What Do Lead Banks Learn from Leveraged Loan Investors?*

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Abstract

We examine the private information held by nonbank lenders in leveraged loan syndications. In these transactions, lead banks gather information about participant demand through bookbuilding and use it to adjust loan spreads. An upward spread adjustment during bookbuilding strongly predicts the borrower's future default and prompts banks to raise their internal risk estimates. This suggests that nonbank syndicate participants' demand reveals 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.

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1 Introduction

Classic theories of lending assign banks a unique ability to screen and monitor borrowers, thereby producing information that is not available to other market participants. This informational advantage explains banks' historical role as primary lenders. However, in the wake of post-crisis regulatory changes —most notably, more stringent bank capital requirements— nonbank institutional investors have become increasingly active in corporate lending markets. The growing prevalence of nonbank lenders raises fundamental questions about the structure of information production in credit markets: Do banks continue to possess a unique informational advantage, or has information production become more decentralized?

This paper studies the information of nonbank investors in the context of the leveraged loan market, a large and important segment of corporate credit. In this market, lead banks originate non-investment-grade syndicated loans and distribute the majority of loan exposures to nonbank institutions, such as collateralized loan obligations (CLOs) and credit-focused investment funds. These investors often devote substantial resources to analyzing borrower fundamentals and participate actively in the syndication process through bookbuilding—a stage at which lead banks solicit investor demand and adjust loan pricing and 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. Using data on the bookbuilding process, we provide evidence that the demand of investors as revealed to lead banks during bookbuilding contains information about the loan's probability of default that is orthogonal to the information revealed by the lead bank at the beginning of the process. Hence, investors have information about the borrower's quality that the lead bank does not have before bookbuilding. This result challenges the canonical view that banks are the sole producers of borrower-specific information. Instead, our finding suggests that both lead banks and nonbank investors hold distinct, imperfectly correlated private signals about borrower quality and that as nonbank investors take on a larger role in corporate lending, the production of information can become more decentralized.

Banks propose an initial spread at the beginning of bookbuilding and then adjust this spread in response to investor demand. We utilize data on the difference between initial spread proposed by the lead bank at the start of bookbuilding and final spread at deal completion. Using the language of market participants, we refer to these adjustments as the "effective spread flex" or "flex" for short. Our analysis delivers three main results relating to flex.

Our first main result replicates a result already in the literature, which is, however, a crucial part of our argument: We show that flex correlates negatively with loan underpricing, conditional on a set of controls. The interpretation of this result is that banks must make it incentive compatible for investors to reveal when they are willing to accept a lower spread – by underpricing loans whenever investors indicate that this is the case. (This result is also known as the "partial adjustment" result, see Hanley, 1993; Bruche, Malherbe, and Meisenzahl, 2020). This result shows that the bookbuilding process allows banks to gain information about investor demand that they do not previously have.

Our second main result is that the flex on a loan correlates positively with subsequent default on the loan, conditional on a set of controls. We show that when a bank increases the spread on a loan by 100 basis points during bookbuilding, this predicts a default rate that is about 3-4% higher than for loans on which the spread is not increased. 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. Since banks increase in spread when investor demand is low, this suggests that investors demand is (at least partially) driven by information about default. 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.

Our third main result is that flex is positively associated with changes in banks' internal estimates of the probability of default. Specifically, an increase in the spread of 100 basis points on a loan during bookbuilding is associated with a subsequent increase in banks' internal estimates of the probability of default for that issuer of about 30 basis points. This result illustrates how banks use the information that is produced by bookbuilding.

We perform several robustness checks. 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, 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.

For a subset of our deals, we can also compute interest rate coverage ratios based on the final loan spread, as well as counterfactual interest rate coverage ratios based on the bank's initially proposed loan spread, as well as difference between the two: the change in interest coverage ratio produced by the change in spread during bookbuilding. We can show that the correlation between flex and default is robust to controlling for this change in the interest rate coverage ratio as produced by bookbuilding.

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

Finally, we also provide some evidence to suggest that not all of the variation in investor demand during bookbuilding reflects investors' information about the borrower's quality, but may also be partially driven by inflows and outflows that these institutional investors are subject to. 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 months, or twelve months, relative to a loan on which the spread is not increased. We interpret this result as follows: Some institutional investors may face, e.g., liquidity constraints due to outflows at the time of loan syndication. These constraints manifest as weak demand during the bookbuilding process, prompting the lead bank to increase the loan spread to place the loan. Just after issuance, the liquidity constraints faced by some institutional investors should also affect secondary markets, where the loan's price would be depressed. As investor liquidity stabilizes post-syndication, the formerly constrained investors re-enter the market and purchase the loan, driving its price upward. This dynamic would generate positive excess returns over relatively short investment horizons that we observe.

In summary, our evidence suggests that investor demand during bookbuilding contains investors' private information about the borrower's credit quality. The lead bank learns about this information via bookbuilding. In the market for leveraged loans, information production is partially decentralized. Not only the lead bank but also investors contribute to producing the information that affects the pricing and allocation of credit.

Related literature Our paper contributes to the literature on loan sales and loan syndication. Classical banking theory posits that it is the banks who produce private information about the borrower to facilitate screening and monitoring (Diamond, 1984; Holmström and Tirole, 1997). A central concern in the literature on loan sales is how informed banks can sell loans to uninformed investors without exacerbating adverse selection or moral hazard problems. Prior work suggests that banks can mitigate these frictions by retaining a portion of the loan to signal quality or to preserve monitoring incentives (Pennacchi, 1988; Gorton and Pennacchi, 1995; Sufi, 2007; Ivashina, 2009), or by establishing a strong reputation with market participants (Booth and Smith II, 1986; Chemmanur and Fulghieri, 1994).

However, when banks anticipate that they will sell loans, their incentives to invest in producing borrower-specific information may decline (Keys et al., 2010). This opens the possibility that outside investors step in as alternative producers of information. Yet, empirical evidence on whether and how third-party investors generate borrower-specific information remains scarce. To our knowledge, our paper is the first to provide direct empirical evidence that non-bank investors also engage in information production about borrowers.

The distribution of information production between banks and investors has important theoretical implications. If investors were informed and banks uninformed, the underlying frictions and optimal contractual arrangements would differ fundamentally from those in traditional models (Axelson, 2007). In practice, it is plausible that both banks and investors possess complementary private information about borrowers. Our empirical findings suggest that such a setting—where information production is distributed across multiple parties—may be realistic and hence interesting to explore theoretically.

Our paper is also related to the literature that examines how banks use bookbuilding to price the assets in response to investor demand. 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 documenting that one of the drivers of investor demand is the private information that they possess 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 nonbanks in corporate lending. Prior research shows that nonbanks demand a 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. There is also the view that nonbanks manage to compete with banks by emphasizing speed over information production (Ben Saïd, Monnet, and Quintin, 2025). By contrast, the nonbank investors in the leveraged loan market appear to perform relatively lengthy and thorough credit analyses which

[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). Bookbuilding appears to provide some useful information about demand even in the presence of subsequent "when-issued" trading (Aussenegg, Pichler, and Stomper, 2006).

inform the pricing of loans. In that sense, they differ substantially from nonbank investors in other markets that may emphasize speed over information production.

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 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 private signal that determines their valuation and hence their demand for the asset being sold. If the signal is 'good', the investor's valuation and demand is high; if the signal is 'bad', the valuation and demand is low. Via the auction, the bank extracts information about investors' private signals. The bank sets the issuance price and quantity to reflect investors' signals. If most investors have good signals, the issuance price and quantity will be high. If most investors have bad signals, the issuance price and quantity will be low.

