What Do Lead Banks Learn from Leveraged Loan Investors?*

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January 2025

Abstract

We examine the private information held by nonbank lenders in leveraged loan syndications. In these transactions, lead banks gather information about participant demand during bookbuilding and incorporate it into loan spread adjustments. A one-percentage-point increase in the loan spread during bookbuilding is associated with a 3% higher probability of subsequent default – but only in deals where participants plausibly have information. This suggests that nonbank syndicate participants' demand conveys information about borrower credit quality unknown to the lead bank before bookbuilding. Our results challenge the conventional view of information asymmetries between banks and nonbank lenders, instead highlighting an element of information complementarity in modern corporate lending.

JEL classifications: G23, G24, G30
Keywords: syndicated loans, nonbanks, 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 our discussants Dominik Damast, Tim Eisert, Maximilian Jager, and Carola Theunisz, and also Rainer Haselmann, Robert Marquez, as well as seminar and conference participants at the USC Macro-Banking Reading Group, the Federal Reserve Board, the City University of Hong Kong, the 2024 EFI Workshop, the 2024 BSE Summer Forum on Financial Intermediation and Risk, the "Banking in the Age of Challenges" Conference at HEC Paris, the 2024 CEPR ESSFM at Gerzensee, the University of Melbourne, and the Banking Workshop Münster for helpful comments. Max Bruche gratefully acknowledges financial support from the German Research Foundation (Deutsche Forschungsgemeinschaft—DFG) - project number 529251067.

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1 Introduction

In classic theories of lending, banks use their superior screening and monitoring technology to produce information about borrowers. They have an informational advantage vis-a-vis other investors. Following stricter bank capital regulation after the global financial crisis, nonbank investors are increasingly replacing banks as lenders. If banks have an informational advantage, then an increased share of nonbank lenders may reduce the efficiency of credit allocation. However, whether banks still have an informational advantage is unclear. Do nonbank investors also produce information about borrowers that is relevant for credit allocation?

This paper studies the information of nonbank investors in the context of the leveraged loan market. Leveraged loans are non-investment-grade syndicated loans. In this trillion-dollar market, so-called 'lead' banks arrange syndication deals in which they originate loans and sell them almost exclusively to nonbank institutional investors such as collateralized loan obligations (CLOs) and specialized funds. These sophisticated investors often devote substantial resources to credit analysis. When arranging the deals, lead banks run a bookbuilding process to assess investors' demand and adjust the loan terms accordingly.

Fundamentally, investors' demand could be driven by information they have about the borrower's quality, or by factors unrelated to such information, e.g., their own liquidity needs at the time of syndication. We provide evidence that the demand of investors as revealed to lead banks during bookbuilding contains information about the loan's probability of default. Hence, investors have information about the borrower's quality that the lead bank does not have before bookbuilding. This finding challenges the traditional view that only banks (or lead banks in syndicated loans) have private information about borrowers. Our results suggest that there could be bilateral private information – both the lead bank and the investors have imperfectly correlated private signals about borrower quality. Consequently, an increase in the share of nonbank lenders does not necessarily imply a reduction in the efficiency of credit allocation.

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 borrower's quality, we examine whether it predicts future default, 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 spread flex-default 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.

It is possible that the spread flex-default relationship is mechanical: An upward spread flex during bookbuilding raises the borrower's future interest payments, thereby increasing the probability of default. However, if this mechanical effect is substantial (despite an empirically small impact of spread flex on the borrower's annual interest expense), it should increase the probability of default irrespective of whether investors have private information about the borrower's quality. To test this, we split our sample along several dimensions to show that the association between spread flex and default is stronger when investors plausibly have private information about the borrower's quality, which indicates that the mechanical effect is unlikely to drive our baseline result.

The main split we consider is between new money deals and refinancing deals. Before a refinancing deal launches, investors can already trade the existing loan in the secondary market. Their information about the borrower's quality will be reflected in the secondary market price, which the lead bank can use for pricing the new loan. Hence, bookbuilding should not reveal additional information about the borrower's quality. In contrast, for a new money deal, no secondary market price is available, and bookbuilding may reveal investors' additional information about the borrower's quality. We find that the relationship between spread flex and default is strong in new money deals but absent in refinancing deals. Similarly, we also split the sample into deals with and without prior bank-borrower relationships, and deals where credit ratings agree and disagree. Results are stronger in the subsamples in which investors' information about the borrower's quality is plausibly more relevant for pricing.

We conduct several robustness checks. We show that spread flex predicts other negative credit events, in particular, downgrades and withdrawals of the borrower's credit ratings. We also show that our result is not sensitive to the time horizons over which default is measured and that it holds consistently across different data sources of default events.

Finally, investor demand during bookbuilding may also reflect factors unrelated

to information about the borrower's quality. For example, nonbanks could have liquidity needs because they suffer outflows at the time of syndication. They would then reveal low demand during bookbuilding, and the lead bank would be forced to increase the spread of the loan. As a result, the price of the loan in the secondary market would be temporarily depressed at issuance. As the money flows investors experience gradually stabilize after the deal, they would buy the loan in the secondary market until its price recovers, creating positive excess returns over certain relatively short time horizons.

We also find evidence that this is the case. We show that an increase in the spread during bookbuilding of 100 basis points (i.e., an "effective spread flex" of +100bp) predicts an unannualized excess return on the loan that is about 0.8% over holding periods of three months, six, or twelve months, relative to a loan on which the spread is not increased. The association of spread flex with excess returns becomes insignificant over long time horizons. This result suggests that other factors, such as nonbanks' liquidity needs, also affect their demand during bookbuilding.

In summary, our evidence suggests that investor demand during bookbuilding can be driven by factors unrelated to the borrower, but it is also driven by investors' private information about the borrower's credit quality. The lead bank learns about this information via bookbuilding.

Related literature Our paper contributes to the literature on loan sales and loan syndication. Classical banking theory posits that banks develop private information on borrowers to facilitate screening and monitoring (Diamond, 1984; Holmström and Tirole, 1997). The presence of such information complicates the sale of loans to third-party investors. To signal loan quality or maintain monitoring incentives, banks must retain a portion of the loan (Pennacchi, 1988; Gorton and Pennacchi, 1995; Sufi, 2007; Ivashina, 2009), or alternatively, establish a strong reputation with loan buyers (Chemmanur and Fulghieri, 1994; Booth and Smith II, 1986). When banks know that they will sell a loan, they have weaker

incentives to invest in generating information about the borrower (Keys et al., 2010). Conversely, the buyers of the loan should have stronger incentives to invest in generating their own information about the borrowers. To our knowledge, our paper is the first to provide empirical evidence that third-party investors possess their own information about the borrowers.

Our paper is also related to the literature that examines how banks use bookbuilding to price the assets they sell. Benveniste and Spindt (1989) model bookbuilding as an auction mechanism designed to extract information about investor demand. Empirical findings support this auction-based explanation.[1] This literature has so far not examined what drives investor demand as revealed in the auction. Investor demand could be driven by factors such as liquidity needs, time-varying regulatory constraints, and risk preferences. But it could also be driven by information that the investors have generated about the borrower. We contribute to this literature by investigating the drivers of investor demand in bookbuilding and find that, in addition to the other factors, investors possess private information about the borrower's probability of default — information that banks must extract through the bookbuilding process.

Our work also expands the work of Blickle et al. (2020) who demonstrate that the loans in which banks retain larger shares exhibit higher default rates. Banks tend to retain larger shares when investor demand is low during bookbuilding (Bruche, Malherbe, and Meisenzahl, 2020). Our findings suggest that when investor demand is low, it may indicate that they have identified that credit risk is higher than anticipated by the bank, offering an interpretation for the results of Blickle et al. (2020).

More broadly, our evidence provides new insights into the role of nonbank lenders in corporate loan pricing. Prior research shows that nonbanks demand a

[1]The key and unique prediction of the model is that when information is positive, banks only "partially adjust" prices upwards so that underpricing occurs (Ibbotson, Sindelar, and Ritter, 1988). Partial adjustment in bookbuilding has been shown to occur in the case of stocks (Hanley, 1993), syndicated loans (Bruche, Malherbe, and Meisenzahl, 2020), and corporate bonds (Wang, 2021).

premium (Lim, Minton, and Weisbach, 2014), with premium size linked to flow-induced buying pressure (Ivashina and Sun, 2011). Additionally, the expansion of nonbank lending correlates with regulatory constraints on traditional banks, particularly for riskier borrowers (Chernenko, Erel, and Prilmeier, 2022). Our contribution to this literature lies in demonstrating that corporate loan pricing reflects not only regulatory and market conditions but also nonbank lenders' private assessment of borrower creditworthiness.

