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November 2023

WP 2023-44

https://doi.org/10.21033/wp-2023-44

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What Do Lead Banks Learn from Leveraged Loan Investors?*

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November 2023

Abstract

In leveraged loan deals, lead banks use bookbuilding to extract price-relevant information from syndicate participants. This paper examines the content of such information. We find that pricing adjustments during bookbuilding are highly informative, not only about investors' required risk premium but also about borrower quality. A one-percentage-point increase in loan spread predicts a 0.8% higher excess return, a proxy for risk premium, over the first 3 months of secondary market trading. More importantly, it also predicts a 3% higher probability of subsequent default, implying that investors have private information about borrower quality that is unknown to the lead bank. Our findings suggest a new view of how information asymmetries affect syndicated lending.

JEL classifications: G23, G24, G30
Keywords: syndicated loans, leveraged loans, underwriting

*The views expressed in this paper are those of the authors and do not necessarily reflect the position of the Federal Reserve System. We would like to thank Robert Marquez as well as seminar participants at the USC Macro-Banking Reading Group, the Federal Reserve Board, and the City University of Hong Kong for helpful comments.

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1 Introduction

In many theories of lending, the key players are institutions with informational advantages. In the context of syndicated lending, it is a common view that lead banks have better information about borrower quality than syndicate participants. If a lead bank has better information about the borrower, it should set the terms of the loan and then convince the potential participants that these terms are correct. However, lead banks often run a bookbuilding process to determine the final loan terms. If lead banks already have better information about borrowers, then why do they need to engage in bookbuilding to obtain information from the participants who invest in the loans?

Bookbuilding extracts information about investors' valuation of the loan. Fundamentally, a valuation consists of two components: an expected cash flow and a risk premium. Hence, two types of information could be extracted via bookbuilding. First, investors may have information about the appropriate risk premium for the loan that the lead bank does not have. Second, investors might have information about expected cash flows—that is, about borrower quality—that the lead bank does not have. However, this would contrast with the common view that investors are unlikely to know anything substantial about borrowers that lead banks do not know. Distinguishing between these two types of information is therefore important for our understanding of the role of lead banks in syndicated lending and of underwriters more generally.

In this paper, we empirically examine the content of information extracted from investors during bookbuilding. We focus on the market for leveraged loans. Leveraged loans are non-investment-grade syndicated loans that finance, e.g., leveraged buyouts. In this large, trillion-dollar market, banks arrange the loans but sell them almost exclusively to institutional investors such as collateralized loan obligations (CLOs) and specialized funds. We provide evidence that lead banks use bookbuilding to extract information that investors have about the required risk premium for the loan, but also extract information about the probability of default (and, hence, expected cash flows). Our results imply that models of asymmetric information in which only the lead bank is privately informed about borrower quality are therefore an incomplete description of reality.

Following the literature, we use the change between initial loan terms proposed by the lead bank and final loan terms at deal completion as a proxy for the private information of investors revealed during the bookbuilding process. We summarize these changes as an adjustment in the proposed spread (or yield) of the loan and, using the language of market participants, refer to it as the "effective spread flex." To see whether effective spread flex contains information about the probability of default or a risk premium, we examine whether it predicts future default or excess returns on the loans, controlling for observable variables in the lead bank's information set at the deal's launch date.

We test our hypotheses using a sample of broadly syndicated leveraged loan deals between 2000–2020. We calculate effective spread flex using data from Pitchbook's Leveraged Commentary & Data, which provides detailed information on loan facilities within each deal, including the initial and finalized loan terms. We supplement this dataset with Moody's Default and Recovery Database and Fitch's LevFin Insights for additional information on defaults and credit ratings, and S&P's IHS Markit for secondary market prices and returns of the loans.

When investors express too little interest in a loan at the terms proposed by the lead bank, the lead bank makes the loan more attractive by increasing the spread. We show that an increase in the spread during bookbuilding of 100 basis points (i.e., an "effective spread flex" of +100bp) predicts a default rate that is about 3-4% higher than for loans in which the spread is not increased. This result holds after controlling for a large set of ex-ante observable variables, including the spread initially proposed by the bank. An increase of 100 basis points is relatively large (about 2 standard deviations), but the outcome that it is associated with is also large relative to the unconditional default rate of about 4% – the default rate nearly doubles.

The large magnitude of the relationship also makes this result practically relevant. Lead banks are exposed to "pipeline risk," that is, the risk that they may have to retain parts of loans on which they have to flex up the spread (Bruche, Malherbe, and Meisenzahl, 2020). Our results here suggest that the loans that lead banks end up retaining are precisely those loans on which they substantially underestimated the credit risk.

We also check whether spread flex predicts excess returns, which can be interpreted as a measure of the risk premium required by investors. We show that an increase in the spread during bookbuilding of 100 basis points (i.e., an "effective spread flex" of +100bp) predicts an excess return on the loan that is about 0.8% higher over a horizon of three months and 0.9% higher over a horizon of six months than for a loan in which the spread is not increased.

We conduct several robustness checks of our main result, that spread flex positively predicts subsequent default. We show that it holds across different subsets of the data and is not sensitive to the time horizons over which default is measured. Consistent with models of bookbuilding, the predictive relationship is more sensitive to downward flexes and holds strongly for newly-issued loans but not for loans that are being refinanced. We also show that spread flex predicts other negative credit events, in particular, downgrades and withdrawals of the borrower's credit ratings.

Related literature There are two theoretical approaches to describing loan sales.

In the first view, "the bank knows best" – the bank has better information than investors about "borrower quality" or is better at obtaining such information. The starting point is that banks exist to acquire better information about potential borrowers than other market participants (Diamond, 1984). When banks arrange and then attempt to sell a loan, the private information they obtain about borrower quality affects how they can do so – they may have to retain specific parts of the loan to signal or to commit to monitoring (Pennacchi, 1988; Gorton and Pennacchi, 1995; Sufi, 2007; Ivashina, 2009). Alternatively, if they maintain a high enough reputation with investors they may be able to sell the entire loan (Chemmanur and Fulghieri, 1994; Booth and Smith II, 1986).

In the second view, "investors know best" – they have better information than the bank, and banks have to extract this information via bookbuilding. For instance, Baron and Holmström (1980) discuss how a borrower should design contracts with the underwriter to mitigate private information that an underwriter obtains from investors via bookbuilding. Benveniste and Spindt (1989) explicitly model the bookbuilding procedure as a form of auction that extracts information from investors. A key and unique prediction of their model is that banks only "partially adjust" prices upwards in response to positive information revealed by investors, such that an issue will be underpriced when investors reveal positive information (Ibbotson, Sindelar, and Ritter, 1988). There is broad empirical evidence for partial adjustment and, hence, that underwriters extract information from investors, for the case of stocks (Hanley, 1993), syndicated loans (Bruche, Malherbe, and Meisenzahl, 2020), and corporate bonds (Wang, 2021).[1]

The "investors know best" view is typically silent about the nature of the information that investors have and that banks extract via bookbuilding. As argued above, the extent to which the two views are compatible depends on the type of information investors have. It would be possible that banks have better information about borrower quality, but that they still turn to investors to learn about the appropriate risk premium. We contribute to the discussion by showing that the information extracted via bookbuilding is not just about the required risk premium but also about the probability of default (that is, "borrower quality"). This means that models that assumes that "the bank knows best" provide an inaccurate description of loan sales. More accurate models need to allow for bilateral asymmetric information.

Our work is also related to that of Blickle et al. (2020), who show that in many loans, lead banks do not retain shares. Apparently, for these loans, banks do not commit to monitoring via retention. Blickle et al. (2020) conclude that information

[1]In addition, there is also evidence that underwriters favor more knowledgeable investors in bookbuilding (Nikolova, Wang, and Wu, 2020).

asymmetries may be less important than previously thought because investors may have almost as much information as banks. We show that information asymmetries can be bilateral as investors actually have information that lead banks do not have. Our results also help to explain their finding that the loans in which lead banks do retain a share are more likely to default: Banks have to flex up the spread when investors know that the bank has underestimated credit risk. And banks retain shares in loans on which they flex up the spread (Bruche, Malherbe, and Meisenzahl, 2020).

Since our paper investigates the nature of the information that determines willingness to pay in auctions, it is also related to the empirical literature on auctions. In this literature, the predominant question has been whether the information of bidders reflects "private values" or "common values" (see, e.g., Milgrom and Weber (1982) for a discussion). This distinction is about whether bidders could learn something about how much they want to bid from the bidding behavior of other bidders ("common values") or not ("private values").[2] Explicitly testing common values versus private values requires information on individual bids. We do not have this information, but instead use an aggregated quantity summarizing all bids to show that in the aggregate, bids in leveraged loan bookbuilding are driven partially by information about potential default. Since default should matter to all investors, the bookbuilding we examine is likely a situation of "common values."[3]

The tests of private versus common values have been applied in the context of single-unit auctions. But in bookbuilding, bidders can indicate an interest in several units of a security. Bookbuilding is therefore more closely related to multi-unit auctions. Empirical research on multi-unit auctions includes, e.g., Hortaçsu

[2]Empirically, Paarsch (1992) proposes a structural approach to distinguish between the two cases. Laffont and Vuong (1996) argue that parametric assumptions are necessary to make the distinction. More recently, Haile, Hong, and Shum (2003) have suggested that it is possible to detect whether bidders have private values or common values using an approach that does not require parametric assumptions and revolves around the "winner's curse" (Capen, Clapp, and Campbell, 1971).

[3]Since we do not have data on individual bids, we cannot rule out, though, that all bidders in the bookbuilding have the *same* information about default, and hence that a bidder would not learn anything from the bidding behavior of another bidder.

and McAdams (2010), who use the model of Wilson (1979) to examine whether a discriminatory price format or a uniform price format can deliver higher revenues in Turkish treasury auctions. To our knowledge, we are the first to investigate the information of bidders in the context of a type of multi-unit auction.

2 Hypotheses

In this section, we explore how the theoretical and empirical literature describes the information content of price adjustments/ spread flex during bookbuilding and how this motivates our empirical tests.

In the model of Benveniste and Spindt (1989), the bank does not have all price-relevant information and conducts an auction to learn from investors. The central prediction of the theory is that the issuance price incorporates the information learned from investors. Empirically, since the initial price proposed by the bank cannot contain information that it has not yet learned from investors, the difference between the initially proposed price and the final issuance price must therefore reflect the information of investors. Hanley (1993) therefore uses price adjustments during bookbuilding as a proxy for the information revealed by investors. Since we are dealing with loans in which primarily spreads or yields are adjusted, we will use spread adjustments or "spread flex" instead (Bruche, Malherbe, and Meisenzahl, 2020). (See Appendix A.1 for a more formal argument.)

Also, the final secondary market price incorporating all information (including that revealed through the bookbuilding process) can, like all prices, be decomposed into an expected cash flow component and a risk premium. We ask whether the value-relevant information revealed by investors during bookbuilding pertains to the expected cash flow component or the risk premium component or both. To answer our questions, we need measures of expected cash flows and risk premia.

As our main measure of expected cash flow, we choose a default indicator. The theories that afford lead banks an informational advantage typically assume that they have private information about the true probability of default of the borrower. The expectation of the default indicator is this probability of default.

For this reason, a default indicator is the most pertinent measure for our questions.

As our main measure of the risk premium, we choose the excess return of the loan over the risk-free rate. If investors in the secondary market were risk neutral and the risk premium were zero, the expected excess return should be zero. Therefore, an excess return that deviates from zero on average is a measure of the risk premium. (See Appendix A.2 for a more formal argument.)

We formulate two basic hypotheses. If, during bookbuilding, investors indicate that they dislike the loan at the terms proposed by the bank, the bank needs to increase the spread, and spread flex would be positive.

First, investors may dislike the loan because they know that the probability of default is higher than what is indicated by the information available to the bank. If they are correct, on average, default should happen more often for such loans.

Hypothesis 1. *Conditional on information known to the lead bank at the beginning of bookbuilding, spread flex is positively associated with default risk.*

Second, investors may dislike the loan at the proposed terms because they think the risk premium implicit in the terms is insufficient. If they are correct, on average, such loans should have a higher excess return.

