# What Do Lead Banks Learn from Leveraged Loan Investors?

Max Bruche, Ralf R. Meisenzahl,
and David X. Xu

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Max Bruche† Ralf R. Meisenzahl‡ David X. Xu§

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**Abstract**

Originate-to-distribute lending weakens banks' incentives to produce information about borrowers, but it may also strengthen loan investors' incentives to produce such information. We show that in leveraged loan syndications, pricing adjustments in response to investor demand during bookbuilding are informative about borrower credit quality. Upward spread adjustments predict higher default rates and larger realized losses given default. After syndication, banks revise their confidential supervisory risk assessments accordingly, consistent with learning about borrowers from investors. These patterns suggest that bookbuilding transmits investors' credit information into loan pricing and bank beliefs, partly mitigating the informational drawback of originate-to-distribute lending.

**JEL classifications:** G23, G24, G30
**Keywords:** syndicated loans, nonbanks, underwriting

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†Humboldt University of Berlin and Berlin School of Economics. Email: max.bruche@hu-berlin.de
‡Federal Reserve Bank of Chicago. Email: ralf.meisenzahl@chi.frb.org
§Southern Methodist University. Email: davidxu@smu.edu

# 1 Introduction

When originators sell loans, they no longer bear the full consequences of borrower default and may therefore have weaker incentives to screen and monitor borrowers. This concern about the originate-to-distribute model of lending has motivated regulatory efforts to ensure that originators retain enough credit exposure, thereby preserving their incentives to produce information about borrower credit quality. Yet loan sales may also have an offsetting effect: By transferring credit exposure to outside investors, they may give those investors incentives to produce information about borrowers that complements banks' own assessments. The key question is whether issuance processes transmit this information back into loan prices and originators' risk assessments. If so, this transmission can partly mitigate an important informational drawback of originate-to-distribute lending.

We study this question in the leveraged loan market by asking what lead banks learn from investor demand during bookbuilding. Does investor demand reveal information about borrower credit quality, or does it mainly reveal information about the required return for the loan? This distinction matters for our understanding of originate-to-distribute lending. If bookbuilding reveals only information about required returns, then selling loans weakens banks' incentives to produce information about borrower credit quality without generating an offsetting source of information. If, instead, investor demand reveals information about borrower credit quality that is fed back into prices and bank beliefs, then bookbuilding partly mitigates a central informational drawback of originate-to-distribute lending.

The leveraged loan market is an important segment of corporate credit, where lead banks originate non-investment-grade syndicated loans and distribute much of the exposure to nonbank institutional investors. Before issuance, lead banks conduct a bookbuilding process in which they solicit indications of interest from investors and adjust the loan's interest spread accordingly. Market participants refer to this adjustment as the "spread flex." Because spread flex is the margin through which investor demand feeds back into loan terms, it provides a natural setting to study what information is transmitted back into prices and bank beliefs.

In our data, spread flex is negatively related to underpricing—the gain investors earn from buying loans at issuance prices below their immediate secondary market prices. This negative relation is the classic partial-adjustment phenomenon: when investors indicate strong demand, banks flex down the spread only partially, rewarding investors for truthfully revealing their favorable views. Hence, lead banks do learn new information from investor demand during bookbuilding. The substantive question is what they learn.

We find that they learn about both: borrower credit quality and required returns. First, upward spread flex predicts worse borrower outcomes. A 50-basis-point upward flex, roughly one standard deviation in our sample, is associated with a 1.3-percentage-point increase in the probability of default over the next four years, relative to an unconditional default rate of about 4 percent. Among the limited set of defaulted loans for which we observe post-default secondary-market prices, the same upward flex is associated with an increase of about 5 percentage points in realized loss given default, relative to an average of about 34 percent. These relations are robust to controlling for the lead bank's initially proposed spread and other observable deal characteristics. They indicate that spread flex contains information about borrower credit quality.

Second, upward spread flex is associated with upward revisions in banks' own internal assessments of the borrower's probability of default and loss given default. The fact that banks revise the risk assessments they confidentially report to regulators suggests that the credit information in spread flex is not fully embedded in their prior beliefs.

We also show that these two findings on credit information are concentrated in settings in which bookbuilding is more likely to reveal new information: the relation between spread flex and subsequent default—and, more tentatively, realized losses—is only present in new-money deals and disappears in refinancing deals. Borrowers who refinance already have traded loans outstanding, so investor information can be incorporated into secondary-market spreads before bookbuilding begins. By contrast, in new-money deals bookbuilding is the first stage at which investor information can be incorporated into a market spread. Consistent with this interpretation, we find that banks update internal loss-given-default assessments more strongly after upward flex in new-money deals than in refinancing deals.

Our robustness checks indicate that the spread-flex-default relation is not explained by public news released during bookbuilding or by the mechanical effect of a higher spread on the borrower's interest burden. The relation is also stronger when informational frictions are likely greater, including among borrowers without prior lead-bank relationships and among deals with greater credit rating agency disagreement.

Third, loans with upward spread flex subsequently earn higher short-horizon excess returns in the secondary market. This result suggests that bookbuilding also reveals information about investor required returns. Taken together, the evidence is consistent with syndication aggregating two types of information not fully embedded in the bank's initial pricing: information about borrower credit quality and information about required returns. Both channels matter for loan pricing, but the borrower-credit channel is the one that speaks most directly to the informational consequences of originate-to-distribute lending. The results do not overturn the standard concern that loan sales may dilute banks' incentives to screen and monitor. They show, instead, that focusing on that concern alone gives an incomplete picture of how loan sales affect information production in credit markets. This is not because investors are better informed than lead banks, but because signals about borrower credit quality are dispersed across banks and investors, and bookbuilding helps transmit complementary information back into origination decisions.

**Related literature** Our paper speaks to a central question in finance: how information is produced and aggregated when credit is originated by one party but ultimately held by others. A central concern in the literature on loan sales, syndicated lending, and the originate-to-distribute model is that once banks can sell credit exposures, they have weaker incentives to screen and monitor, reducing information production about borrower credit quality (Gorton and Pennacchi, 1995; Parlour and Plantin, 2008; Keys, Mukherjee, Seru, and Vig, 2010; Purnanandam, 2011; Wang and Xia, 2014; Daley, Green, and Vanasco, 2020). Related work studies how markets mitigate these informational frictions through reputation and certification (Booth and Smith II, 1986; Chemmanur and Fulghieri, 1994) and through syndicate design, including lead-bank retention, and the composition of the lending syndicate (Sufi, 2007; Ivashina, 2009; Berlin, Nini, and Yu, 2020). We contribute to this literature by arguing that syndicated lending can also mitigate these frictions through a different channel: bookbuilding allows lead banks to learn from investors and to incorporate investor information into pricing and into their own assessments of borrower risk. These findings suggest that the informational structure of originate-to-distribute lending is not purely one-sided, but instead reflects bilateral and complementary information production by banks and nonbank investors.

Our paper highlights that banks learn two types of information from investors: information about borrower credit quality and information about investor required returns. Existing work on institutional demand in leveraged loans focuses on the required-return channel: demand pressure driven by funding flows affects loan pricing (Ivashina and Sun, 2011). We complement this literature by providing evidence that investor demand also reveals information about borrower credit quality that is incremental to the lead bank's initial pricing and internal risk assessments.

Our paper also relates to work on whether nonbank investors in credit markets possess borrower-specific information. Survey and loan-level evidence suggests that private credit investors devote substantial resources to due diligence, monitoring, and intervention, implying that outside investors may produce information rather than merely absorb risk (Block, Jang, Kaplan, and Schulze, 2024; Jang, 2025). In leveraged loans, however, the evidence on investor information is more limited. Cordell, Roberts, and Schwert (2023) find that the average CLO manager does not exhibit skill in selecting leveraged loans, although some managers do generate persistent outperformance. We provide direct evidence that nonbank investor demand in leveraged loan syndication contains information about borrower credit quality that is not embedded in the lead bank's initial pricing. This evidence suggests that institutional investors in syndicated loans are not only passive providers of capital, but may also produce borrower-specific information.

Finally, our paper contributes to the literature on bookbuilding as a mechanism for eliciting private information from investors. Benveniste and Spindt (1989) show that bookbuilding can induce investors to reveal information through partially adjusted pricing, and prior empirical work documents such partial adjustment in equity and bond offerings (Hanley, 1993; Wang, 2021). In leveraged lending, Bruche, Malherbe, and Meisenzahl (2020) also show partial adjustment and furthermore that weak demand during bookbuilding is associated with higher lead-bank retention. Our contribution relative to this literature is to provide evidence that information revealed during bookbuilding contains borrower credit quality information that is new to the lead bank. Our results imply that syndication is not only a mechanism for distributing credit risk, but also a mechanism for aggregating dispersed information about borrower credit quality across banks and nonbank investors. Our results also help interpret recent evidence on retention and ex post performance. Together with Bruche, Malherbe, and Meisenzahl (2020) and Blickle, Fleckenstein, Hillenbrand, and Saunders (2025), our evidence suggests that the loans retained by lead banks when investor demand is weak perform poorly precisely because syndication reveals that lead banks had underestimated borrower risk for those loans.

# 2 Hypotheses

This section presents a simple model of information revelation during bookbuilding and derives testable hypotheses. The framework is a simplified version of Benveniste and Spindt (1989). For clarity, we first state the model in terms of prices and price adjustments and then map the predictions to spreads and spread flexes used in the leveraged loan market and in our empirical analysis.

## 2.1 Information structure and loan pricing

We begin with a standard asset-pricing decomposition for a loan's valuation $V$. Let $X$ denote the loan's cash flows and $M$ the stochastic discount factor. Then

$$V = \mathbb{E}[M \cdot X] = \frac{\mathbb{E}[X]}{R_f} + \mathrm{Cov}(X, M), \tag{1}$$

where $R_f = \frac{1}{\mathbb{E}[M]}$. The two terms on the right-hand side of equation (1) can be interpreted as the component driven by expected cash flows (that is, by borrower credit quality), $V^{CF} =$

$\frac{\mathbb{E}[X]}{R_f}$, and the component driven by required returns, $V^{DR} = \mathrm{Cov}(X, M)$.

Suppose that

$$\begin{aligned} V^{CF} &= W^{CF} + B^{CF} + I^{CF}, \\ V^{DR} &= W^{DR} \qquad\quad\;\; + I^{DR}. \end{aligned}$$

Here, $W^{CF}$ and $W^{DR}$ denote public information about cash flows and required returns. The bank has private information only about cash flows, denoted $B^{CF}$, consistent with its screening and monitoring role. Investors, however, can have private information about both expected cash flows, $I^{CF}$, and required returns, $I^{DR}$. They may have private information about cash flows because performance-based compensation generates incentives to produce it through proprietary credit analyses,[1] repeated coverage, or nonpublic diligence in related financing transactions. They also possess private information about required returns because they observe their own liquidity conditions, funding shocks, portfolio constraints, or risk preferences more precisely than the bank.[2]

Letting $W = W^{CF} + W^{DR}$ denote total public information and $I = I^{CF} + I^{DR}$ denote investors' total private information, the full-information value of the loan is

$$V = W + B^{CF} + I. \tag{2}$$

Because the expression for the secondary-market price in Benveniste and Spindt (1989) is, like our $V$, linear in information, the two expressions can be written in equivalent form. Unless otherwise stated, we assume without loss of generality that $W, B^{CF}, I^{CF}$, and $I^{DR}$

[1] $I^{CF}$ could include conclusions that investors draw about expected cash flows from data the bank shares during bookbuilding, including through the confidential information memorandum and the dataroom. If the bank has the data but not drawn the conclusion, the investor is producing information.

[2] When these investor-side forces produce temporary price pressure in the secondary market (Elkamhi and Nozawa, 2022; Xu, 2026), they could also affect required returns in the primary market (Ivashina and Sun, 2011; Corwin, 2003; Siani, 2025).

are mutually orthogonal and that $B^{CF}, I^{CF}$, and $I^{DR}$ are mean-zero.

## 2.2 Bookbuilding

Suppose that the bank reveals its information $B^{CF}$ to investors at the beginning of bookbuilding. For instance, suppose the bank sets an initial price, $P_0$, equal to its expectation of $V$ based on its initial information $\Omega_B = \{W, B^{CF}\}$:

$$P_0 = \mathbb{E}[\, V \mid \Omega_B \,] = W + B^{CF}. \tag{3}$$

After observing the initial price, investors' information set $\Omega_I$ now contains all price-relevant information, including $B^{CF}$.

The view that banks reveal their information through the initial price is plausible for several reasons.[3] First, auction theory suggests that doing so is in the bank's interest. Bookbuilding is most naturally modeled as a common-value auction with affiliated signals. In such auctions, the *linkage principle* of Milgrom and Weber (1982) implies that an auctioneer with private, value-relevant information should disclose it before the auction. Disclosure reduces bidders' reliance on their own signals, mitigates the winner's curse, induces more aggressive bidding, and thereby increases expected revenue. Second, banks have contractual incentives not to conceal unfavorable information at the outset. Banks are remunerated via an underwriting fee that is typically reduced when there is upward flex. An unsuccessful attempt to conceal negative information can be very costly because it results in upward flex, a loss in underwriting fee, and, under firm-commitment underwriting, costly loan retention (Bruche, Malherbe, and Meisenzahl, 2020). Third, banks repeatedly interact with both

[3] In practice, lead banks launch syndication deals at a spread and fee that they believe will clear the market (S&P Global Market Intelligence, 2016, p. 3).

investors and borrowers and risk losing reputation if market participants learn that they systematically suppress positive or negative information (Chemmanur and Fulghieri, 1994).

After setting $P_0$, the bank conducts an auction that gives investors incentives to truthfully reveal their valuations, and thus their additional information $I$, (Benveniste and Spindt, 1989). As shown in Benveniste and Spindt (1989, Theorem 1), incentive compatibility requires the bank to adjust the price only partially upward when investors reveal positive information, but fully downward when they reveal negative information. If investors indicate that the asset is worth \$1 more than the bank thought, the bank must raise the issuance price by less than \$1 and thus reward investors through underpricing, since otherwise they would have no incentive to reveal their private signals. If investors indicate that the asset is worth \$1 less than the bank thought, the bank can reduce the issuance price by the full \$1.[4] It follows that the issuance price $P_I$ is

$$P_I = W + B^{CF} + I - f(I), \tag{4}$$

where $f(\cdot)$ denotes underpricing, for example $f(x) = \gamma \cdot \max(x, 0)$ for some $0 < \gamma < 1$. Price adjustments are therefore increasing and concave in investors' information:

$$P_I - P_0 = I - f(I). \tag{5}$$

Because spreads are inversely related to prices and convex in prices, spread adjustments, or spread flexes, are decreasing and convex in $I$.