Given our focus on the information that influences demand discovery via auctions, our study also relates to the empirical literature on auctions. A central question in this field concerns whether bidder information reflects "private values" or "common values" (Milgrom and Weber, 1982). This distinction hinges on whether bidders would adjust their valuation based on others' bids ("common values") or whether valuations are independent ("private values"). Empirical tests distinguishing between these cases typically require data on individual bids (Laffont and Vuong, 1996). More recently, Haile, Hong, and Shum (2003) propose a non-parametric method for identifying common versus private values based on the "winner's curse" (Capen, Clapp, and Campbell, 1971). While our study does not utilize individual bid data, we show that in aggregate, bids in leveraged loan bookbuilding partially reflect default risk. Since default risk is relevant to all investors, the bookbuilding auction here is more likely to exhibit "common values."

Prior research on auctions has primarily focused on single-unit auctions. However, bookbuilding involves bidders expressing interest in multiple units of a security, making it more akin to multi-unit actions. Studies such as Hortaçsu and McAdams (2010) build on Wilson's (1979) model to compare revenue outcomes under different auction formats in the Turkish treasury market. 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 conducts an auction to learn about investor demand. More specifically, the theory posits that each investor receives a signal that determines their valuation and hence their demand for the asset being sold. If the signal is 'good', the investor's valuation is high; if the signal is 'bad', the valuation is low. Via the auction, the bank extracts information about investors' signals. The central prediction of the theory is that the bank sets the issuance price to reflect investors' signals. If most investors have good signals, the issuance price will be high. If most investors have bad signals, the issuance price will be low. Several tests in Appendix 1.2 show that the model describes our data very well. This should not be surprising, as it has been generally found to be a good description of data on bookbuilding (Hanley, 1993; Bruche, Malherbe, and Meisenzahl, 2020; Wang, 2021).

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 investor's signals. Hanley (1993) therefore uses price adjustments during bookbuilding as a proxy for the information revealed by investors. (We provide a more formal version of this argument in Appendix 1.1.) Since banks and investors discuss the pricing of loans in terms of yields rather than prices, we will use spread adjustments or "spread flex" rather than price adjustments (Bruche, Malherbe, and Meisenzahl, 2020). This will be our main independent variable.

The theory is silent about what drives the signal that determines an investor's demand. A signal could be 'good' and the investor's demand high because an investor has positive information about borrower quality. Also, a signal could be 'good' and the investor's demand high because the investor has had inflows. In practice, variation in a proxy of the aggregate investor demand, such as our spread

flex, could be driven by investors' information about borrower quality or by their inflows and outflows, or by both.

Fundamentally, any valuation can be decomposed into a expected discounted cash flow component and a risk premium component. To the extent that aggregate investor demand contains information about borrower quality, aggregate investor demand should predict the expected discounted cash flows of the loan. To the extent that aggregate investor demand contains information about inflows or outflows that cause temporary price deviations from fundamental value, aggregate investor demand should predict (time-varying) risk premia that can be earned when investing in the secondary market.

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 (time-varying) risk premium, we choose the excess return of the loan over the risk-free rate over different holding periods. (See Appendix 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 exhibit low demand for a 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 exhibit low demand for a loan because they are suffering outflows and are temporarily constrained. If this is the case, on average, the

secondary market prices for such loans should be temporarily depressed. The loans should have a higher excess return over some horizons as prices revert.

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

We can test both hypotheses by running regressions of the type

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

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.

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.[2] 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.[3] 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 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.

We elaborate on the relationship between the effective spread flex and the

[2]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.

[3]Spread flexes and OID flexes are positively correlated (See Figure A.1 in Appendix.

model of Benveniste and Spindt (1989) in Appendix 1.1 and explore it empirically in Appendix 1.2. In summary, the effective spread flex can be interpreted as a "surprise" to the lead bank, in that it contains information previously unknown to the bank. The average effective spread flex is not statistically different from zero and is difficult to predict using the econometrician's available information, with R^2 values ranging from 2 to 5%. By contrast, the "talk spread" initially proposed by the lead bank is substantially more predictable, exhibiting R^2 values as high as 58%. The high predictability reflects, for example, that banks set higher spreads for loans with lower initial credit ratings. Overall, consistent with the prediction of Chemmanur and Fulghieri (1994), banks appear to set the talk spread equal to their expectation of the final spread, conditional on their initial information set. In private discussions, bankers have explained to us that they follow this practice because they perceive their role as providing a service to both issuers and investors, necessitating fairness to both sides of the market – a verbal counterpart to the formal argument presented by Chemmanur and Fulghieri (1994).

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.[4]

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–

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

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 mitigates 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.[5] Using this panel, we create a sample of LCD deals for which we can track future ratings as well as rating withdrawals.

[5] A larger value of numeric rating corresponds to a better letter rating. Table A.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.

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.

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 during the n-year period, we calculate an interest payment based on a fixed spread and a floating 3-month LIBOR that resets at the end of the previous quarter.[6] These interest payments are compounded to the final price date based on reinvestment at the prevailing LIBOR rate.[7] Finally, we calculate an annualized n-year holding period return as

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

where the total value of cumulative cash flows is added to the secondary market price to reflect investor payoff from the loan.[8]

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

[7]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.

[8]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

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.[9] 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.

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 $650 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.

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.

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

[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. 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.[10]

[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.[11]

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

[10] 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 1.1).

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

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

In this section, we present our empirical results. We start by establishing that spread flex is positively associated with default, as predicted by Hypothesis 1. Spread flex could be positively associated with default because investors reveal their private information about the probability of default during bookbuilding. Spread flex could also be positively associated with default because the increased interest payments mechanically raise the borrower's probability of default. To assess which of these explanations is more likely, we split our main sample into subsamples. We show that the association is present and strong in subsamples in which investors plausibly have information but absent or weak in subsamples in which investors have little or no information. We do find substantial variation across the subsamples, indicating that the association is driven by private information of nonbank investors, and that the effect is not mechanical. We also show that the association does not depend on the exact choice of the measure of credit risk and that positive spread flex also predicts negative rating events.

We then show that spread flex is also positively associated with excess returns in the secondary market over shorter time horizons, as predicted by Hypothesis 2. This result indicates that investor demand during bookbuilding is not only driven by information they have about the probability of default but also by other, unrelated factors, likely to be related to constraints or liquidity concerns (e.g., inflows and outflows). Anecdotally, sectoral constraints of CLOs play a role. We investigate these formally but cannot find evidence that this is the case.

4.1 Does spread flex predict default?

Baseline. To formally test Hypothesis 1 in Section 2, we use our leveraged loan syndication deals sample. According to this hypothesis, if investors have private information about the 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 showing the average probability of default by spread flex buckets exhibits 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 large upward (positive) flexes, that is, investors required a higher interest rate during the syndication process. In particular, among deals with greater than +50 spread flexes, 9.1% defaulted, whereas among deals with $(0, +50]$ spread flexes, 5.0% defaulted. These frequencies are economically substantially larger than deal groups with no flexes (3.7%). Deals with downward (negative) flexes exhibit even smaller default rates (2.6%-3.1%).

[Insert Figure 3 here]

We conduct univariate tests for these differences in default probability. 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 ($t = 6.8$). We also tests the difference between the groups with the largest upward ($\geq$+50) and largest downward ($\leq$-50) in Figure 3. The difference in default probability is 5.9%, almost double the average default rate, and statistically significant at the 1% level.

A formal test of Hypothesis 1 requires us to estimate the relationship between spread flex and future default, conditional on the lead bank's information set at the beginning of bookbuilding. The best measure of the banks information set are the loan characteristics and here especially the talk loan spread—the interest rate the lead bank initially proposes during the bookbuilding process. Hence, we conduct this test by regressing a binary default outcome on spread flex, controlling for a large set of ex-ante variables including the talk spread. 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 2 here]

Table 2 reports our estimation results. In column (1), our point estimate is statistically significant and indicates a sizable economic effect. A one-percentage-point upward flex in the effective spread is associated with a 3.2 percentage point higher default probability, a 80 percent increase relative to the sample average of 4 percent.

Column (2) controls for an important proxy for public information about the borrower's default risk, the deal's credit rating. Our estimated coefficient of spread flex remains almost the same controlling for public information. Turning the to lead bank's information, in column (3), we also control for talk effective spread proposed by the lead bank. Consistent with private information of investors being reflected in the spread flex, the estimated coefficient on spread flex is only slightly smaller when controlling for the lead bank's information. However, consistent with lead banks producing information before the bookbuilding starts, the initial pricing summarizing the lead bank's information at the beginning of bookbuilding positively predicts default and 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 and therefore provides the first piece of evidence that investors have private information about the loan deal.