Hypothesis 2. *Conditional on information known to the lead bank at the beginning of bookbuilding, spread flex is positively associated with excess return.*

In our context, we interpret the notion of a risk premium very broadly. It describes anything that might explain a deviation from the price that risk-neutral investors would set. For instance, if large trades tend to produce temporary price pressure for a given type of asset (Elkamhi and Nozawa, 2022; Coval and Stafford, 2007), this could also affect price dynamics around offerings of that type of asset (Ivashina and Sun, 2011; Corwin, 2003; Siani, 2022). In the context of our tests, we would describe such dynamics as a (time-varying) risk premium.

We can test both hypotheses by running regressions of the type

$$Y_i = \beta \cdot \mathit{Spread\ Flex}_i + \Gamma' X_i + \epsilon_i \tag{1}$$

where Y_i is either a default indicator for the borrower in deal i or the excess return of the loan in question for deal i, $\textit{Spread Flex}_i$ is the adjustment in the spread during bookbuilding, and our controls X_i include variables that are in the information set of the lead bank at the start of the bookbuilding. Hypotheses 1 and 2 predict that the coefficient β should be positive when Y_i is a default indicator or an excess return, respectively.

An additional implication of the theory that we can test relates to the "partial adjustment." Underpricing should only occur when investors have value-positive information, as in the following numerical example: Suppose that investors indicate that the value should be \$1 lower. Theory predicts that the bank will decrease the price by \$1. Suppose instead that investors indicate that the value should be \$2 higher. Theory predicts that the bank will increase the price by *less* than \$2, e.g., by only \$1. (This is necessary to ensure that it is incentive-compatible for investors to reveal that the price can be raised.) For our purposes, this means that price increases convey more information than price decreases of the same size, or that negative spread flex conveys more information than positive spread flex. This additional implication can be tested via a version of the specification in Equation 1 in which we estimate separate coefficients for the positive parts and negative parts of spread flex, respectively.

3 Data

3.1 Data sources and variable construction

We combine several proprietary datasets for our analysis.

Syndication Deals.We obtain data on leveraged loan syndication deals from Pitchbook's Leveraged Commentary & Data ("LCD"). Between 2000 and 2020, there are a total of 15,871 such deals in LCD that are denominated in US dollars, representing a total of 5,613 unique borrowers.

Each deal consists of one or more loan facilities. We run our analysis at the deal level and aggregate across facilities by putting particular emphasis on the so-called "institutional" facilities. These are the bullet term loans (also called Term Loan B, C, D, or Cov-Lite loans) favored by institutional investors. Since the main target audience for LCD are institutional investors, it provides the most comprehensive information for these "institutional" term loans.

To include a deal in our sample, we require LCD to have information on pricing, amount, and maturity for at least one institutional term loan facility in that deal. There are two relevant elements of pricing: The pread and the discount to par at which the loan is sold (called the "original issue discount" or OID). We always require information on the spread and the OID proposed at the beginning of the bookbuilding process (the "talk" spread and "talk" OID) as well as information on the final spread and OID at issuance. This filter results in a sample of 7,870 deals issued by 2,741 unique borrowers.

We define the pricing of a deal as the pricing of its first-lien institutional loan facility.[4] Following market convention, we combine the two dimensions of deal pricing, namely the spread and OID, into an effective spread, defined as

$$\text{Effective Spread} = \text{Spread} + \frac{\text{Discount}}{4}, \tag{2}$$

where *Discount* is the OID, converted from its original format into a net discount to par format, in basis point. For example, an OID of 0.97 in LCD data is equivalent to a 300-basis-point discount to par. The market convention implicitly assumes that the discount is amortized over an average effective maturity of 4 years to compute a yield or spread (Bruche, Malherbe, and Meisenzahl, 2020). For each deal, we compute the effective spread (at issuance) as well as (the initially proposed) "talk" effective spread.

Our main variable of interest, effective spread flex, is the difference between the effective spread and the talk effective spread.[5] In 36.3% of LCD deals, the talk spread is reported as a range (e.g., 375–400) rather than a numeric value. For these deals, we calculate the effective spread flex as the difference between the

[4]Only 6 deals in our sample include more than one institutional loan facility. We verified that such facilities within the same deal always have identical spread and OID.

[5]Spread flexes and OID flexes are positively correlated (See Figure B.2 in Appendix.

edge of the corresponding range and the effective spread at issuance. If the the effective spread at issuance is within the range, we set the effective spread flex to zero.

Default Events. We track default events using three databases: LCD, Moody's Default and Recovery Database ("DRD"), and LevFin Insights ("LFI", for years from 2016). We define a corporate event as default if it involves any bankruptcy filing, missed interest payments (beyond the grace period), debt restructuring, or distressed exchange. Since no database covers all default events of leveraged loan borrowers, we combine the three databases to improve our measurement of defaults.[6]

In our main tests, we consider all borrower-level default events. We do so by constructing a comprehensive list of default events as follows. First, we manually match LCD's Loan Default List to the borrower's identifier in LCD syndication deals, which generates 472 borrower–default date pairs. Second, we carefully match borrowers in DRD and LCD based on borrower names. This generates 1,909 DRD–LCD borrower pairs, corresponding to 5,173 LCD deals and 442 borrower–default date pairs according to DRD. Third, we match LFI-reported default events with borrowers in LCD, which yields 217 borrower–default date pairs. Finally, we append all default events above and remove duplicate records if the same LCD borrower is reported to default by multiple databases with default dates within 60 calendar days. This procedure results in 846 default events between 2000–2022.

[Insert Figure 2 here]

Figure 2 summarizes the annual number of borrower-level default events across these three databases. While some events are reported in more than one database, our combined list captures a considerably larger set of default events. Using this list, we determine a syndication deal as subsequently defaulted if the borrower experiences a default event during a 4-year period after issuance. This choice mit-

[6]The definition of default is consistent across our data sources, with the exception that LCD does not consider distressed exchange events as default.

igates concerns about incomplete loan-level default information and is consistent with the common use of cross-default provisions among senior secured loans.

In our robustness tests, we consider using only default events from either LCD or DRD, measuring borrower-level defaults over various time horizons, or examining deal-level default based on default events of debt instruments within the deal. The results of these tests are discussed in Subsection 4.5.

Credit Ratings. We use Moody's DRD to track changes in credit ratings. For 1,306 borrowers in LCD we can find a matching borrower in DRD. DRD contains data on a total of 8,477 senior secured first lien loans denominated in US dollars for these borrowers. In total, these debt instruments experienced 19,519 long-term rating events between 1995–2022. We convert the original Moody's letter ratings into numerical ratings and construct a borrower–month panel between 2000–2022 that reflects a borrower's current active rating for senior secured first lien debt.[7] Using this panel, we create a sample of LCD deals for which we can track future ratings as well as rating withdrawals.

Secondary Market Prices. We measure secondary market leveraged loan prices using daily price quotes from S&P IHS Markit Loan Pricing Database ("Markit"). There are 35,252 Markit loan facilities with amount and maturity information and at least 12 months of secondary price quotes. We manually match the borrowers of these loans with LCD borrowers based on firm names and get 2,769 matched LCD–Markit borrower pairs. Within each borrower, we apply a strict rule to match Markit loan facilities and LCD deals. Specifically, for any deal in LCD, we select institutional loan facilities of the same borrower in Markit that have the same spread, a similar issuance date (no more than 1 month apart), and a similar amount (no more than a 2% difference). After requiring information on the loan's break date and break price, we have 1,896 LCD deals that are matched with Markit loans.

[7] A larger value of numeric rating corresponds to a better letter rating. Table B.1 details the conversion between letter and numeric ratings. In only 4.3% of borrower–month pairs, the borrower has multiple debt instruments whose current ratings are different, and we take their average as the borrower's current rating.

We then calculate realized holding period returns for these loans based on bid-ask midpoint prices in Markit and 3-month LIBOR from Bloomberg. We measure returns over different n-year horizons, starting from the deal's break date, for n taking values of $\frac{1}{4}$, $\frac{1}{2}$, 1, 2, 3, and 4. For each n-year return, we use the last secondary price observed during a 30-day window that ends $365n$ calendar days after issuance. For every quarter-end date during the n-year period, we calculate an interest payment based on a fixed spread and a floating 3-month LIBOR, which resets at the previous quarter's end.[8] These interest payments are compounded to the final price date based on reinvestment at the prevailing LIBOR rate.[9] Finally, we calculate an annualized n-year holding period return as

$$Return = \Big(\frac{\text{secondary price} + \text{compounded interest payments}}{\text{break price}} - 1\Big)^{1/n}, \tag{3}$$

where the total value of cumulative cash flows is added to the secondary market price to reflect investor payoff from the loan.[10]

CLO Portfolios. Investors often face a maximum permitted portfolio weight for each industry that is meant to prevent excessive industry concentration. Anecdotal evidence suggests that these portfolio limits can affect their demand for loans during bookbuilding. To measure investor portfolio constraints, we obtain data on portfolio holdings of the largest group of leveraged loan investors, Collateralized Loan Obligations (CLOs), from Acuris Creditflux CLO-i database. We begin with 22.3 million loan holding records of 2,824 unique CLOs between 2010–2020.[11] Using Moody's 35 Industry Categories, we calculate an industry-level portfolio weight by aggregating the par amounts of each CLO's loan holdings in a given monthly snapshot, which yields 3.4 million CLO–month–borrower industry trios.

[8]If a quarter is partially included during the period of return measurement, we adjust interest payments for the number of days.

[9]A data limitation is that, when a borrower misses a certain number of interest payments, our return measure would overstate the actual return earned by investors.

[10]This is the return of a portfolio that invests in the loan and in cash. An alternative would be to compute the returns of the portfolio that reinvests coupon payments into the loan. We opt for the first method because it does not require loan prices to be available on all coupon dates and therefore allows us to compute returns for a bigger set of loans.

[11]See Xu (2023) for detailed steps of cleaning this dataset.

It is standard market practice for CLOs to face a 15% portfolio industry limit. For each industry and month, we therefore calculate an average CLO portfolio slackness with respect to this limit as well as the fraction of CLOs that currently exceed this limit. Next, we calculate the average effective spread flex, credit rating, maturity, and total deal amount for LCD syndication deals for each industry in a month. Finally, we combine these loan deal measures with CLO constraint measures to form a panel sample, which consists of 4,224 industry-month observations.

3.2 Summary statistics

Syndication Deals: Main Sample. Panel A of Table 1 presents a summary of our sample of leveraged loan syndication deals. The typical deal has around $600 million loan amount and 6 years of maturity, and the institutional term loan facility has a spread equal to 400 basis points. On average, 4% of deals default over a 4-year period after issuance. Roughly 18% of deals are arranged by a relationship bank, i.e., an institution that served as a lead bank for the borrower during the past 5 years. The vast majority of deals have credit ratings, and more than half of deals have a PE sponsor and a cov-lite loan. 46% of deals include a revolver, but fewer than 10% of deals include Term Loan A or bonds.[12]

[Insert Table 1 here]

While the average effective spread flex is close to zero, there is a large variation across deals: one standard deviation of spread flex is 47 basis points. Panel (a) of Figure 1 displays a histogram of spread flexes for these deals. Consistent with theories that predict lead banks' strategic underpricing, downward flexes appear to have a smaller magnitude than upward flexes: Whereas downward flexes are typically within 100 basis points, a considerable fraction of deals experience upward flexes of more than 100 basis points.

[12]Although we do not conduct an explicit test, these empirical distributions conform to what one would expect if the distribution of the (aggregated) signal of investors was symmetric (see Figure A.2, Appendix A.1).