The model yields four empirical implications. The first implication is the standard partial

[4] The bank must also reduce the quantity allocated to investors when they indicate a low valuation, to make such reports less attractive.

adjustment prediction: Since secondary-market participants can infer $B^{CF}$ and $I$ from $P_0$ and $P_I$, the secondary-market price $P_S$ reflects the full-information value $V = W + B^{CF} + I$. Partial adjustment then implies that loans with positive price adjustments, $P_I - P_0 > 0$, must be underpriced relative to the secondary-market price, so that $P_I < P_S$ for such loans. Loans with negative price adjustments are not underpriced. Hence, price adjustments should be positively correlated with underpricing, while spread flex should be negatively correlated with underpricing (Hanley, 1993; Bruche, Malherbe, and Meisenzahl, 2020).

**Validation Hypothesis (Partial Adjustment).** *Spread flex is negatively associated with underpricing.*

Having established the empirical signature of information revelation during bookbuilding, we next turn to the paper's main question: whether the information revealed by investor demand concerns borrower credit quality and is new to the lead bank. $I^{CF}$ reflects investors' information about expected cash flows, which could consist of information about the probability of default as well as information about potential losses given default. If $I$ contains cash-flow information through $I^{CF}$, then spread flex, as a function of $I$, should predict subsequent borrower default and/or losses:

**Hypothesis 1 (Borrower Default).** *Spread flex is positively associated with subsequent default events and/or realized loss given default.*

Moreover, since the banks learn $I^{CF}$ during bookbuilding, they should revise their internal risk assessments after observing spread flex:

**Hypothesis 2 (Bank Belief Updating).** *Spread flex is positively associated with changes in banks' internal assessments of the borrower's probability of default and/or loss given default.*

Finally, investor demand may convey not only information about borrower cash flows, but also information about required returns. Our final hypothesis captures this additional channel. The standard asset-pricing decomposition implies the following relation for the excess return, defined as expected cash flows relative to the secondary-market price $P_S$, minus the risk-free rate:

$$\frac{\mathbb{E}[X]}{P_S} - R_f = -\frac{R_f}{P_S}\operatorname{Cov}(M, X). \tag{6}$$

In our setup, investors have information $I^{DR}$ about $V^{DR} = \operatorname{Cov}(M, X)$. Since the price adjustment is increasing in $I^{DR}$, spread flex is decreasing in $I^{DR}$, and the excess return is negatively related to $I^{DR}$, we obtain the following hypothesis:

**Hypothesis 3** (**Required Returns**). *Spread flex is positively associated with subsequent excess returns in the secondary market.*

## 2.3 Identification and alternative interpretations

Our interpretation is that spread flex reflects information revealed during bookbuilding about borrower credit quality and, potentially, about required returns. The main empirical challenge is to distinguish this interpretation from other mechanisms that could also generate a relation between spread flex and subsequent outcomes.

**Withheld Bank Information**. One possibility is that the bank does not fully incorporate its own information about expected cash flows into the initial price. If some of this withheld information is later revealed during bookbuilding, spread flex would partly reflect information the bank already held rather than incremental information produced by investors. Because such withheld information can itself predict subsequent default and loss given default, the relation between spread flex and realized credit outcomes (Hypothesis 1) is not sufficient evidence of bank learning new information from investor demand.

Hypothesis 2 separates these two interpretations. The key is that a bank's internal risk assessment reflects its own belief about the borrower, whereas the talk spread is only a pricing decision and may not perfectly reveal that belief. The two interpretations then differ in a simple, testable way. If the information in the flex was already known by the bank, as under the withheld-information interpretation, the bank's belief (and hence its internal assessment) already reflected it before bookbuilding, so the assessment should not change when the flex makes that information public. If instead the flex carries information that is new to the bank, the bank's belief changes, and its internal assessment should be revised after bookbuilding. A positive association between spread flex and the revision in the internal assessment is therefore the signature of new information, and is difficult to reconcile with the withheld-information interpretation.

Testing Hypothesis 2 requires measuring the bank's beliefs about the borrower's default probability and loss given default. As discussed in Section 3, we measure bank beliefs using confidential data on supervisory credit assessments and examine revisions of these assessments around syndication. These revisions reflect updates in bank beliefs about the borrower's credit quality: If banks believe that investor demand reveals information only about required returns, they would be unlikely to revise their assessments of credit quality after bookbuilding.[5]

**Public News**. A second possibility is that spread flex responds to public information arriving between the deal's launch and completion dates. If so, spread flex would capture the market's response to newly released public news rather than private information revealed through bookbuilding. We address this concern by controlling for borrower-specific and

[5]Banks may potentially revise their assessments in response to investor demand through a rollover-risk channel, which we address later in this section.

industry-level public news released during the syndication window.

**Aggregate Shocks**. A third possibility is that spread flex partially reflects aggregate shocks to borrowers' credit quality and investors' required returns, both of which could be driven by credit-market conditions, investor flows, or intermediary balance-sheet capacity. Such forces could affect syndication, default outcomes, and bank beliefs even in the absence of any borrower-specific information revelation. Our specifications therefore include time fixed effects, so identification comes from cross-sectional variation in spread flex within period rather than from aggregate time-series movements in credit conditions.

**Interest Burden**. A fourth possibility is the mechanical effect of interest spread on default. An upward spread flex raises the contractual borrowing rate and may therefore increase subsequent default risk by worsening the borrower's interest coverage. To assess this possibility, we examine whether the results are accounted for by the implied change in interest coverage.

**Refinancing Risk**. A fifth possibility is that changes in investors' required returns might be persistent. If so, weak demand at a loan's issuance could predict refinancing difficulty, raising default through a rollover channel, even in the absence of any information about cash flows. Because our specifications include year-month fixed effects that absorb aggregate shocks, this channel would require a borrower-specific component of required returns that persists for years until refinancing. Two sets of our empirical tests address this possibility. First, our tests on realized loss given default and banks' revisions of their loss-given-default assessments: The channel operates through default probability rather than loss given default, because rollover affects whether a borrower defaults, not the value recovered from its assets conditional on default. Second, our comparison of new-money and refinancing deals: a rollover-risk channel would, if anything, imply a stronger flex–default relation for borrowers that repeatedly refinance, the opposite of what the information channel implies.

No single test is conclusive on its own. Taken together, however, the evidence on default, bank belief updating, secondary-market returns, and cross-sectional heterogeneity helps assess whether the data are more consistent with information revelation during bookbuilding than with explanations based on omitted bank information, public news, aggregate market conditions, or mechanical effects of pricing.

# 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 the so-called "institutional" facilities. These are non-amortizing term loans (also called Term Loan B, C, D, or Cov-Lite loans) targeting institutional investors. Since the main target audience for LCD is 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 equal-weighted average pricing of its institutional term loan facilities. Following market convention for the computation of yields, we combine the two dimensions of deal pricing, namely the spread and OID, into an effective spread, defined as

$$\text{Effective Spread} = \text{Spread} + \frac{\text{Discount}}{4}, \tag{7}$$

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

Our main variable of interest, effective spread flex, is the difference between the effective spread and the talk effective spread.[6] 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 effective spread at issuance and the edge of the corresponding range. If the effective spread at issuance is within the range, we set the effective spread flex to zero.

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

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

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.

An important limitation of the LCD data is that it does not include information on the identities of bookbuilding participants or their bids. This limitation precludes analyses of the type conducted by Cornelli and Goldreich (2001).

**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.[7]

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]

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

Figure 1 summarizes the annual number of borrower default events across these three databases. While some events are reported in more than one database, our combined list captures a considerably larger set of default events. Using this list, we determine a syndication deal as subsequently defaulted if the borrower experiences a default event during a 4-year period after issuance. This choice mitigates concerns about incomplete loan-level default information and is consistent with the common use of cross-default provisions among senior secured loans.[8] 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.

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

For each defaulted deal in this matched sample, we measure the realized loss given default as 100 minus the deal-level average 30-day post-default bid price. We first average daily bid quotes over the 30 calendar days following the borrower's first default event for each matched

[8]In Section 2.7 of the Appendix, we present additional results based on default events at the syndication deal level.

loan facility, then take the average across the deal's facilities. Because default is rare and many defaulted loans are not actively traded, only a small number of deals have post-default bid prices that allow us to construct this measure. We further restrict to deals for which we have more than one observation within each industry and each deal issuance year, so that we can include fixed effects for these categories in our regressions. These filters lead to a sample of 75 defaulted deals.[9]

**Banks' Internal Risk Assessments**. We use confidential supervisory data from the Federal Reserve's Y-14, Schedule H.1, which reports banks' internal estimates for the probability of default and loss given default since 2012. The estimates are drawn from the banks' own internal risk-rating systems. For banks subject to the advanced approaches to regulatory capital, they are the internal-ratings-based parameters used to compute regulatory capital; for other banks, they are the probability of default attached to the bank's internal rating of the borrower and its own loss-given-default estimate. Recent literature uses these estimates to measure banks' information and shows that they predict various borrower-level outcomes (e.g., Howes and Weitzner, 2025; Beyhaghi, Howes, and Weitzner, 2025). In our tests, we use the revisions in these internal estimates to measure updates in the bank's information about borrower credit quality.

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.[10] This leaves us with 2,069 syndication deals for loans originated between 2012 and 2020. Since the

[9]Markit post-default prices are the most complete source of realized recoveries available for this sample. Although Moody's DRD (used above to identify defaults) also reports recoveries, matching its recovery data to our defaulted deals yields fewer deal-level observations— a subset of the Markit-based sample. We therefore measure realized loss given default from Markit post-default prices throughout.

[10]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.

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. We account for the fact that monitoring incentives may differ by exposure and weight the reported default measures by the bank-reported exposure at default amount when averaging.[11]

**Secondary Market Returns**. Using the 1,896 LCD–Markit matched deals described above, we calculate realized holding period returns 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, and 2. 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.[12] These interest payments are compounded to the final price date based on reinvestment at the prevailing LIBOR rate.[13] Finally, we calculate an annualized $n$-year holding period return as

$$Return = \left(\frac{\text{secondary price} + \text{compounded interest payments}}{\text{break price}}\right)^{1/n} - 1, \tag{8}$$

where the total value of cumulative cash flows is added to the secondary market price to reflect investor payoff from the loan.[14]

[11] Gustafson, Ivanov, and Meisenzahl (2021) show that banks with larger exposure monitor more.

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

[13] 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.

[14] 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.

### 3.2 Summary statistics

**All Syndication Deals Sample**. Panel A of Table 1 presents a summary of our main sample, which consists of 7,763 leveraged loan syndication deals after excluding singleton observations for regression analysis. The typical deal has around $650 million loan amount and a maturity of about 6 years, 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. We note that the shape of these empirical distributions conforms to the predictions of the theory of Benveniste and Spindt (1989) (see Figure A.2, Appendix 1).

[Insert Figure 2 here]

**Markit LGD Sample.** Panel B of Table 1 summarizes the 75 defaulted deals for which we observe the realized loss given default. The average realized LGD is 33.7%, which is consistent with the average S&P recovery rating of 69.7%. The LGD has large dispersion across deals, ranging from 6.2% at the 25th percentile to 90.4% at the 95th. Compared to the full sample in Panel A, deals in this defaulted subsample are noticeably riskier ex ante. The average talk spread is 73 basis points higher, and the average spread flex is 26 basis points compared to 3 in the full sample. Deals in this sample are also larger on average ($905 million vs. $650 million), while maturity and cov-lite incidence are similar to the full sample.

**Banks' Internal Risk Assessments Sample.** Panel C of Table 1 summarizes the sample of syndication deals that are matched with banks' internal assessments for probability of default and loss given default. After requiring the variables used in the regressions and dropping singleton observations, the sample contains 2,016 deals. This sample has a lower average talk spread than the sample in Panel A because all borrowers here have loans on at least one bank's balance sheet. Banks tend to sell off riskier loans and hence this subsample is skewed to less risky borrowers. Consequently, we do observe somewhat smaller flexes across the loans in this sample. However, there are significant adjustments to the default variables as indicated by the standard deviations of the change in these variables from the quarter before syndication to the quarter after it.

**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 the 2-year horizon. 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.

# 4 Results

This section presents the main empirical results. We begin by validating the bookbuilding mechanism: consistent with the Validation Hypothesis, spread flex is negatively related to underpricing. We then examine whether spread flex contains information about borrower credit quality. Consistent with Hypothesis 1, upward spread flex predicts subsequent default and realized losses. We next show that banks' internal credit assessments move in the same direction: upward flex is followed by upward revisions in internal probability-of-default and loss-given-default assessments, consistent with Hypothesis 2. We then use the distinction between new-money and refinancing loans to test whether these relations are stronger when investor information is more likely to be incremental to the information already available to banks. Finally, we examine short-horizon secondary-market returns and show that spread flex is positively related to excess returns, consistent with Hypothesis 3.

## 4.1 Spread flex and underpricing

To test the Validation Hypothesis 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. We test this prediction by estimating the following equation:

$$\text{Underpricing}_{it} = \beta\text{Spread Flex}_{it} + \gamma X_{it} + \delta_t + \epsilon_{it} \tag{9}$$

where $\text{Underpricing}_{it}$ is the difference between the first secondary market price and the primary market price for loan $i$ in month $t$, $X_{it}$ a rich set of loan characteristics (talk spread, log(amount), log(maturity), and dummies for has relationship, is sponsored, is covenant-lite, has revolver, has a term-loan A, has bond outstanding) as well as fixed effects (credit rating, lead arranger, deal purpose, and borrower industry), and $\delta_t$ the year-month fixed effect.

[Insert Table 2 here]

Table 2 reports the results of estimating equation (9). Over all four specifications, the partial correlation between Spread Flex and Underpricing is negative and significant as predicted by the hypothesis. The coefficients indicate that a positive flex in the spread during bookbuilding of 50 basis points is associated with a decrease in underpricing of between 2 and 2.5 basis points.[15] This validates that banks use bookbuilding to extract information from investors that they do not have prior to bookbuilding.