[Insert Table 3 here]

New Money Deals vs Refinancing. If the relationship between spread flex and default is driven by investors' information about borrowers, this relationship should be stronger when investors can plausibly have private information orthogonal to the lead bank's information. One type of loan for which investors are unlikely to have significant private information is a loan that refinances an existing loan. If investors have private information on the borrower prior to a refinancing deal, they can profit from this information by trading the existing loan in the secondary market. The spread on the existing loan should then reflect this information, and the lead bank can use it directly without having to extract it via bookbuilding. Also, for such loans, lead banks have already interacted with the borrowers and are likely well-informed about their quality as lead banks engage in monitoring of existing loans (see Gustafson, Ivanov, and Meisenzahl, 2021).

As Figure 4 shows, new money deals exhibit a larger dispersion in spread flexes, suggesting the revelation of more private information. We re-estimate the specifications in Table 2 with subsamples, starting with a sample split between new money deals and refinancing deals.

Columns (1)–(2) in Table 3 Panel A are based on a subsample of new money deals. Consistent with investors having private information about the borrower's quality, our estimates for the coefficient of spread flex are not only qualitatively similar and statitically significant, but also the economic magnitude is considerably larger. In this subsample of newm oney deals and controlling for all information (column 2), one-percentage-point upward flex in the effective spread is associated with a 3.7 percentage point higher default probability compared to 2.8 percentage points in the full sample (Table 2, column 5). In contrast and consistent with investors have no additional information in refinancing deals, the estimates for this coefficient in columns (3)–(4) are small and statistically insignificant. Notably, our estimate for the coefficient of talk spread is larger for refinancing deals, suggesting that for these deals, lead banks who generally monitored the refinanced loan have more information about borrowers.

Credit Rating Agency Disagreement. Table 3, Panel B shows results when splitting the sample by whether credit rating agencies differ in their risk assessment of the loan by at least 2 notches. Disagreement between credit rating agencies indicate that the credit risk of the borrower is hard to assess and the deal is opaque, and hence, that investors' complementary information is more likely to matter. Consistent with complementary information from investors, the point estimate on spread flex in the ratings disagreement subsample (columns (1) and (2)) is three times the magnitude of the coefficient in the subsample of deals in which rating agency agree (columns (3) and (4)).

Bank-Borrower Relationships. We expect that banks have more information about borrowers with whom they had prior relationships and hence, nonbanks to provide less complementary information in these deals. Columns (1)-(2) in Panel D of Table 3 show that the spread flex-default relationship is concentrated in deals without prior bank-borrower relationship, in magnitude comparable with the baseline. In contrast, the coefficient on spread flex in deals with prior bank-borrower relationship is only half the size and statistically insignificant. This finding is consistent with nonbanks providing complementary information in deals for which banks have comparatively less information.

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 also predict future credit events even before a default materializes. For this reason, we provide additional evidence from the changes in the borrower's credit ratings that are indicative of changes in the borrower's financial conditions.

[Insert Table 4 here]

We estimate regressions of the borrower's future credit rating changes on spread

flexes and report the results in Table 4. For readability, we code the dependent variable as follows: -100 for a downgrade, 0 for no change, and 100 for an upgrade.

Table 4 reports the results. Column (1) shows a negative and statistically significant relationship between spread flexes and rating changes. The magnitude is economically meaningful. A one-percentage-point upward flex predicts an 11% larger probability 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.

One concern is that the magnitude of the estimated coefficients understate the changes in credit quality because ratings are often withdrawn after significant credit deterioration. We therefore 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 8.7% larger probability of rating withdrawal. Column (4) includes additional deal variables as controls and finds a similar result.

Overall, the evidence from rating changes and rating withdrawals is consistent with investor demand revealing private information about borrower quality that is unknown to lead banks.

4.3 Does spread flex predict excess return?

Next, we proceed to test Hypothesis 2, which predicts a positive relationship between spread flex during bookbuilding and the excess return on a loan. (Since we include time fixed effects that absorb the risk-free rate when estimating the relationship between spread flexes and risk premiums over a given time horizon, we use annualized raw return as the dependent variable.)

The intuition behind Hypothesis 2 can be summarized as follows: When nonbanks suffer outflows, they show low demand during bookbuilding, and the lead bank must increase the spread. As a result, the price is (temporarily) depressed. If money flows revert back to average over some time horizon, then the nonbanks that are also active in the secondary market would use the money to buy in the

secondary market and drive up the price. This would produce positive (excess) returns over the given time horizon.

For all time horizons, we regress annualized 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 5 here]

Table 5 reports our estimation results. We find strong evidence for a positive association between spread flex and secondary market returns, but only over shorter horizons. Column (1), (2), and (3) indicate that a one-percentage-point upward flex predicts an annualized excess return that is higher by 3%, 1.6%, and 0.7%, over horizons of 3, 6, and 12 months, respectively. Looking at the raw, de-annualized returns, we can furthermore see that it also predicts a return that is higher by an almost identical amount of $3.0\%/4 \approx 0.8\%$, $1.6\%/2 = 0.8\%$, and $0.7\%/1 = 0.7\%$, and $0.8 \times 2 \approx 1.6\%$, respectively, suggesting that most of the return is generated over the first 3 months. From a time horizon of about 2 years (columns (4), (5), and (6)), our sample size decreases substantially and coefficients eventually become indistinguishable from zero.[12] These results suggest that investor demand revealed during bookbuilding is highly informative about the required risk premium over short time horizons, which provides evidence for Hypothesis 2.

4.4 Does spread flex reflect investor constraints?

A possible type of constraints that could cause fluctuations in nonbank demand during bookbuilding are the industry-level portfolio constraints faced by CLOs, the largest group of leveraged loan investors. Typically, a CLO cannot hold more

[12] 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.

than 15% of loans from any industry. If the real-time portfolio allocations of the CLO managers participating in bookbuilding are not known to the lead bank, the lead bank may be negatively surprised when these constraints unexpectedly bind and would then have to flex up the spread.

[Insert Table 6 here]

We use our industry-level monthly panel to test whether this is the case. Table 6 reports our results from regressing industry–month average spread flex on different measures of CLO industry-level 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, we find no no evidence that CLO industry-level portfolio constraints affect demand in the 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, our finding is robust to defining default events over alternative time horizons. In Table A.6, we replace the 4-year horizon in Table 2 with various alternative time horizons.[13] In columns (1)–(4), 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 the probability of default.

[13]Figure A.2 in Appendix shows that most default events occur between 1 year and 5 years after syndication deals.

Second, similar results hold when we use default events covered by just one of the databases. For example, one can replicate our results exclusively based on justLCD data. In Table A.7, we track borrower-level default events using only LCD's Loan Default List and reproduce our main results. 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. Likewise, in Table A.8, 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.

Finally, in Appendix 3 we discuss our results based on deals for which we can track default 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 A.3 and Table A.9.

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 nonbank investors in the syndicate. Yet when banks arrange leveraged loans, they often run a bookbuilding process to extract price-relevant information from nonbank investors. Whether this fact is consistent with the view that lead banks have an informational advantage depends on what drives the demand of the nonbank investors during bookbuilding.

We provide evidence that the demand of investors as revealed to lead banks during bookbuilding contains information about the loan's probability of default. Hence, investors have information about the borrower's quality that the lead bank does not have before bookbuilding. This finding challenges the prevailing view that only banks (or lead banks in syndicated loans) have private information about borrowers. Our results suggest that there could be bilateral private information – both the lead bank as well as the investors have private information about borrower quality. We show that part of the variation in demand of nonbank investors during

bookbuilding is plausibly explained by information that these investors have about the probability of default. Lead banks use bookbuilding to complement their information about default with the information that nonbanks have.

