+1}}$ for every $R \geq R^*(t_i)$ and every $t \in [t_{i-1}, t_i]$, because it can be verified that $\sqrt[t]{\frac{1}{t+1}}$ is strictly decreasing and continuous for every $t > 0$. To this end, we write

$$R^*(t_i) \geq \sqrt[t_i]{\frac{1}{t_i+1}} \quad \Leftrightarrow \quad \sqrt[t_i+1]{(t_i+1)c(t_i)} \geq \sqrt[t_i]{\frac{1}{t_i+1}}$$

$$\Leftrightarrow \quad c(t_i) \geq (\frac{1}{t_i+1})^{2+\frac{1}{t_i}}$$

One can check that the function $(\frac{1}{t+1})^{2+\frac{1}{t}}$ is a strictly decreasing and continuous function for $t > 0$ with $\lim_{t\to 0}(\frac{1}{t+1})^{2+\frac{1}{t}} = \frac{1}{e}$ and $\lim_{t\to\infty}(\frac{1}{t+1})^{2+\frac{1}{t}} = 0$. Moreover, we know that the cost function $c(t)$ is an increasing function with $c(0) < \frac{1}{e}$ according to our assumption. Therefore, there exists $\tilde{t}$ such that for every $t \geq \tilde{t}$ we have $c(t) \geq (\frac{1}{t+1})^{2+\frac{1}{t}}$. The graph below illustrates this. In the graph we have $c(t) = 0.01t^2 + 0.02$.



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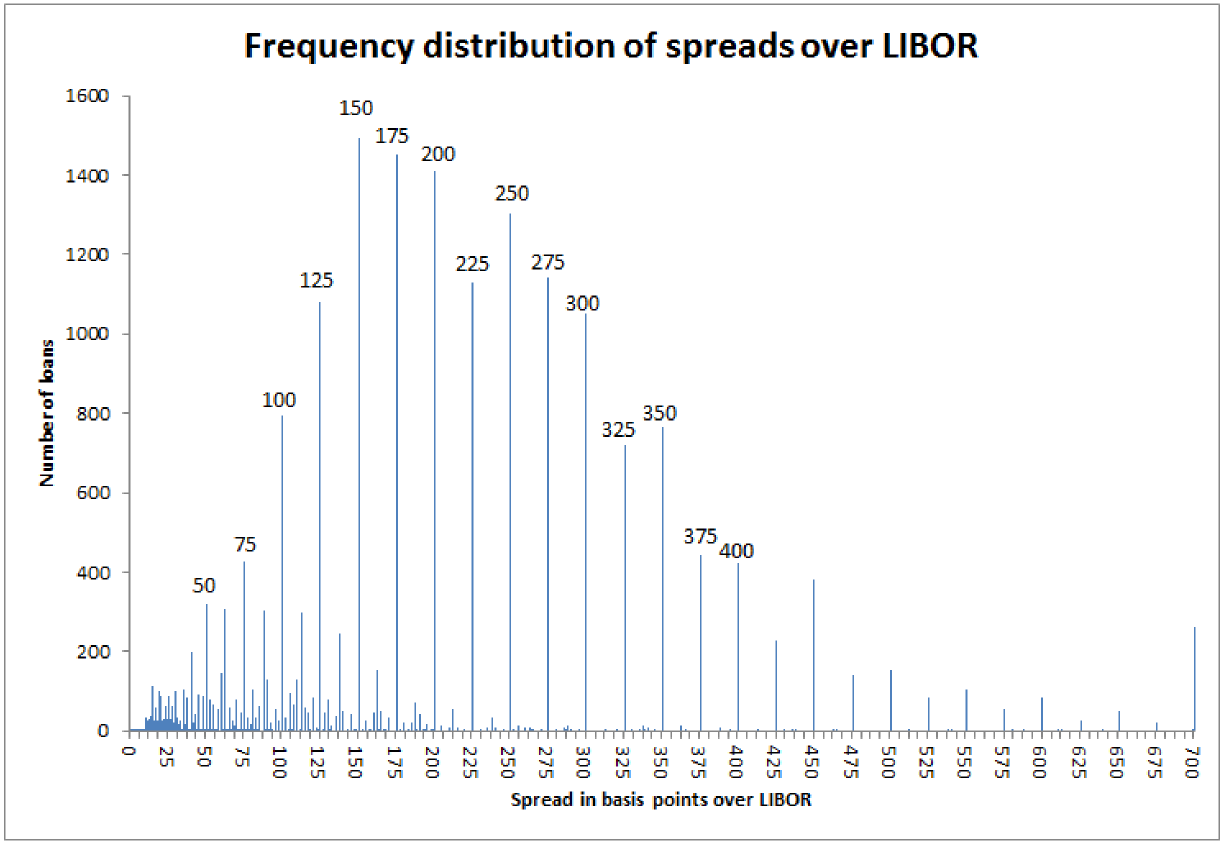

Figure 1: This figure shows the frequency distribution of spreads in basis points over LIBOR.