In the auction that the bank sets up it must be incentive compatible for investors to reveal their private signals. To achieve this, the bank must "partially adjust" the price when investors reveal positive information: Investors must know that when they indicate that the asset is worth \$1 more than the bank thought, the bank will increase the issuance price by less than \$1 and hence leave some money on the table for investors in the form of underpricing —otherwise, the investors cannot have any incentives to reveal their private signals. Conversely, if investors indicate that the asset is worth \$1 less than the bank thought, the bank can decrease the issuance price by the full \$1.[2] In the empirical literature following Hanley (1993), partial adjustment has been tested by checking that price adjustments during bookbuilding are positively correlated with underpricing. Evidence of this (partial) correlation has been interpreted as conclusive evidence that bookbuilding extracts private information from investors (see Appendix 1 for a more detailed discussion).

It is central to our argument that banks extract investors' private signals via bookbuilding. We therefore repeat the "partial adjustment" test of Hanley (1993) on our leveraged loan data. 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, which should be negatively correlated with underpricing (Bruche, Malherbe, and Meisenzahl, 2020):

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

The null hypothesis here would be that information is imperfect but symmetric – demand for the loan is is revealed to both the lead bank and investors at the same time. In this case, spread flex would be uncorrelated with underpricing.

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.

More 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

[2]The bank also needs to decrease the quantity allocated to investors when these indicate a low valuation, to make this less attractive. In general, a very large class of auction models/ mechanism design models in which the valuation of bidders is private information to the bidder will make these predictions (Guesnerie and Laffont, 1984; Maskin and Riley, 1984).

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. More generally, aggregate investor demand could contain information about the market's required risk premium.

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 formal justification for this measure.)

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

Second, investors may also 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 3. *Conditional on information known to the lead bank at the beginning of bookbuilding, spread flex is positively associated with excess return.*

We can test all three hypotheses by estimating regression

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

where Y_i is either underpricing in deal i, a default indicator for the borrower in deal i, or the excess return of the loan in question for deal i. *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. Hypothesis 1 predicts that the coefficient β should be negative when Y_i is underpricing. Hypotheses 2 and 3 predict that the coefficient β should be positive when Y_i is a default indicator or an excess return, respectively.

When using price or spread adjustments during bookbuilding as a proxy for investor demand, the literature following Hanley (1993) has implicitly made an identifying assumption, which we also make, but choose to state here explicitly:

Assumption 1. *In regression* (1), ϵ_i *is mean-independent of any variation in Spread Flex that is not driven by the demand revealed by investors during bookbuilding.*

In the case of Hanley (1993), the assumption requires that residual variation in underpricing is uncorrelated with any part of the variation in price adjustments that is unrelated to the demand revealed by investors. In the case of our Hypothesis 3, the assumption is that residual variation in the default indicator is uncorrelated with any part of the variation in flex that is unrelated to the demand revealed by investors.

This assumption would not be satisfied, for instance, if banks strategically set talk spreads that are "too low" when they have private information that indicates that the default probability is higher than publicly observable information would suggest. If banks did this and subsequently revealed their private information during bookbuilding, then this would produce positive flex precisely for those borrowers that are more likely to end up in default. In this case (part of) the association between flex and default would be driven by banks' strategic behavior rather than by the revelation of investors' demand.

We do not believe that this specific example should be a concern, however. First, banks often need to give up part of their fee to flex (Bruche, Malherbe, and Meisenzahl, 2020), and so have an incentive to set a talk spread as close as possible to their estimate of the final spread. Second, in private conversations, bankers describe their long-run profitability as depending on making both issuers and investors happy. To make the issuer happy, the spread cannot be too high. To make investors happy, the spread cannot be too low. Bankers need to have a reputation for being able to price loans accurately and therefore want to avoid talk spreads that turn out to be systematically too high or too low.

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) targeting 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 senior secured first lien institutional term loan facility in that deal. There are two relevant elements of pricing: The spread 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. If the deal includes a second lien facility, we require the same information for that facility as well. This filter results in a sample of 7,812 deals issued by 2,716 unique borrowers.

We define the pricing of a deal as the average pricing of its institutional term loan facilities. 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.

We also measure the underpricing of a deal as the difference between its "break price", i.e., the loan's first secondary market price at deal completion, and its primary market issuance price, given by OID. We convert the underpricing into basis points. For example, if the deal with a 0.97 OID has a break price of 0.985 in LCD data, its underpricing is 150 basis points.

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.

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–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 1 here]

Figure 1 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

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

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

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 also consider measuring borrower-level defaults over various time horizons and using only default events from either LCD or DRD.

Borrower financials. We obtain borrower financials from two sources: Compustat for publicly traded firms and confidential supervisory data from Federal Reserve's Y-14, schedule H.1 for private firms. We match public firms in LCD to their Compustat identifiers (GVKEYs) through Pitchbook and CRSP databases. Specifically, we first link the firm's LCD identifier to its CRSP permanent security identifier (PERMNO) via its historical exchange ticker symbol obtained via a customized project with Pitchbook.[5] We then match the PERMNO to GVKEY using the CRSP/Compustat link history table provided by WRDS. We match the private firms in LCD to the Y-14 using the firm's name only. From both Compustat and the Y14, schedule H.1, we obtain the firm's interest expenses and operating income (EBIT) to construct an interest coverage ratio (ICR) in the appropriate quarter. Moreover, we construct a counterfactual ICR, which excludes the impact of the deal's spread flex on the observed interest expenses. From the two sources, we obtain these financial variables for 3,163 syndication deals.

Banks' internal estimates of probability of default and loss given default. We use the Y-14 data on banks' internal estimates for probability of default and loss given default. Because these estimates are reported at the borrower level rather than the loan level, we match borrowers in LCD using firm names only. For matched borrowers, we require Y-14 data for the quarter before the syndication deal and for the quarter of loan issuance.[6] This leaves us with 2,069 syndication deals. Since the bookbuilding outcomes are publicly reported in the financial press, we average the probabilities of default and loss given default in case that more than one bank reports them.

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

[5]We require the historical ticker from Pitchbook to be within its time period in CRSP. To ensure linking accuracy, we also manually check the names of matched firmed in LCD, Pitchbook, and CRSP.

[6]If the loan was issued in the last month of a quarter, we instead use the following quarter's estimates to ensure that banks had time to incorporate information revealed during the bookbuilding process.

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.[7] These interest payments are compounded to the final price date based on reinvestment at the prevailing LIBOR rate.[8] Finally, we calculate an annualized n-year holding period return as

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

where the total value of cumulative cash flows is added to the secondary market price to reflect investor payoff from the loan.[9]

Credit Rating Changes. 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.[10]

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

[8]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.

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

[10]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.

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

3.2 Summary statistics

All Syndication Deals 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, loans are underpriced by 75 basis points in the primary market, and 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.

[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 2 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.[11]

[Insert Figure 2 here]

Borrower Financials Sample. Panel B of Table 1 shows that on average, syndication deals matched with borrower financials data have a moderately larger size and a lower talk spread, suggesting that these deals are less risky than the full sample. The borrower's interest coverage ratio before the deal is 3.8 times on average, with substantial dispersion across deals. Overall, spread flex has a very small impact on interest burden as measured by this ratio.

[11] 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).

Banks' Internal Risk Estimates Sample. Panel C of Table 1 summarizes the sample of syndication deals that are matched with banks' internal estimates for probability of default and loss given default. This sample has an even lower talk spread, and hence is on average less risky, than Panel B because all borrowers here have loans on at least one bank's balance sheet. However, there are significant adjustments to the default variables as indicated by the change in these variables from the quarter before and to the quarter after syndication.

Secondary Market Return Sample. Panel D 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.