## 4.2 Spread flex and borrower credit quality

According to Hypothesis 1 in Section 2, if investors have private information about the probability of default or loss given default that is unknown to the lead bank, spread flex would be positively associated with realized default or realized loss given default. Consistent with the first part of this prediction, Figure 3 plots the average probability of default by spread flex buckets and shows a salient pattern: across 5 deal groups formed based on spread flexes

[15] 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 3.5 basis points.

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, 8.9% defaulted, whereas among deals with $(0, +50]$ spread flexes, 5.1% defaulted. These frequencies are economically substantially larger than deal groups with no flexes (3.6%). Deals with downward (negative) flexes exhibit even smaller default rates (2.7%-3.4%).

[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 ($\geq$+50) and largest downward ($\leq$-50) in Figure 3. The difference in default probability is 5.5% and statistically significant at the 1% level.

**A formal test of Hypothesis 1** We now test Hypothesis 1, which states that the spread flex should be positively associated with future default and loss given default, conditional on the lead bank's information set at the beginning of bookbuilding. The best proxy for this information set is the set of loan characteristics, particularly the talk spread—the interest spread proposed by the lead bank at the beginning of bookbuilding. Accordingly, we conduct this test by regressing a binary default outcome (Default) or realized loss given default on spread flex, respectively, controlling for a rich 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 the deal's year-month levels. Specifically, we estimate the following equations:

$$\text{Default}_{it} = \beta \text{Spread Flex}_{it} + \gamma X_{it} + \delta_t + \epsilon_{it}, \tag{10}$$

$$\text{Loss Given Default}_{it} = \beta \text{Spread Flex}_{it} + \gamma X_{it} + \delta_t + \epsilon_{it}, \tag{11}$$

where $X_{it}$ is the vector of control variables as in equation (9). Equation (10) is estimated unconditionally; equation (11) can only be estimated conditional on default.

[Insert Table 3 here]

Table 3 reports the results of estimating equation (10). In column (1), our point estimate is statistically significant and indicates a sizable economic effect. A 50 basis point upward flex in the effective spread is associated with a 1.6 percentage point higher default probability, a 40 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 decreases only very slightly. Turning to the 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. 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.

[Insert Table 4 here.]

Table 4 reports the results of estimating equation (11) on our sample of defaulted loans for which we can observe loss given default. Because even for high-yield loans, default is a rare event, we have a relatively small number of observations for this regression, forcing us to use fewer and less granular fixed effects than in Table 3. In column (1), (2), and (3), our point estimate indicates that a 50 basis point upward flex in the effective spread is associated with roughly a 6.5 percentage point higher realized loss given default. In column (1), we control for (deal-)year fixed effects as well as industry fixed effects only. Column (2) adds the talk spread proposed by the lead bank as a control, which here is not significantly related to loss given default. In column (3), we add S&P's deal-level loan recovery rating score. As expected, this control is negatively related to realized loss given default, suggesting that these ratings are informative about loss given default/ recoveries. However, the size of the coefficient on Spread Flex barely changes, indicating that the information in recovery ratings is orthogonal to the information in Spread Flex. In Column (4), we add default-year fixed effects, since loss given default tends to be higher in years with many defaults. The coefficient on Spread Flex decreases slightly and the standard error increases, but the coefficient is still significant at 10%.

Our first result in Subsection 4.1 indicates that banks learn about investors' demand via bookbuilding. The second result in Tables 3 and 4 here suggests that investors' demand could be driven by information that investors have about default probabilities and loss given default, that is, about borrower credit quality.

In Appendix 2, we rule out several alternative interpretations. We focus on predictions for default because of the very small number of observations of realized loss given default. Spread flex and default could jointly be driven by the release of public credit-relevant news during the bookbuilding window. We show that the relationship between spread flex and default is robust to controlling for industry returns as well as a measure that encodes credit-relevant public news articles during the bookbuilding window. Spread flex mechanically decreases interest coverage and could therefore causally produce default. We show that the relationship between spread flex and default survives when explicitly controlling for the changes induced in interest coverage by spread flex. We also show that the results are robust for different versions of the default measure, and that spread flex is also associated with credit events in the form of credit rating downgrades and upgrades.

## 4.3 Spread flex and revisions in bank internal risk assessments

We next test Hypothesis 2. If spread flexes contain information about the borrower that is incremental 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 the probability of default and loss given default using the subsample of loans for which we observe such estimates in the Federal Reserve's Y-14 data. We estimate our baseline regression (equation (10)) with the change in banks' reported probability of default and loss given default after loan origination as outcome variables. Note that here, the banks' estimated loss given default is also available for issuers that do not actually default. Unlike in the case above where we used realized loss given default, we therefore do not have to condition on default when running this regression.

[Insert Table 5 here]

Table 5, Panel A shows the results of estimating the effect of spread flex on the change in banks' internal probability of default assessments. Consistent with positive (negative) spread flexes indicating adverse (favorable) information about the borrower, the point estimate is positive and statistically significant. In the specification that includes the full set of controls (column 4), an upward spread flex of 50 basis points is associated with a 0.25 percentage point increase in the banks' estimated annual probability of default. We can compare the magnitude of the effect to that in Table 3, as follows. There, a 50 basis point upward spread flex is associated with an increase in the probability of a default occurring over the next four years of about 1.3 percentage points in column 4. Since our default indicator in that regression denotes default in the 4 years following issuance (see Section 3), this implies an increase in the probability of default *per annum* of roughly $1.3/4 = 0.325$ percentage points. So the reaction of banks' internal assessments to Spread Flex is slightly smaller than what our estimates in Table 3 would predict, but roughly of the same magnitude.

In Panel B of Table 5, we estimate the effect of spread flexes on loss given default. Consistent with positive (negative) spread flexes indicating adverse (favorable) information about the borrower, the point estimate is again positive and statistically significant. In the specification that includes the full set of controls (column 4), an upward spread flex of 50 basis points is associated with an increase in the banks' internal assessments of loss given default of 0.55 percentage points. We can compare the magnitude of the effect to that in Table 4, where in column (4) an upward flex of 50 basis points is associated with an increase in realized loss given default of 5.05 percentage points. This is an order of magnitude larger, but note that the coefficient in Table 4 is relatively imprecisely estimated on the basis of only 72 observations. We furthermore note that the loans in our Bank Internal Assessments Sample are safer (see, e.g., the differences in mean Talk Spread between the samples in Panels A and C of Table 1), which may also have an impact on the relative magnitudes of effects.

Taken together, the results show that banks' risk assessments move in the direction implied by syndication outcomes. Because these are the bank's internal assessments, reported confidentially to its regulator, their revision following spread flex is hard to reconcile with the view that flex merely reflects information the bank already held. Instead, the evidence is consistent with the view that bookbuilding reveals new information about borrower credit quality to banks.

## 4.4 New money versus refinancing sample split

Refinancing loans provide a useful setting in which the information content of bookbuilding should be weaker. If investors have private information about a borrower before a refinancing, they can trade on that information in the secondary market for the existing loan. The secondary-market price, and hence the refinancing spread, should already reflect this information. In addition, lead banks have monitored the outstanding loan and are therefore likely to be relatively well informed about the borrower's credit quality (see Gustafson, Ivanov, and Meisenzahl, 2021). We therefore expect the relation between Spread Flex and subsequent credit outcomes to be stronger for new-money loans than for refinancing loans.[16]

We test this prediction by re-estimating the specifications in Tables 3 and 4 separately for new-money and refinancing deals. Table 6, Panel A reports the default regressions. For new-money deals, the coefficient on Spread Flex is positive, statistically significant, and economically larger than in the full sample. In the specification with the full set of controls, a 50 basis point upward flex is associated with a 1.7 percentage point increase in the probability of default, compared with 1.3 percentage points in the full sample specification reported in column (4) of Table 3. By contrast, the corresponding coefficients for refinancing deals are small and statistically insignificant.

[16] Figure A.1 in the Appendix shows that new-money deals exhibit greater dispersion in spread flexes, consistent with more information being revealed during bookbuilding.

[Insert Table 6 here]

Panel B shows a pattern for realized losses consistent with the default results, though we caution that these regressions rest on very few defaulted deals with observable recoveries (36 new-money and 31 refinancing deals with full controls). Among new-money deals, the coefficients on Spread Flex are positive and qualitatively similar to those in Table 4; among refinancing deals they are negative and statistically insignificant. The point estimates are consistent with the predictive content of Spread Flex for loss given default being concentrated in deals where investor information is more likely to be relevant, but the small samples do not let us sharply distinguish the two subsamples, and we treat this evidence as suggestive.

Panels C and D examine whether this information is reflected in banks' internal risk assessments. In Panel C, the coefficients on Spread Flex in the probability-of-default updating regressions do not differ significantly across new-money and refinancing deals. The estimates therefore do not allow us to determine whether banks update their internal default probabilities more strongly in one subsample than in the other. In Panel D, however, the evidence is sharper. The coefficients on Spread Flex are positive and statistically significant for new-money deals, indicating that banks revise their internal loss-given-default assessments upward following positive spread flexes. The corresponding coefficients for refinancing deals are much smaller and statistically insignificant.

Overall, the sample split supports the interpretation that Spread Flex contains investor information about borrower credit quality. The contrast is clearest for default, estimated on the full sample: Spread Flex predicts default for new-money deals but not for refinancing deals. The realized-loss results point the same way but, resting on few defaulted deals with observable recoveries, are best read as suggestive. Banks' updating of loss-given-default estimates follows the same pattern, although the evidence for updating of probability-of-default estimates is less conclusive.

We explore additional sample splits in Appendix 2.5.

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

[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, especially over shorter horizons. Columns 1 to 4 indicate that a 50 basis point upward flex predicts an annualized excess return that is higher by 1.5%, 0.8%, 0.35%, and 0.4% over horizons of 3, 6, 12, or 24 months, respectively. Looking at the raw, de-annualized returns, we can furthermore see that it also predicts a return that is higher by an amount of $1.5\%/4 \approx 0.4\%$, $0.8\%/2 = 0.4\%$, $0.35\%/1 = 0.35\%$, and $0.4 \times 2 \approx 0.8\%$, respectively, suggesting that most of the return is generated over the first 3 months. As older loans are less likely to be traded, our sample size starts decreasing beyond a time horizon of about 12 months.

These results suggest that investor demand revealed during bookbuilding contains information about required returns. Appendix 2.9 provides related evidence using time a loan spends in syndication, following Ivashina and Sun (2011). Longer "time on market" is associated with higher issuance spreads and higher subsequent secondary-market returns, consistent with weak investor demand during syndication containing required-return information. The concentration of predictability at short horizons is consistent with this information reflecting time-varying investor risk-bearing capacity or demand pressure. For example, if key investors experience outflows, they may temporarily require higher returns to absorb a loan. Their lower demand during bookbuilding would lead the bank to flex the spread upward. If these constraints subsequently ease, required returns decline, secondary-market prices rise, and the loan earns positive short-horizon excess returns.

Taken together, the evidence suggests that spread flex contains information about required returns in addition to information about borrower cash-flow risk.

# 5 Conclusion

This paper studies how information is produced and aggregated in the originate-to-distribute model of lending. A central concern in this model is that once banks can sell credit exposures, they have weaker incentives to screen and monitor borrowers. But loan sales may also create incentives for outside investors to produce information, and syndication may provide a mechanism through which that information is revealed and incorporated into prices.

We provide evidence that bookbuilding in leveraged loan syndication performs this role. As lead banks observe investor demand during syndication, they appear to learn information about borrower risk from investors and to incorporate that information into both loan pricing and their own internal assessments of borrower risk. Upward spread flex predicts subsequent borrower default and loss given default, and upward revisions in banks' internal assessments of the probability of default and the loss given default. These patterns are strongest in settings in which investor information should matter most, such as new-money deals, deals without prior bank-borrower relationships, and deals with greater rating disagreement. We also find that loans with upward spread flex subsequently earn higher short-horizon excess returns, consistent with part of spread flex reflecting information about required returns in addition to information about borrower credit quality.

Overall, our findings imply that the informational structure of modern credit markets is not purely one-sided. In syndicated lending, banks do not simply originate loans and distribute them to investors who passively absorb risk. Rather, banks and nonbank investors may each produce borrower-specific information, and the syndication process aggregates these complementary signals into prices and risk assessments. Syndication is therefore not only a mechanism for distributing credit risk, but also a mechanism for transmitting information about borrower credit quality back into prices and bank beliefs, and thereby partly mitigates a central informational drawback of originate-to-distribute lending.

These results do not overturn the standard concern that loan sales may weaken banks' incentives to screen and monitor. But they do show that focusing on this concern alone gives an incomplete picture of how originate-to-distribute lending works in practice. This is not because investors are better informed than lead banks, but because information about borrower credit quality is dispersed across banks and investors, and bookbuilding helps reveal the part that is new to the lead bank. More broadly, our evidence suggests that information production in corporate credit is more decentralized than is commonly assumed: understanding modern credit markets requires understanding not only who ultimately bears risk, but also how information about borrowers is produced and incorporated into prices.

# References


Benveniste, L. M., and P. A. Spindt. 1989. How investment bankers determine the offer price and allocation of new issues. *Journal of Financial Economics* 24:343–61.

Berlin, M., G. Nini, and E. G. Yu. 2020. Concentration of control rights in leveraged loan syndicates. *Journal of Financial Economics* 137:249–71.

Beyhaghi, M., C. Howes, and G. Weitzner. 2025. The information advantage of banks: Evidence from their private credit assessments. Working paper.

Blickle, K., Q. Fleckenstein, S. Hillenbrand, and A. Saunders. 2025. Do lead arrangers retain their lead shares? Journal of Finance (forthcoming).

Block, J., Y. S. Jang, S. N. Kaplan, and A. Schulze. 2024. A survey of private debt funds. *Review of Corporate Finance Studies* 13:335–83.

Booth, J. R., and R. L. Smith II. 1986. Capital raising, underwriting and the certification hypothesis. *Journal of Financial Economics* 15:261–81.

Bruche, M., F. Malherbe, and R. Meisenzahl. 2020. Pipeline risk in leveraged loan syndication. *Review of Financial Studies* 33:5660–705.

Chemmanur, T. J., and P. Fulghieri. 1994. Investment bank reputation, information production, and financial intermediation. *Journal of Finance* 49:57–79.

Cordell, L., M. R. Roberts, and M. Schwert. 2023. CLO performance. *Journal of Finance* 78:1235–78.