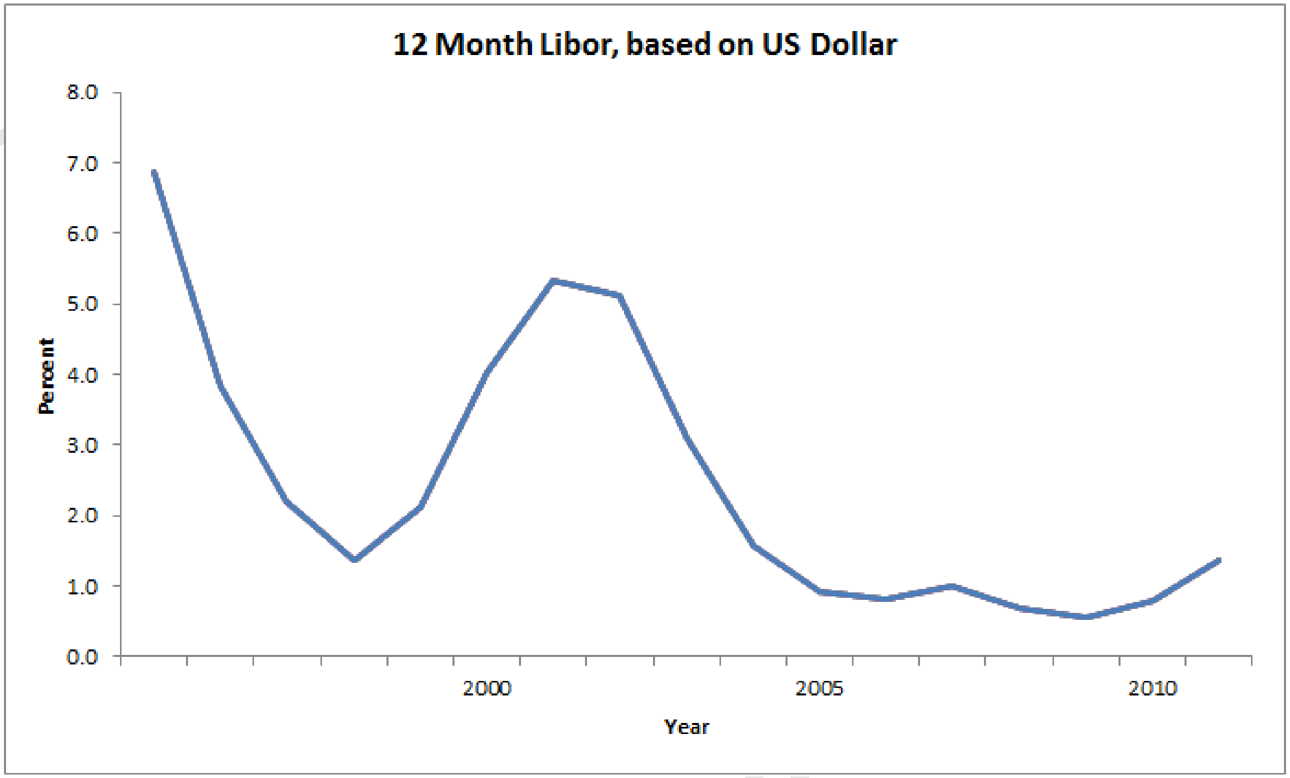

Figure 4: This figure shows the 12-Month LIBOR, based on US dollar from 1995 to 2015.

Table 1: **Summary statistics for syndicated loan tranches**

This table presents summary statistics for the sample of 21,855 syndicated loan tranches representing 4,718 firms from 2000 through 2015. A spread is considered to be rounded if it is a multiple of 25 basis points above LIBOR.