Credit Rating Changes Sample. Panel E 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.[12]

4 Results

In this section, we present our empirical results. We start by establishing that spread flex is negatively associated with underpricing, as predicted by Hypothesis 1. We then establish that spread flex is positively associated with default, as predicted by Hypothesis 2. 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 subsamplejs. 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.

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

We also show that the association between flex and default is unaffected when controlling for the changes in interest rate coverage ratios produced by flex directly, for the subsample of borrowers for which we can compute these. 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 3. 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).

4.1 Spread flex and underpricing

To test Hypothesis 1 in Section 2, we use our leveraged loan syndication deal sample. According to the hypothesis, banks must make it incentive compatible for investors to reveal the private signals that drive their demand: When investors reveal positive information, the bank can decrease the spread but must ensure that the loan ends up being underpriced. When investors reveal negative information, the bank has to increase the spread and the loan does not have to be underpriced. Hence, the empirical prediction is that spread flex should be negatively correlated with underpricing, conditional on information known to the bank at the start of bookbuilding.

[Insert Table 2 here]

Table 2 reports the estimation results. Over all four specifications, the partial correlation between Spread Flex is negative and significant as predicted by the hypothesis. The coefficients indicate that a positive flex in the spread during bookbuilding of 100 basis points is associated with a decrease in underpricing of between 4 and 5 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. This "smoking gun" shows that banks use bookbuilding to extract information from investors that they do not have prior to bookbuilding.

4.2 Spread flex and default

According to Hypothesis 2 in Section 2, 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 4.4% more likely to default than deals that experienced downward spread flexes, and this difference is highly statistically significant ($t = 6.7$). We also test the difference between the groups with the largest upward (≥+50) and largest downward (≤-50) in Figure 3. The difference in default probability is 5.5%, almost double the average default rate, and statistically significant at the 1% level.

4.2.1 A formal test of Hypothesis 2

A formal test of Hypothesis 2 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 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 3 here]

Table 3 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 percentage points.

Column (2) controls for an important proxy for public information about the borrower's default risk, the deal's credit rating via fixed effects. 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 the talk 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.

Our first result in Subsection 4.1 indicates that banks learn about investors' demand via bookbuilding. This second result here suggests that investors' demand could be driven by information that investors have about default.

4.2.2 Subsample analyses

If the relationship between spread flex and default is driven by investors' information about borrowers, this relationship should be weaker or absent in deals in which investors are plausibly less likely to have private information.

We now investigate several ways of splitting our data to see whether the partial correlation between flex and subsequent varies across subsamples.

[Insert Table 4 here]

New Money Deals vs Refinancing. 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 in 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).

Figure A.1 in Appendix shows that new money deals exhibit a larger dispersion in spread flexes, suggesting the revelation of more private information. We re-estimate the specifications in Table 3 with subsamples, starting with a sample split between new money deals and refinancing deals.

Columns (1)–(2) in Table 4 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 new money 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 3, 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 4, 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 4 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.

4.2.3 Controlling for the effect of spread flex on interest burden

One concern with the baseline specifications is that the relationship between spread flex and default could be mechanical. A positive spread flex increases the interest burden of the firm and hence, the firm may be more likely to default due to higher interest burden. To assess this possibility, we complement our primary market data with borrower financials from Compustat (public firms) and the Y-14 (private firms). For each firm, we construct the interest rate coverage ratio (ICR) of the firm before the deal. Firms with higher ICRs are more likely to be able to meet their debt obligations as the interest payments are small relative to cash flow. We then construct the additional change in the ICR stemming from the spread flex—that is, we construct the counterfactual ICR without the spread flex and subtract it from the ICR with the actual interest rate.

[Insert Table 5 here]

Table 5, column (1) show the results of estimating our baseline regression in the subsample of borrowers with matched financial information. The point estimate in this subsample is a bit smaller than in the full sample but remains statistically significant. In column (2), we add the pre-deal ICR as additional control. While the point estimate for the pre-deal ICR is negative and significant as expected, the result for spread flex is unchanged. We then add the change in the ICR and loan controls (columns (3) and (4)) and find that the estimated effect of spread flex on default remains unchanged. Moreover, we do not detect any effect of the change in the ICR on default.

In columns (5) and (6), we estimate the regressions with a dummy that is equal to 1 if the spread flex is equal or larger than 50 basis points. In this specification, we find a positive and significant effect of larger positive spread flexes on default rate. A spread flex equal or larger than 50 basis points increases the probability of default by 4.6 percent points while the change in the ICR remains insignificant.

Taken together, the evidence does not support the interpretation that the relationship between spread flex and default is mechanical and driven by higher interest payments, but rather that it is driven by information that investors have.

4.3 Spread flex and updates in bank internal risk estimates

If spread flexes contain information about the borrower that is orthogonal to the lead bank's information, then we should see banks updating their estimates for default probability and losses after the loan is syndicated. We test whether banks update their estimates of default using the subsample of loans for which we observe default estimates in the Federal Reserve's Y-14 data.

[Insert Table 6 here]

Table 3, Panel A shows the results of estimate the effect of spread flex on the change in banks' internal probability of default estimates. Columns (1) shows the correlation without controls. Consistent with positive (negative) spread flexes indicating adverse (favorable) information about the borrower, the point estimate is positive and statistically significant. A 100 basis point increase in the flex is associated with a 0.3 percentage point increase in the bank's probability of default estimate. Adding fixed effects and controls (Columns (2)-(4)) does not affect this result.

In Panels B and C of table 3, we estimate the effect of spread flexes on loss given default and expected losses, respectively. As for the probability of default, we find a positive and statistically significant association of spread flex with loss given default and expected losses.

Taken together, since banks respond to syndication outcomes by updating their default estimates, the results in this section indicate that nonbanks reveal information about the borrower during the syndication process that is orthogonal to the banks' information.

4.4 Spread flex and excess return

Next, we proceed to test Hypothesis 3, 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 can use the annualized raw return as the dependent variable.)

Hypothesis 3 suggests that the demand of investors may be driven by information they have not about borrower fundamentals, but rather about the risk premium that the market requires for the loan. 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.

An intuitive version of the argument would be as follows: Suppose that some key investors suffer outflows, so that they show low demand during bookbuilding. The lead bank would have to flex the spread up. These investors also cannot buy in the secondary market, at least not immediately, so that the secondary market price would initially be "too low." If or when money flows back into the previously constrained investors, they then can buy the loan in the secondary market. This drives up the price until it reaches "normal" levels. The corresponding increase in the price implies a positive (excess) return over the time horizon over which money flows revert to their mean.

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 7 here]

Table 7 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.[13] 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 3.

These results suggest that flex can reflect other factors (e.g., inflows and outflows of institutional investors) in addition to information that investors possess.

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 4.2.

[13] 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.

Different definitions of default We first 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 8, Panel A we replace the 4-year horizon in Table 3 with various alternative time horizons.[14] 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.

[Insert Table 8]

Second, similar results hold even if we use default events covered by just one of the databases. For example, one can replicate our results exclusively based on just LCD data. In Table 8, Panel B 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. Likewise, in Table 8, Panel C 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.

Alternative outcome: rating changes and rating withdrawals Our Hypothesis 2 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 9 here]

We estimate regressions of the borrower's future credit rating changes on spread flexes and report the results in Table 9. For readability, we code the dependent variable as follows: -100 for a downgrade, 0 for no change, and 100 for an upgrade.

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

Table 9 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.