Cornelli, F., and D. Goldreich. 2001. Bookbuilding and strategic allocation. *Journal of Finance* 56:2337–69.

Corwin, S. A. 2003. The determinants of underpricing for seasoned equity offers. *Journal of Finance* 58:2249–79.

Daley, B., B. Green, and V. Vanasco. 2020. Securitization, ratings, and credit supply. *Journal of Finance* 75:1037–82.

Elkamhi, R., and Y. Nozawa. 2022. Fire-sale risk in the leveraged loan market. *Journal of Financial Economics* 146:1120–47.

Gorton, G. B., and G. G. Pennacchi. 1995. Banks and loan sales: Marketing non-marketable assets. *Journal of Monetary Economics* 35:389–411.

Gustafson, M., I. Ivanov, and R. Meisenzahl. 2021. Bank monitoring: Evidence from syndicated loans. *Journal of Financial Economics* 139:383–417.

Hanley, K. W. 1993. The underpricing of initial public offerings and the partial adjustment phenomenon. *Journal of Financial Economics* 34:231–50.

Howes, C., and G. Weitzner. 2025. Bank information production over the business cycle. Review of Economic Studies (forthcoming).

Ivashina, V. 2009. Asymmetric information effects on loan spreads. *Journal of Financial Economics* 92:300–19.

Ivashina, V., and Z. Sun. 2011. Institutional demand pressure and the cost of corporate loans. *Journal of Financial Economics* 99:500–22.

Jang, Y. S. 2025. Are direct lenders more like banks or arm's-length investors? Evidence from loan agreements and COVID-related distress. Working paper.

Keys, B. J., T. Mukherjee, A. Seru, and V. Vig. 2010. Did securitization lead to lax screening? evidence from subprime loans. *Quarterly Journal of Economics* 125:307–62.

Milgrom, P. R., and R. J. Weber. 1982. A theory of auctions and competitive bidding. *Econometrica* 50:1089–122.

Parlour, C. A., and G. Plantin. 2008. Loan sales and relationship banking. *Journal of Finance* 63:1291–314.

Purnanandam, A. 2011. Originate-to-distribute model and the subprime mortgage crisis. *Review of Financial Studies* 24:1881–915.

Siani, K. Y. 2025. Raising bond capital in segmented markets. *Review of Financial Studies* .

S&P Global Market Intelligence. 2016. A guide to the U.S. loan market. Leveraged Commentary & Data (LCD).

Sufi, A. 2007. Information asymmetry and financing arrangements: Evidence from syndicated loans. *Journal of Finance* 62:629–68.

Wang, L. 2021. Lifting the veil: The price formation of corporate bond offerings. *Journal of Financial Economics* 142:1340–58.

Wang, Y., and H. Xia. 2014. Do lenders still monitor when they can securitize loans? *Review of Financial Studies* 27:2354–91.

Xu, D. X. 2026. Portfolio dynamics and the supply of safe securities. *Management Science* .

Zhang, D., Y. Zhang, and Y. Zhao. 2024. Lending relationships and the pricing of syndicated loans. *Management Science* 70:1113–36.

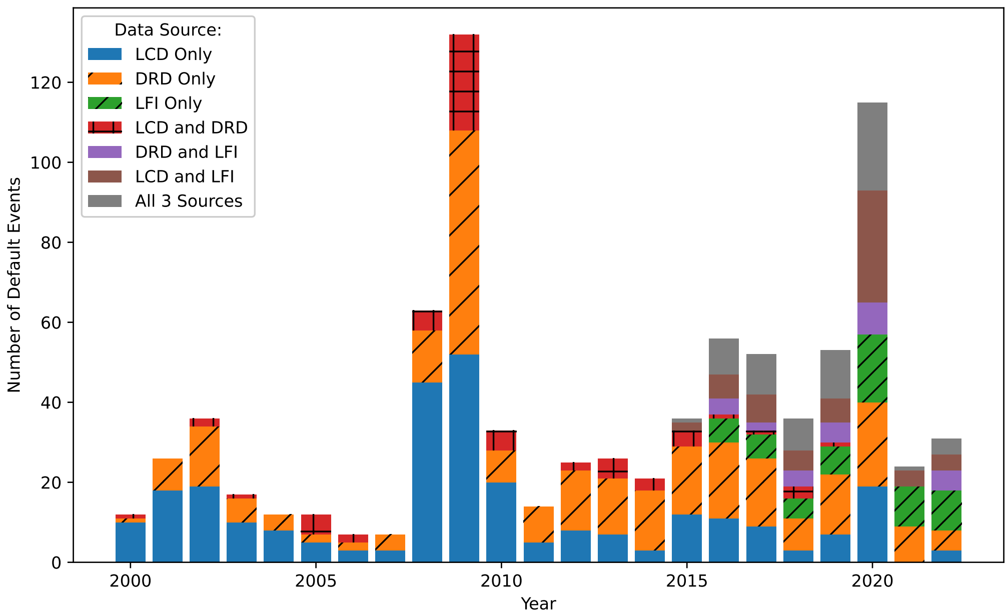



Figure 1. **Leveraged Loan Default Events.**
This figure presents the annual number of default events for borrowers in our deal sample between 2000–2022, as reported by three data sources: Pitchbook's Leveraged Commentary & Data (LCD), Default and Recovery Database (DRD), and LevFin Insights (LFI).

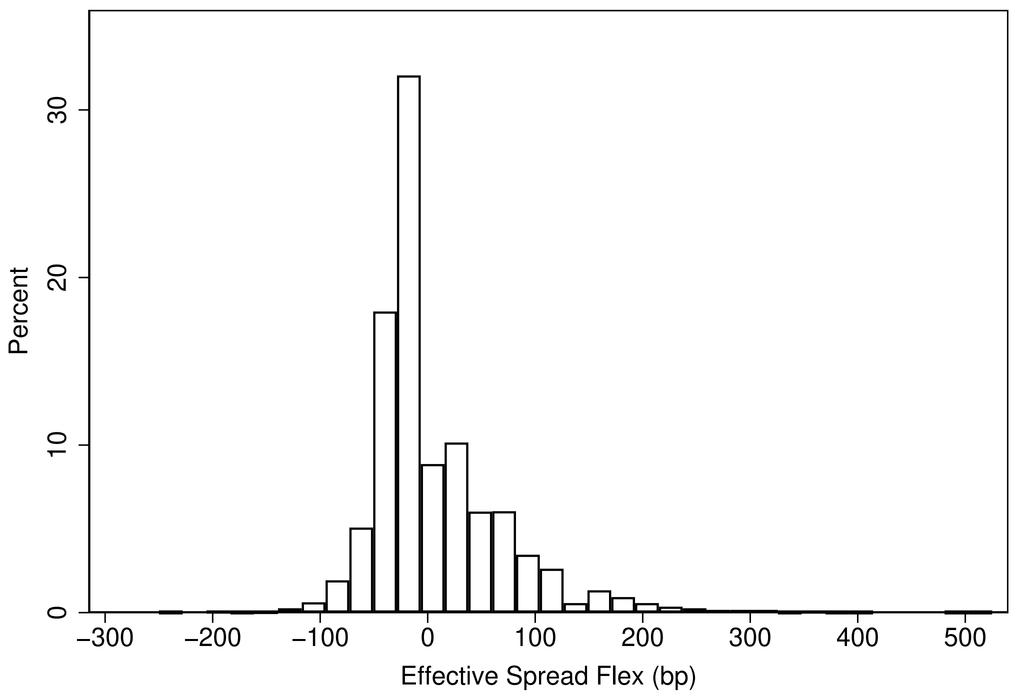



Figure 2. **Distribution of Spread Flex.**
This figure presents the distribution of effective spread flex in syndication deals, for all syndication deals in our sample. Source: Pitchbook's Leveraged Commentary & Data (LCD).

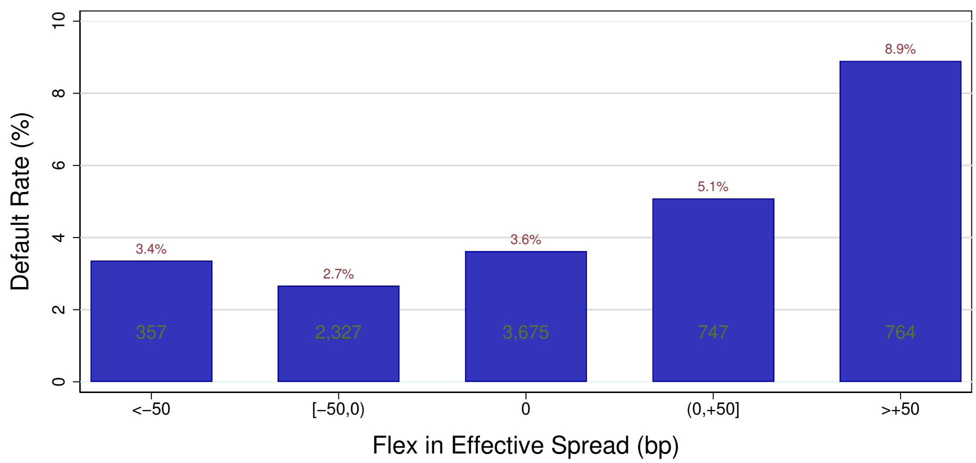



Figure 3. **Spread Flex and Default: Nonparametric Comparison.**
This figure presents the fraction of syndication deals that subsequently default. Sample deals are divided into 5 groups based on flex in effective spread during the bookbuilding process. The number inside each bar indicates the number of deals in the group. Difference in default 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. *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. *Underpricing* is the difference between the secondary market break price and the primary market issuance price. Panel B summarizes the subsample of defaulted deals matched to Markit IHS bid prices. *LGD* is 100 minus the deal-level average 30-day post-default bid price across the deal's loan facilities, scaled to percentage points. *Recovery Rating* is S&P's deal-level loan recovery rating score (0–100, higher is stronger recovery). Panel C summarizes bank internal risk assessments, where $\Delta$*Default Probability* and $\Delta$*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. The probability of default and loss given default in level and changes are weighted by the bank-level exposure at default for loans with more than one lender reporting these variables. The sample includes only data from 2012–2020. Panel D summarizes annualized secondary market returns over different time horizons.

**Panel A: All Syndication Deals Sample**

| | N | mean | sd | p5 | p25 | p50 | p75 | p95 |
|---|---|---|---|---|---|---|---|---|
| Default (%) | 7,763 | 3.92 | 19.40 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| Talk Spread | 7,763 | 443.37 | 148.62 | 237.5 | 337.5 | 425.0 | 525.0 | 700.0 |
| Spread Flex | 7,763 | 3.48 | 46.64 | -50.0 | -12.5 | 0.0 | 0.0 | 87.5 |
| Credit Rating | 7,763 | 6.29 | 2.34 | 0.0 | 6.0 | 6.0 | 8.0 | 10.0 |
| Amount ($ million) | 7,763 | 652.90 | 755.81 | 65.6 | 215.0 | 400.0 | 800.0 | 2,065.0 |
| Maturity | 7,763 | 6.01 | 1.09 | 4.0 | 5.4 | 6.0 | 7.0 | 7.0 |
| Relationship | 7,763 | 0.18 | 0.39 | 0.0 | 0.0 | 0.0 | 0.0 | 1.0 |
| Sponsored | 7,763 | 0.67 | 0.47 | 0.0 | 0.0 | 1.0 | 1.0 | 1.0 |
| Cov Lite | 7,763 | 0.57 | 0.50 | 0.0 | 0.0 | 1.0 | 1.0 | 1.0 |
| Has Revolver | 7,763 | 0.46 | 0.50 | 0.0 | 0.0 | 0.0 | 1.0 | 1.0 |
| Has TLA | 7,763 | 0.04 | 0.20 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| Has Bond | 7,763 | 0.10 | 0.29 | 0.0 | 0.0 | 0.0 | 0.0 | 1.0 |
| Underpricing | 6,265 | 76.27 | 43.61 | 30.0 | 50.0 | 70.0 | 100.0 | 150.0 |

Table 1: **Summary Statistics - Continued**

**Panel B: Markit LGD Sample**

| | N | mean | sd | p5 | p25 | p50 | p75 | p95 |
|---|---|---|---|---|---|---|---|---|
| LGD (%) | 75 | 33.65 | 29.51 | 0.0 | 6.2 | 24.7 | 62.4 | 90.4 |
| Spread Flex | 75 | 26.48 | 76.62 | -50.0 | -12.5 | 0.0 | 50.0 | 187.5 |
| Talk Spread | 75 | 516.23 | 154.82 | 300.0 | 390.3 | 500.0 | 637.5 | 825.0 |
| Recovery Rating | 75 | 69.67 | 15.14 | 45.0 | 60.0 | 70.0 | 80.0 | 90.0 |
| Amount ($ million) | 75 | 905.39 | 1,094.83 | 150.0 | 325.0 | 500.2 | 1,200.0 | 3,100.0 |
| Maturity | 75 | 6.03 | 1.16 | 4.3 | 5.0 | 6.0 | 7.0 | 7.0 |
| Cov Lite | 75 | 0.52 | 0.50 | 0.0 | 0.0 | 1.0 | 1.0 | 1.0 |

**Panel C: Bank Internal Risk Assessments Sample**

| | N | mean | sd | p5 | p25 | p50 | p75 | p95 |
|---|---|---|---|---|---|---|---|---|
| Default Probability | 2,016 | 3.37 | 6.44 | 0.31 | 0.90 | 1.91 | 3.75 | 9.76 |
| Loss Given Default | 2,016 | 34.60 | 11.60 | 11.45 | 28.68 | 36.69 | 42.22 | 50.00 |
| ΔDefault Probability | 2,016 | -0.01 | 3.97 | -1.83 | -0.07 | 0.00 | 0.05 | 1.66 |
| ΔLoss Given Default | 2,016 | -0.16 | 4.85 | -7.00 | -0.57 | 0.00 | 0.42 | 6.00 |
| Talk Spread | 2,016 | 377.89 | 125.89 | 200.00 | 287.50 | 362.50 | 448.75 | 587.50 |
| Spread Flex | 2,016 | -0.65 | 33.39 | -37.50 | -10.00 | 0.00 | 0.00 | 62.50 |
| Credit Rating | 2,016 | 6.93 | 1.91 | 5.00 | 6.00 | 7.00 | 8.00 | 10.00 |
| Amount ($ million) | 2,016 | 796.25 | 822.23 | 75.00 | 260.00 | 521.05 | 1,050.00 | 2,340.00 |
| Maturity | 2,016 | 6.06 | 1.09 | 3.92 | 5.40 | 6.39 | 7.00 | 7.01 |