Variable	No of loans	Mean	Median	SD
Firm characteristics				
Unrated	21,855	0.41	0.00	0.49
No Ticker	21,855	0.06	0.00	0.24
Existing borrower	21,855	0.68	1.00	0.47
Lender characteristics				
Top 5 lead arranger	21,855	0.47	0.00	0.50
Former arranger	21,855	0.31	0.00	0.46
Loan characteristics				
Spread	21,855	207.31	175.00	148.50
Loan size	21,855	923.13	424.63	1738.08
Loan to sales ratio	21,855	8.21	0.33	121.10
Maturity in days	21,855	1458	1825	654
Tranche	21,855	0.30	0.00	0.46
Term loan	21,855	0.30	0.00	0.46
Covenant	21,855	0.22	0.00	0.41

Table 2: **Evidence of rounding of spreads**

This table shows evidence of rounding of spreads over LIBOR by using logit regressions. The marginal effect is reported in the top row and the z-statistic is reported in the bottom row. In addition to the reported variables all regressions include year and industry dummies. Standard errors are heteroskedasticity robust and clustered at both the borrower and the lender level.

Dependent variable	Rounded spread dummy					
	(1)		(2)		(3)	
Unrated borrower	0.50	***	0.50	***	0.27	***
	(15.82)		(9.75)		(4.86)	
Private borrower	0.31	***	0.31	**	0.27	**
	(4.52)		(2.30)		(2.11)	
Borrower size					-0.30	***
					(-12.78)	
Loan to sales ratio					-0.01	
					(-0.73)	
Tranche					0.30	***
					(5.88)	
Term loan					1.37	***
					(21.54)	
Year dummies	no		no		no	
Industry dummies	no		no		no	
Borrower and lender fixed effects	no		yes		yes	
Log pseudolikelihood	-12,891.96		-12,891.96		-11,950.56	
Pseudo R^2	0.106		0.106		0.083	
N	21,855		21,855		21,855	

*Significant at the 10% level, **significant at 5% level, ***significant at 1% level.

Table 3: **Evidence of rounding of spreads**

This table shows evidence of rounding of spreads over LIBOR by using logit regressions. The marginal effect is reported in the top row and the z-statistic is reported in the bottom row. In addition to the reported variables all regressions include year and industry dummies. Standard errors are heteroskedasticity robust and clustered at both the borrower and the lender level.

Dependent variable	Rounded spread dummy					
	(1)		(2)		(3)	
Opaque borrower	0.32	***	0.29	***	0.29	***
	(5.52)		(4.97)		(4.94)	
Existing borrower			-0.28	***	-0.22	***
			(-4.78)		(-3.45)	
Former lender					-0.14	**
					(-2.10)	
Borrower size	-0.39	***	-0.38	***	-0.38	***
	(-15.31)		(-14.79)		(-14.80)	
Loan to sales ratio	-0.02		-0.02		-0.02	
	(-1.32)		(-1.43)		(-1.46)	
Tranche	0.34	***	0.33	***	0.33	***
	(6.57)		(6.41)		(6.37)	
Term loan	1.22	***	1.22	***	1.22	***
	(18.90)		(18.96)		(18.89)	
Ln(maturity)	0.40	***	0.39	***	0.39	***
	(10.22)		(9.98)		(9.92)	
Covenant	0.22	***	0.20	***	0.20	***
	(2.88)		(2.65)		(2.60)	
Year dummies	yes		yes		yes	
Industry dummies	yes		yes		yes	
Borrower and lender fixed effects	yes		yes		yes	
Log pseudolikelihood	-10,772.36		-10,746.45		-10,741.10	
Pseudo R^2	0.173		0.175		0.176	
N	21,855		21,855		21,855	

*Significant at the 10% level, **significant at 5% level, ***significant at 1% level.

Table 4: **Summary statistics for syndicated loan tranches with rounded and non-rounded spreads**

This table presents summary statistics for the subsample of 15,659 syndicated loan tranches with rounded spreads and 6,196 loan tranches with non-rounded spreads from January 2000 through December 2015. A spread is considered to be rounded if it is a multiple of 25 basis points above LIBOR.