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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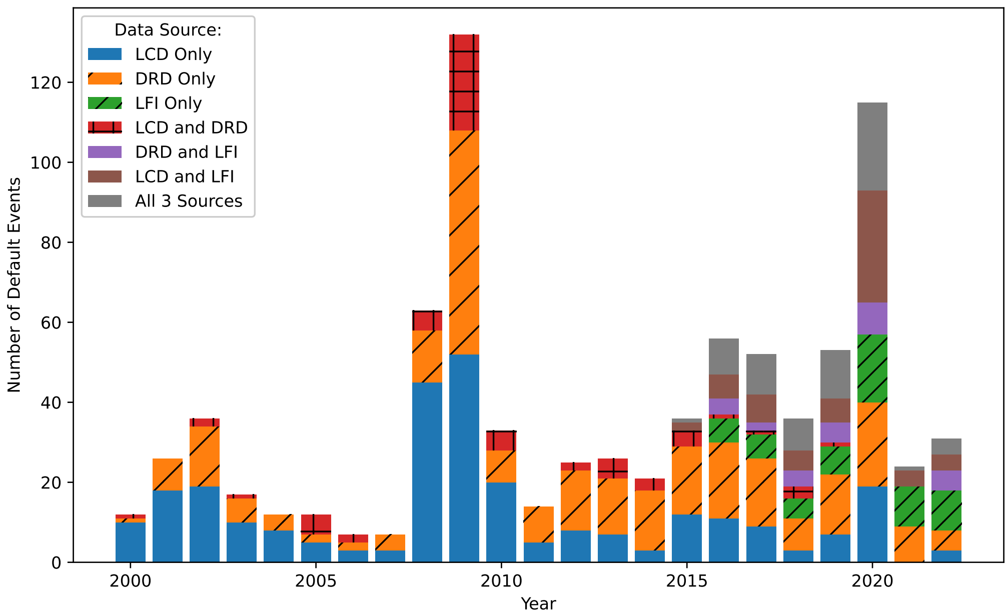


Figure 1. **Leveraged Loan Default Events.**
This figure presents the annual number of default events for borrowers in our deal sample between 2000–2022, as reported by three data sources: Pitchbook's Leveraged Commentary & Data (LCD), Default and Recovery Database (DRD), and LevFin Insights (LFI).

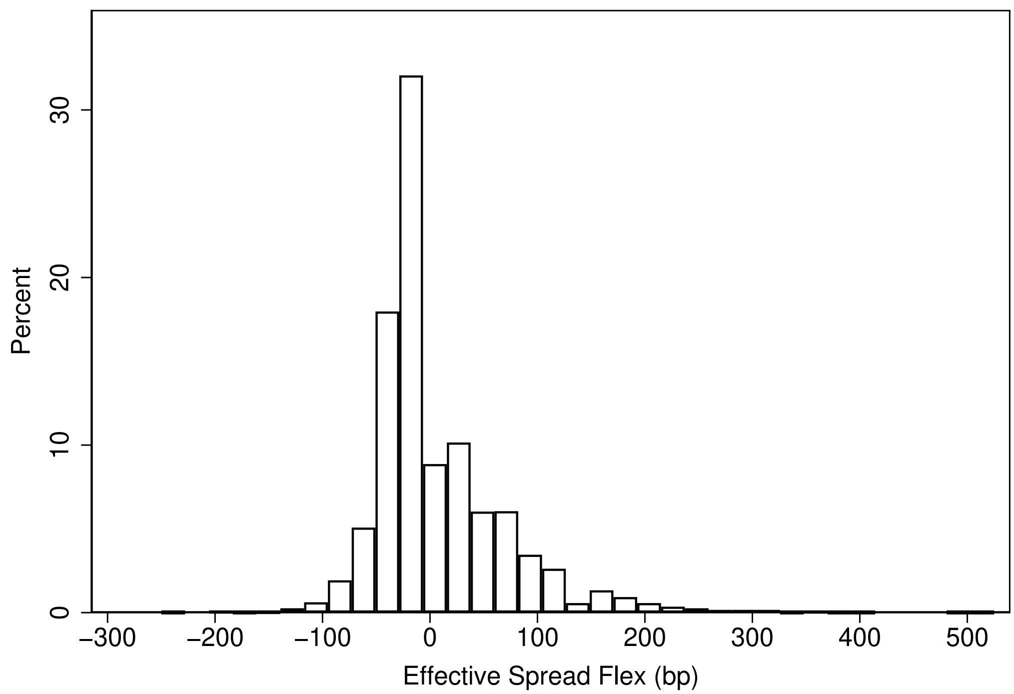


Figure 2. **Distribution of Spread Flex.**
This figure presents the distribution of effective spread flex in syndication deals, for all syndication deals in our sample. Source: Pitchbook's Leveraged Commentary & Data (LCD).

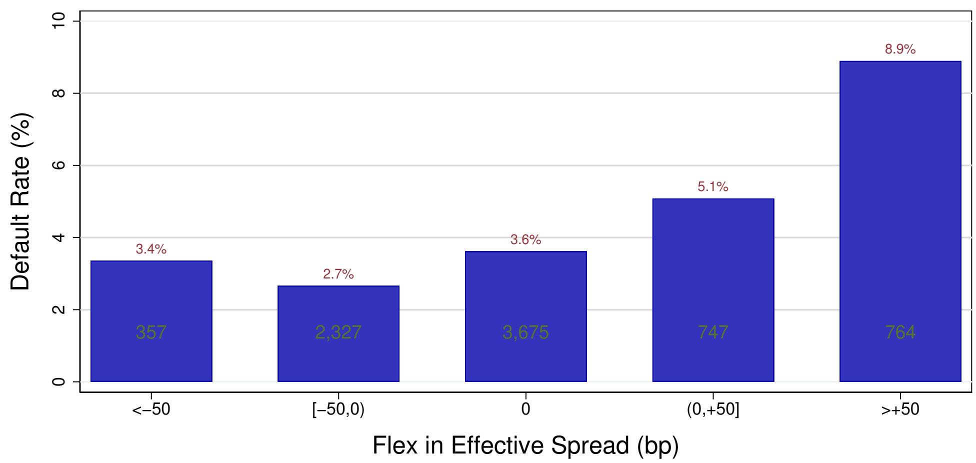


Figure 3. **Spread Flex and Default: Nonparametric Comparison.**
This figure presents the fraction of syndication deals that subsequently default. Sample deals are divided into 5 groups based on flex in effective spread during the bookbuilding process. The number inside each bar indicates the number of deals in the group. Difference in defaul rate between the two extreme groups is $8.9\% - 3.4\% = 5.5\%$ ($t = 3.4$). Source: Pitchbook's Leveraged Commentary & Data (LCD), Default and Recovery Database (DRD), and LevFin Insights (LFI).