[Insert Figure 1 here]

Credit Rating Changes Sample. Panel B of Table 1 summarizes our sample of syndication deals for which we can track the changes in Moody's long-term senior secured first lien loan ratings. Among deals for which a rating is available 3 years after issuance, the change in rating is fairly symmetric, with more than 50% of borrowers being either downgraded or upgraded. 5 years after issuance, 45% of the borrowers' ratings disappeared in our borrower–month panel that tracks rating changes, likely because Moody's decided to withdraw the ratings after adverse credit events.[13]

Secondary Market Return Sample. Panel C of Table 1 summarizes our sample of realized loan returns over different time horizons. The average return is higher for shorter horizons, decreasing from 5.0% for the 3-month horizon to below 3% for horizons beyond 2 years. The dispersion of returns is also decreasing in the horizon. As the horizon increases, our sample size declines due to the availability of secondary market quotes.

CLO Portfolio Constraint Sample. Panel D of Table 1 summarizes this sample, where there are 2,508 industry-month pairs with at least 1 deal issued during the month. For most industries, the typical CLO portfolio constraint is not binding: the average slackness is 12%. But there are industry-month pairs for which CLOs are likely constrained. For example, at the 95th percentile, 6% of CLOs are exceeding the 15% limit and hence may refrain from adding loans of the industry into their portfolios.

4 Results

4.1 Does spread flex predict default?

We test Hypothesis 1 in Section 2 using our leveraged loan syndication deals sample. According to this hypothesis, if investors have private information about the

[13]See Moody's Policy for Withdrawal of Credit Ratings for related details.

probability of default that is unknown to the lead bank, spread flex would be positively associated with realized default. Consistent with this prediction, Figure 3 shows a salient pattern: across 5 deal groups formed based on spread flexes during syndication, the frequency of default is clearly higher for deals that experienced larger upward flexes. In particular, among deals with greater than +50 spread flexes, 9.1% defaulted, followed by a 5.0% default frequency among deals with $(0, +50]$ spread flexes. These frequencies are economically large compared to other deal groups, which default with a frequency between 2.6% and 3.7%.

[Insert Figure 3 here]

We conduct univariate tests for these differences in default likelihood. Panel (a) of Table 2 shows that on average, deals that experienced upward spread flexes are 4.5% more likely to default than deals that experienced downward spread flexes, and this difference is highly statistically significant ($t = 6.8$). Panel (b) tests the difference between the extreme groups in Figure 3. The difference in default likelihood is 5.9%, and it is significant at the 1% level. These results provide suggestive evidence for Hypothesis 1.

[Insert Table 2 here]

More precisely, a formal test of Hypothesis 1 would require us to estimate the relationship between spread flex and future default, conditional on the lead bank's information set at the beginning of bookbuilding. We conduct this test by regressing a binary default outcome on spread flex while controlling for a large set of ex-ante variables, including the talk spread initially proposed by the lead bank. To account for the potential impact of lead banks, capital usages, industry heterogeneities, and macroeconomic conditions on spread flex and default, our specifications include several dimensions of fixed effects at the lead bank, deal purpose, borrower industry, and deal month levels.

[Insert Table 3 here]

Table 3 reports our estimation results. In column (1), our point estimate indicates that a one-percentage-point upward flex in the effective spread is associated with a 3.2% higher default likelihood, which is both economically and statistically significant. Column (2) controls for the deal's credit rating, an important proxy for public information about the borrower's default risk. Indeed, there is a strong negative correlation between rating and default, but our estimate for the coefficient of spread flex remains almost the same. In column (3), we also control for talk effective spread proposed by the lead bank. Consistent with that this initial pricing summarizes the lead bank's information at the beginning of book-building, it not only positively predicts default, but also subsumes the predictive power of credit ratings. Nonetheless, our point estimate for spread flex remains quantitatively and qualitatively similar. Column (4) further includes a large set of deal characteristics and still generates a similar estimate. Column (5) uses an alternative specification based on credit rating fixed effects, which addresses any nonlinear relationship between ratings and default. Our estimate for spread flex remains almost the same. Overall, our estimates reject the null hypothesis that spread flex is uncorrelated with default.

[Insert Table 4 here]

If the relationship between spread flex and default is driven by investors' information about borrowers, this relationship should be stronger when investors have more private information. One type of loan for which investors are unlikely to have significant private information is a loan that refinancing an existing loan, because for these loans, lead banks have already interacted with the borrowers and are likely well-informed about their quality. As Panel (b) in Figure 1 shows, non-refi deals exhibit a larger dispersion in spread flexes, suggesting the revelation of more private information. Exploiting this difference in information structures, we re-estimate the specifications in Table 3 with subsamples. Columns (1)–(2) in Table 4 are based on a subsample of non-refinancing deals. Clearly, our estimates for the coefficient of spread flex are qualitatively similar but have larger magnitudes. In contrast, the estimates for this coefficient in columns (3)–(4), which are based on a subsample of refinancing deals, are small and statistically insignificant. Moreover, our estimate for the coefficient of talk spread is larger for refinancing deals, suggesting that for these deals, lead banks have more information about borrowers.

[Insert Table 5 here]

Tables 2–4 have provided evidence that investor demand reveals information about borrower quality that is unknown to the lead bank. Next, we explore a potential nonlinearity in the relationship between spread flex and default. As argued at the end of Section 2, because lead banks partially adjust prices when investors reveal strong demand, the association between spread flex and default should be stronger for more negative flexes. We decompose spread flex into two piecewise-linear variables, defined as $\textit{Spread Flex}^{+} = \max\{\textit{Spread Flex}, 0\}$ and $\textit{Spread Flex}^{-} = \min\{\textit{Spread Flex}, 0\}$, and separately estimate their associations with future default. Moreover, we compare the estimates in subsamples for deals that originate new loans versus deals that refinance existing loans.

In column (1) of Table 5, the estimates for both piecewise-linear variables are statistically significant. The coefficient of $\textit{Spread Flex}^{-}$, 0.032, is 30% greater than that of $\textit{Spread Flex}^{+}$, which is 0.024. This is consistent with a stronger association between spread flex and default for downward flexes. However, the difference is not statistically significant. Column (2) controls for additional deal characteristics and both estimates remain similar. Columns (3)–(4) repeat the regression with subsamples. For non-refinancing deals, point estimates of both spread flex variables are significant and have even greater magnitudes, but for refinancing deals, they both become indistinguishable from zero. These results are consistent with the implications of underpricing.

4.2 Does spread flex predict rating changes?

Our Hypothesis 1 is formulated with a focus on default, but default events are relatively infrequent: the unconditional default rate over a 4-year period is only 4%.

If investor demand revealed during bookbuilding is informative about borrower quality, spread flexes should predict future credit events even before a default materializes. Now we examine an important type of such credit events, namely the changes in the borrower's credit ratings.

[Insert Table 6 here]

We estimate regressions of the borrower's future credit rating changes on spread flexes and report the results in Table 6. Column (1) indicates that a one-percentage-point upward flex predicts an 11% larger likelihood of downgrade over a 3-year period. After controlling for deal variables including original rating and talk effective spread in column (2), this estimate becomes slightly larger. Arguably, the magnitude of this coefficient may understate the changes in credit quality because ratings are often withdrawn after significant credit deterioration. We explore this conjecture by replacing the dependent variable with rating withdrawal after 5 years in column (3). Our point estimate suggests that a one-percentage-point upward flex is associated with a 7.8% larger likelihood of rating withdrawal. Column (4) includes additional deal variables as controls and finds a similar result. Overall, the evidence here is consistent with investor demand revealing private information about borrower quality that is unknown to lead banks.

4.3 Does spread flex reflect risk premium?

Next, we proceed to test Hypothesis 2, which predicts a positive relationship between spread flex during bookbuilding and investors' required risk premium, as measured by the excess return on a loan. Since we will be running regressions that include time fixed effects, and the risk-free rate varies only over time (but not across deals), we can run regressions with the return rather than excess return as a dependent variable.

For all time horizons, we regress loan returns on spread flex and control for original credit rating, talk spread, and the amount and maturity of the loans. We also include month fixed effects, thereby estimating the coefficients using variation across loans within the deal's month.

[Insert Table 7 here]

Table 7 reports our estimation results. Consistent with our argument that expected excess return in the secondary market captures investors' required risk premium, the loans' realized returns are positively correlated with talk effective spread. This correlation is sizable for up to 1-year horizon and vanishes thereafter. Moreover, the loan's amount is negatively correlated with excess returns over all time horizons.

We find strong evidence for a positive association between spread flex and secondary market returns. Column (1) indicates that a one-percentage-point upward flex predicts a $3.0\%/4 \approx 0.8\%$ higher return over the first 3 months of the loan's secondary market trading. This association remains similar in size for the 6-month ($0.15\%/2 \approx 0.8\%$, column (2)) and 1-year (0.7%, column (3)) horizons but becomes insignificant for horizons beyond 2 years (columns (5)–(6)).[14] These results suggest that investor demand revealed during bookbuilding is highly informative about the required risk premium over short time horizons and hence provide evidence for Hypothesis 2.

4.4 Does spread flex reflect investor constraints?

One reason that spread flex predicts returns over short horizons is that investors who participate in bookbuilding may be constrained. If binding portfolio constraints temporarily depress prices, we would observe higher subsequent returns as prices revert. Now we test whether spread flex reflects information about investor constraints during bookbuilding. Specifically, we consider industry-level portfolio constraints faced by CLOs, the largest group of leveraged loan investors, that could drive the required risk premium in syndication deals. Typically, a CLO cannot hold more than 15% of loans from any industry. If real-time portfolio weights are CLO managers' private information, when CLOs are overall constrained from

[14]A potential reason that we do not find a significant positive association over longer time horizons is sample selection: financially distressed borrowers are more likely to have secondary price quotes than borrowers with higher realized loan returns.

buying loans in a particular industry, lead banks of these deals would receive lower demand during bookbuilding and thus may have to flex up the spread.

[Insert Table 8 here]

We use our industry-level monthly panel to test for this prediction. Table 8 reports our results from regressing industry–month average spread flex on measures of CLO portfolio constraints. Our specifications include industry fixed effects and month fixed effects to account for the persistence of industry portfolio weights and macroeconomic conditions. We find that, regardless of which constraint measure we use and whether control variables are included, there is no significant association between CLO constraints and spread flexes: the coefficients are statistically indistinguishable from zero. In other words, there is no evidence that lead banks extract information about investor constraints via the bookbuilding process.

4.5 Robustness

Our main finding, that spread flexes during bookbuilding positively predicts subsequent default, is based on borrower-level default events over a 4-year period after issuance in Subsection 4.1. Now we demonstrate that this finding is not sensitive to the definition or sampling of default events.

First, similar results hold when we use default events covered by only one of the databases. For example, one can replicate our findings exclusively based on LCD data. In Table 9, we track borrower-level default events using only LCD's Loan Default List and reproduce our results in Tables 2–3. Although treating omitted default events outside LCD data as no default leads to a lower average default rate, we find qualitatively similar empirical patterns in Panels A–C.

[Insert Tables 9–10 here]

Likewise, in Table 10, we restrict the sample to LCD deals for which we can track borrower-level default events solely based on DRD. The results still indicate a significant positive association between spread flexes and defaults.

Second, we replace the 4-year horizon in Table 3 with various alternative time horizons over which to measure default events.[15] In columns (1)–(4) of Table 11, we consider 3 years after issuance, from issuance and the contractual maturity, skipping the first year after issuance, or anytime after issuance. Across all these horizons, we find consistent evidence for investors' private information about default likelihood.

[Insert Table 11]

Finally, in Appendix B we discuss our results based on deals for which we can track default events at the deal level rather than at the borrower level. Despite a smaller sample size, we continue to find an economically significant association between spread flexes and default in Figure B.4 and Table B.2.

5 Conclusion

The literature on banks or lead banks in loan syndicates often assumes that lead banks have an informational advantage with respect to borrower quality vis-a-vis potential investors in the syndicate. Yet when banks place leveraged loans, they tend to run a bookbuilding procedure to extract price-relevant information from investors. Whether this fact is consistent with the view that lead banks have an informational advantage depends on the nature of the information extracted from investors. Price-relevant information could be about expected cash flows or about the appropriate risk premium for the loan. We find evidence that during bookbuilding, the lead banks learn not only about the risk premium required by the market but also about default risk–that is, the key determinant of borrower quality. Our findings suggest that investors have private information about borrower quality, which casts doubt on the view that lead banks have an informational advantage vis-a-vis investors. At the very least, the lead bank and syndicate investors *both* have private information about borrower quality.