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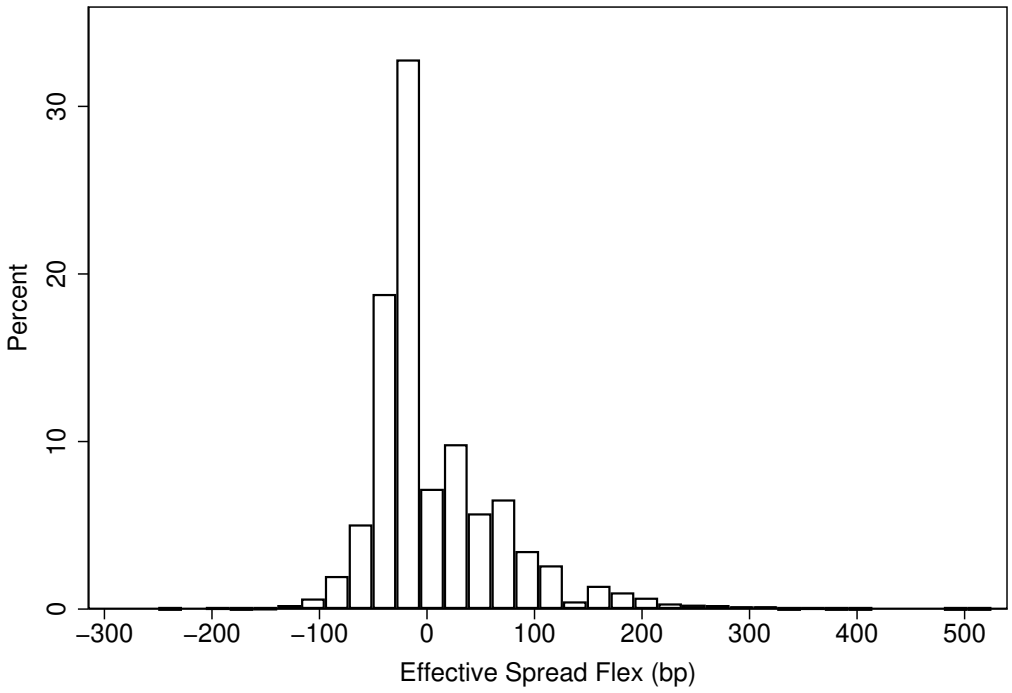


Figure 1. **Distribution of Spread Flex.**
This figure presents the distribution of effective spread flex in syndication deals, for all syndication deals in our sample. Source: PitchBook Data, Inc.

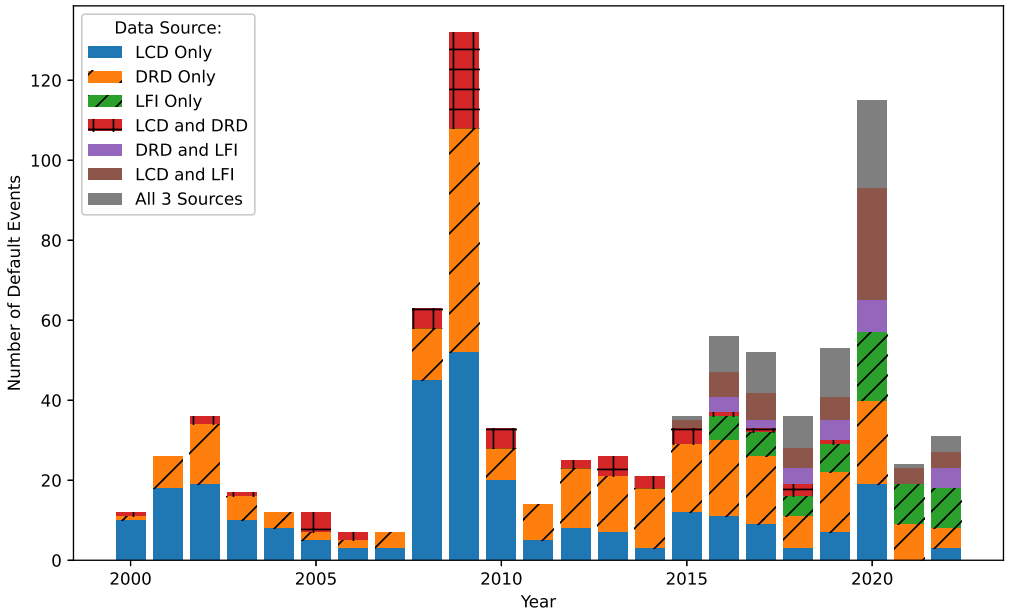


Figure 2. **Leveraged Loan Default Events.**
This figure presents the annual number of default events for borrowers in our deal sample between 2000–2022, as reported by three data sources: Pitchbook's Leveraged Commentary & Data (LCD), Default and Recovery Database (DRD), and LevFin Insights (LFI).

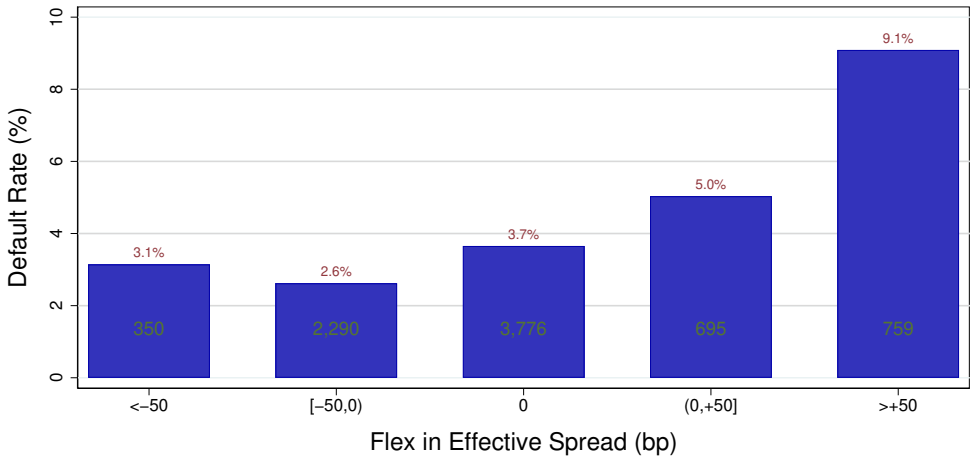


Figure 3. **Spread Flex and Default: Nonparametric Comparison.** This figure presents the fraction of syndication deals that subsequently default. Sample deals are divided into 5 groups based on flex in effective spread during the bookbuilding process. The number inside each bar indicates the number of deals in the group. Difference in defaul rate between the two extreme groups is $9.1\% - 3.1\% = 5.9\%$ ($t = 3.6$).

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

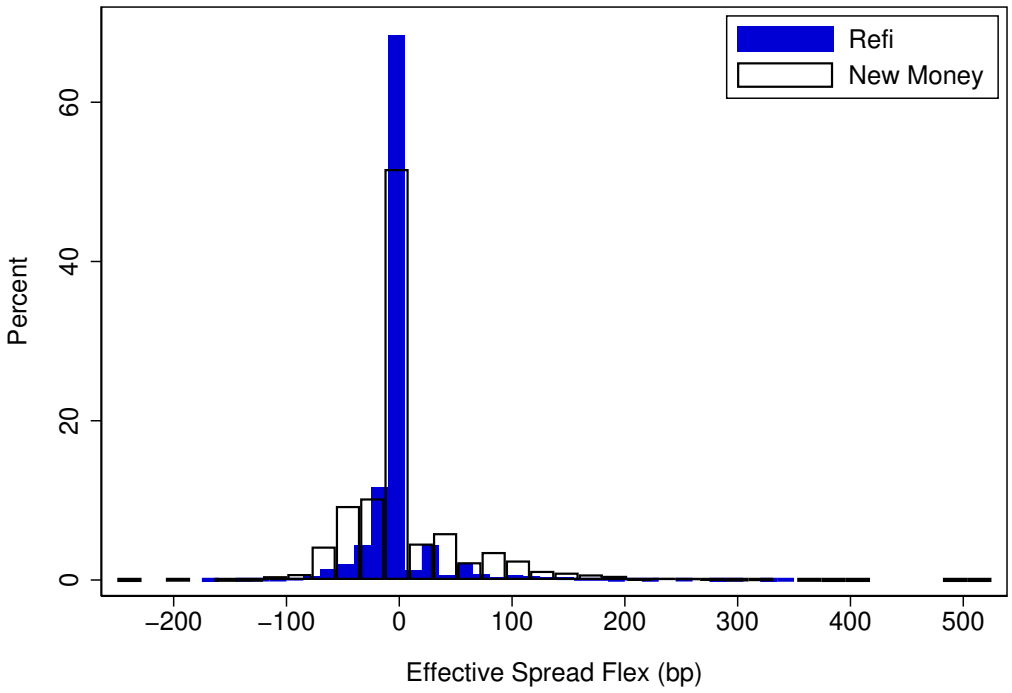


Figure 4. **Distribution of Spread Flex: New Money and Refinance.** This figure presents the distribution of effective spread flex in syndication deals for new money deals and refinance deals, respectively. Source: PitchBook Data, Inc.