Table 1: **Summary Statistics**

This table presents summary statistics. Panel A summarizes syndication deals between 2000–2020. *Underpricing* is the difference between secondary market break price and primary market issuance price. *Default* is a dummy that indicates whether the borrower defaults over a 4-year period after issuance, scaled up by 100. *Talk Spread* is the effective spread the lead bank proposed at deal launch. *Spread Flex* is the change in effective spread during syndication. *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 bank internal risk estimates, where Δ*Default Probability* and Δ*Loss Given Default* are changes in probability of default and loss given default during the quarter of syndication, respectively, and are measured in percentage points. Panel C 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 A: All Syndication Deals Sample

	N	mean	sd	p5	p25	p50	p75	p95
Underpricing	6,299	76.3	44.1	30	50	70	100	150
Default (%)	7,812	4.0	19.5	0	0	0	0	0
Talk Spread	7,812	443.8	149.0	237.5	337.5	425.0	525.0	700.0
Spread Flex	7,812	3.7	46.8	-50.0	-12.5	0.0	0.0	88.9
Amount ($ million)	7,812	651	756	65	215	400	799	2,065
Maturity	7,812	6.0	1.1	4.0	5.3	6.0	7.0	7.0
Relationship	7,812	0.18	0.39	0	0	0	0	1
Sponsored	7,812	0.67	0.47	0	0	1	1	1
Cov Lite	7,812	0.56	0.50	0	0	1	1	1
Has Revolver	7,812	0.46	0.50	0	0	0	1	1
Has TLA	7,812	0.04	0.20	0	0	0	0	0
Has Bond	7,812	0.10	0.29	0	0	0	0	1

Panel B: Borrower Financials Sample

	N	mean	sd	p5	p25	p50	p75	p95
Pre-Deal ICR	3,163	3.8	1.01	-0.2	1.5	2.5	4.4	17.6
ΔICR	3,163	0.1	1.0	-0.0	0	0	0	0.1
Talk Spread	3,163	405.1	145.3	212.5	300	375	487.5	666.7
Spread Flex	3,163	0.7	40.5	-50.0	-12.5	0	0	75.0
Amount ($ million)	3,163	771.0	825.2	75.0	260.0	500.0	995.0	2,284.0
Maturity	3,163	6.0	1.1	3.92	5.3	6.1	7.0	7.0

Table 1: **Summary Statistics - Continued**

Panel C: Bank Internal Estimate Sample

	N	mean	sd	p5	p25	p50	p75	p95
Default Probability	2,069	3.3	5.8	0.3	0.9	1.9	3.7	9.5
Loss Given Default	2,065	35.4	11.1	12.1	30.0	37.5	42.5	50.0
Expected Loss	2,065	1.2	2.1	0.1	0.3	0.6	1.3	3.5
ΔDefault Probability	2,069	-0.1	3.1	-1.9	-0.0	0.0	0.0	1.5
ΔLoss Given Default	2,061	-0.2	4.3	-6.3	-0.2	0.0	0.0	5.6
ΔExpected Loss	2,061	-0.0	1.2	-0.7	-0.0	0.0	0.0	0.6
Talk Spread	2,069	379.3	126.4	200.0	287.5	362.5	450.0	587.5
Spread Flex	2,069	-0.5	33.4	-37.5	-10.0	0.0	0.0	62.5
Amount ($ million)	2,069	785.7	815.5	70	255	505	1,017	2,308
Maturity	2,069	6.1	1.1	3.9	5.4	6.4	7.0	7.0

Panel D: Secondary Market Return Sample

	N	mean	sd	p5	p25	p50	p75	p95
Return: 3 month	1,873	4.9	8.8	-9.2	2.5	5.4	8.5	16.7
Return: 6 month	1,876	3.6	7.5	-8.4	1.8	4.3	6.9	12.3
Return: 9 month	1,877	3.7	5.9	-4.7	2.3	4.1	6.2	10.4
Return: 1 year	1,878	3.6	5.4	-4.4	2.8	4.1	5.7	9.4
Return: 2 year	1,186	2.6	5.8	-6.6	2.3	3.7	5.0	7.3
Talk Spread	1,880	442.3	145.7	230.0	337.5	425.0	525.0	700.7
Spread Flex	1,880	5.6	53.7	-59.9	-25.0	0.0	0.0	100.0
Amount ($ million)	1,880	765.7	797.5	160	300	490	910	2,275
Maturity	1,880	6.2	1.0	4.5	6.0	6.5	7.0	7.0

Panel E: Moody's Credit Rating Sample

	N	mean	sd	p5	p25	p50	p75	p95
ΔCredit Rating	2,573	-5.0	77.9	-100	-100	0	100	100
Rating Withdraw	3,052	44.9	49.7	0	0	0	100	100
Talk Spread	3,413	418.7	142.1	225.0	312.5	400.0	500.0	677.1
Spread Flex	3,413	1.1	44.0	-50.0	-12.5	0.0	0.0	87.5
Amount ($ million)	3,413	761.8	823.6	80	260	498	990	2,284
Maturity	3,413	6.0	1.1	3.9	5.2	6.0	7.0	7.0

Table 2: **Spread Flex and Underpricing**

This table reports results from regressing *Underpricing*, the difference between the deal's secondary market break price and primary market 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. *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, clustered at the deal's month level, are reported in parentheses. *, **, *** represent 10%, 5%, and 1% levels of statistical significance.

Dependent Variable: Underpricing

	(1)	(2)	(3)	(4)
Spread Flex	-0.050***	-0.042***	-0.046***	-0.040**
	(0.016)	(0.016)	(0.016)	(0.016)
Talk Spread	0.123***	0.126***	0.134***	0.131***
	(0.007)	(0.008)	(0.007)	(0.008)
Log(Amount)		0.742		0.361
		(0.645)		(0.658)
Log(Maturity)		0.613		-0.270
		(3.071)		(3.005)
Relationship		-1.349		-1.628
		(1.442)		(1.448)
Sponsored		-6.333***		-5.340***
		(1.281)		(1.302)
Cov Lite		2.429*		2.581*
		(1.327)		(1.339)
Has Revolver		7.364***		7.686***
		(1.237)		(1.205)
Has TLA		-2.290		-2.916
		(2.243)		(2.240)
Has Bond		8.731***		8.574***
		(1.678)		(1.682)
Credit Rating FEs	N	N	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	6,265	6,265	6,265	6,265
R^2	0.382	0.397	0.388	0.401

Table 3: **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 industry and the deal's quarter 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***	0.028***	0.025***	0.026***
	(0.009)	(0.009)	(0.009)	(0.009)
Talk Spread			0.025***	0.026***
			(0.004)	(0.005)
Log(Amount)				0.330
				(0.233)
Log(Maturity)				-2.140*
				(1.263)
Relationship Deal				-0.398
				(0.710)
Sponsored				-1.180
				(0.898)
Cov Lite				1.027
				(1.129)
Has Revolver				-0.620
				(0.674)
Has TLA				-0.533
				(1.272)
Has Bond				2.628***
				(0.900)
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	7,763	7,763	7,763	7,763
R^2	0.088	0.097	0.114	0.117

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

This table reports results from estimating predictive regressions in Table 3 in 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 3. In Panel A, syndication deals are divided into subsamples of new money deals and refinance deals. In Panel B, syndication deals are divided into subsamples based on whether Moody's and S&P's credit ratings for the deal's senior secured first lien facility differ by at least one notch. In Panel C, syndication deals are divided into subsamples based on whether the lead bank has pre-existing relationship with the borrower. Standard errors, two-way clustered at the borrower industry and the deal's quarter 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	0.035***	0.034***	0.008	0.004
	(0.008)	(0.008)	(0.019)	(0.018)
Talk Spread		0.019***		0.041***
		(0.004)		(0.008)
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	4,427	4,427	3,298	3,298
R^2	0.124	0.137	0.142	0.179

Panel B: Credit Rating Agency Disagreement

	Ratings Disagree		Ratings Agree	
	(1)	(2)	(3)	(4)
Spread Flex	0.063***	0.065***	0.024**	0.021**
	(0.020)	(0.020)	(0.010)	(0.010)
Talk Spread		0.021*		0.026***
		(0.011)		(0.005)
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	918	918	6,811	6,811
R^2	0.336	0.353	0.097	0.117

Table 4: **Spread Flex and Default: Subsample Analyses - Continued**

Panel C: Pre-Existing Relationship with Lead Bank

	Non-Relationship		Relationship	
	(1)	(2)	(3)	(4)
Spread Flex	0.029***	0.028***	0.007	0.006
	(0.009)	(0.009)	(0.044)	(0.045)
Talk Spread		0.023***		0.041***
		(0.004)		(0.010)
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	6,329	6,329	1,427	1,427
R^2	0.110	0.128	0.132	0.167

Table 5: **Spread Flex and Default: Controlling for Borrower Financials**

This table reports results from estimating predictive regressions of default events in Table 3 using a sample with the borrower's financial information. 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. *Pre-Deal ICR* is the borrower's interest coverage ratio in the quarter before the deal. ΔICR is the change in interest coverage ratio caused by the impact of spread flex on the borrower's interest expenses. Control variables are the same as in column (4) of Table 3. Standard errors, two-way clustered at the borrower industry and the deal's quarter levels, are reported in parentheses. *, **, *** represent 10%, 5%, and 1% levels of statistical significance.