**Panel D: Secondary Market Return Sample**

| | N | mean | sd | p5 | p25 | p50 | p75 | p95 |
|---|---|---|---|---|---|---|---|---|
| Return: 3 month | 1,857 | 4.88 | 8.64 | -9.2 | 2.5 | 5.3 | 8.4 | 16.5 |
| Return: 6 month | 1,860 | 3.47 | 7.37 | -8.4 | 1.8 | 4.3 | 6.9 | 12.0 |
| Return: 1 year | 1,862 | 3.54 | 5.37 | -4.3 | 2.8 | 4.1 | 5.7 | 9.3 |
| Return: 2 year | 1,171 | 2.57 | 5.77 | -6.4 | 2.2 | 3.7 | 5.0 | 7.2 |
| Spread Flex | 1,880 | 5.64 | 53.74 | -59.9 | -25.0 | 0.0 | 0.0 | 100.0 |
| Talk Spread | 1,880 | 442.28 | 145.73 | 230.0 | 337.5 | 425.0 | 525.0 | 700.7 |
| Amount ($ million) | 1,880 | 765.68 | 797.49 | 160.0 | 300.0 | 490.0 | 910.0 | 2,274.5 |
| Maturity | 1,880 | 6.24 | 0.96 | 4.5 | 6.0 | 6.5 | 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, two-way clustered at the borrower industry and the deal's year-quarter levels, 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** |
| | (0.020) | (0.019) | (0.019) | (0.019) |
| Talk Spread | 0.123*** | 0.127*** | 0.134*** | 0.131*** |
| | (0.005) | (0.006) | (0.006) | (0.006) |
| Log(Amount) | | 0.742 | | 0.361 |
| | | (0.503) | | (0.494) |
| Log(Maturity) | | 0.613 | | -0.270 |
| | | (2.505) | | (2.347) |
| Relationship | | -1.349 | | -1.628 |
| | | (0.977) | | (1.021) |
| Sponsored | | -6.333*** | | -5.340*** |
| | | (1.387) | | (1.251) |
| Cov Lite | | 2.429** | | 2.581** |
| | | (1.103) | | (1.112) |
| Has Revolver | | 7.364*** | | 7.686*** |
| | | (1.598) | | (1.586) |
| Has TLA | | -2.290 | | -2.916 |
| | | (2.293) | | (2.281) |
| Has Bond | | 8.731*** | | 8.574*** |
| | | (1.375) | | (1.373) |
| 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 |
| Year-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 year-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 |
| Year-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 Realized LGD**

This table reports results from estimating predictive regressions of realized loss given default for defaulted deals matched to IHS Markit post-default secondary market prices. Every observation is a syndication deal between 2000–2020 with an issuer-level default event and at least one term loan facility matched to Markit. The dependent variable, *LGD*, is 100 minus the deal-level average 30-day post-default bid price across the deal's loan facilities. *Spread Flex* is the deal's effective spread flex during bookbuilding. *Talk Spread* is the effective spread the lead bank proposed at deal launch. *Recovery Rating* is S&P's deal-level loan recovery rating score. *Log(Amount)* and *Log(Maturity)* are logarithms of the total amount and average maturity for term loans in the deal. *Cov Lite* is a dummy indicating that the deal includes a cov-lite loan. Heteroskedasticity-robust standard errors are reported in parentheses. *, **, *** represent 10%, 5%, and 1% levels of statistical significance.

**Dependent Variable: Realized LGD**

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Spread Flex | 0.133*** | 0.134*** | 0.130** | 0.101* |
| | (0.043) | (0.044) | (0.048) | (0.058) |
| Talk Spread | | -0.006 | 0.006 | 0.007 |
| | | (0.024) | (0.038) | (0.045) |
| Recovery Rating | | | -0.540* | -0.567* |
| | | | (0.302) | (0.333) |
| Log(Amount) | | | -6.321 | -8.745 |
| | | | (4.161) | (5.398) |
| Log(Maturity) | | | 28.132* | 26.335 |
| | | | (15.222) | (25.241) |
| Cov Lite | | | 9.592 | 6.188 |
| | | | (9.486) | (10.872) |
| Industry FEs | Y | Y | Y | Y |
| Year FEs | Y | Y | Y | Y |
| Default-Year FEs | N | N | N | Y |
| N | 75 | 75 | 75 | 72 |
| $R^2$ | 0.376 | 0.377 | 0.504 | 0.637 |

Table 5: **Spread Flex and Bank Internal Risk Assessments**

This table reports results from regressing changes in bank internal risk assessments about a borrower around its deal on the deal's characteristics, using the Y-14 quarterly bank credit register. Every observation is a syndication deal between 2012–2020. In Panel A, the dependent variable is the change in bank-estimated probability of default during the syndication quarter (in percentage points), averaged across the deal's lending banks with weights equal to each bank's exposure at default. In Panel B, the dependent variable is the change in bank-estimated loss given default during the syndication quarter (in percentage points), averaged across the deal's lending banks with weights equal to each bank's exposure at default. *Spread Flex* is the deal's effective spread flex during bookbuilding. *Talk Spread* is the effective spread the lead bank proposed at deal launch. *Cov Lite*, *Has Revolver*, and *Has Bond* are dummies indicating that the deal includes a cov-lite loan, a revolving credit facility, and a bond outstanding, respectively. *Sponsored* indicates a private-equity-sponsored borrower. *Public* indicates a publicly listed borrower. *Log(Amount)* and *Log(Maturity)* are logarithms of the total amount and average maturity for term loans in the deal. Standard errors, clustered at the industry-year level, are reported in parentheses. *, **, *** represent 10%, 5%, and 1% levels of statistical significance.

**Panel A: Δ Probability of Default**

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Spread Flex | 0.005** | 0.005** | 0.005* | 0.005* |
| | (0.003) | (0.003) | (0.003) | (0.003) |
| Talk Spread | | | 0.000 | -0.000 |
| | | | (0.004) | (0.003) |
| Cov Lite | | | | -0.597** |
| | | | | (0.293) |
| Has Revolver | | | | 0.030 |
| | | | | (0.414) |
| Has Bond | | | | -0.250 |
| | | | | (0.280) |
| Sponsored | | | | 0.249 |
| | | | | (0.317) |
| Public | | | | 0.143 |
| | | | | (0.377) |
| Log(Maturity) | | | | -0.123 |
| | | | | (0.867) |
| Log(Amount) | | | | -0.065 |
| | | | | (0.121) |
| 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 |
| Year-Quarter FEs | Y | Y | Y | Y |
| N | 2,016 | 2,016 | 2,016 | 2,016 |
| $R^2$ | 0.091 | 0.102 | 0.102 | 0.106 |

Table 5: **Spread Flex and Bank Internal Risk Assessments - Continued**

**Panel B: Δ Loss Given Default**

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Spread Flex | 0.011*** | 0.012*** | 0.011*** | 0.011*** |
| | (0.004) | (0.004) | (0.004) | (0.004) |
| Talk Spread | | | 0.001 | 0.001 |
| | | | (0.002) | (0.002) |
| Cov Lite | | | | 0.168 |
| | | | | (0.303) |
| Has Revolver | | | | 0.115 |
| | | | | (0.343) |
| Has Bond | | | | -0.782* |
| | | | | (0.458) |
| Sponsored | | | | -0.043 |
| | | | | (0.309) |
| Public | | | | -0.083 |
| | | | | (0.340) |
| Log(Maturity) | | | | 0.274 |
| | | | | (0.524) |
| Log(Amount) | | | | -0.030 |
| | | | | (0.150) |
| 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 |
| Year-Quarter FEs | Y | Y | Y | Y |
| N | 2,016 | 2,016 | 2,016 | 2,016 |
| $R^2$ | 0.103 | 0.104 | 0.105 | 0.107 |

Table 6: **New Money versus Refinance: Subsample Analysis**

This table reports results from estimating predictive regressions of default outcomes in subsamples of new money deals and refinance deals. *Spread Flex* is the deal's effective spread flex during bookbuilding. *Talk Spread* is the effective spread the lead bank proposed at deal launch. In Panel A, the dependent variable is a dummy indicating whether the borrower defaults over a 4-year period after issuance, scaled up by 100; controls and fixed effects in columns (2) and (4) match column (4) of Table 3. In Panel B, the dependent variable is realized LGD, defined as 100 minus the deal-level average Markit 30-day post-default bid; controls and fixed effects in columns (2) and (4) match column (3) of Table 4. In Panels C and D, the dependent variables are the changes in bank-estimated probability of default and loss given default during the syndication quarter; controls and fixed effects in columns (2) and (4) match column (4) of Table 5. Standard errors are two-way clustered at the borrower industry and the deal's year-quarter levels in Panel A, heteroskedasticity-robust in Panel B, and clustered at the industry-year level in Panels C and D. *, **, *** represent 10%, 5%, and 1% levels of statistical significance.

**Panel A: Default**

| | 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 |
| Year-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: Realized LGD**

| | New Money | | Refi | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Spread Flex | 0.108* | 0.146*** | -0.159 | -0.148 |
| | (0.061) | (0.039) | (0.158) | (0.200) |
| Talk Spread | | 0.082 | | -0.047 |
| | | (0.052) | | (0.062) |
| Additional Controls | N | Y | N | Y |
| Industry FEs | Y | Y | Y | Y |
| Year FEs | Y | Y | Y | Y |
| N | 44 | 36 | 34 | 31 |
| $R^2$ | 0.503 | 0.652 | 0.344 | 0.687 |

Table 6: **New Money versus Refinance: Subsample Analysis - Continued**

**Panel C: Δ Probability of Default (Y-14)**

| | New Money | | Refi | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Spread Flex | 0.003* | 0.003 | 0.015 | 0.014 |
| | (0.002) | (0.002) | (0.012) | (0.012) |
| Talk Spread | | -0.005 | | 0.005 |
| | | (0.004) | | (0.004) |
| Additional Controls | N | Y | N | Y |
| Credit Rating FEs | Y | Y | Y | Y |
| Lead Arranger FEs | Y | Y | Y | Y |
| Deal Purpose FEs | Y | Y | Y | Y |
| Industry FEs | Y | Y | Y | Y |
| Year-Quarter FEs | Y | Y | Y | Y |
| N | 961 | 961 | 1,042 | 1,042 |
| $R^2$ | 0.147 | 0.164 | 0.157 | 0.177 |

**Panel D: Δ Loss Given Default (Y-14)**

| | New Money | | Refi | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Spread Flex | 0.013*** | 0.013*** | 0.005 | 0.006 |
| | (0.005) | (0.005) | (0.006) | (0.007) |
| Talk Spread | | 0.001 | | -0.000 |
| | | (0.003) | | (0.002) |
| 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 |
| Year-Quarter FEs | Y | Y | Y | Y |
| N | 961 | 961 | 1,042 | 1,042 |
| $R^2$ | 0.138 | 0.146 | 0.166 | 0.170 |

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 the effective spread the lead bank proposed at deal launch. Standard errors are clustered at the deal's year-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 |
| Year-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 |

# Appendix

## 1 Distribution of Spread Flex with Partial Adjustment

In Section 2, we explain how the "partial adjustment" in the model of Benveniste and Spindt (1989) affects price adjustments or spread flex during bookbuilding. Here, we show that partial adjustment implies that even if the distribution of investor information is symmetric, the distribution of spread flexes will take a specific, asymmetric form.

The model implies that the issuance price $P_I$ should take the form

$$P_I = P_0 + Z - f(Z) \tag{A.1}$$

and price adjustments during bookbuilding should take the form

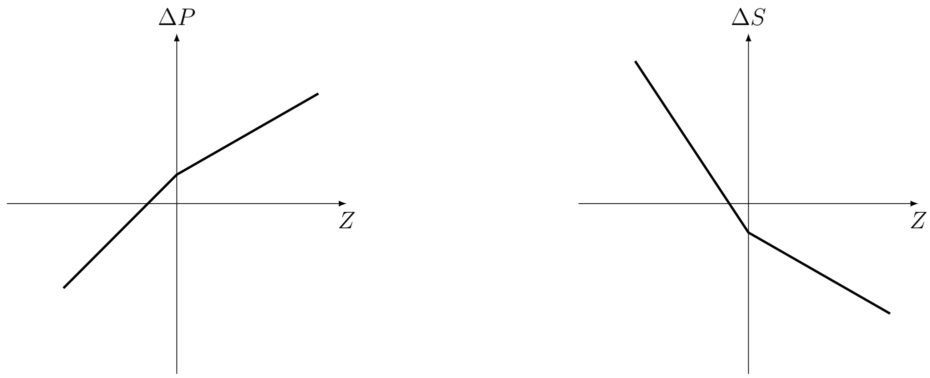
$$\Delta P := P_I - P_0 = Z - f(Z) \tag{A.2}$$

where $f(\cdot)$ represents underpricing, e.g.,

$$f(Z) = \gamma \cdot \max(Z, 0) \tag{A.3}$$

for some constant $0 < \gamma < 1$, and $Z$ is the information revealed by investors during bookbuilding. (E.g., under our two-sided information interpretation, $Z = I^{CF} + I^{DR}$; see Section 2.)

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 $Z$.[17] The spread flex $\Delta S := S_I - S_0$ is therefore also decreasing and convex in $Z$. Figure A.1 illustrates the relationship between price adjustments/ spread flexes and information revealed by investors, $Z$, when there is partial adjustment.




(a) Price adjustment

(b) Spread adjustment

Figure A.1. **Adjustments as a function of investor information**
"Partial adjustment" in the model of Benveniste and Spindt (1989) implies that price adjustments $\Delta P := P_I - P_0$ during bookbuilding are increasing and concave in $Z$ and that the corresponding spread flexes $\Delta S := S_I - S_0$ are decreasing and convex in $Z$. For the graph in Panel (b), we consider a continuously compounded spread and use the approximation $S_I - S_0 \overset{\propto}{\approx} -\frac{1}{P_0}(P_I - P_0)$.

The concavity and convexity of price adjustments and spread flexes imply 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 $\Delta p$, 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

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

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

using the concavity of $P_I$ in $Z$ and the fact that the function $S(P)$ is decreasing and convex in its argument.