	Loans with rounded spread				Loans with non-rounded spread			
Variable	No of loans	Mean	Median	SD	No of loans	Mean	Median	SD
Firm characteristics								
Opaque	15,659	0.48	0.00	0.50	6,196	0.36	0.00	0.48
Existing borrower	15,659	0.66	1.00	0.47	6,196	0.74	1.00	0.44
Lender characteristics								
Top 5 lead arranger	15,659	0.44	0.00	0.50	6,196	0.54	1.00	0.50
Former arranger	15,659	0.30	0.00	0.46	6,196	0.33	0.00	0.47
Loan characteristics								
Spread	15,659	254.21	225.00	144.30	6,196	88.79	72.50	74.40
Loan size	15,659	823.66	370.00	1596.70	6,196	1174.52	539.23	2030.98
Loan to sales ratio	15,659	7.60	0.29	117.00	6,196	9.77	0.41	131.00
Maturity in days	15,659	1541	1825	624	6,196	1248	1460	683
Tranche	15,659	0.34	0.00	0.47	6,196	0.21	0.00	0.41
Term loan	15,659	0.36	0.00	0.48	6,196	0.12	0.00	0.33
Covenant	15,659	0.21	0.00	0.41	6,196	0.24	0.00	0.43

Table 5: **Evidence of upward rounding of spreads**

This table shows evidence of upward rounding of spreads over LIBOR by using OLS regression. For each independent variable, the coefficient is reported in the top row and the t-statistic is reported in the bottom row. In addition to the reported variables all regressions include year and industry dummies. Standard errors are heteroscedasticity robust and clustered at the borrower and the lender level.

Dependent variable	Spread above LIBOR			
	(1)		(2)	
Rounded spread	125.38	***	104.57	***
	(47.20)		(43.15)	
RatingB	73.97	***	57.75	***
	(22.46)		(19.30)	
RatingC	218.60	***	189.73	***
	(9.66)		(9.41)	
RatingD	225.92	***	201.26	***
	(11.97)		(11.23)	
Unrated borrower	62.54	***	50.40	***
	(16.14)		(14.35)	
Borrower size	-11.09	***	-14.89	***
	(-8.76)		(-12.71)	
Loan to sales ratio	1.16	*	0.47	
	(1.91)		(0.95)	
Tranche			15.8	
			(6.19)	
Term loan			85.27	***
			(28.52)	
Ln(maturity)			2.29	***
			(0.98)	
Covenant			-1.87	
			(-0.55)	
Year dummies	yes		yes	
Industry dummies	yes		yes	
Borrower and lender fixed effects	yes		yes	
R^2	0.362		0.436	
N	21,855		21,855	

*Significant at the 10% level, **significant at 5% level, ***significant at 1% level

Table 6: **Unobserved credit risk is not related to rounding**

This table shows evidence that unobserved credit risk is not related to rounding of spreads over LIBOR by using logit regressions. The marginal effect is reported in the top row and the z-statistic is reported in the bottom row. In addition to the reported variables all regressions include year and industry dummies. Standard errors are heteroscedasticity robust and clustered at the borrower and the lender level.

Dependent variable	Spread above LIBOR			
	(1)		(2)	
Opaque borrower	0.25	***	0.29	***
	(4.25)		(4.94)	
Residual	0.00		0.00	
	(-0.04)		(0.72)	
Existing borrower	-0.25	***	-0.22	***
	(-3.88)		(-3.44)	
Former lender	-0.22	***	-0.14	**
	(-3.19)		(-2.09)	
Borrower size	-0.32	***	-0.38	***
	(-12.34)		(-14.83)	
Loan to sales ratio	-0.01		-0.02	
	(-0.56)		(-1.46)	
Tranche			0.33	***
			(6.38)	
Term loan			1.22	***
			(18.84)	
Ln(maturity)			0.39	***
			(9.93)	
Covenant			0.19	***
			(2.59)	
Year dummies	yes		yes	
Industry dummies	yes		yes	
Borrower and lender fixed effects	yes		yes	
Log pseudolikelihood	-11,536.55		-10,740.54	
Pseudo R^2	0.115		0.176	
N	21,855		21,855	

*Significant at the 10% level, **significant at 5% level, ***significant at 1% level

Table 7: **Intertemporal changes in spread over LIBOR**

This table shows intertemporal changes in spreads over LIBOR by using OLS regression. For each independent variable, the coefficient is reported in the top row and the t-statistic is reported in the bottom row. In addition to the reported variables all regressions include year and industry dummies. Standard errors are heteroscedasticity robust and clustered at the borrower and the lender level.