Depdent Variable: Default

	(1)	(2)	(3)	(4)
Spread Flex	0.022*	0.023*	0.023*	0.025*
	(0.012)	(0.013)	(0.013)	(0.013)
Talk Spread	0.036***	0.036***	0.036***	0.039***
	(0.007)	(0.007)	(0.007)	(0.008)
Pre-Deal ICR		-0.209**	-0.212**	-0.197**
		(0.083)	(0.084)	(0.088)
ΔICR			0.079	0.113
			(0.205)	(0.202)
Additional Controls	N	N	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	3,163	3,163	3,163	3,163
R^2	0.185	0.187	0.187	0.195

Table 6: **Spread Flex and Bank Internal Risk Estimates**

This table reports results from regressing changes in bank internal risk estimates about a borrower around its deal on the deal's characteristics. Every observation is a syndication deal between 2000–2020. In Panel A, the dependent variable in the change in bank-estimated probability of default. In Panel B, the dependent variable in the change in bank-estimated loss given default. In Panel C, the dependent variable in the change in expected loss, i.e., the product of bank-estimated probability of default and loss given default. *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 3. Standard errors, two-way clustered at the borrower industry and the deal's quarter levels, are reported in parentheses. *, **, *** represent 10%, 5%, and 1% levels of statistical significance.

Panel A: Probability of Default

	(1)	(2)	(3)	(4)
Spread Flex	0.003***	0.004***	0.004***	0.004**
	(0.000)	(0.001)	(0.001)	(0.002)
Talk Spread			-0.002	-0.002
			(0.002)	(0.002)
Additional Controls	N	N	N	Y
Credit Rating FEs	N	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	Y	Y	Y
N	2,065	2,056	2,054	2,054
R^2	0.000	0.110	0.110	0.110

Panel B: Loss Given Default

	(1)	(2)	(3)	(4)
Spread Flex	0.009***	0.010***	0.010***	0.010***
	(0.003)	(0.003)	(0.003)	(0.003)
Talk Spread			0.000	-0.000
			(0.001)	(0.001)
Additional Controls	N	N	N	Y
Credit Rating FEs	N	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	Y	Y	Y
N	2,057	2,048	2,046	2,046
R^2	0.010	0.100	0.100	0.110

Table 6: **Spread Flex and Bank Internal Risk Estimates - Continued**

Panel C: Expected Loss

	(1)	(2)	(3)	(4)
Spread Flex	0.001***	0.002***	0.002***	0.002***
	(0.000)	(0.000)	(0.001)	(0.001)
Talk Spread			-0.001	-0.001
			(0.001)	(0.001)
Additional Controls	N	N	N	Y
Credit Rating FEs	N	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	Y	Y	Y
N	2,057	2,048	2,046	2,046
R^2	0.000	0.100	0.100	0.110

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

This table reports results from estimating predictive regressions of secondary market loan returns. Every observation in the sample is a syndication deal in LCD between 2000–2020 for which the term loan facility is matched to IHS Markit secondary market price quotes. The dependent variable is the loan's (annualized) 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), and 2 years in column (4). *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: Secondary Market Return

	3m	6m	1y	2y
	(1)	(2)	(3)	(4)
Spread Flex	0.030***	0.016***	0.007**	0.008*
	(0.003)	(0.003)	(0.003)	(0.004)
Talk Spread	0.014***	0.010***	0.006***	0.000
	(0.002)	(0.001)	(0.001)	(0.002)
Log(Amount)	-0.596***	-0.379**	-0.529***	-0.266
	(0.200)	(0.154)	(0.166)	(0.209)
Log(Maturity)	-0.721	-1.353**	-0.976*	-1.262*
	(0.598)	(0.656)	(0.548)	(0.758)
Credit Rating FEs	Y	Y	Y	Y
Month FEs	Y	Y	Y	Y
N	1,857	1,860	1,862	1,171
R^2	0.664	0.626	0.449	0.334

Table 8: **Spread Flex and Default: Alternative Default Measures**

This table reports results from estimating predictive regressions in Table 3 using alternative measures of default events. Every observation is a syndication deal between 2000–2020. The dependent variable is a dummy that indicates whether the borrower defaults after issuance, scaled up by 100. Panel A uses different time horizons for measuring borrower default events. Specifically, default is measured over a 3-year period after issuance in column (1), between issuance and the deal's institutional term loan's contractual maturity date in column (2), between the first year of issuance and contractual maturity date in column (3), and anytime after the deal until 2022, the last year of our default data, in column (4). Panel B uses only default events over a 4-year period after issuance in LCD database. Panel C uses only default events ver a 4-year period after issuance in DRD database. *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 3. Standard errors, two-way clustered at the borrower industry and the deal's quarter levels, are reported in parentheses. *, **, *** represent 10%, 5%, and 1% levels of statistical significance.

Panel A: Default Over Different Horizons

	[0, 3y]	[0, mature]	[1y, mature]	[0, ∞)
	(1)	(2)	(3)	(4)
Spread Flex	0.015**	0.026**	0.025**	0.027***
	(0.006)	(0.011)	(0.011)	(0.010)
Talk Spread	0.022***	0.036***	0.033***	0.034***
	(0.004)	(0.006)	(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	7,763	7,763	7,763	7,763
R^2	0.116	0.138	0.131	0.163

Table 8: **Spread Flex and Default: Alternative Default Measures - Continued**

Panel B: Default Events in LCD

	(1)	(2)	(3)	(4)
Spread Flex	0.023***	0.020***	0.018**	0.019**
	(0.007)	(0.007)	(0.007)	(0.007)
Talk Spread			0.019***	0.019***
			(0.004)	(0.005)
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	7,763	7,763	7,763	7,763
R^2	0.077	0.082	0.099	0.102

Panel C: Default Events in DRD

	(1)	(2)	(3)	(4)
Spread Flex	0.017**	0.016**	0.014**	0.015**
	(0.007)	(0.006)	(0.006)	(0.007)
Talk Spread			0.013***	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	7,763	7,763	7,763	7,763
R^2	0.068	0.075	0.083	0.083

Table 9: **Spread Flex and Moody's Credit Rating Changes**

This table reports results from estimating predictive regressions of post-issuance changes in Moody's credit ratings. Every observation is a syndication deal between 2000–2020. In columns (1)–(2), the dependent variable is *Rating Change*, which takes value in $\{-100, 0, +100\}$ and indicates downgrade, no change, or upgrade 3 years after issuance. In columns (3)–(4), the dependent variable *Rating Withdraw* is a dummy indicating whether Moody's has already withdrawn the borrower's senior secured first lien term loan rating 5 years after issuance, scaled up by 100. Control variables are the same as in column (4) of Table 3. Standard errors, two-way clustered at the borrower's industry and the deal's quarter 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	-0.119***	-0.124***	0.065***	0.049***
	(0.030)	(0.029)	(0.010)	(0.013)
Talk Spread		-0.088***		0.046***
		(0.014)		(0.012)
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	2,540	2,540	3,020	3,020
R^2	0.147	0.169	0.142	0.178

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.