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 underpricing function $f(\cdot)$ takes the form indicated above. Then the probability that the realization of the price adjustment $\Delta P := P_I - P_0$ is less than some number $\Delta p$ is:

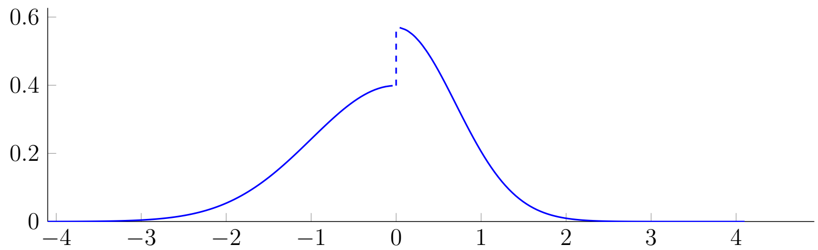
$$\Pr(\Delta P \leq \Delta p) = \begin{cases} \Pr(Z < \Delta p) & \text{if } \Delta p \leq 0, \\ \Pr((1-\gamma)Z < \Delta p) & \text{if } \Delta p > 0. \end{cases} \tag{A.4}$$

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

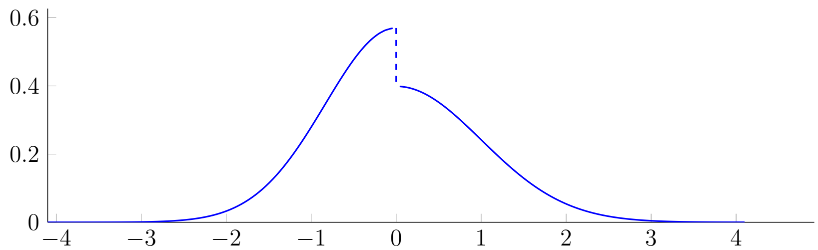
$$g(\Delta p) = \begin{cases} \frac{1}{\sigma}\varphi\left(\frac{\Delta p}{\sigma}\right) & \text{if } \Delta p \leq 0 \\ \frac{1}{\sigma(1-\gamma)}\varphi\left(\frac{\Delta p}{\sigma(1-\gamma)}\right) & \text{if } \Delta p > 0, \end{cases} \tag{A.5}$$

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 $1 - \gamma < 1$ 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




(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 (4), with $\bar{Z} = 0$ and $\gamma = 0.3$, 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 $\Delta S \mathrel{\underset{\sim}{\propto}} -(1/P_0)\Delta P$.

spread implies that for small $\Delta S$

$$\Delta S \approx -\frac{1}{P_0}\Delta P. \tag{A.6}$$

We use this approximation to compute an approximation of the density $h(\Delta s)$ from $g(\Delta p)$ 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 $\Delta s$ is the derivative of this expression w.r.t. $\Delta s$, that is,

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

So

$$h(\Delta s) \approx \begin{cases} \frac{1}{\sigma(1-\gamma)/P_0}\varphi\left(\frac{\Delta s}{\sigma(1-\gamma)/P_0}\right) & \text{if } \Delta s < 0, \\ \frac{1}{\sigma/P_0}\varphi\left(\frac{\Delta s}{\sigma/P_0}\right) & \text{if } \Delta s \geq 0\ . \end{cases} \tag{A.7}$$

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 Robustness

This appendix performs additional tests that rule out some alternative interpretations.

## 2.1 Additional variables

In our robustness checks, we use measures of public information released during bookbuilding, of borrower financials, and of credit rating changes, and define three subsamples in which these measures are available.

**Public Information During Bookbuilding.** We measure both industry-level and borrower-specific public news for deals that have a break date in LCD. First, we use daily stock returns of 30 industry portfolios from Ken French's website as a proxy for industry-level public news. We match the borrower's industry in LCD with one of the 30 industry portfolios and calculate cumulative returns from the deal's launch date to its break date. Second, we collect public news articles associated with the borrower from Dow Jones Factiva. In total, 67,529 news articles are released between the launch and break dates of 3,547 deals, originating from 3,189 unique news sources. Figure A.3 in the Appendix summarizes the top-20 sources of these articles.

We combine the title, source, date, and full text of news articles released between each deal's launch and break dates, remove duplicate content, and analyze it with the OpenAI large language model. The prompt, provided along with other details in Section 3 of the Appendix, instructs the model to map each deal's news into a discrete variable that takes values of -1, 0, and 1, indicating bad news, no news, or good news about a borrower's credit quality. Given Factiva's broad news coverage, for deals without news articles during bookbuilding, we assume no public news and assign a value of zero.

**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.[18] 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.

**Credit Rating Changes**. We use Moody's DRD to track changes in credit ratings. We are able to find a matched borrower in DRD for 1,306 borrowers in LCD. 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.[19] Using this panel, we create a sample of LCD deals for which we can track future rating changes.

[18] 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 firms in LCD, Pitchbook, and CRSP.

[19] A larger value of numeric rating corresponds to a better letter rating (e.g., AAA= 20). 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.

## 2.2 Additional Summary Statistics

[Insert Table A.1 here]

**Public News Sample** Panel A of Table A.1 reports the subsample of deals for which we can measure public information released during bookbuilding. This subsample contains the majority of deals in the main sample in Panel A of Table 1 (6,240 out of 7,763 deals). The average industry return during bookbuilding is 0.34%, with substantial dispersion: the 5th and 95th percentiles are -4.9% and 5.1%, respectively. The borrower news measure has a median of zero and an interquartile range of zero, indicating that the typical deal has no credit-relevant borrower-specific public news during bookbuilding. Relative to the main sample, the public-news sample is modestly tilted toward larger and somewhat less risky deals.

**Borrower Financials Sample**. Panel B of Table A.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.

**Credit Rating Changes Sample.** Panel C of Table A.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 roughly 30% of borrowers being either downgraded or upgraded.

## 2.3 Controlling for public news during bookbuilding

One concern with the baseline result is that the relationship between spread flex and default could be driven by public news released during the bookbuilding process. When public news indicates a deterioration in the borrower's credit quality, the lead bank flexes up the spread precisely because the borrower is expected to default with a higher probability. To address this concern, we include our proxies for industry-level and borrower-specific news as additional control variables into our baseline specifications. The sample includes syndication deals that have a break date, which allows us to focus on news released during the bookbuilding process.

[Insert Table A.2 here]

Table A.2, column (1) shows that the results of estimating our baseline specification (equation 10) in this subsample are similar to those of the full sample. Column (2) includes the industry stock portfolio return, which proxies for industry-level news. Our estimate indicates that a one-standard-deviation increase in industry return during bookbuilding (3.1%) is associated with 42 basis points lower probability of default, and this association is weakly statistically significant. Column (3) includes the credit quality change implied by news articles associated with the borrower. This variable is negatively correlated with default. However, its coefficient is small and statistically insignificant, suggesting that borrower-specific public news released during bookbuilding is noisy or irrelevant to credit risk. Column (4) controls for both of these news variables, and column (5) further controls for other loan characteristics. Our estimates remain almost the same. Overall, the evidence shows that the flex-default relationship we document is unlikely driven by public news released during the bookbuilding process.

## 2.4 Controlling for the effect of spread flex on interest burden

A second concern with the baseline result 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 A.3 here]

Table A.3, column (1) shows the result of estimating our baseline regression (equation (10)) in the subsample of borrowers with matched financial information. The point estimate in this subsample is slightly smaller than in the full sample and remains statistically significant at the 10% level. 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.

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.

## 2.5 Further 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 additional ways of splitting our data to see whether the partial correlation between flex and subsequent default varies across subsamples.

[Insert Table A.6 here]

**Credit Rating Agency Disagreement**. Table A.6, Panel A 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 indicates 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 agencies agree (columns (3) and (4)).

**Bank-Borrower Relationships**. Following Zhang, Zhang, and Zhao (2024), 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 B of Table A.6 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 a quarter of the size and statistically insignificant. This finding is consistent with nonbanks providing complementary information in deals for which banks have comparatively less information.

## 2.6 Different definitions of default

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. We demonstrate below that this finding is not sensitive to the definition or sampling of default events. First, our finding is robust to defining default events over alternative time horizons. In Table A.5, Panel A we replace the 4-year horizon in Table 3 with various alternative time horizons.[20] 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 evidence consistent with investors having private information about the probability of default.

[Insert Table A.5 here]

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 A.5, 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 A.5, 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.

[20] Figure A.4 in the Appendix shows that most default events occur between 1 year and 5 years after the syndication deal.

## 2.7 Default events at the syndication deal level

Our main tests of the relationship between spread flex and default focus on borrower-level default events. Here, we report complementary results using default events at the syndication deal level, which are consistent with our main findings.

[Insert Figure A.5 and Table A.7 here]

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, only 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.5 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.7 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.

## 2.8 Alternative outcomes: rating changes

Our Hypothesis 1 is formulated with a focus on default, but default events are relatively infrequent: the unconditional default rate over a 4-year period is only 4%. If investor demand revealed during bookbuilding is informative about borrower quality, spread flexes should also predict future credit events even before a default materializes. For this reason, we provide additional evidence from the changes in the borrower's credit ratings that are indicative of changes in the borrower's financial conditions. We estimate our baseline regression, equation 10, with credit rating downgrade and upgrade after loan origination as outcome variables.

[Insert Table A.8 here]

Table A.8 reports the results. The estimates show a statistically significant relationship between spread flexes and future rating changes. Positive spread flex predicts a higher probability of a downgrade or a lower probability of an upgrade. The magnitude is economically meaningful. A 50 basis point upward flex predicts an increase of about 2.3% in the probability of a downgrade over a 3-year period. It also predicts a 1.4% lower probability of an upgrade. After controlling for deal variables including original rating and talk effective spread in column (2), this estimate remains similar.

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

## 2.9 Time on market and investor demand during bookbuilding

We provide additional evidence on the role of investor demand using time on market, following Ivashina and Sun (2011). Time on market measures the number of days between a deal's launch date and break date. Ivashina and Sun (2011) interpret longer Time on Market as a proxy for weaker institutional demand during syndication. In our setting, this variable provides a useful benchmark for interpreting the required-return component of spread flex.

[Insert Table A.9 here]

Table A.9 first relates time on market to effective issuance spreads. Consistent with Ivashina and Sun (2011), loans that remain in syndication longer are issued with higher spreads. This relation is robust to credit rating fixed effects, lead arranger fixed effects, deal purpose fixed effects, industry fixed effects, year-month fixed effects, and deal controls. Thus, time on market behaves in our sample as in prior work: longer syndication is associated with weaker investor demand and higher promised yields at issuance.

[Insert Table A.10 here]

Table A.10 relates Time on Market to secondary-market returns. The results show that loans with longer Time on Market earn higher subsequent returns over horizons of 3 months, 6 months, 1 year, and 2 years. This pattern is consistent with the demand-pressure interpretation in Ivashina and Sun (2011). When investor demand is weak during syndication, investors require higher compensation to absorb the loan. If this demand pressure later abates, prices rise and the loan earns positive secondary-market returns. These results complement the evidence in Table 7: both Spread Flex and Time on Market are positively related to subsequent loan returns, consistent with investor demand during bookbuilding revealing information about required returns.

We next examine whether Time on Market can also predict default.

[Insert Table A.11 here]

Table A.11 reports predictive regressions of borrower default on Time on Market, Spread Flex, and Talk Spread. Column (1) shows that loans that remain in syndication longer are more likely to default. In our setting, weak investor demand can reflect not only a higher required return, but also adverse information about borrower credit quality. Time on Market, as an alternative measure of demand, also predicts default. However, the coefficient on Time on Market becomes small and statistically insignificant once we include Spread Flex. Spread Flex, by contrast, remains positive and statistically significant across specifications. These results are consistent with Time on Market being a noisy measure of investor demand, while Spread Flex more directly captures the credit-risk component of the information revealed during bookbuilding.

Taken together, the time-on-market results support three conclusions. First, consistent with Ivashina and Sun (2011), longer Time on Market is associated with higher issuance spreads. Second, Time on Market is positively related to subsequent secondary-market returns, consistent with investor demand containing required-return information. Third, Time on Market is also positively related to borrower default when included on its own, suggesting that weak investor demand contains borrower credit quality information. However, this borrower credit quality component is captured more directly by Spread Flex, which remains predictive of default after controlling for Time on Market.

# 3 Construction of the public-news measure

We use OpenAI's large language model GPT-5-mini (version *gpt-5-mini-2025-08-07*, accessed on October 20, 2025) to process public news articles about borrowers released during book-building. We instruct the model to analyze the text of news articles with the following prompt.