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 A.1. *Amount* and *Maturity* are the total amount (in million USD) and average maturity (in year) of 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
Amount	7,870	650	754	66	215	400	795	2,064
Maturity	7,870	6.0	1.1	4.0	5.3	6.0	7.0	7.0
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**

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 that indicates 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 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.

Dependent Variable: Default				
	(1)	(2)	(3)	(4)
Spread Flex	0.032***	0.029***	0.025***	0.027***
	(0.007)	(0.007)	(0.007)	(0.007)
Talk Spread			0.028***	0.029***
			(0.004)	(0.004)
Log(Amount)				0.586
				(0.372)
Log(Maturity)				-2.168
				(1.465)
Relationship				-0.336
				(0.985)
Sponsored				-1.037
				(0.823)
Cov Lite				1.354*
				(0.766)
Has Revolver				-0.596
				(0.637)
Has TLA				-0.713
				(1.110)
Has Bond				1.940*
				(0.995)
Credit Rating FEs	N	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	7,182	7,182
R^2	0.074	0.079	0.087	0.094

Table 3: **Spread Flex and Default: Subsample Analyses**

This table reports results from estimating regressions in Table 2 based on subsamples. 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. *Talk Spread* is effective spread the lead bank proposed at deal launch. Control variables are the same as in column (4) of Table 2. 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.

Panel A: New Money vs Refinance

	New Money		Refi	
	(1)	(2)	(3)	(4)
Spread Flex	0.036***	0.035***	0.007	0.004
	(0.008)	(0.008)	(0.016)	(0.016)
Talk Spread		0.020***		0.043***
		(0.004)		(0.007)
Additional Controls	N	Y	N	Y
Credit Rating FEs	Y	Y	Y	Y
Lead Arranger FEs	Y	Y	Y	Y
Deal Purpose FEs	Y	Y	N	N
Industry FEs	Y	Y	Y	Y
Month FEs	Y	Y	Y	Y
N	4,470	4,470	3,309	3,309
R^2	0.126	0.137	0.142	0.178

Panel B: Credit Rating Disagreement

	Ratings Disagree		Ratings Agree	
	(1)	(2)	(3)	(4)
Spread Flex	0.063***	0.063***	0.024***	0.022***
	(0.022)	(0.022)	(0.007)	(0.007)
Talk Spread		0.019*		0.031***
		(0.010)		(0.004)
Additional Controls	N	Y	N	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	921	921	6,861	6,861
R^2	0.334	0.349	0.100	0.121

Panel C: Pre-Existing Relationship with Lead Bank

	Non-Relationship		Relationship	
	(1)	(2)	(3)	(4)
Spread Flex	0.029***	0.028***	0.012	0.015
	(0.007)	(0.007)	(0.040)	(0.040)
Talk Spread		0.027***		0.042***
		(0.004)		(0.011)
Additional Controls	N	Y	N	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	6,382	6,382	1,429	1,429
R^2	0.113	0.133	0.132	0.161

Table 4: **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 2. 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.

Dependent Variable: Moody's Credit Rating Changes

	Rating Change		Rating Withdrawal	
	(1)	(2)	(3)	(4)
Spread Flex	-0.106***	-0.114***	0.070***	0.055***
	(0.039)	(0.039)	(0.021)	(0.021)
Talk Spread		-0.081***		0.059***
		(0.024)		(0.015)
Additional Controls	N	Y	N	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	2,553	2,553	3,035	3,035
R^2	0.145	0.164	0.142	0.180

Table 5: **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. *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.

Dependent Variable: Annualized Secondary Market Return

	3m	6m	1y	2y	3y	4y
	(1)	(2)	(3)	(4)	(5)	(6)
Spread Flex	0.030***	0.016***	0.007**	0.008*	-0.001	-0.003
	(0.003)	(0.003)	(0.003)	(0.004)	(0.006)	(0.010)
Talk Spread	0.018***	0.013***	0.008***	0.001	0.001	0.001
	(0.002)	(0.002)	(0.001)	(0.003)	(0.002)	(0.003)
Log(Amount)	-0.394*	-0.201	-0.424**	-0.242	-0.443**	-0.674**
	(0.209)	(0.158)	(0.163)	(0.220)	(0.192)	(0.301)
Log(Maturity)	-0.088	-0.831	-0.645	-1.111	1.514	-1.847
	(0.617)	(0.665)	(0.533)	(0.810)	(1.677)	(2.637)
Credit Rating FEs	Y	Y	Y	Y	Y	Y
Month FEs	Y	Y	Y	Y	Y	Y
N	1,874	1,877	1,879	1,179	753	410
R^2	0.670	0.632	0.463	0.331	0.303	0.355

Table 6: **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 an industry during the month. The variable of interest, *CLO Constraint*, is CLO portfolio constraint for the industry-month. 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 fixed effects are based on the average of S&P and Moody's first lien credit ratings 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.

Dependent Variable: Spread Flex				
	(1)	(2)	(3)	(4)
CLO Slackness	-42.3	-42.3		
	(54.5)	(54.5)		
Binding CLOs			-10.1	-10.1
			(29.3)	(29.4)
Log(Amount)		0.0		0.0
		(0.8)		(0.8)
Log(Maturity)		-0.9		-0.9
		(5.5)		(5.6)
Credit Rating FEs	Y	Y	Y	Y
Industry FEs	Y	Y	Y	Y
Month FEs	Y	Y	Y	Y
N	2,506	2,506	2,506	2,506
R^2	0.212	0.212	0.212	0.212

Appendix

1 The Benveniste and Spindt (1989) model

In this appendix, we provide a more formal description of the model of Benveniste and Spindt (1989), but with a focus on the empirical implications of the model. We then discuss the empirical evidence for this model in the context of our data.

1.1 Description of the model

Each investor who participates in the bookbuilding receives a signal that determines his or her demand. The signals are binary and either 'good' (with probability p) or 'bad' (with probability $1-p$), and are independent of each other. The number of good signals follows a binomial distribution and is a sufficient statistic for p. The expected value of the asset is a linear and increasing function of the number of good signals that investors have received. Let H be the total number of investors and let h be the number of investors with a good signal. We can then define a variable $Z = h/H - p$, the (de-meaned) fraction of good signals, which is a sufficient statistic of the aggregate information of investors. Departing from the model, suppose before bookbuilding, the bank already has all other price-relevant information X. The set of all price relevant information then would be $\Omega = \{X, Z\}$, where w.l.o.g. $X \perp\!\!\!\perp Z$.

If the actions of the bank and the bookbuilding procedure reveal both X and Z to market participants, the secondary market price should reflect 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 is a version of the expression for the secondary market price in Benveniste and Spindt (1989).[14] In their model, the underwriter learns about the analog of our Z via bookbuilding and sets an issuance price P_I to incorporate it.

[14] For the secondary market price, they write $P_h = A - (H - h)\alpha$ (cf. p. 347). Setting $\alpha = 1/H$ and $X = A - (1 - p)$, we obtain the same expression.

Measuring the information of investors The model of Benveniste and Spindt (1989) 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. (E.g., the bank could propose an initial price equal its expectation of the issuance price, $P_0(X) = E[P_I|X]$, which would be consistent with the model of Chemmanur and Fulghieri (1994).) Regardless of how precisely the bank sets the initial price as a function of X, the price adjustment

$$\text{price adjustment} = P_I(X, Z) - P_0(X) \tag{A.2}$$

must be 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

$$\text{spread flex } = S_I(X, Z) - S_0(X) \tag{A.3}$$

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.*

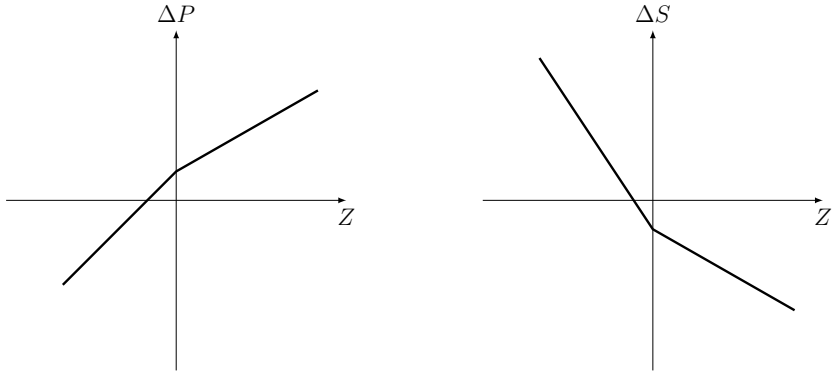
The first implication of the theory therefore is that price adjustments (or spread flex) are a suitable proxy variable for Z.