Each investor who participates in the bookbuilding receives a signal that determines his or her demand. These signals are not observed by the bank/ underwriter. Each investor's signal is binary and either 'good' (with probability p) or 'bad' (with probability $1-p$). The signals are independent across investors and the number of investors with good signals therefore follows a binomial distribution. The expected value of the asset is a linear and increasing function of the number of investors with good signals. 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).[15] In the model, the underwriter learns about the analog of our Z via bookbuilding and sets an issuance price P_I to incorporate it.

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

[15]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.

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.*

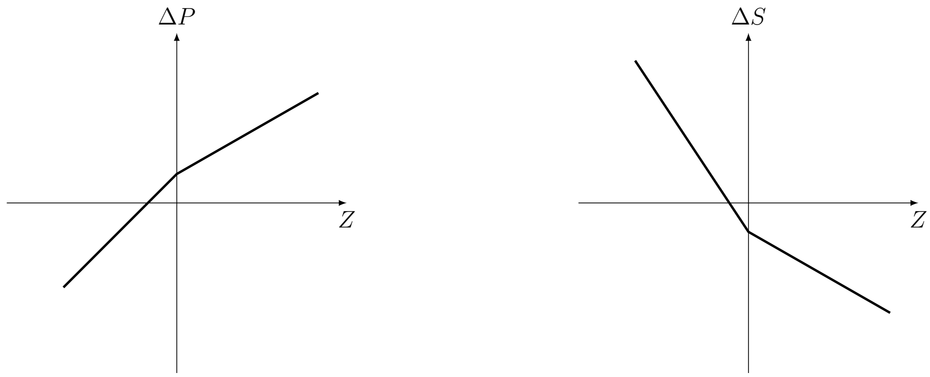
The first implication of the theory therefore is that price adjustments (or spread flex) contain information about Z.

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 the bank must reduce the quantity of the asset it allocates to investors. When Z is high, the full quantity is allocated to investors, but 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 how the theory describes the relationship between price adjustments/ spread flexes and information revealed by investors Z. (For a simplified model adapted to the context of leveraged loan issuance that makes these points, see also Bruche, Malherbe, and Meisenzahl (2020), Section 3.)

"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



(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 $\Delta S \overset{\propto}{\sim} -P_0 \Delta P$.

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.)*

See also our Hypothesis 1.

The density of price adjustments and spread adjustments In addition, the theory also suggests that the price adjustment should be concave in Z. Furthermore, 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).[16] The fact that price adjustments are

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

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

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, as we will now describe.

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 as suggested by the model. 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

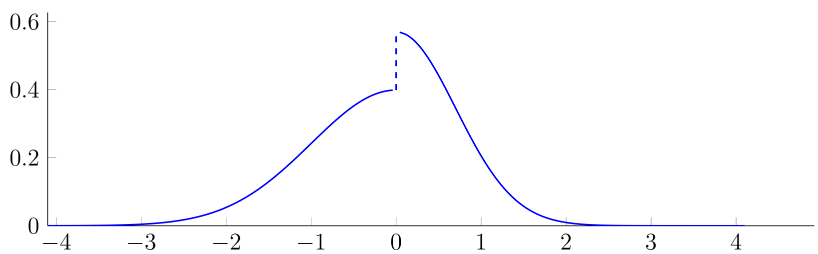
$$f(\Delta p) = \begin{cases} \frac{1}{\sigma}\varphi\left(\frac{\Delta p}{\sigma}\right) & \text{if } \Delta p \leq 0 \\ \frac{1}{\sigma(1-\gamma)}\varphi\left(\frac{\Delta p}{\sigma(1-\gamma)}\right) & \text{if } \Delta p > 0, \end{cases} \tag{A.7}$$

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 than the part of the density that describes negative price adjustments, as illustrated in Figure A.2. This is because the bank only partially adjusts to value-positive information and only increases the price by a fraction $1 - \gamma < 0$ of Z.

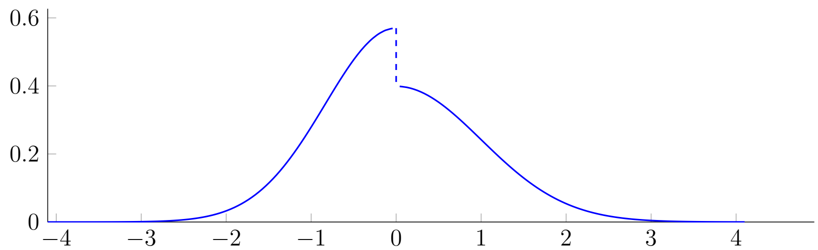
There are several ways to define a spread implicit in a price. E.g., with continuous compounding, we could define the spread S as the solution to $P \equiv e^{-(r_F+S)T}$, where P is the price, r_F is the risk-free rate, and T a maturity parameter. (In the following, T is an uninteresting scale parameter,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

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

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 $S(P)$.



(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 $\Delta S \underset{\sim}{\propto} -(1/P_0)\Delta P$.

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

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

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.

Although we provide no formal test, we note that empirical distribution of effective spread flex in Figure 2 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.)

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:

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

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 appendix presents results 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.4 presents the fraction of deals that subsequently default for different ranges of spread flex. Among deals that experienced an upward spread flex of more than 50 basis points, 8.3% default. The group with less than 50 basis points of upward flex has 5.3% of deals default. These default probabilities are economically larger than deals that experienced zero or a downward spread flex. Table A.2 presents the results of repeating our nonparametric analyses in this sample with deal-level default events. Deals that experienced upward spread flex are 3.5% more likely to default, and this sizable difference is statistically significant at the 5% level.

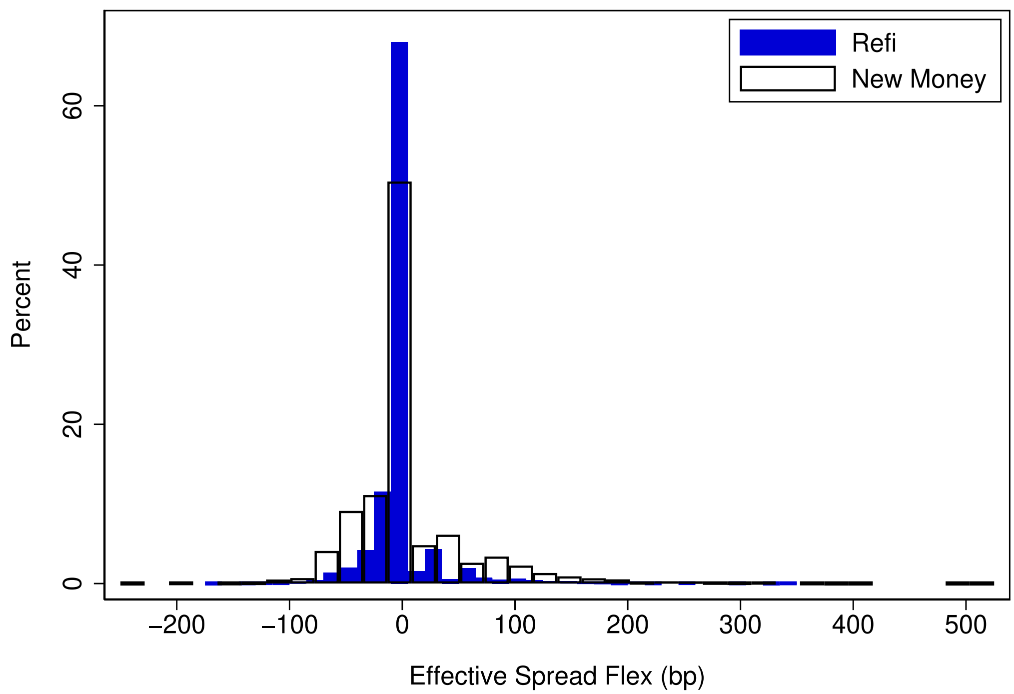


Figure A.1. **Distribution of Spread Flex: New Money and Refinance.**
This figure presents the distribution of effective spread flex in syndication deals for new money deals and refinance deals, respectively. Source: 's Leveraged Commentary & Data (LCD)