Dependent variable	Spread above LIBOR			
	(1)		(2)	
	Subsample from 2000 to 2005		Subsample from 2009 to 2015	
Rounded spread	118.66	***	87.12	***
	(27.22)		(27.39)	
RatingB	44.56	***	74.49	***
	(10.02)		(17.51)	
RatingC	147.97	***	210.76	***
	(4.10)		(7.71)	
RatingD	130.69	***	302.36	***
	(9.17)		(8.42)	
Unrated borrower	35.61	***	62.73	***
	(7.06)		(12.31)	
Borrower size	-10.88	***	-20.74	***
	(-5.75)		(-12.40)	
Loan to sales ratio	1.77		0.55	
	(0.80)		(1.05)	
Tranche	7.41		23.43	***
	(1.48)		(6.80)	
Term loan	76.41	***	95.47	***
	(13.34)		(23.78)	
Ln(maturity)	8.33	**	-1.65	
	(2.39)		(-0.38)	
Covenant	10.03	**	-32.02	***
	(2.34)		(-5.84)	
Year dummies	yes		yes	
Industry dummies	yes		yes	
Borrower and lender fixed effects	yes		yes	
R^2	0.505		0.352	
N	8,915		9,685	

*Significant at the 10% level, **significant at 5% level, ***significant at 1% level

Table 8: **Level of rounded spread over different ranges of spread over LIBOR**

This table shows level of rounded spread over different ranges of spread over LIBOR by using OLS regression. For each independent variable, the coefficient is reported in the top row and the t-statistic is reported in the bottom row. In addition to the reported variables all regressions include year and industry dummies. Standard errors are heteroscedasticity robust and clustered at the borrower and the lender level.

Dependent variable	Spread above LIBOR					
	(1)		(2)		(3)	
	Subsample with spread over LIBOR from 0 to 99		Subsample with spread over LIBOR from 100 to 199		Subsample with spread over LIBOR above 199	
Rounded spread	8.03	***	8.24	***	22.55	***
	(7.71)		(8.27)		(2.91)	
RatingB	22.49	***	21.43	***	28.47	***
	(19.27)		(11.12)		(2.75)	
RatingC	3.45		34.66	***	135.97	***
	(0.28)		(4.84)		(5.78)	
RatingD					122.32	***
					(5.76)	
Unrated borrower	15.24	***	22.36	***	30.20	***
	(11.49)		(11.00)		(2.89)	
Borrower size	-4.29	***	-1.40	***	-10.18	***
	(-8.78)		(-3.03)		(-5.76)	
Loan to sales ratio	0.51	**	0.25		-0.21	
	(2.21)		(0.77)		(-0.39)	
Tranche	-0.16		3.47	***	7.58	**
	(-0.16)		(3.86)		(2.05)	
Term loan	6.81	***	7.50	***	72.46	***
	(3.60)		(7.83)		(18.64)	
Ln(maturity)	1.92	***	1.49	*	-18.25	***
	(3.22)		(1.95)		(-4.57)	
Covenant	4.32	***	0.96		-22.66	***
	(3.18)		(0.71)		(-4.21)	
Year dummies	yes		yes		yes	
Industry dummies	yes		yes		yes	
Borrower and lender fixed effects	yes		yes		yes	
R^2	0.415		0.123		0.147	
N	4,763		6,742		10,350	

*Significant at the 10% level, **significant at 5% level, ***significant at 1% level

Table 9: **Evidence of rounding of spreads by the type of industry**

This table shows evidence of rounding of spreads over LIBOR by the type of industry using logit regressions. The marginal effect is reported in the top row and the z-statistic is reported in the bottom row. In addition to the reported variables all regressions include year dummies. Standard errors are heteroskedasticity robust and clustered at the borrower level only.