Partial adjustment 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.

$$P_I(X, Z) = \begin{cases} X + Z & \text{if } Z \leq \bar{Z} \\ X + Z - \gamma Z & \text{if } Z > \bar{Z} \ , \end{cases} \tag{A.4}$$

for some $0 < \gamma < 1$ and $\bar{Z}$. 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.) 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 model 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.4) and (A.2)), 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 $\Delta S \lesssim -P_0 \Delta P$.

"Partial adjustment" is the key testable implication of the model. Underpricing can be measured by comparing the secondary market price to issuance price. Price adjustments or spread adjustments are a proxy for Z (see Lemma A.1). The theory therefore makes the following testable prediction (first tested by Hanley, 1993):

Lemma A.2. *The price adjustment during bookbuilding is positively correlated with underpricing. (The spread adjustment during bookbuilding is negatively correlated with underpricing.)*

Non-linearity in the information of investors In addition, the theory also suggests that the price adjustment should be concave in Z. Since the issuance

spread $S_I(P_I)$ is decreasing and convex in the issuance price P_I, the issuance spread $S_I(X, Z) := (S \circ P_I)(X, Z)$ is decreasing and convex in Z (see Figure A.1).[15]

The concavity of price adjustments/ convexity of spread adjustments imply the following:

Lemma A.3. *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).

The density of price adjustments and spread adjustments 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.

[15] 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 $S(P)$.

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 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.4) 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:

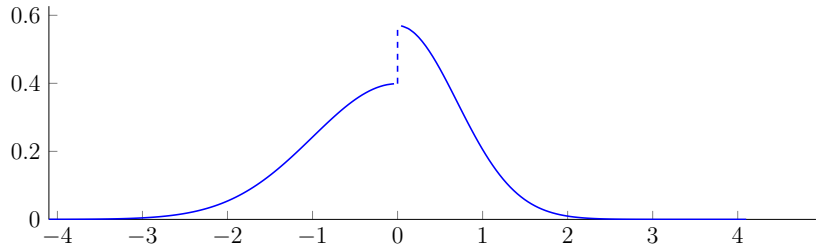
$$\Pr(\Delta P \leq \Delta p) = \begin{cases} \Pr(Z < \Delta p) & \text{if } Z \leq 0, \\ \Pr((1-\gamma)Z < \Delta p) & \text{if } Z > 0. \end{cases} \tag{A.6}$$

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

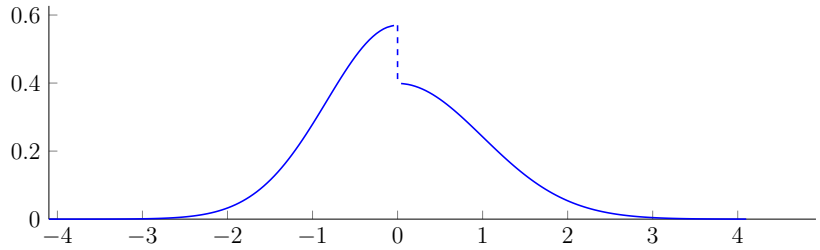
$$f(\Delta p) = \begin{cases} \frac{1}{\sigma}\varphi\left(\frac{\Delta p}{\sigma}\right) & \text{if } \Delta p \leq 0 \\ \frac{1}{\sigma(1-\gamma)}\varphi\left(\frac{\Delta p}{\sigma(1-\gamma)}\right) & \text{if } \Delta p > 0, \end{cases} \tag{A.7}$$

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 thanwthe 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



(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.4), 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 $\Delta S \lessapprox -(1/P_0)\Delta P$.

simplify.) This definition of the spread implies that for small ΔS

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

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

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

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

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

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.2. This is because the bank only partially adjusts to value-positive information that *decreases* the spread.

1.2 Evidence for the model

We present tests of the predictions of the model in the sequence in which we discuss these in the previous subsection. Of these, the sharpest prediction is that of "partial adjustment" (Lemma A.2), that price updates and underpricing should be positively correlated, or that spread flex and underpricing should be negatively correlated. There is evidence of such a correlation in stock initial public offerings, corporate bond offerings, and in leveraged loan deals (Hanley, 1993; Bruche, Malherbe, and Meisenzahl, 2020; Wang, 2021). We show that spread flex and

underpricing is indeed negatively correlated in our data and therefore, that the model is a good description of our data also.

To provide a more complete picture, we also discuss how some of the less sharp predictions of the model hold up in our data.

Measuring information of investors (Lemma A.1) In the model, the signals that investors receive are private information. The bank only learns about the signals during bookbuilding. This implies that the bank should not be able to predict the realization of the signals, or, in terms of our notation, $E[Z|X] = E[Z]$. As econometricians, we do not have the full information set of the bank but do access to a subset of the information, such as deal and issuer characteristics, and the identity of the lead bank. If it is not possible to predict investor information Z, it should also not be possible to predict Z with the subset of the information of the bank that we have access to. We can check whether this is the case by running predictive regressions for our proxy for Z, the Effective Spread Flex, and examining the percent of explained variation, the R^2.

Furthermore, in the "Talk Spread" (i.e., the spread that the bank proposes to investors before soliciting bids during bookbuilding), we also have a variable that is potentially a function of *all* information that the bank possesses. E.g., if the bank computes the Talk Spread from an initial price P_0 where it sets $P_0 = E[P_2(X, Z)|X]$, then it should be a sufficient statistic of the information in the bank's information set X. We therefore include the Talk Spread as a regressor in the predictive regressions. Table A.2 shows the results.

[Insert Table A.2 here]

In column (1), we include the Talk Spread, the logs of amount and maturity, and credit rating fixed effects as explanatory variables. The R^2 of this regression is extremely low, indicating that only about 2% of the variation in Effective Spread Flex can be explained by this model. When adding lead arranger fixed effects, deal purpose fixed effects, and industry fixed effects in column (2), this increases the

explained part of the variation only by an additional 3%, to about 5%. Consistent with the model, Effective Spread Flex, our proxy of investor information Z, is hard to predict. We can increase the R^2 somewhat by including month fixed effects, which we do in column (3) and in column (4), which is the model with the largest number of explanatory variables. The R^2 increases to about 16-17% when we do so. This suggests that Effective Spread Flex is driven in part by aggregate factors. Even taking this into account, the overall predictability is quite low.

To what extent does the Talk Spread, which is a function of the bank's information set, reflect information in the econometrician's information set? We examine this question by running predictive regressions, again using deal characteristics and fixed effects. We report the results of these regressions in Table A.3.

[Insert Table A.3 here]

The R^2s in Table A.3 are much higher than those in Table A.2 and range from about 28% to about 58% in the most saturated model. Taken together with the R^2s in Table A.2, they suggest that it much easier for an outside observer to guess the initial spread that a bank will propose than to guess whether spread will be flexed up or down during bookbuilding, because the bank sets the initial spread partially on the basis of public information. The information subsequently revealed during bookbuilding is information that is not public and not known to the bank. The fact that R^2s in Table A.3 are substantially below 100% may also suggest, however, that there is information in the bank's information set that influences its setting of the talk spread which is not public information.

Partial adjustment (Lemma A.2) The key "partial adjustment" implication of the theory that has been tested in the data. Hanley (1993); Wang (2021) show that price adjustments during bookbuilding are positively correlated with underpricing in stocks and in corporate bonds, respectively. Similarly, in the context of leveraged loans, (Bruche, Malherbe, and Meisenzahl, 2020) show that spread adjustments are negatively correlated with underpricing. We replicate this partial adjustment test in Table A.4, on the data used in this paper.

Over all four specifications, the partial correlation between Spread Flex is negative and significant. The coefficients indicate that a positive flex in the spread during bookbuilding of 100 basis points is associated with an decrease in underpricing of just under 4 basis points. This effect is slightly smaller than that in the data of Bruche, Malherbe, and Meisenzahl (2020), who report a corresponding decrease in underpricing of around 7 basis points. However, the coefficients are clearly negative and significant, indicating "partial adjustment." Also in the data used in this paper, changes in the spread during bookbuilding are negatively associated. Since only models in the spirit of Benveniste and Spindt (1989) predict this negative correlation, this is strong evidence in favor of the model.