> *You are a senior credit analyst. You will be given a collection of news articles released during a borrower's debt financing transaction window. Your task is to identify whether these news contain information that could affect how investors assess the borrower's credit quality at issuance. Important rules:*
>
> 1. *Focus only on new and unexpected information about the borrower's fundamentals (e.g., earnings surprises, legal developments, material demand shocks, supply/operational disruptions, frauds, unexpected management/strategic changes, etc.). Treat expected or routine information as 0 (no material public credit signal).*
> 2. *If the news only involves corporate growth or PR items but indicates no clear credit profile changes, such as acquisitions/M&A, expansions, IPOs, openings, franchise growth, new products, partnerships, marketing, distribution channels, hiring plans, or CAPEX announcements, do NOT classify as credit improvement.*
> 3. *Ignore details of the financing transaction itself and its features (e.g., leverage, pricing, structure, acquisition). Do NOT assign any credit impact based on the fact that the borrower is issuing new debt or changing its capital structure.*

*4. If the news is ambiguous, mixed, or not credit relevant, classify as 0.*

*Classification:*

- *-1: Negative public credit signal (bad news about fundamentals)*
- *0: Neutral or no credit-relevant information*
- *+1: Positive public credit signal (good news about fundamentals)*

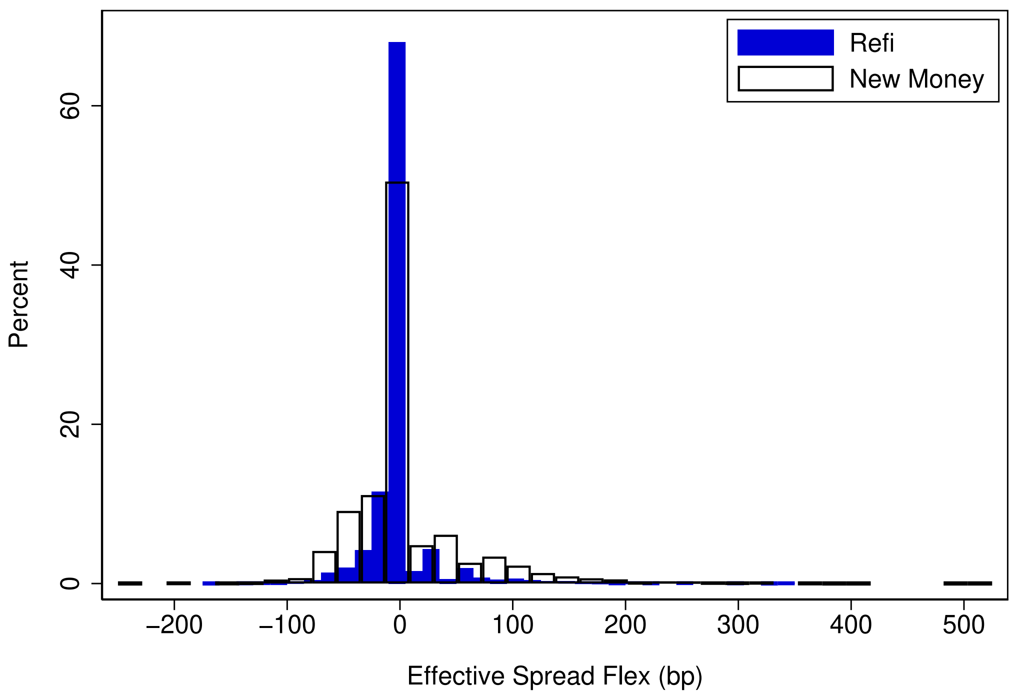



Figure A.1. **Distribution of Spread Flex: New Money and Refinance.**
This figure presents the distribution of effective spread flex in syndication deals for new money deals and refinance deals, respectively. Source: Pitchbook's Leveraged Commentary & Data (LCD)

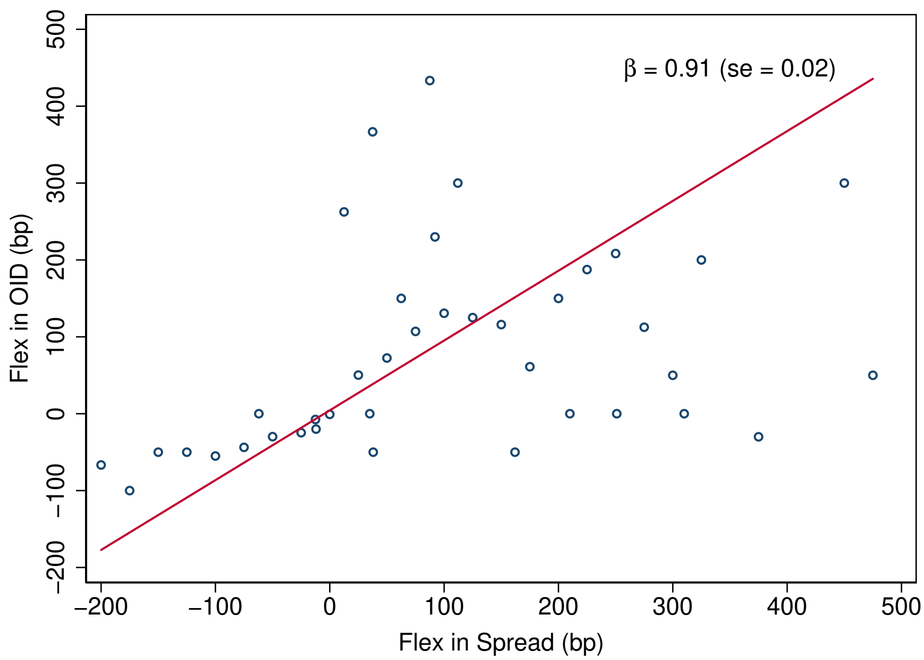



Figure A.2. **Relationship Between Spread Flex and OID Flex.**
This figure presents a scatter plot that groups syndication deals into 100 bins based on flex in loan spread and depicts the average flex in OID within each bin. The fitted line represents an OLS slope estimate, with heteroskedasticity-robust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

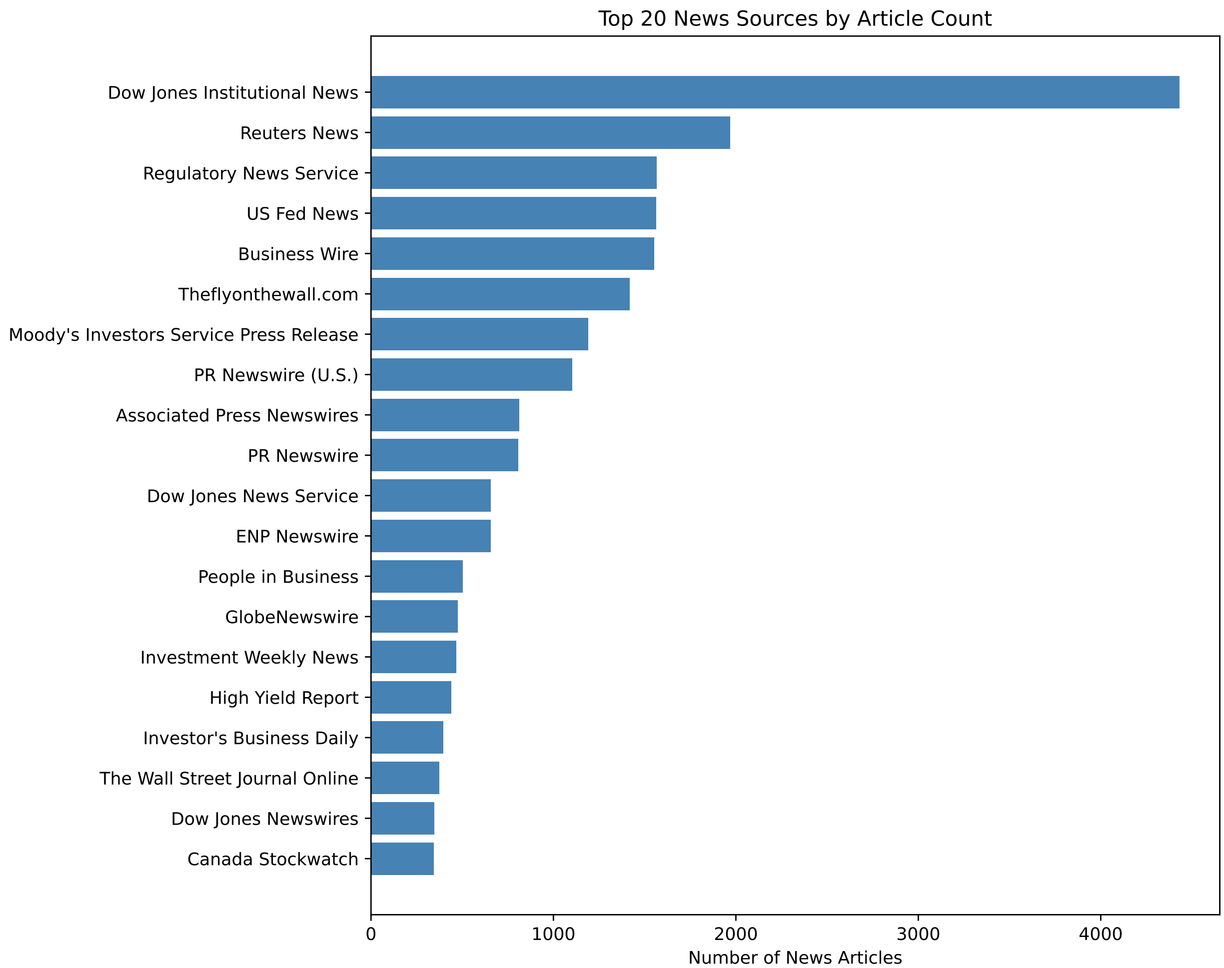



Figure A.3. **Sources of News During Bookbuilding.**
This figure presents the top-20 sources of news articles released between syndication deals' launch and break dates. Source: Pitchbook's Leveraged Commentary & Data (LCD), Dow Jones Factiva.

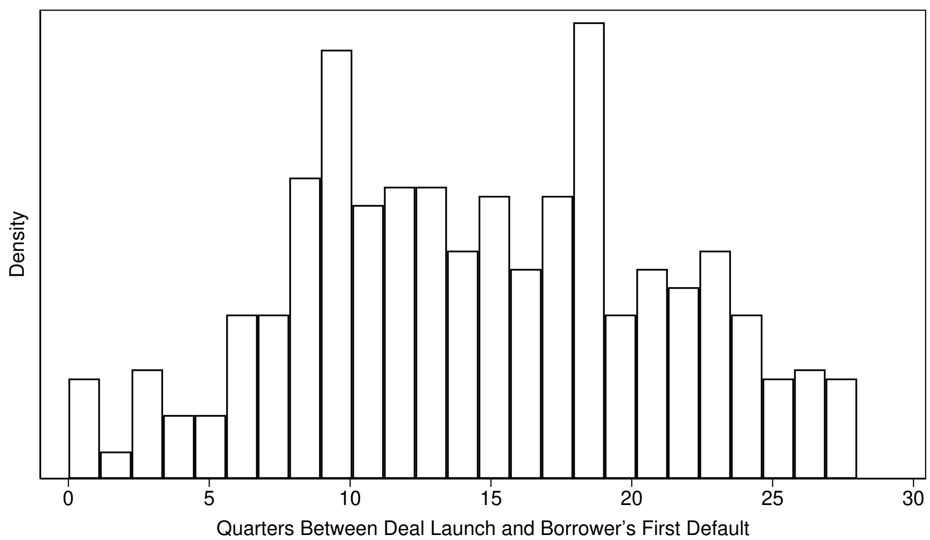



Figure A.4. **Time Between Syndication Deal and Default.**
This figure presents the distribution of the number of quarters between a syndication deal and the borrower's default for all default events. Source: Pitchbook's Leveraged Commentary & Data (LCD), Default and Recovery Database (DRD), and LevFin Insights (LFI).

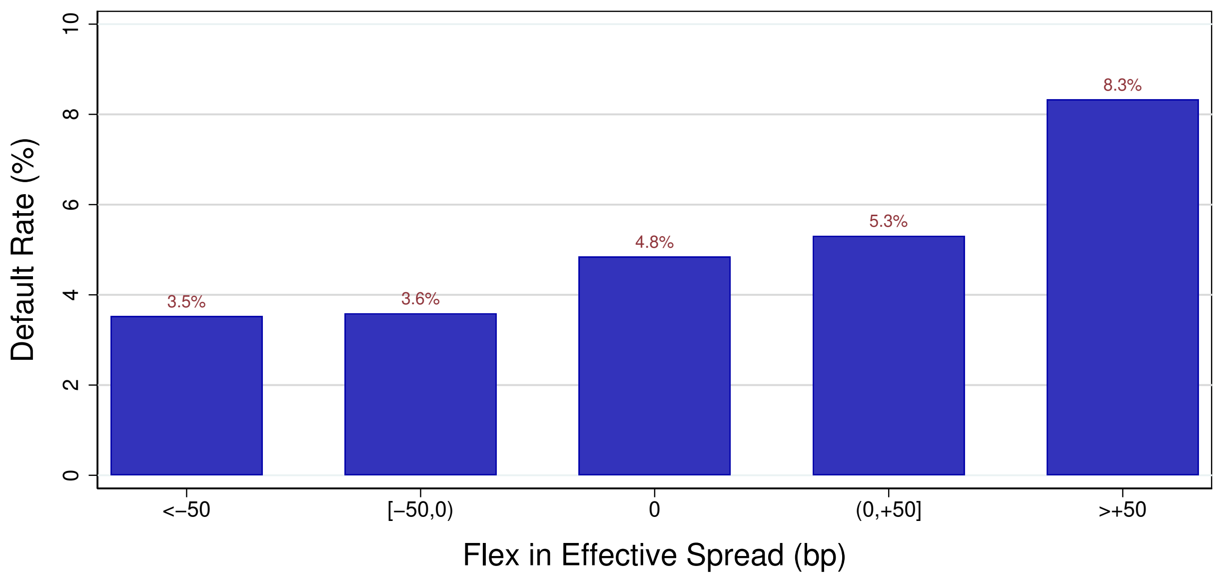



Figure A.5. **Spread Flex and Deal-Level Default: Nonparametric Comparison.** This figure presents the fraction of syndication deals that subsequently default. The sample consists of 1,030 Pitchbook LCD deals for which the institutional term loan is matched to a debt instrument in DRD. The deals are 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: **Additional Summary Statistics**

This table reports summary statistics for the appendix subsamples used in the robustness tests. Panel A summarizes the public-news subsample, the set of deals with launch and break dates matched to industry returns and borrower-specific news during bookbuilding. *Industry Return* is the cumulative 30-industry portfolio return for the borrower's industry between the deal's launch and break dates. *Borrower News* is a discrete variable taking values $-1$, 0, and 1, indicating credit-quality changes implied by news articles released between the deal's launch and break dates. Panel B summarizes the borrower-financials subsample, where the borrower's financial information is matched from Compustat (public firms) and the Y-14 register (private firms). *Pre-Deal ICR* is the borrower's interest coverage ratio in the quarter before the deal. $\Delta ICR$ is the change in interest coverage ratio caused by the impact of spread flex on the borrower's interest expenses. Panel C summarizes the Moody's credit-ratings subsample. *Downgrade* and *Upgrade* are dummies indicating a downgrade and upgrade, respectively, in Moody's first-lien rating within 3 years of issuance, scaled up by 100. Other variables are defined as in Table 1.