Dependent variable	Rounded spread dummy				
	(1)	(2)	(3)	(4)	(5)
	Engery and Power	Industrials	Materials	Consumer Products and Services	Technology
Opaque borrower	0.55 ***	0.16	0.53 ***	0.46 **	0.40 *
	(4.14)	(1.07)	(2.64)	(2.28)	(1.81)
Borrower size	-0.28 ***	-0.41 ***	-0.36 ***	-0.37 ***	-0.61 ***
	(-4.78)	(-6.00)	(-4.23)	(-3.84)	(-6.17)
Loan to sales ratio	-0.03	0.16	0.60	0.03	0.36
	(-1.48)	(0.72)	(1.26)	(0.20)	(1.14)
Tranche	0.17	0.48 ***	-0.14	0.28	0.70 ***
	(1.39)	(3.30)	(-0.77)	(1.51)	(2.98)
Term loan	1.51 ***	1.60 ***	1.12 ***	1.46 ***	1.34 ***
	(7.91)	(7.49)	(5.20)	(6.35)	(5.73)
Ln(maturity)	0.30 ***	0.35 ***	0.51 ***	0.44 ***	0.44 **
	(3.29)	(3.28)	(3.88)	(3.12)	(2.40)
Covenant	0.64 ***	0.13	0.05	0.09	0.51 *
	(3.37)	(0.65)	(0.20)	(0.36)	(1.66)
Year dummies	yes	yes	yes	yes	yes
Borrower and lender fixed effects	yes	yes	yes	yes	yes
Log pseudolikelihood	-1,974.08	-1,494.80	-985.93	-804.85	-720.03
Pseudo R2	0.145	0.172	0.152	0.172	0.234
N	3,575	3,127	1,899	1,838	1,882

*Significant at the 10% level, **significant at 5% level, ***significant at 1% level

Table 10: **Interest rate clustering before, during and after the financial crisis**

This table shows evidence of rounding of spreads over LIBOR before, during and after the financial crisis by using logit regressions. The marginal effect is reported in the top row and the z-statistic is reported in the bottom row. In addition to the reported variables all regressions include year and industry dummies. Standard errors are heteroskedasticity robust and clustered at both the borrower and lender level.

Dependent variable	Rounded spread dummy					
	(1)		(2)		(3)	
	Subsample from 2000 to 2007		Subsample from 2008 to 2010		Subsample from 2011 to 2015	
Opaque borrower	0.35	***	0.55	***	0.23	***
	(4.38)		(3.17)		(2.66)	
Borrower size	-0.43	***	-0.39	***	-0.32	***
	(-11.65)		(-4.81)		(-9.30)	
Loan to sales ratio	-0.05		-0.05		-0.01	
	(-1.16)		(-0.62)		(-0.58)	
Tranche	-0.06		0.62	***	0.62	***
	(-0.77)		(3.27)		(8.28)	
Term loan	1.91	***	0.70	***	0.74	***
	(16.04)		(3.95)		(9.57)	
Ln(maturity)	0.60	***	0.33	***	-0.11	
	(10.83)		(2.94)		(-1.50)	
Covenant	0.27	***	0.00		-0.19	
	(2.98)		0.00		(-1.57)	
Year dummies	yes		yes		yes	
Industry dummies	yes		yes		yes	
Borrower and lender fixed effects	yes		yes		yes	
Log pseudolikelihood	-6,083.34		-893.72		-3,570.39	
Pseudo R2	0.181		0.137		0.122	
N	11,224		2,521		8,093	

*Significant at the 10% level, **significant at 5% level, ***significant at 1% level.

Table 11: **Evidence against tacit collusion hypothesis**

This table shows evidence against tacit collusion hypothesis by using logit regressions. The marginal effect is reported in the top row and the z-statistic is reported in the bottom row. In addition to the reported variables all regressions include year and industry dummies. Standard errors are heteroskedasticity robust and clustered at both the borrower and the lender level.

Dependent variable	Spread above LIBOR			
	(1)		(2)	
Opaque borrower	0.28	***	0.28	***
	(4.74)		(4.73)	
Top 5 lead arranger	-0.32	***	-0.31	***
	(-5.37)		(-5.19)	
Existing borrower	-0.27	***	-0.24	***
	(-4.63)		(-3.76)	
Former lender			-0.07	
			(-1.04)	
Borrower size	-0.37	***	-0.37	***
	(-14.51)		(-14.52)	
Loan to sales ratio	-0.03		-0.03	
	(-1.49)		(-1.50)	
Tranche	0.32	***	0.32	***
	-6.21		-6.19	
Term loan	1.19	***	1.19	***
	(18.46)		(18.44)	
Ln(maturity)	0.4	***	0.39	***
	(9.97)		(9.95)	
Covenant	0.13	*	0.13	*
	(1.75)		(1.76)	
Year dummies	yes		yes	
Industry dummies	yes		yes	
Borrower and lender fixed effects	yes		yes	
Log pseudolikelihood	-10,704.64		-10,703.37	
Pseudo R^2	0.179		0.179	
N	21,855		21,855	

*Significant at the 10% level, **significant at 5% level, ***significant at 1% level

Table 12: **Evidence of rounding of spreads with clustered at borrower level only**

This table shows evidence of rounding of spreads over LIBOR by using logit regressions. The marginal effect is reported in the top row and the z-statistic is reported in the bottom row. In addition to the reported variables all regressions include year and industry dummies. Standard errors are heteroskedasticity robust and clustered at the borrower level only.