[15] Figure B.3 in Appendix shows that most default events occur between 1 year and 5 years after syndication deals.

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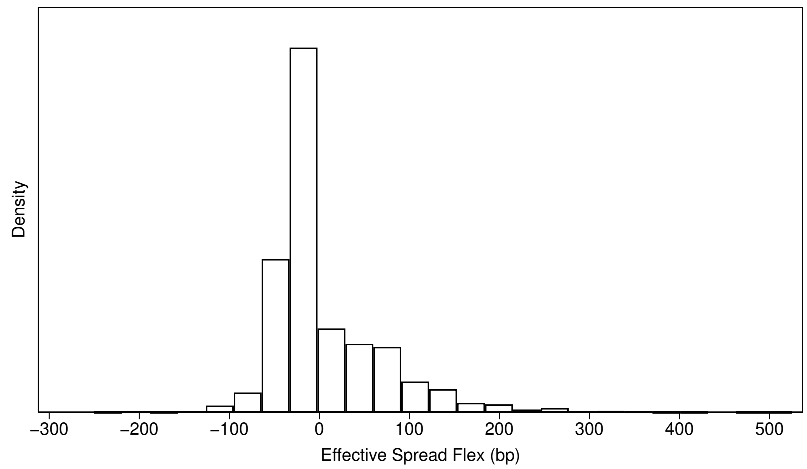
(a) All Sample Deals



(b) Refi versus Non-Refi Deals

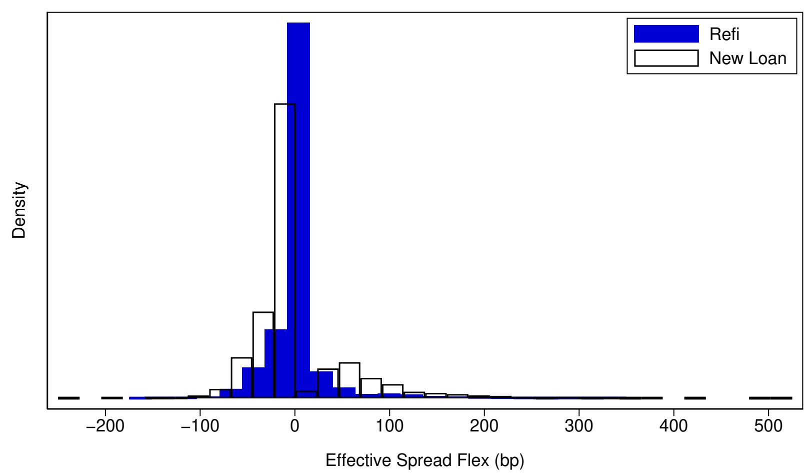


Figure 1. **Distribution of Spread Flex.**
This figure presents the distribution of effective spread flex in syndication deals. Panel A is a histogram of effective spread flex for all syndication deals in our sample. Panel B compares the histograms of refinance deals and other deals. Source: PitchBook Data, Inc.

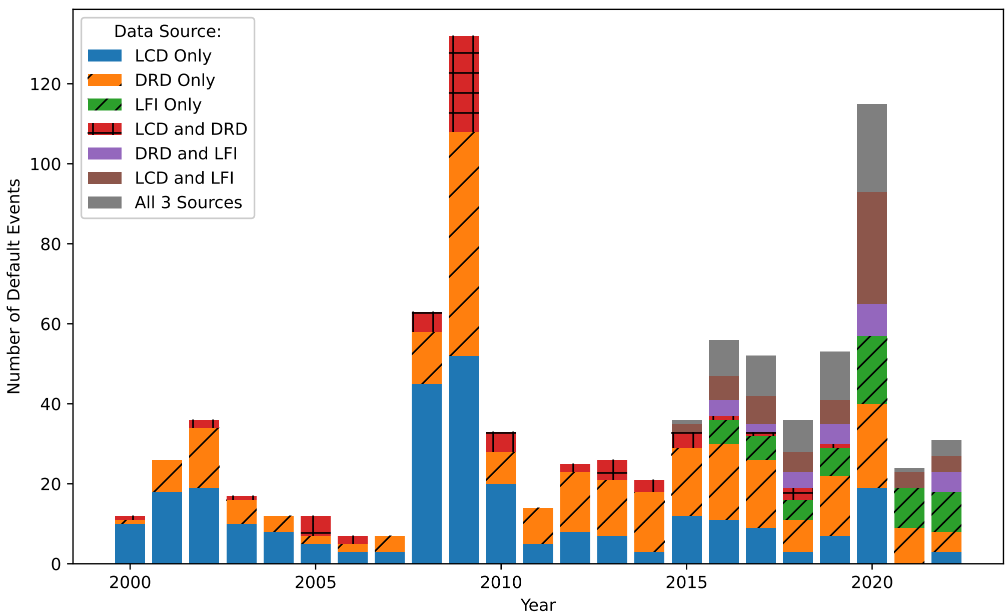


Figure 2. **Leveraged Loan Default Events.**
This figure presents the annual number of default events for borrowers in our deal sample between 2000–2022, as reported by three data sources: Pitchbook's Leveraged Commentary & Data (LCD), Default and Recovery Database (DRD), and LevFin Insights (LFI).

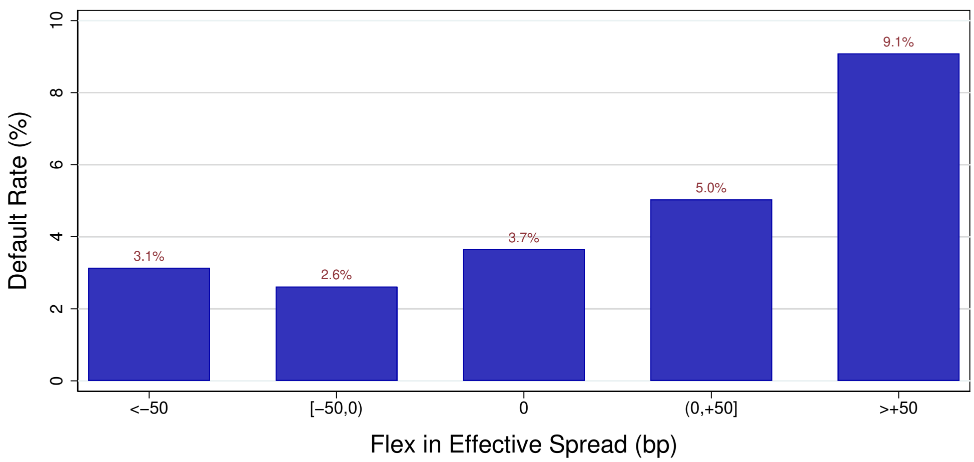


Figure 3. **Spread Flex and Default: Nonparametric Comparison.** This figure presents the fraction of syndication deals that subsequently default. Sample deals are divided into 5 groups based on flex in effective spread during the bookbuilding process.

Source: PitchBook Data, Inc, Default and Recovery Database (DRD), and LevFin Insights (LFI).

Table 1: **Summary Statistics**

This table presents summary statistics for the main variables. Panel A summarizes syndication deals in LCD between 2000–2020. *Default* is a dummy that indicates whether the borrower defaults over a 4-year period after issuance, scaled up by 100. *Spread Flex* is the change in the deal's effective spread during syndication, and *Talk Spread* is the effective spread the lead bank proposed at deal launch. *Credit Rating* is the average of the deal's S&P and Moody's first lien credit ratings, which are converted to numeric values as in Table B.1. *Log(Amount)* and *Log(Maturity)* are logarithms of the total amount and average maturity for term loans in the deal. *Relationship*, *Sponsored*, *Cov Lite*, *Has Revolver*, *Has TLA*, and *Has Bond* are dummies indicating that the deal is arranged by a relationship bank, has a private equity sponsor, includes a cov-lite loan, a revolving credit facility, a term loan A, and a bond, respectively. Panel B summarizes post-issuance changes in Moody's long-term senior secured first lien credit ratings. *Rating Change*, which takes value in $\{-100, 0, +100\}$, indicates downgrade, no change, or upgrade 3 years after issuance. *Rating Withdraw* is a dummy variable indicating whether Moody's has withdrawn rating 5 years after issuance, scaled up by 100. Panel C summarizes annualized secondary market returns over different time horizons for loan facilities in IHS Markit that are matched to LCD syndication deals. Panel D summarizes the industry-month panel for CLO portfolio industry constraints for months between 2010–2020. *CLO Slackness* is CLOs' average portfolio slackness relative to a 15% industry limit for a given industry–month, and *Binding CLOs* is the fraction of CLOs currently exceeding this limit.

Panel A: Syndication Deals

	N	mean	sd	p5	p25	p50	p75	p95
Default	7,870	3.98	19.54	0	0	0	0	0
Spread Flex	7,870	3.9	47.3	-50.0	-12.5	0.0	0.0	100.0
Talk Spread	7,870	427.2	138.6	237.5	337.5	412.5	500.0	662.5
Credit Rating	7,222	7.1	1.5	5.0	6.0	7.0	8.0	10.0
Log(Amount)	7,870	6.0	1.0	4.2	5.4	6.0	6.7	7.6
Log(Maturity)	7,870	1.8	0.2	1.4	1.7	1.8	1.9	1.9
Relationship	7,870	0.18	0.39	0	0	0	0	1
Rated	7,870	0.92	0.27	0	1	1	1	1
Sponsored	7,870	0.67	0.47	0	0	1	1	1
Cov Lite	7,870	0.56	0.50	0	0	1	1	1
Has Revolver	7,870	0.46	0.50	0	0	0	1	1
Has TLA	7,870	0.04	0.20	0	0	0	0	0
Has Bond	7,870	0.09	0.29	0	0	0	0	1

Table 1: **Summary Statistics - Continued**

Panel B: Moody's Credit Rating Changes

	N	mean	sd	p5	p25	p50	p75	p95
Rating Change	2,587	-5.0	78.0	-100	-100	0	100	100
Rating Withdraw	3,070	45.0	49.8	0	0	0	100	100

Panel C: Secondary Market Returns (%)

	N	mean	sd	p5	p25	p50	p75	p95
Return: 3 month	1,889	5.0	8.8	-9.2	2.5	5.4	8.5	16.8
Return: 6 month	1,892	3.6	7.5	-8.1	1.9	4.4	7.0	12.5
Return: 1 year	1,894	3.6	5.5	-4.4	2.8	4.1	5.8	9.5
Return: 2 year	1,195	2.6	5.8	-6.9	2.3	3.7	5.0	7.3
Return: 3 year	771	2.9	4.3	-4.4	2.7	3.7	4.7	6.7
Return: 4 year	456	2.9	4.1	-4.3	2.9	3.8	4.7	6.4

Panel D: CLO Portfolio Industry Constraints

	N	mean	sd	p5	p25	p50	p75	p95
CLO Slackness	4,224	0.12	0.03	0.07	0.10	0.13	0.15	0.15
Binding CLOs	4,224	0.01	0.04	0.00	0.00	0.00	0.01	0.06
Deal Count	4,224	1.8	2.6	0	0	1	2	7
Log(Amount)	4,224	4.2	3.6	0.0	0.0	5.8	7.4	8.7
Log(Maturity)	2,508	1.8	0.2	1.5	1.7	1.8	1.9	1.9
Spread Flex	2,508	3	39	-43	-13	0	9	75
Credit Rating	2,425	7.1	1.2	6	6	7	8	10

Table 2: **Spread Flex and Default: Univariate Tests**

This table reports the results of univariate tests for the relationship between effective spread flex of a syndication deal and the likelihood of subsequent default. Default is determined by whether the borrower defaults over a 4-year period after issuance. Panel A divides sample deals between 2000–2020 into 3 groups depending on whether the deal experiences an upward, downward, or no flex in effective spread. Panel B divides deals into 5 groups based on the range of effective spread flex, measured in basis points. T-tests of the null hypothesis that the two extreme groups have the same likelihood of default are reported in each panel. *, **, *** represent 10%, 5%, and 1% levels of statistical significance.