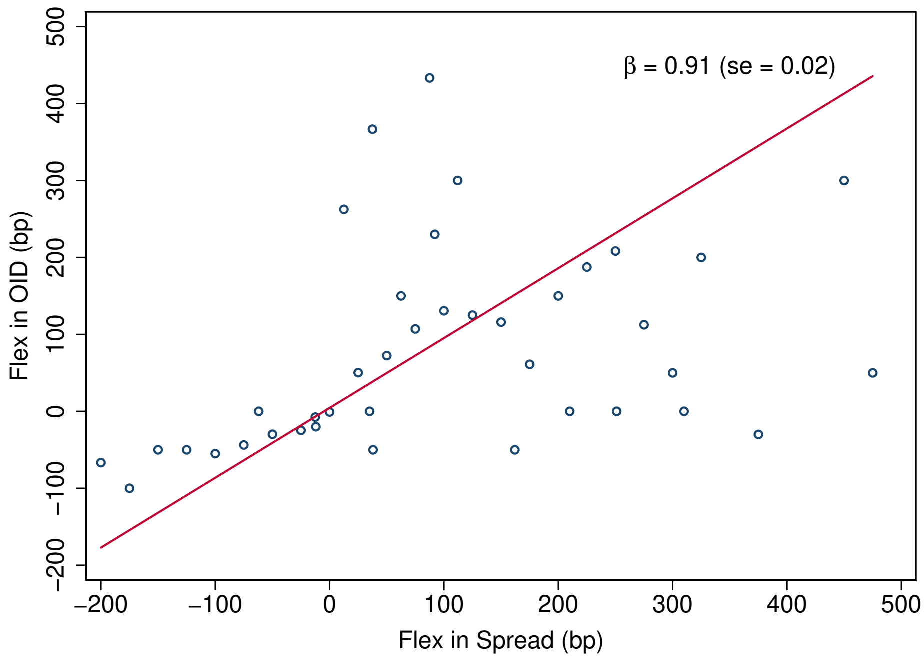


Figure A.2. **Relationship Between Spread Flex and OID Flex.**
This figure presents a scatter plot that groups syndication deals into 100 bins based on flex in loan spread and depicts the average flex in OID within each bin. The fitted line represents an OLS slope estimate, with heteroskedasticity-robust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

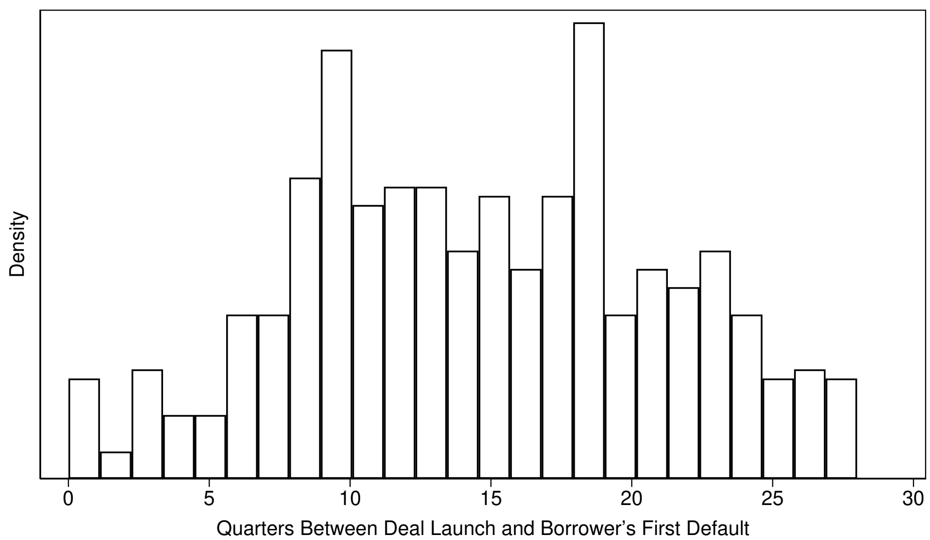


Figure A.3. **Time Between Syndication Deal and Default.**
This figure presents the distribution of the number of quarters between a syndication deal and the borrower's default for all default events. Source: Pitchbook's Leveraged Commentary & Data (LCD).

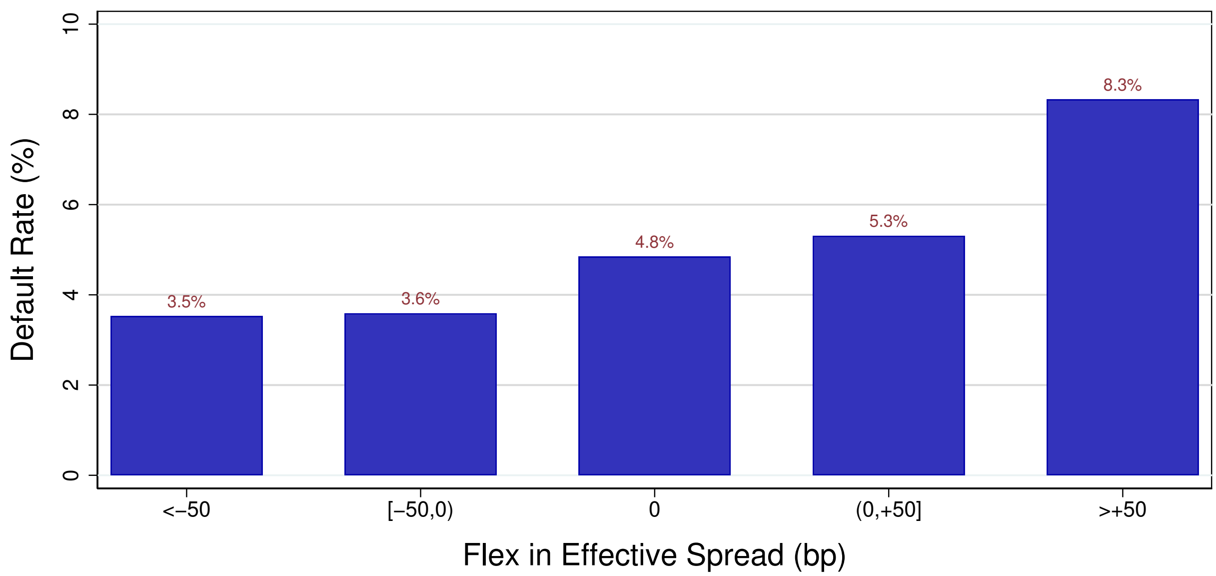


Figure A.4. **Spread Flex and Deal-Level Default: Nonparametric Comparison.** This figure presents the fraction of syndication deals that subsequently default. The sample consists of 1,030 Pitchbook LCD deals for which the institutional term loan is matched to a debt instrument in DRD. The deals are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

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: **Spread Flex and Default: Deal-Level Defaults in DRD**

This table reports univariate analyses of 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. Deals are divided into 3 groups depending on whether the deal experiences an upward, downward, or no flex in effective spread. *, **, *** represent 10%, 5%, and 1% levels of statistical significance.

	Effective Spread Flex		
	downward	zero	upward
Default (%)	3.6	4.8	7.1
N	419	330	281
Difference: $7.1\% - 3.6\% = 3.5\%^{**}$ ($t = 2.1$)			