Dependent variable	Rounded spread dummy											
	(1)		(2)		(3)		(4)		(5)		(6)	
Opaque borrower	0.50	***	0.50	***	0.28	***	0.32	***	0.29	***	0.29	***
	(16.05)		(8.53)		(4.62)		(5.10)		(4.60)		(4.57)	
Existing borrower									-0.28	***	-0.22	***
									(-4.61)		(-3.34)	
Former lender											-0.14	**
											(-2.12)	
Borrower size					-0.30	***	-0.39	***	-0.38	***	-0.38	***
					(-11.39)		(-13.87)		(-13.39)		(-13.40)	
Loan to sales ratio					-0.01		-0.02		-0.02		-0.02	
					(-0.49)		(-1.12)		(-1.23)		(-1.25)	
Tranche					0.30	***	0.34	***	0.33	***	0.33	***
					(5.49)		(6.37)		(6.22)		(6.18)	
Term loan					1.37	***	1.22	***	1.22	***	1.22	***
					(19.26)		(17.63)		(17.69)		-17.61	
Ln(maturity)							0.40	***	0.39	***	0.39	***
							(9.84)		(9.61)		-9.56	
Covenant							0.22	***	0.20	**	0.20	**
							(2.74)		(2.52)		(2.48)	
Year dummies	no		no		no		yes		yes		yes	
Industry dummies	no		no		no		yes		yes		yes	
Borrower fixed effects	no		yes		yes		yes		yes		yes	
Log pseudolikelihood	-12,899.20		-12,899.20		-11,953.92		-10,772.36		-10,746.45		-10,741.10	
Pseudo R^2	0.010		0.010		0.083		0.173		0.175		0.176	
N	21,855		21,855		21,855		21,855		21,855		21,855	

*Significant at the 10% level, **significant at 5% level, ***significant at 1% level

Table 13: **Evidence of rounding of spreads for non-financial firms only**

This table shows evidence of rounding of spreads over LIBOR for non-financial firms only by using logit regressions. The marginal effect is reported in the top row and the z-statistic is reported in the bottom row. In addition to the reported variables all regressions include year and industry dummies. Standard errors are heteroskedasticity robust and clustered at the borrower and the lender level only.

Dependent variable	Rounded spread dummy											
	(1)		(2)		(3)		(4)		(5)		(6)	
Opaque borrower	0.51	***	0.51	***	0.32	***	0.33	***	0.30	***	0.30	***
	(15.88)		(9.54)		(5.48)		(5.46)		(4.86)		-4.84	
Existing borrower									-0.31	***	-0.25	***
									(-5.15)		(-3.73)	
Former lender											-0.16	**
											(-2.31)	
Borrower size					-0.28	***	-0.38	***	-0.37	***	-0.37	***
					(-11.51)		(-14.27)		(-13.74)		(-13.73)	
Loan to sales ratio					-0.01		-0.02		-0.02		-0.02	
					(-0.59)		(-1.19)		(-1.28)		(-1.32)	
Tranche					0.31	***	0.35	***	0.34	***	0.34	***
					(5.87)		(6.41)		(6.23)		-6.18	
Term loan					1.33	***	1.20	***	1.20	***	1.20	***
					(20.38)		(18.18)		(18.25)		-18.18	
Ln(maturity)							0.42	***	0.41	***	0.41	***
							(10.17)		(9.91)		-9.85	
Covenant							0.23	***	0.22	***	0.21	***
							(2.97)		(2.76)		(2.71)	
Year dummies	no		no		no		yes		yes		yes	
Industry dummies	no		no		no		yes		yes		yes	
Borrower fixed effects	no		yes		yes		yes		yes		yes	
Log pseudolikelihood	-11,933.99		-11,933.99		-11,104.58		-10,002.00		-9,971.86		-9,965.36	
Pseudo R^2	0.107		0.107		0.0794		0.1708		0.1733		0.1739	
N	20,417		20,417		20,417		20,417		20,417		20,417	

*Significant at the 10% level, **significant at 5% level, ***significant at 1% level