Panel A: Upward and Downward Flexes

	Spread Flex		
	downward	zero	upward
Default (%)	2.7	3.7	7.2
N	2,640	3,776	1,454
Difference: $7.2\% - 2.7\% = 4.5\%^{***}$ ($t = 6.8$)			

Panel B: Deal Groups By Spread Flex

	Spread Flex (bp)				
	< -50	$[-50, 0)$	0	$(0, +50]$	$> +50$
Default (%)	3.1	2.6	3.7	5.0	9.1
N	350	2,290	3,776	695	759
Difference: $9.1\% - 3.1\% = 5.9\%^{***}$ ($t = 3.6$)					

Table 3: **Spread Flex and Default: Regressions**

This table reports results from estimating predictive regressions of default events. Every observation is a syndication deal between 2000–2020. The dependent variable is a dummy indicating whether the deal's borrower defaults over a 4-year period after issuance, scaled up by 100. *Spread Flex* is the deal's effective spread flex during bookbuilding. *Credit Rating* is the average of the deal's S&P and Moody's first lien credit ratings, which are converted to numeric values as in Table B.1. *Talk Spread* is the effective spread the lead bank proposed at deal launch. *Log(Amount)* and *Log(Maturity)* are logarithms of the total amount and average maturity for term loans in the deal. *Relationship*, *Sponsored*, *Cov Lite*, *Has Revolver*, *Has TLA*, and *Has Bond* are dummies indicating that the deal is arranged by a relationship bank, has a private equity sponsor, includes a cov-lite loan, a revolving credit facility, a term loan A, and a bond, respectively. Standard errors, two-way clustered at the borrower and deal month levels, are reported in parentheses. *, **, *** represent 10%, 5%, and 1% levels of statistical significance.

	(1)	(2)	(3)	(4)	(5)
Spread Flex	0.032***	0.030***	0.026***	0.027***	0.028***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.008)
Credit Rating		-0.981***	0.288	0.087	
		(0.220)	(0.222)	(0.247)	
Talk Spread			0.031***	0.033***	0.033***
			(0.004)	(0.004)	(0.005)
Log(Amount)				0.740**	0.690*
				(0.373)	(0.383)
Log(Maturity)				-3.798**	-3.780**
				(1.671)	(1.727)
Relationship				-0.455	-0.492
				(0.966)	(0.991)
Sponsored				-1.475*	-1.178
				(0.854)	(0.861)
Cov Lite				1.656**	1.760**
				(0.790)	(0.812)
Has Revolver				-1.206**	-1.060
				(0.598)	(0.679)
Has TLA				-0.011	-0.209
				(1.172)	(1.197)
Has Bond				1.697*	1.604*
				(0.897)	(0.956)
Credit Rating FEs	N	N	N	N	Y
Lead Arranger FEs	Y	Y	Y	Y	Y
Deal Purpose FEs	Y	Y	Y	Y	Y
Industry FEs	Y	Y	Y	Y	Y
Month FEs	Y	Y	Y	Y	Y
N	7,818	7,182	7,182	7,182	7,182
R^2	0.091	0.100	0.121	0.126	0.129

Table 4: **Spread Flex and Default: Subsample Analysis**

This table reports results from estimating regressions in Table 3 based on subsamples. Every observation is a syndication deal between 2000–2020. Columns (1)–(2) are based on a subsample that excludes deals for refinance purposes, whereas columns (3)–(4) use only refinancing deals. The dependent variable is a dummy indicating whether the deal's borrower defaults over a 4-year period after issuance, scaled up by 100. *Spread Flex* is the deal's effective spread flex during bookbuilding. *Talk Spread* is effective spread the lead bank proposed at deal launch. Control variables are the same as in column (5) of Table 3. Standard errors, two-way clustered at the borrower and deal month levels, are reported in parentheses. *, **, *** represent 10%, 5%, and 1% levels of statistical significance.

	(1)	(2)	(3)	(4)
	Non-Refi		Refi	
Spread Flex	0.038***	0.037***	0.017	0.003
	(0.008)	(0.009)	(0.016)	(0.017)
Talk Spread		0.025***		0.045***
		(0.005)		(0.008)
Additional Controls	N	Y	N	Y
Credit Rating FEs	N	Y	N	Y
Lead Arranger FEs	Y	Y	Y	Y
Deal Purpose FEs	Y	Y	Y	Y
Industry FEs	Y	Y	Y	Y
Month FEs	Y	Y	Y	Y
N	4,471	3,982	3,309	3,162
R^2	0.120	0.147	0.126	0.179

Table 5: **Spread Flex and Default: Piecewise Linear Specifications**

This table reports results from estimating regressions in Table 3 with piecewise linear specifications. The sample consists of syndication deals between 2000–2020. Column (3) is based on a subsample that excludes deals for refinance purposes, whereas column (4) uses only refinancing deals. The dependent variable is a dummy indicating whether the borrower defaults over a 4-year period after issuance, scaled up by 100. Piecewise linear versions of effective spread flex are defined as $\textit{Spread Flex}^{+} = \max\{\textit{Spread Flex}, 0\}$ and $\textit{Spread Flex}^{-} = \min\{\textit{Spread Flex}, 0\}$. *Talk Spread* is effective spread the lead bank proposed at deal launch. Control variables are the same as in column (5) of Table 3. Standard errors, two-way clustered at the borrower and deal month levels, are reported in parentheses. *, **, *** represent 10%, 5%, and 1% levels of statistical significance.

	(1)	(2)	(3)	(4)
	All Deals		Non-Refi	Refi
Spread Flex^{+}	0.024**	0.025***	0.034***	-0.001
	(0.010)	(0.010)	(0.011)	(0.020)
Spread Flex^{-}	0.032**	0.035**	0.045***	0.014
	(0.014)	(0.015)	(0.015)	(0.032)
Talk Spread	0.031***	0.033***	0.025***	0.045***
	(0.005)	(0.005)	(0.005)	(0.008)
Additional Controls	N	Y	Y	Y
Credit Rating FEs	Y	Y	Y	Y
Lead Arranger FEs	Y	Y	Y	Y
Deal Purpose FEs	Y	Y	Y	Y
Industry FEs	Y	Y	Y	Y
Month FEs	Y	Y	Y	Y
N	7,182	7,182	3,983	3,162
R^2	0.125	0.129	0.148	0.179

Table 6: **Spread Flex and Moody's Rating Changes**

This table reports results from estimating predictive regressions of post-issuance changes in Moody's credit ratings. Every observation is a syndication deal between 2000–2020. In columns (1)–(2), the dependent variable is *Rating Change*, which takes value in $\{-100, 0, +100\}$ and indicates downgrade, no change, or upgrade 3 years after issuance. In columns (3)–(4), the dependent variable *Rating Withdraw* is a dummy indicating whether Moody's has already withdrawn the borrower's senior secured first lien term loan rating 5 years after issuance, scaled up by 100. Control variables are the same as in column (4) of Table 3. Standard errors, two-way clustered at the borrower and deal month levels, are reported in parentheses. *, **, *** represent 10%, 5%, and 1% levels of statistical significance.

	(1)	(2)	(3)	(4)
	Rating Change		Rating Withdraw	
Spread Flex	-0.112***	-0.118***	0.087***	0.065***
	(0.039)	(0.038)	(0.022)	(0.022)
Credit Rating		-6.434***		2.211*
		(1.780)		(1.141)
Talk Spread		-0.087***		0.063***
		(0.024)		(0.014)
Additional Controls	N	Y	N	Y
Lead Bank FEs	Y	Y	Y	Y
Deal Purpose FEs	Y	Y	Y	Y
Industry FEs	Y	Y	Y	Y
Month FEs	Y	Y	Y	Y
N	2,553	2,541	3,020	3,020
R^2	0.139	0.161	0.148	0.172

Table 7: **Spread Flex and Secondary Market Returns**

This table reports results from estimating predictive regressions of secondary market loan returns. Every observation in the sample is a syndication deal in LCD between 2000–2020 for which the term loan facility is matched to IHS Markit secondary market price quotes. The dependent variable is the loan's realized return between the deal's break date and the end of the time horizon, which is 3 months in column (1), 6 months in column (2), 1 year in column (3), 2 years in column (4), and so on. *Credit Rating* is the average of the deal's S&P and Moody's first lien credit ratings, which are converted to numeric values as in Table B.1. *Talk Spread* is effective spread the lead bank proposed at deal launch. Standard errors are clustered at the deal month level and reported in parentheses. *Log(Amount)* and *Log(Maturity)* are logarithms of the total amount and average maturity for term loans in the deal. *, **, *** represent 10%, 5%, and 1% levels of statistical significance.

	(1)	(2)	(3)	(4)	(5)	(6)
	3m	6m	1y	2y	3y	4y
Spread Flex	0.030***	0.015***	0.007**	0.008*	0.000	-0.004
	(0.003)	(0.003)	(0.003)	(0.005)	(0.005)	(0.010)
Credit Rating	0.292**	0.233**	0.085	-0.113	-0.019	0.039
	(0.115)	(0.101)	(0.085)	(0.149)	(0.102)	(0.119)
Talk Spread	0.018***	0.013***	0.007***	-0.001	0.001	-0.000
	(0.002)	(0.002)	(0.001)	(0.003)	(0.002)	(0.003)
Log(Amount)	-0.448**	-0.236	-0.475***	-0.338	-0.503***	-0.660**
	(0.220)	(0.172)	(0.173)	(0.212)	(0.178)	(0.290)
Log(Maturity)	-0.064	-1.085	-0.772	-1.143	2.102	-1.801
	(0.722)	(0.783)	(0.602)	(0.969)	(1.813)	(2.695)
Month FEs	Y	Y	Y	Y	Y	Y
N	1,768	1,771	1,772	1,115	710	410
R^2	0.673	0.631	0.466	0.306	0.259	0.345

Table 8: **CLO Portfolio Industry Constraints and Spread Flex**

This table reports results from estimating regressions of industry–month average leveraged loan deal spread flexes on CLOs' industry portfolio constraints. The sample is an industry-month panel for all Moody's 35 Industry Categories between 2000–2020. The dependent variable is the average effective spread flex across deals in industry i issued during t. The variable of interest, *CLO Constraint*$_{i,t}$, is CLO portfolio constraint for industry i and month t. It is measured with CLOs' average slackness relative to the 15% portfolio industry limit in columns (1)–(2) and the fraction of CLOs whose industry portfolio weights exceed 15% in columns (3)–(4). *Credit Rating* is the average of S&P and Moody's first lien credit ratings, converted to numeric values as in Table B.1, across deals in the industry-month. *Log(Amount)* and *Log(Maturity)* are logarithms of the total amount and average maturity for term loans across deals in the industry. Standard errors are clustered at the deal month level and reported in parentheses. *, **, *** represent 10%, 5%, and 1% levels of statistical significance.

	(1)	(2)	(3)	(4)
CLO Slackness	-60.2	-40.5		
	(53.9)	(53.2)		
Binding CLOs			0.4	-6.8
			(29.9)	(29.1)
Credit Rating		-3.9***		-3.9***
		(0.8)		(0.8)
Log(Amount)		0.4		0.3
		(0.8)		(0.8)
Log(Maturity)		-8.8		-8.8
		(7.9)		(8.0)
Industry FEs	Y	Y	Y	Y
Month FEs	Y	Y	Y	Y
N	2,508	2,425	2,508	2,425
R^2	0.191	0.209	0.191	0.209

Table 9: **Spread Flex and Default: Borrower-Level Defaults in LCD**

This table reports robustness tests using borrower-level default events exclusively based on LCD. The sample consists of all sample deals in LCD between 2000–2020. Panel A and Panel B repeat the analysis in Table 2. Panel A divides deals into 3 groups depending on whether the deal experiences an upward, downward, or no flex in effective spread. Panel B divides deals into 5 groups based on the range of effective spread flex. Panel C reports the results of regressing a dummy indicating default (scaled up by 100) on effective spread flex during the syndication process. Control variables are the same as in Table 3. Standard errors are clustered at the borrower level and reported in parentheses. *, **, *** represent 10%, 5%, and 1% levels of statistical significance.