Over all four specifications, the coefficients on Spread Flex are also relatively stable. Column (1) provides results for a basic specification for estimation the relationship between Spread Flex and Underpricing, controlling for talk spread, deal, industry, and month fixed effects, as well as lead arranger fixed effects, only. Column (2) adds a set of deal characteristics as additional controls. Column (3) reverts to the simpler specification in Column (1), but replaces lead arranger fixed effects with more granular lead arranger – year fixed effects. Column (4) adds the additional controls to the specification with lead arranger – year fixed effects.

Overall, swapping lead arranger fixed effects with the more granular lead arranger – year fixed effects has hardly any effect on the size of the coefficient on Spread Flex at all. It can be seen that the additional deal-level characteristics in columns (2) and (4) lead to a very slight decrease in the absolute size of the coefficient on Spread Flex. However, the coefficients remain negative and significant and they are only very slightly closer to zero. The coefficients on the deal level controls is similar to the coefficients reported in Table 3 of Bruche, Malherbe, and Meisenzahl (2020).

Non-linearity in the information of investors (Lemma A.3) The concavity of price adjustments/ convexity of spread adjustments in Z imply that, for a given size of effective spread flex, positive flexes should be associated with bigger changes in, e.g., default probability than negative flexes.

Consequently, we replicate the tests in Table 2 but allow for a potential non-linearity in the relationship between spread flex and default. We interact Spread Flex with dummy variable that is equal to 1 when Spread Flex is negative and zero otherwise.

Column (1) of Table A.5 is a version of the specification in column (3) of Table 2, but allowing for non-linearities in the relationship between Spread Flex and default. Column (2) of Table A.5 is a version of the more complicated specification in column (4) of Table 2 which adds deal-level controls, and also allows for non-linearities in the relationship between Spread Flex and default.

The coefficients on Spread Flex and the interaction term in Table A.5 are qualitatively similar across the two specifications. In both specifications, the coefficient on Spread Flex is positive and significant but the interaction is slightly negative and insignificant. We cannot reject the null that the relationship is linear.

The density of price adjustments and spread adjustments Although we provide no formal test, we note that empirical distribution of effective spread flex in Figure 1 appears to match the asymmetry of the distribution of spread adjustments predicted by theory as depicted in Figure A.2

2 Default indicators and excess returns

This appendix provides a more formal description of the arguments that motivate our choice of left-hand side variables in our regressions, as described in Section 2. (We describe the choice of our main right-hand side variable in Appendix 1.1.)

Consider a one-period consumption-based asset pricing model for an asset (meant to represent a loan) that pays a cash flow C. Suppose that all price-relevant information can be described by the variables in the information set Ω. 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:

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

where r_f is the risk-free rate. If the information revealed by investors during bookbuilding is price-relevant, it is contained in Ω. It 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.

It is important to note that in this 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 constraints or inflows or outflows produce temporary price pressure for a given type of asset, potentially because investors are temporarily liquidity constrained (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.

To see whether the information revealed by investors during bookbuilding is relevant specifically 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 information revealed by investors, the spread adjustments during bookbuilding,

controlling for all other price-relevant variables available before bookbuilding.

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:

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

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

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

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

3 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 A.3 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 probabilities are economically larger than deals that experienced zero or a downward spread flex.

Table A.9 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 probability 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 probability of default.

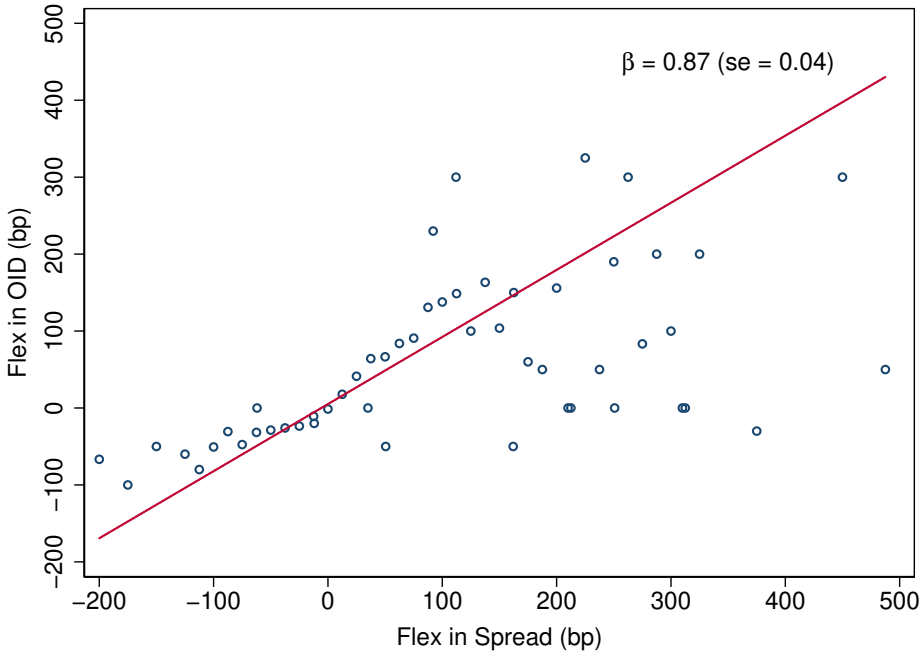


Figure A.1. **Relationship Between Spread Flex and OID Flex.** This figure presents a scatter plot that groups syndication deals into 100 bins based on flex in loan spread and depicts the average flex in OID within each bin. The fitted line represents an OLS slope estimate, with heteroskedasticity-robust standard error in parentheses. Source: PitchBook Data, Inc.

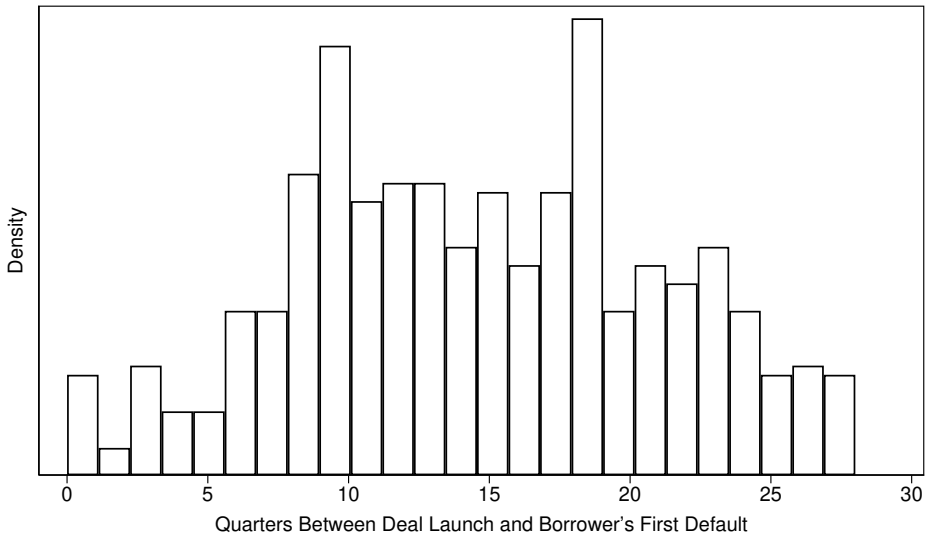


Figure A.2. **Time Between Syndication Deal and Default.** This figure presents the distribution of the number of quarters between a syndication deal and the borrower's default for all default events. Source: PitchBook Data, Inc.

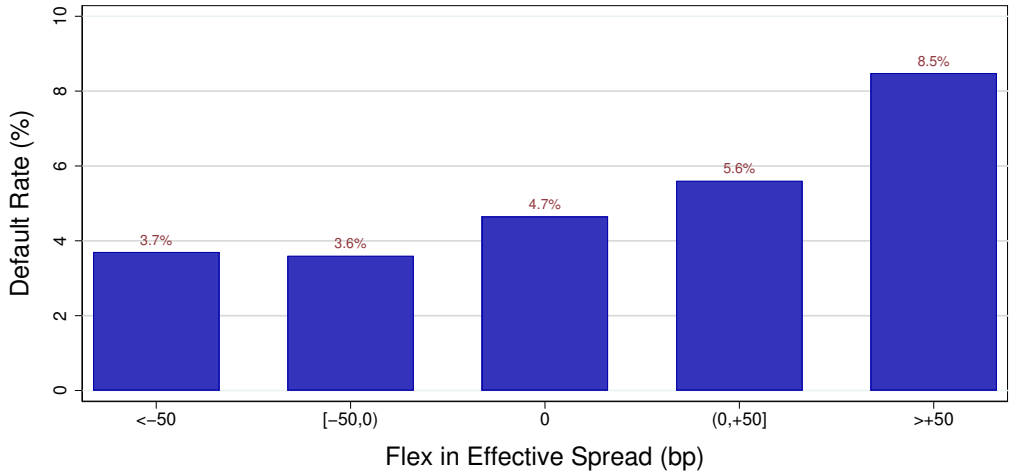


Figure A.3. **Spread Flex and Deal-Level Default: Nonparametric Comparison.**
This figure presents the fraction of syndication deals that subsequently default. The sample consists of 1,030 Pitchbook LCD deals for which the institutional term loan is matched to a debt instrument in DRD. The deals are 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.