Panel A: Upward and Downward Flexes

	Effective Spread Flex		
	downward	zero	upward
Default (%)	1.6	2.0	4.5
N	2,640	3,776	1,454
Difference: $4.5\% - 1.6\% = 2.8\%^{***}$ $(t = 5.5)$			

Panel B: Deal Groups By Spread Flex

	Effective Spread Flex (bp)				
	< -50	$[-50, 0)$	0	$(0, +50]$	$> +50$
Default (%)	1.4	1.6	2.0	2.9	5.9
N	350	2,290	3,776	695	759
Difference: $5.9\% - 1.4\% = 3.4\%^{***}$ $(t = 3.4)$					

Panel C: Regressions

	(1)	(2)	(3)	(4)
Effective Spread Flex	0.023***	0.021***	0.018***	0.019***
	(0.006)	(0.006)	(0.006)	(0.006)
Credit Rating		-0.713***	0.247	0.029
		(0.177)	(0.176)	(0.195)
Talk Effective Spread			0.024***	0.025***
			(0.004)	(0.004)
Additional Controls	N	N	N	Y
Lead Bank FEs	Y	Y	Y	Y
Deal Purpose FEs	Y	Y	Y	Y
Industry FEs	Y	Y	Y	Y
Month FEs	Y	Y	Y	Y
N	7,818	7,182	7,182	7,182
R^2	0.083	0.086	0.107	0.111

Table 10: **Spread Flex and Default: Borrower-Level Defaults in DRD**

This table reports robustness tests using borrower-level default events exclusively based on DRD. The sample consists of all sample deals in LCD between 2000–2020. Panel A and Panel B repeat the analysis in Table 2. Panel A divides deals into 3 groups depending on whether the deal experiences an upward, downward, or no flex in effective spread. Panel B divides deals into 5 groups based on the range of effective spread flex. Panel C reports the results of regressing a dummy indicating default (scaled up by 100) on effective spread flex during syndication process. Control variables are the same as in Table 3. Standard errors are clustered at the borrower level and reported in parentheses. *, **, *** represent 10%, 5%, and 1% levels of statistical significance.

Panel A: Upward and Downward Flexes

	downward	zero	upward
Default (%)	1.5	2.0	3.8
N	2,640	3,776	1,454
Difference: $3.8\% - 1.5\% = 2.3\%^{***}$ $(t = 4.7)$			

Panel B: Deal Groups By Spread Flex

	Effective Spread Flex (bp)				
	< -50	$[-50, 0)$	0	$(0, +50]$	$> +50$
Default (%)	2.0	1.4	2.4	2.9	4.6
N	350	2,290	3,776	695	759
Difference: $4.6\% - 2.0\% = 2.6\%^{**}$ $(t = 2.1)$					

Panel C: Regressions

	(1)	(2)	(3)	(4)
Effective Spread Flex	0.017***	0.018***	0.016***	0.017***
	(0.006)	(0.006)	(0.006)	(0.006)
Credit Rating		-0.443**	0.263	0.170
		(0.174)	(0.171)	(0.198)
Talk Effective Spread			0.017***	0.019***
			(0.003)	(0.003)
Additional Controls	N	N	N	Y
Lead Bank FEs	Y	Y	Y	Y
Deal Purpose FEs	Y	Y	Y	Y
Industry FEs	Y	Y	Y	Y
Month FEs	Y	Y	Y	Y
N	7,818	7,182	7,182	7,182
R^2	0.068	0.082	0.092	0.099

Table 11: **Spread Flex and Default: Different Time Horizons**

This table reports robustness tests using different time horizons for measuring firm-level default events. The sample consists of syndication deals between 2000–2020. The dependent variable is a dummy that indicates whether the borrower defaults over different time periods after issuance (scaled up by 100). In column (1), default is measured over a 3-year period after issuance. In column (2), default is measured between issuance and the deal's institutional term loan's contractual maturity date. In column (3), this period skips the first year of issuance. Column (4) considers any default event of the borrower after the deal until 2022, the last year of our default data. Control variables are the same as in Table 3. Standard errors are clustered at the borrower level and reported in parentheses. *, **, *** represent 10%, 5%, and 1% levels of statistical significance.

	(1)	(2)	(3)	(4)
	[0, 3y]	[0, mature]	[1y, mature]	[0, ∞)
Effective Spread Flex	0.015***	0.026***	0.026***	0.027***
	(0.005)	(0.009)	(0.008)	(0.009)
Credit Rating	-0.139	-0.297	-0.125	-0.149
	(0.224)	(0.367)	(0.361)	(0.501)
Talk Effective Spread	0.028***	0.043***	0.040***	0.042***
	(0.004)	(0.005)	(0.005)	(0.007)
Additional Controls	Y	Y	Y	Y
Lead Bank FEs	Y	Y	Y	Y
Deal Purpose FEs	Y	Y	Y	Y
Industry FEs	Y	Y	Y	Y
Month FEs	Y	Y	Y	Y
N	7,182	7,182	7,182	7,182
R^2	0.126	0.142	0.136	0.165

Appendix

A Formal description of hypotheses

This appendix provides a more formal description of the arguments behind our hypotheses as presented in Section 2. In particular, we first motivate the main right-hand side variable we use throughout the paper, effective spread flex, and then explain the two left-hand side variables (the default indicator and the excess loan return) that we use in our regressions. We also discuss how the partial adjustment/ underpricing predicted by the theory should affect the distribution of price adjustments/ spread flex.

A.1 Right-hand side variable

We start by providing a slightly more formal version of the argument of Hanley (1993) who uses price adjustments during bookbuilding as a proxy for the information revealed by investors during bookbuilding.

Suppose all price-relevant information can be described by the variables X and the variable Z. X is known to the lead bank before bookbuilding begins. Z is the (aggregated) private signal of investors (where $Z \perp\!\!\!\perp X$ and $E[Z] = 0$). If the actions of the bank and the bookbuilding procedure reveal both X and Z to market participants, the secondary market price should reflect both X and Z. To simplify, assume that the secondary market price P_2 is given by

$$P_2(X, Z) = X + Z \tag{A.1}$$

This corresponds directly to the expression for the secondary market price in Benveniste and Spindt (1989), up to some scaling parameters.[16]

[16]For the secondary market price, they write $P_h = A - (H - h)\alpha$ (cf. p. 347), where H is the total number of investors receiving the signal, and h is the number of investors who receive a positive signal. The probability of receiving a positive signal is p. Setting $Z = (h - np)\alpha$ and $X = A - H\alpha + np\alpha$, we obtain our formulation, where Z is a scaled, binomially distributed random variable with mean zero.

In their model, the underwriter learns about the analog of our Z via book-building and sets an issuance price P_I to incorporate it. The key result of the model, expressed in our context, is that when Z is low, the issuance price fully takes into account the (low) value of Z. But when Z is high, the issuance price only partially takes into account the (high) value of Z.

$$P_I(X, Z) = \begin{cases} X + Z & \text{if } Z \leq \bar{Z} \\ X + Z - \gamma Z & \text{if } Z > \bar{Z} \end{cases}, \tag{A.2}$$

for some $0 < \gamma < 1$. In the language of Ibbotson, Sindelar, and Ritter (1988), the bank only "partially adjusts" the issuance price upwards when it receives positive information from investors so that the issue is underpriced. This leaves money on the table for investors when they reveal to the bank that they have positive information, and, therefore, makes it incentive-compatible for them to reveal this positive information (cf. Benveniste and Spindt (1989), Theorem 1.)

The theory is silent on the price the bank initially proposes at the beginning of bookbuilding, P_0. However, since the bank has information on X only, P_0 can be a function of X only.[17] This implies that the price adjustment

$$\text{price adjustment} = P_I(X, Z) - P_0(X) \tag{A.3}$$

is an increasing function of Z. Also, since the issuance spread S_I is inversely related to the issuance price P_I, the corresponding spread flex

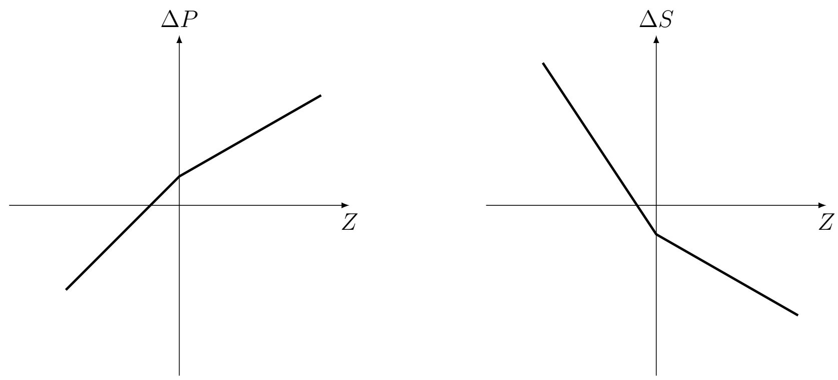
$$\text{spread flex } = S_I(X, Z) - S_0(X) \tag{A.4}$$

is also a decreasing function of Z. More precisely:

Lemma A.1. *The price adjustment during bookbuilding (the spread flex) is a monotonic increasing (decreasing) function of Z.*

[17] E.g., the bank could propose an initial price equal its expectation of the secondary market price, $P_0(X) = E[P_2|X] = X$, or equal to its expectation of the issuance price, $P_0(X) = E[P_I|X] = X - \gamma E[Z I_{\{Z>\bar{Z}\}}]$.

The first implication of the theory therefore is that price adjustments (or spread flex) are a suitable proxy variable for Z.[18] Figure A.1 illustrates the relationship how theory describes the relationship between price adjustments/ spread flexes and information revealed by investors Z.



(a) Price adjustment

(b) Spread adjustment

Figure A.1. **Adjustments as a function of investor information**
In the bookbuilding theory of Benveniste and Spindt (1989), the bank sets the issuance price $P_I(X,Z)$ to reflect the (aggregate) private signal of investors Z. To give investors incentives to part with their private information, the bank underprices and only partially adjusts when the information of investors is more positive. The extent of underreaction to Z is γZ. This implies that price adjustments $\Delta P \equiv P_I(X,Z) - P_0(X)$ are increasing and concave in Z (see Equations (A.2) and (A.3)), and that the corresponding spread adjustments ΔS are decreasing and convex in Z. For the graph in Panel (b), we consider a continuously compounded spread and use the approximation $\Delta S \underset{\sim}{\propto} -P_0 \Delta P$.

Due to the "partial adjustment"/ underpricing, we also know that the function $P_I(X,Z)$ is increasing and concave in Z (cf. Benveniste and Spindt (1989), Theorem 1). Furthermore, since the issuance spread $S_I(P_I)$ is decreasing and convex of the issuance price P_I, the issuance spread $S_I(X,Z) := (S \circ P_I)(X,Z)$ is decreasing

[18] This argument was first used (more implicitly) by Hanley (1993).

and convex in Z.[19] We illustrate the concavity/ convexity of price adjustments and spread adjustments in Figure A.1. It implies the following:

Lemma A.2. *Negative deviations from the expected price adjustment (positive deviations from the expected spread flex) are more informative about Z than positive deviations from the expected price adjustment (negative deviations from the expected spread flex) of the same size.*

To illustrate this, consider spread flex, and suppose that the spread flex is zero on average (expected spread flex is zero), which is roughly true in the data. Now imagine two levels of Z that would cause a bank to increase the spread by 100 basis points (Z^{bad} because investors have bad news about valuation) or decrease the spread by 100 basis points (Z^{good} because investors have good news about valuation), respectively. The convexity of $S_I(X, Z)$ in Z implies that $|Z^{\text{bad}}| \geq |Z^{\text{good}}|$. That is, an increase in the issuance spread of 100 basis points is very bad news, whereas a decrease of 100 basis points is only mildly good news (cf. Figure A.1b).

Implications for the densities of price adjustments/ spread flex The fact that price adjustments are concave and spread flexes are convex in Z also implies that even if the distribution of Z is symmetric, the distribution of price adjustments or spread flexes will not be. Below, we illustrate this with an example.

Let $F(\Delta p)$ and $f(\Delta p)$ denote the cumulative density function and the density function of price adjustments Δp, respectively. We want to derive expressions for these functions. In the model of Benveniste and Spindt (1989), Z is binomially

[19]Note that for any $\lambda \in (0, 1)$,

$$\begin{aligned}(S \circ P)(X, \lambda Z_1 + (1-\lambda)Z_2) &= S\left(P(X, \lambda Z_1 + (1-\lambda)Z_2)\right) \\ &\leq S\left(\lambda P(X, Z_1) + (1-\lambda)P(X, Z_2)\right) \\ &\leq \lambda S(P(X, Z_1)) + (1-\lambda)S(P(X, Z_2)) \\ &= \lambda(S \circ P)(X, Z_1) + (1-\lambda)(S \circ P)(X, Z_2)\end{aligned}$$

where the second step follows from the concavity of $P(X, Z)$ in Z and the fact that $S(P)$ is decreasing, and the third step follows from convexity of $S(P)$.

distributed. If the number of investors who receive signals becomes large, Z is approximately normal. Suppose, therefore, that $Z \sim N(0, \sigma^2)$, so that the distribution of Z is symmetric. Suppose also that the issuance price is given by Equation (A.2) with $\bar{Z} = 0$, and that the bank sets the initial price equal to $P_0(X) = X$. Under these assumptions, we have that the price adjustment is

$$\Delta P := P_I(X, Z) - P_0(X) = \begin{cases} Z & \text{if } Z \leq 0 \\ Z - \gamma Z & \text{if } Z > 0 \end{cases} \tag{A.5}$$

for some $0 < \gamma < 1$. If γ is just a constant, then the probability that the realization of the price adjustment ΔP is less than some number Δp is:

$$\Pr(\Delta P \leq \Delta p) = \begin{cases} \Pr(Z < \Delta p) & \text{if } Z \leq 0, \\ \Pr((1-\gamma)Z < \Delta p) & \text{if } Z > 0. \end{cases} \tag{A.6}$$

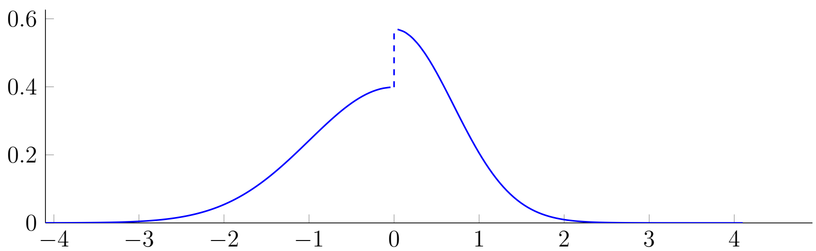
The random variables Z and $(1-\gamma)Z$ both have mean zero, but their standard deviations are σ and $(1-\gamma)\sigma$, respectively. So the density of Δp is

$$f(\Delta p) = \begin{cases} \frac{1}{\sigma}\varphi\left(\frac{\Delta p}{\sigma}\right) & \text{if } \Delta p \leq 0 \\ \frac{1}{\sigma(1-\gamma)}\varphi\left(\frac{\Delta p}{\sigma(1-\gamma)}\right) & \text{if } \Delta p > 0, \end{cases} \tag{A.7}$$

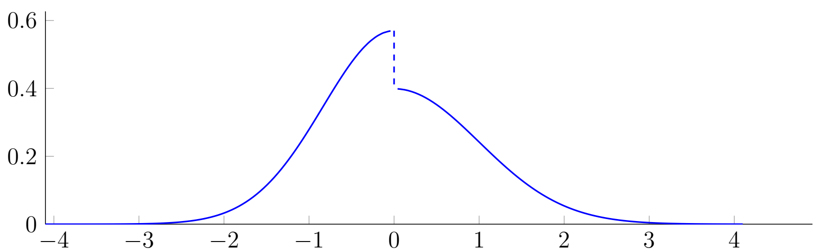
where $\varphi(\cdot)$ is the density of the standard normal distribution. We can see that the part of the density that describes positive price adjustments has lower variance and so smaller tails than the part of the density that describes negative price adjustments, as illustrated in Figure A.2. This is because the bank only partially adjusts to value-positive information and only increases the price by a fraction $1 - \gamma < 0$ of Z.

There are several ways to define a spread implicit in a price. E.g., with continuous compounding, we could define the spread S as the solution to $P \equiv e^{-(r_F+S)T}$, where P is the price, r_F is the risk-free rate, and T a maturity parameter. (In the following, T is an uninteresting scale parameter, so we will set it to $T = 1$ to simplify.) This definition of the spread implies that for small ΔS

$$\Delta S \approx -\frac{1}{P_0}\Delta P. \tag{A.8}$$



(a) Density of price adjustments



(b) Density of spread adjustments

Figure A.2. **Densities of price adjustments/ spread flex**
Due to "partial adjustment," the density of price adjustments $P_I(X, Z) - P_0(X)$ or spread flex $S_I(X, Z) - S_0(X)$ is asymmetric even when the distribution of investor information is symmetric. In this example, the distribution of from which investor information Z is drawn is standard normal. The plot assumes an issuance price as in Equation (A.2), with $\bar{Z} = 0$ and $\gamma = 0.2$, and an initial price of $P_0(X) = X$. For the graph in Panel (b), we consider a continuously compounded spread and use the approximation $\Delta S \underset{\sim}{\propto} -(1/P_0)\Delta P$.

We use this approximation to compute an approximation of the density $g(\Delta s)$ from $f(\Delta p)$ as follows. First note that

$$\begin{aligned}\Pr(\Delta S \leq \Delta s) &\approx \Pr\left(-\frac{1}{P_0}\Delta P \leq \Delta s\right) \\ &= \Pr(\Delta P \geq -P_0 \Delta s) \\ &= 1 - \Pr(\Delta P < -P_0 \Delta s) \\ &= 1 - F(-P_0 \Delta s).\end{aligned}$$

Our approximation for the density of Δs is the derivative of this expression w.r.t. Δs, that is,

$$g(\Delta s) \equiv \frac{\partial \Pr(\Delta S \leq \Delta s)}{\partial \Delta s} \approx f(-P_0 \Delta s) P_0.$$

So

$$g(\Delta s) \approx \begin{cases} \frac{1}{\sigma(1-\gamma)/P_0}\varphi\left(\frac{\Delta s}{\sigma(1-\gamma)/P_0}\right) & \text{if } \Delta s < 0, \\ \frac{1}{\sigma/P_0}\varphi\left(\frac{\Delta s}{\sigma/P_0}\right) & \text{if } \Delta s \geq 0\ . \end{cases} \tag{A.9}$$

We can see that the part of the density that describes *negative* spread flex has lower variance and so a smaller tail than the part of the density that describes positive spread adjustments, as illustrated in Figure A.1b. This is because the bank only partially adjusts to value-positive information that *decreases* the spread.

A.2 Left-hand side variables

Consider a one-period consumption-based asset pricing model for an asset (meant to represent a loan) that pays a cash flow C. As above, suppose that all price-relevant information can be described by the variables X and Z (where X is known to the lead bank before bookbuilding begins, Z is the aggregate signal of investors, and $Z \perp\!\!\!\perp X$). The actions of the bank and the bookbuilding procedure reveal both X and Z to all market participants so that the secondary market price P_2 reflects this information. In terms of the cash flow C and the stochastic discount factor M, we can decompose the secondary market price into an expected cash flow component and a risk premium component:

$$P_2 = E[M \cdot C \mid X, Z] = \underbrace{\frac{1}{1+r_f} E[C \mid X, Z]}_{\text{expected cash flow component}} + \underbrace{\text{Cov}(M, C \mid X, Z)}_{\text{risk premium component}}$$

where r_f is the risk-free rate. The information revealed by investors, Z, could be price-relevant because it is informative about the expected cash flow component or because it is informative about the risk premium component, or both.

To see whether the information revealed by investors is relevant for expected cash flows, we can run a linear regression in which we try to predict variables that affect related to realized cash flows using our proxy of Z (spread adjustments), controlling for variables in the bank's information set (X). Since theory that affords banks an informational advantage typically specifies that banks have/ can acquire private information about the true default probability of investors, the most interesting measure of realized cash flows for our purposes is a default indicator.

To see whether the information revealed by investors is relevant for the risk premium, we can run a linear regression in which we try to predict the realized excess returns because the expected excess return is a measure of the risk premium. The realized return when buying in the secondary market after issuance and holding the asset until maturity/ until it pays off the cash flow C is:

$$\begin{aligned} \frac{\mathrm{C} - P_2}{P_2} - r_f &= \frac{\mathrm{C} - (1+r_f)P_2}{P_2}, \\ &= \frac{\mathrm{C} - E[\mathrm{C}] - (1+r_f)\,\text{Cov}(M, \mathrm{C})}{P_2}. \end{aligned}$$

where r_f is the risk-free rate and we have used Equation (A.2). Taking expectations produces:

$$E\left[\frac{\mathrm{C} - P_2}{P_2} - r_f\right] = \frac{(1+r_f)\,(-\,\text{Cov}(M, \mathrm{C}))}{P_2}$$

which is a function of the risk premium $\text{Cov}(M, C)$.

B Default events at the syndication deal level

Our main tests for the relationship between spread flex and default focus on default events at the borrower level. This section presents robustness tests using default events at the syndication deal level.

We create a sample of deals with accurate loan default information as follows. For each LCD borrower with a match in DRD, we find the institutional term loan within its deal(s) with senior secured debt instruments in DRD based on the issuance date and loan amount. After this, 1,030 LCD deals have a matched debt instrument in DRD. We then determine a deal as subsequently defaulted if the specific debt instrument is reported to default in DRD.

Figure B.4 presents the fraction of deals that subsequently default for different ranges of spread flex. Among deals that experienced an upward spread flex of more than 50 basis points, 8.5% default. The group with less than 50 basis points of upward flex has 5.6% of deals default. These default likelihoods are economically larger than deals that experienced zero or a downward spread flex.

Table B.2 presents the results of repeating our main nonparametric and regression analyses in this sample with deal-level default events. In Panel A, deals that experienced upward spread flex are 3.7% more likely to default, and this sizable difference is statistically significant at the 5% level. Panel B tests the difference in the likelihood of default between the two extreme groups. While the difference, 4.8%, is economically large, it is statistically insignificant due to the small sample size: in these two groups, only 3 and 14 deals default, respectively. Panel C estimates regressions with similar specifications as before. The results indicate that a 100-basis-point increase in spread flex predicts a nearly 3% increase in the likelihood of default.

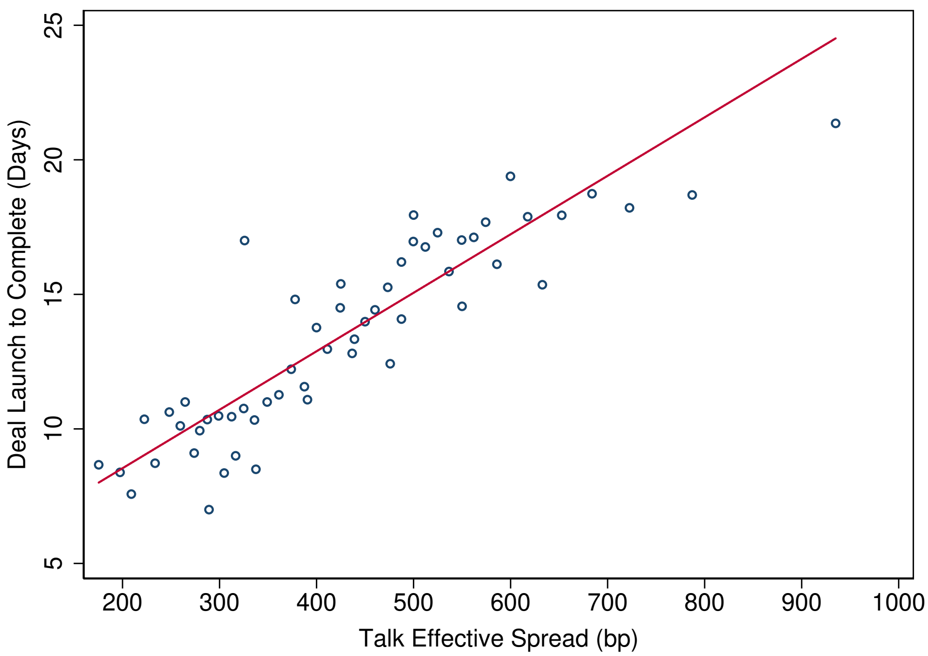


Figure B.1. **Talk Effective Spread and Number of Days For A Deal to Complete.**
This figure presents a scatter plot that groups syndication deals into 100 bins based on talk effective spread proposed by the lead bank and depicts the average number of calendar days for the deal to complete within each bin. Source: PitchBook Data, Inc.