Table A.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 A.2: **Predicting Spread Flex**

This table reports results from regressing *Spread Flex*, the deal's effective spread flex during bookbuilding, on deal characteristics and a set of fixed effects. Every observation is a syndication deal between 2000–2020. *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.

Dependent Variable: Spread Flex				
	(1)	(2)	(3)	(4)
Talk Spread	0.021**	0.018*	0.025***	0.016**
	(0.010)	(0.010)	(0.008)	(0.008)
Log(Amount)	-0.605	-1.124*	0.117	0.952*
	(0.615)	(0.664)	(0.567)	(0.558)
Log(Maturity)	-0.867	-1.746	-2.817	-2.110
	(2.578)	(2.638)	(2.723)	(2.851)
Relationship				-3.887**
				(1.807)
Sponsored				-1.531
				(1.343)
Cov Lite				-7.475***
				(1.339)
Has Revolver				1.880
				(1.637)
Has TLA				-5.564*
				(3.000)
Has Bond				-11.806***
				(2.133)
Credit Rating FEs	Y	Y	Y	Y
Lead Arranger FEs	N	Y	Y	Y
Deal Purpose FEs	N	Y	Y	Y
Industry FEs	N	Y	Y	Y
Month FEs	N	N	Y	Y
N	7,870	7,839	7,818	7,818
R^2	0.021	0.054	0.163	0.174
Within R^2	0.003	0.003	0.003	0.015

Table A.3: **Predicting Talk Spread**

This table reports results from regressing *Talk Spread*, the deal's effective spread the lead bank proposed at deal launch, on the deal's characteristics. Every observation is a syndication deal between 2000–2020. *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.

Dependent Variable: Talk Spread				
	(1)	(2)	(3)	(4)
Log(Amount)	-21.236***	-19.728***	-14.116***	-14.747***
	(2.265)	(1.996)	(1.793)	(1.657)
Log(Maturity)	-42.111***	-50.078***	-19.884**	-30.279***
	(12.296)	(11.209)	(9.069)	(8.985)
Relationship				-39.410***
				(3.700)
Sponsored				-8.950**
				(3.930)
Cov Lite				-44.140***
				(4.248)
Has Revolver				23.517***
				(3.855)
Has TLA				-16.324***
				(6.209)
Has Bond				9.274**
				(3.910)
Credit Rating FEs	Y	Y	Y	Y
Lead Arranger FEs	N	Y	Y	Y
Deal Purpose FEs	N	Y	Y	Y
Industry FEs	N	Y	Y	Y
Month FEs	N	N	Y	Y
N	7,818	7,182	7,182	7,182
R^2	0.277	0.365	0.547	0.579
Within R^2	0.041	0.039	0.021	0.090

Table A.4: **Underpricing and Spread Flex**

This table reports results from regressing *Underpricing*, the difference between the deal's break price and original issuance price (in basis point), on *Spread Flex*, the deal's effective spread flex during bookbuilding. Every observation is a syndication deal between 2000–2020 with a break price. *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. *Has Revolver*, *Rated*, *Sponsored*, *Cov Lite*, and *Second Lien* are dummies indicating that the deal a revolving credit facility, has credit rating(s), has a private equity sponsor, includes a cov-lite loan, a second lien facility, 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.

Dependent Variable: Underpricing

	(1)	(2)	(3)	(4)
Spread Flex	-0.033**	-0.030*	-0.034**	-0.031**
	(0.016)	(0.015)	(0.016)	(0.015)
Log(Talk Spread)	56.424***	60.417***	55.819***	59.386***
	(3.116)	(3.689)	(3.142)	(3.703)
Has Revolver		6.776***		7.080***
		(1.201)		(1.261)
Rated		6.712***		5.719**
		(2.483)		(2.415)
Sponsored		-8.386***		-8.636***
		(1.265)		(1.240)
Cov Lite		2.322*		2.230*
		(1.243)		(1.308)
Second Lien		0.026		-0.181
		(1.593)		(1.652)
Log(Amount)		1.988***		1.609**
		(0.674)		(0.671)
Log(Maturity)		-0.747		-0.162
		(2.995)		(3.022)
Lead Arranger FEs	Y	Y	N	N
Lead Arranger - Year FEs	N	N	Y	Y
Deal Purpose FEs	Y	Y	Y	Y
Industry FEs	Y	Y	Y	Y
Month FEs	Y	Y	Y	Y
N	6,293	6,293	6,228	6,228
R^2	0.378	0.392	0.419	0.433

Table A.5: **Spread Flex and Default: Interaction Specifications**

This table reports results from estimating regressions in Table 2 with interaction specifications. The sample consists of syndication deals between 2000–2020. The dependent variable is a dummy indicating whether the borrower defaults over a 4-year period after issuance, scaled up by 100. $1(SpreadFlex < 0)$ is an indicator variable that equals one if *Spread Flex*, the deal's effective spread flex during bookbuilding, is negative. Control variables are the same as in column (5) of Table 2. 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.

Dependent Variable: Default		
	(1)	(2)
Spread Flex	0.024***	0.025***
	(0.009)	(0.009)
1(Spread Flex < 0)	-0.569	-0.498
	(0.628)	(0.615)
Spread Flex × 1(Spread Flex <0)	-0.008	-0.003
	(0.020)	(0.021)
Talk Spread	0.028***	0.029***
	(0.004)	(0.004)
Log(Amount)		0.579
		(0.370)
Log(Maturity)		-2.128
		(1.473)
Relationship		-0.332
		(0.995)
Sponsored		-1.042
		(0.824)
Cov Lite		1.367*
		(0.769)
Has Revolver		-0.551
		(0.643)
Has TLA		-0.689
		(1.115)
Has Bond		1.976**
		(0.995)
Credit Rating FEs	Y	Y
Lead Arranger FEs	Y	Y
Deal Purpose FEs	Y	Y
Industry FEs	Y	Y
Month FEs	Y	Y
N	7,818	7,818
R^2	0.117	0.120

Table A.6: **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 2. 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.

Dependent Variable: Default				
	[0,3y]	[0,mature]	[1y,mature]	[0,∞)
	(1)	(2)	(3)	(4)
Spread Flex	0.016***	0.027***	0.026***	0.027***
	(0.005)	(0.009)	(0.009)	(0.009)
Talk Spread	0.026***	0.040***	0.036***	0.040***
	(0.004)	(0.005)	(0.005)	(0.006)
Additional Controls	Y	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	7,818	7,818	7,818	7,818
R^2	0.122	0.139	0.132	0.165

Table A.7: **Spread Flex and Default: Default Events in LCD**

This table reports robustness tests using borrower-level default events covered by LCD. The sample consists of all sample deals in LCD between 2000–2020. Panel A and Panel B present univariate analyses. 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 2. 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.

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)
Spread Flex	0.023***	0.021***	0.018***	0.019***
	(0.006)	(0.006)	(0.006)	(0.006)
Talk Spread			0.021***	0.022***
			(0.003)	(0.003)
Additional Controls	N	N	N	Y
Credit Rating FEs	N	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	7,818	7,818	7,818	7,818
R^2	0.083	0.088	0.106	0.109

Table A.8: **Spread Flex and Default: Default Events 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 present univariate analyses. 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 2. 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.

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)
Spread Flex	0.017***	0.016**	0.014**	0.015**
	(0.006)	(0.006)	(0.006)	(0.006)
Talk Spread			0.015***	0.014***
			(0.003)	(0.003)
Additional Controls	N	N	N	Y
Credit Rating FEs	N	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	7,818	7,818	7,818	7,818
R^2	0.068	0.074	0.082	0.081

Table A.9: **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 present univariate analyses. 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 2. 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)
Spread Flex	0.030**	0.026*	0.025*	0.027*
	(0.014)	(0.014)	(0.014)	(0.014)
Talk Spread			0.012*	0.010
			(0.007)	(0.007)
Additional Controls	N	N	N	Y
Credit Rating FEs	N	Y	Y	Y
N	1,030	1,030	1,030	1,030
R^2	0.007	0.027	0.030	0.046