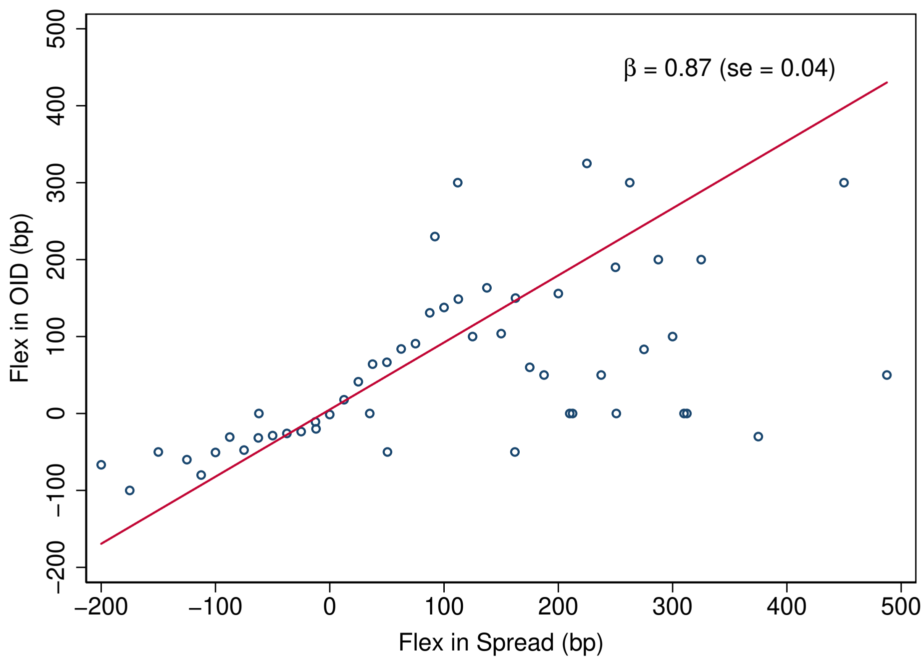


Figure B.2. **Relationship Between Spread Flex and OID Flex.**
This figure presents a scatter plot that groups syndication deals into 100 bins based on flex in loan spread and depicts the average flex in OID within each bin. The fitted line represents an OLS slope estimate, with heteroskedasticity-robust standard error in parentheses. Source: PitchBook Data, Inc.

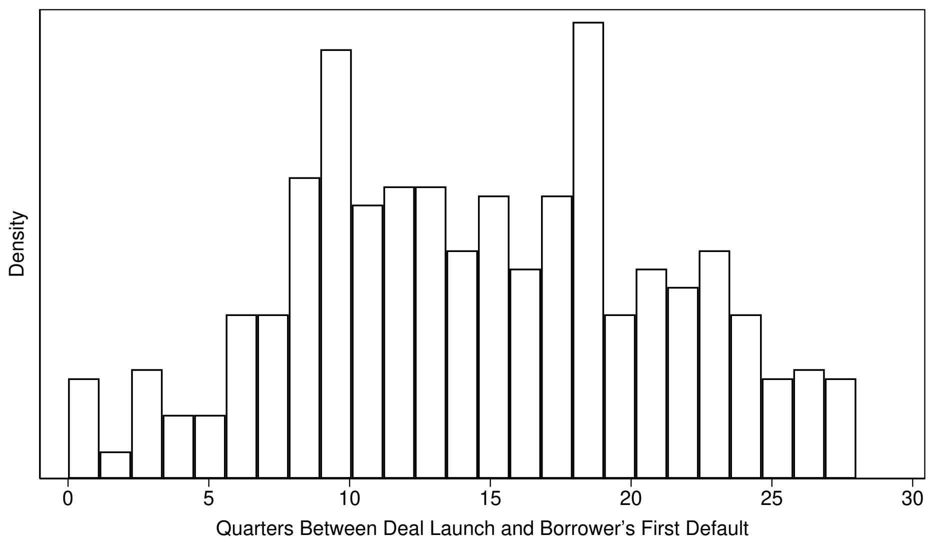


Figure B.3. **Time Between Syndication Deal and Default.**
This figure presents the distribution of the number of quarters between a syndication deal and the borrower's default for all default events. Source: PitchBook Data, Inc.

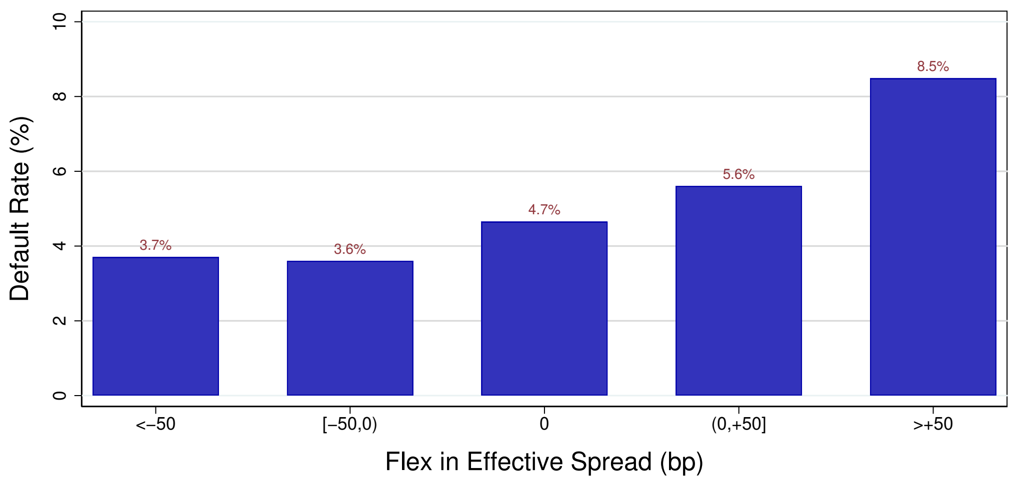


Figure B.4. **Spread Flex and Deal-Level Default: Nonparametric Comparison.**
This figure presents the fraction of syndication deals that subsequently default. The sample consists of 1,030 Pitchbook LCD deals for which the institutional term loan is matched to a debt instrument in DRD. The deals are divided into 5 groups based on flex in effective spread during the bookbuilding process. Default is determined based on debt instrument default events in DRD.

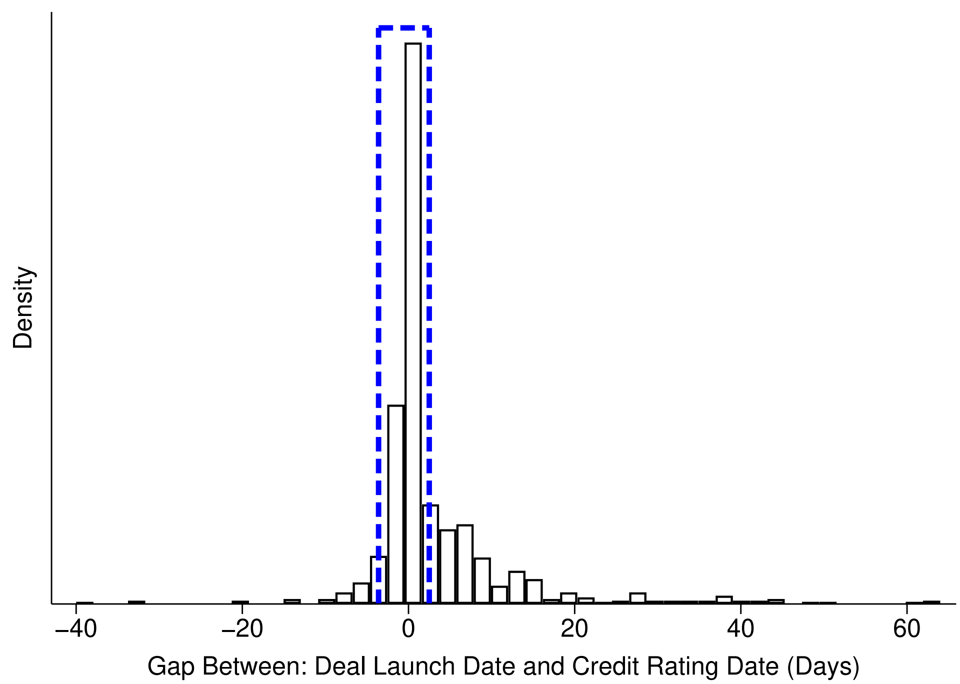


Figure B.5. **Timing of Moody's Credit Ratings.**
This figure presents a histogram of the number of days between a deal's launch date and Moody's assignment of debt instrument rating for the first lien institutional term loan(s) in the deal.

Table B.1: **Letter Ratings and Numerical Ratings**

This table presents the conversion from letter ratings to numerical ratings, for credit ratings by Moody's and S&P.

Letter Rating		Numeric Rating
Moody's	S&P	
Aaa–A3	AAA–A-	14
Baa1	BBB+	13
Baa2	BBB	12
Baa3	BBB-	11
Ba1	BB+	10
Ba2	BB	9
Ba3	BB-	8
B1	B+	7
B2	B	6
B3	B-	5
Caa1	CCC+	4
Caa2	CCC	3
Caa3	CCC-	2
Ca	CC, C	1
C	SD, D	0

Table B.2: **Spread Flex and Default: Deal-Level Defaults in DRD**

This table reports robustness tests using deal-level default events. The sample consists of 1,030 deals in Pitchbook LCD for which the institutional term loan is matched to a debt instrument in DRD. Default is determined based on debt instrument default events in DRD. Panel A and Panel B repeat the analysis in Table 2. Panel A divides deals into 3 groups depending on whether the deal experiences an upward, downward, or no flex in effective spread. Panel B divides deals into 5 groups based on the range of effective spread flex. Panel C reports the results of regressing a dummy indicating default (scaled up by 100) on effective spread flex during syndication process. Control variables are the same as in Table 3. Standard errors are clustered at the borrower level and reported in parentheses. *, **, *** represent 10%, 5%, and 1% levels of statistical significance.

Panel A: Upward and Downward Flexes

	Effective Spread Flex		
	downward	zero	upward
Default (%)	3.6	4.7	7.4
N	414	344	272
Difference: $7.4\% - 3.6\% = 3.7\%^{**}$ ($t = 2.2$)			

Panel B: 5 Groups of Deals By Spread Flex

	Effective Spread Flex (bp)				
	< -50	$[-50, 0)$	0	$(0, +50]$	$> +50$
Default (%)	3.7	3.6	4.7	5.6	8.5
N	81	333	344	107	165
Difference: $8.5\% - 3.7\% = 4.8\%$ ($t = 1.4$)					

Panel C: Regressions

	(1)	(2)	(3)	(4)
Effective Spread Flex	0.028^{**}	0.026^{*}	0.024^{*}	0.027^{*}
	(0.014)	(0.014)	(0.014)	(0.014)
Credit Rating		-0.746	-0.119	-0.111
		(0.521)	(0.526)	(0.610)
Talk Effective Spread			0.016^{**}	0.014^{*}
			(0.008)	(0.007)
Additional Controls	N	N	N	Y
Deal Purpose FEs	Y	Y	Y	Y
N	1,030	1,023	1,023	1,023
R^2	0.014	0.016	0.023	0.039