**Panel A: Public News Sample**

| | N | mean | sd | p5 | p25 | p50 | p75 | p95 |
|---|---|---|---|---|---|---|---|---|
| Industry Return | 6,240 | 0.34 | 3.08 | -4.9 | -1.2 | 0.4 | 2.1 | 5.1 |
| Borrower News | 6,240 | -0.05 | 0.43 | -1.0 | 0.0 | 0.0 | 0.0 | 1.0 |
| Default (%) | 6,240 | 3.81 | 19.16 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| Talk Spread | 6,240 | 434.31 | 140.55 | 237.5 | 330.0 | 412.5 | 522.5 | 677.4 |
| Spread Flex | 6,240 | 1.94 | 46.54 | -50.0 | -16.7 | 0.0 | 0.0 | 87.5 |
| Credit Rating | 6,240 | 6.59 | 2.06 | 3.0 | 6.0 | 7.0 | 8.0 | 10.0 |
| Amount ($ million) | 6,240 | 736.40 | 792.14 | 100.0 | 275.0 | 475.0 | 900.0 | 2,200.0 |
| Maturity | 6,240 | 6.11 | 1.05 | 4.0 | 5.5 | 6.3 | 7.0 | 7.0 |
| Relationship | 6,240 | 0.19 | 0.39 | 0.0 | 0.0 | 0.0 | 0.0 | 1.0 |
| Sponsored | 6,240 | 0.65 | 0.48 | 0.0 | 0.0 | 1.0 | 1.0 | 1.0 |
| Cov Lite | 6,240 | 0.60 | 0.49 | 0.0 | 0.0 | 1.0 | 1.0 | 1.0 |
| Has Revolver | 6,240 | 0.48 | 0.50 | 0.0 | 0.0 | 0.0 | 1.0 | 1.0 |
| Has TLA | 6,240 | 0.04 | 0.21 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| Has Bond | 6,240 | 0.11 | 0.32 | 0.0 | 0.0 | 0.0 | 0.0 | 1.0 |

**Panel B: Borrower Financials Sample**

| | N | mean | sd | p5 | p25 | p50 | p75 | p95 |
|---|---|---|---|---|---|---|---|---|
| Pre-Deal ICR | 3,163 | 3.80 | 4.16 | -0.2 | 1.5 | 2.5 | 4.4 | 17.6 |
| ΔICR | 3,163 | 0.10 | 1.01 | -0.0 | 0.0 | 0.0 | 0.0 | 0.1 |
| Talk Spread | 3,163 | 405.10 | 145.30 | 212.5 | 300.0 | 375.0 | 487.5 | 666.7 |
| Spread Flex | 3,163 | 0.70 | 40.50 | -50.0 | -12.5 | 0.0 | 0.0 | 75.0 |
| Amount ($ million) | 3,163 | 771.00 | 825.20 | 75.0 | 260.0 | 500.0 | 995.0 | 2,284.0 |
| Maturity | 3,163 | 6.00 | 1.10 | 3.9 | 5.3 | 6.1 | 7.0 | 7.0 |

Table A.1: **Additional Summary Statistics - Continued**

**Panel C: Credit Ratings Sample**

| | N | mean | sd | p5 | p25 | p50 | p75 | p95 |
|---|---|---|---|---|---|---|---|---|
| Downgrade (%) | 3,634 | 31.62 | 46.50 | 0.0 | 0.0 | 0.0 | 100.0 | 100.0 |
| Upgrade (%) | 3,634 | 28.21 | 45.01 | 0.0 | 0.0 | 0.0 | 100.0 | 100.0 |
| Spread Flex | 3,634 | 0.76 | 44.03 | -50.0 | -12.5 | 0.0 | 0.0 | 75.0 |
| Talk Spread | 3,634 | 416.24 | 144.64 | 217.5 | 312.5 | 387.5 | 500.0 | 675.0 |
| Amount ($ million) | 3,634 | 777.64 | 838.65 | 84.0 | 270.0 | 500.0 | 1,000.0 | 2,325.0 |
| Maturity | 3,634 | 5.96 | 1.10 | 3.9 | 5.2 | 6.0 | 7.0 | 7.0 |
| Relationship | 3,634 | 0.22 | 0.41 | 0.0 | 0.0 | 0.0 | 0.0 | 1.0 |
| Sponsored | 3,634 | 0.58 | 0.49 | 0.0 | 0.0 | 1.0 | 1.0 | 1.0 |
| Cov Lite | 3,634 | 0.54 | 0.50 | 0.0 | 0.0 | 1.0 | 1.0 | 1.0 |
| Has Revolver | 3,634 | 0.43 | 0.49 | 0.0 | 0.0 | 0.0 | 1.0 | 1.0 |
| Has TLA | 3,634 | 0.06 | 0.23 | 0.0 | 0.0 | 0.0 | 0.0 | 1.0 |
| Has Bond | 3,634 | 0.15 | 0.36 | 0.0 | 0.0 | 0.0 | 0.0 | 1.0 |

Table A.2: **Spread Flex and Default: Controlling for Public Information During Bookbuilding**

This table reports results from estimating predictive regressions of default events in Table 3 using a sample with the deal's launch and break dates. 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 the effective spread the lead bank proposed at deal launch. *Industry Return* is the cumulative 30-industry portfolio return for the borrower's industry between the deal's launch and break dates. *Borrower News* is a discrete variable that takes values of -1, 0, and 1, indicating changes in the borrower's credit quality based on public news articles released between the deal's launch and break dates. 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 year-quarter levels, are reported in parentheses. *, **, *** represent 10%, 5%, and 1% levels of statistical significance.

**Dependent Variable: Default**

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| Spread Flex | 0.023** | 0.023** | 0.023** | 0.023** | 0.024** |
| | (0.010) | (0.010) | (0.010) | (0.010) | (0.010) |
| Talk Spread | 0.029*** | 0.029*** | 0.029*** | 0.029*** | 0.031*** |
| | (0.005) | (0.005) | (0.005) | (0.005) | (0.005) |
| Industry Return | | -0.136* | | -0.136* | -0.137* |
| | | (0.076) | | (0.076) | (0.080) |
| Borrower News | | | -0.033 | -0.039 | 0.158 |
| | | | (0.516) | (0.509) | (0.520) |
| Additional Controls | N | N | N | N | Y |
| Credit Rating FEs | Y | Y | Y | Y | Y |
| Lead Arranger FEs | Y | Y | Y | Y | Y |
| Deal Purpose FEs | Y | Y | Y | Y | Y |
| Industry FEs | Y | Y | Y | Y | Y |
| Year-Month FEs | Y | Y | Y | Y | Y |
| N | 6,240 | 6,240 | 6,240 | 6,240 | 6,240 |
| $R^2$ | 0.129 | 0.129 | 0.129 | 0.130 | 0.134 |

Table A.3: **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. *Spread Flex* is the deal's effective spread flex during bookbuilding. *Talk Spread* is the 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. $\Delta ICR$ 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, clustered at the industry-year level, are reported in parentheses. *, **, *** represent 10%, 5%, and 1% levels of statistical significance.

**Dependent Variable: Default**

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Spread Flex | 0.022* | 0.023* | 0.023* | 0.025* |
| | (0.013) | (0.013) | (0.013) | (0.013) |
| Talk Spread | 0.036*** | 0.036*** | 0.036*** | 0.039*** |
| | (0.005) | (0.005) | (0.005) | (0.005) |
| Pre-Deal ICR | | -0.209* | -0.212* | -0.197* |
| | | (0.115) | (0.114) | (0.118) |
| ΔICR | | | 0.079 | 0.113 |
| | | | (0.175) | (0.178) |
| 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 |
| Year-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 A.4: **Spread Flex and Default: Additional Sample Splits**

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 the 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 based on whether Moody's and S&P's credit ratings for the deal's senior secured first lien facility differ by at least two notches. In Panel B, syndication deals are divided into subsamples based on whether the lead bank has a pre-existing relationship with the borrower. Standard errors, two-way clustered at the borrower industry and the deal's year-quarter levels, are reported in parentheses. *, **, *** represent 10%, 5%, and 1% levels of statistical significance.

**Panel A: 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 |
| Year-Month FEs | Y | Y | Y | Y |
| N | 918 | 918 | 6,811 | 6,811 |
| $R^2$ | 0.336 | 0.353 | 0.097 | 0.117 |

**Panel B: 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 |
| Year-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 A.5: **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 over a 4-year period after issuance in DRD database. *Spread Flex* is the deal's effective spread flex during bookbuilding. *Talk Spread* is the 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 year-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, $\infty$) |
|---|---|---|---|---|
| | (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 |
| Year-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 A.5: **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 |
| Year-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 |
| Year-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 A.6: **Spread Flex and Default: Additional Sample Splits**

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 the 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 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 B, syndication deals are divided into subsamples based on whether the lead bank has a pre-existing relationship with the borrower. Standard errors, two-way clustered at the borrower industry and the deal's year-quarter levels, are reported in parentheses. *, **, *** represent 10%, 5%, and 1% levels of statistical significance.

**Panel A: 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 |
| Year-Month FEs | Y | Y | Y | Y |
| N | 918 | 918 | 6,811 | 6,811 |
| $R^2$ | 0.336 | 0.353 | 0.097 | 0.117 |

**Panel B: 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 |
| Year-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 A.7: **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: $7.1\% - 3.6\% = 3.5\%^{**}$ ($t = 2.1$) | | | |

Table A.8: **Spread Flex and Moody's Credit Rating Changes**

This table reports results from estimating predictive regressions of post-issuance changes in Moody's first-lien credit ratings. Every observation is a syndication deal between 2000–2020 with a Moody's first-lien rating at issuance. In columns (1)–(2), the dependent variable is *Downgrade*, a dummy indicating that the borrower's Moody's first-lien rating is downgraded within 3 years of issuance, scaled up by 100. In columns (3)–(4), the dependent variable is *Upgrade*, a dummy indicating that the rating is upgraded within 3 years of 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 year-quarter levels, are reported in parentheses. *, **, *** represent 10%, 5%, and 1% levels of statistical significance.

| | Downgrade | | Upgrade | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Spread Flex | 0.043*** | 0.047*** | -0.028* | -0.028** |
| | (0.015) | (0.017) | (0.014) | (0.012) |
| Talk Spread | | 0.049*** | | -0.024** |
| | | (0.007) | | (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 |
| Year-Month FEs | Y | Y | Y | Y |
| N | 3,634 | 3,634 | 3,634 | 3,634 |
| $R^2$ | 0.100 | 0.118 | 0.127 | 0.146 |

Table A.9: **Time on Market and Effective Spread**

This table reports regressions of effective spread on time on market in Ivashina and Sun (2011). Every observation is a syndication deal between 2000–2020. The dependent variable is the deal's effective spread (in basis points). *Time on Market* is the number of days between the deal's launch and break dates. Control variables in column (3) are the same as in column (4) of Table 3. Standard errors, two-way clustered at the borrower industry and the deal's year-quarter levels, are reported in parentheses. *, **, *** represent 10%, 5%, and 1% levels of statistical significance.

| **Dependent Variable: Effective Spread** | | | |
|---|---|---|---|
| | (1) | (2) | (3) |
| Time on Market | 6.455*** | 5.643*** | 5.412*** |
| | (0.652) | (0.526) | (0.494) |
| Log(Amount) | | | -13.193*** |
| | | | (1.702) |
| Log(Maturity) | | | -27.193** |
| | | | (10.306) |
| Relationship Deal | | | -36.409*** |
| | | | (5.980) |
| Sponsored | | | -1.220 |
| | | | (5.221) |
| Cov Lite | | | -39.555*** |
| | | | (4.782) |
| Has Revolver | | | 5.725 |
| | | | (4.132) |
| Has TLA | | | -43.937*** |
| | | | (8.048) |
| Has Bond | | | 11.620** |
| | | | (5.218) |
| Credit Rating FEs | N | Y | Y |
| Lead Arranger FEs | Y | Y | Y |
| Deal Purpose FEs | Y | Y | Y |
| Industry FEs | Y | Y | Y |
| Year-Month FEs | Y | Y | Y |
| N | 6,240 | 6,240 | 6,240 |
| $R^2$ | 0.446 | 0.595 | 0.625 |

Table A.10: **Time on Market and Secondary Market Returns**

This table replicates the regression of secondary market loan returns on time on market in Ivashina and Sun (2011). Every observation is a syndication deal between 2000–2020 with a term loan facility 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: 3 months in column (1), 6 months in column (2), 1 year in column (3), and 2 years in column (4). *Time on Market* is the duration between the deal's launch and break dates. *Log(Amount)* and *Log(Maturity)* are logarithms of the total amount and average maturity for term loans in the deal. Standard errors clustered at the deal's year-month level are reported in parentheses. *, **, *** represent 10%, 5%, and 1% levels of statistical significance.

**Dependent Variable: Secondary Market Return**

| | 3m | 6m | 1y | 2y |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Time on Market | 0.099*** | 0.104*** | 0.056*** | 0.066*** |
| | (0.029) | (0.018) | (0.015) | (0.021) |
| Log(Amount) | -0.874*** | -0.483*** | -0.592*** | -0.155 |
| | (0.219) | (0.160) | (0.158) | (0.191) |
| Log(Maturity) | -2.096*** | -2.355*** | -1.515*** | -1.610** |
| | (0.679) | (0.641) | (0.532) | (0.752) |
| Credit Rating FEs | Y | Y | Y | Y |
| Year-Month FEs | Y | Y | Y | Y |
| N | 1,857 | 1,860 | 1,862 | 1,171 |
| $R^2$ | 0.617 | 0.608 | 0.439 | 0.337 |

Table A.11: **Time on Market, Spread Flex, and Default**

This table reports results from estimating predictive regressions of default events on time on market, spread flex, and talk spread. Every observation is a syndication deal between 2000–2020. The dependent variable is a dummy indicating whether the borrower defaults over a 4-year period after issuance, scaled up by 100. *Time on Market* is the duration between the deal's launch and break dates. *Spread Flex* is the deal's effective spread flex during bookbuilding. *Talk Spread* is the effective spread the lead bank proposed at deal launch. Control variables in column (5) are the same as in column (4) of Table 3. Standard errors, two-way clustered at the borrower industry and the deal's year-quarter levels, are reported in parentheses. *, **, *** represent 10%, 5%, and 1% levels of statistical significance.

**Dependent Variable: Default**

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| Time on Market | 0.113** | 0.048 | 0.041 | -0.086 | -0.072 |
| | (0.055) | (0.053) | (0.053) | (0.054) | (0.051) |
| Spread Flex | | 0.028*** | 0.025** | 0.028*** | 0.028*** |
| | | (0.010) | (0.010) | (0.009) | (0.009) |
| Talk Spread | | | | 0.031*** | 0.032*** |
| | | | | (0.005) | (0.005) |
| Additional Controls | N | N | N | N | Y |
| Credit Rating FEs | N | N | Y | Y | Y |
| Lead Arranger FEs | Y | Y | Y | Y | Y |
| Deal Purpose FEs | Y | Y | Y | Y | Y |
| Industry FEs | Y | Y | Y | Y | Y |
| Year-Month FEs | Y | Y | Y | Y | Y |
| N | 6,240 | 6,240 | 6,240 | 6,240 | 6,240 |
| $R^2$ | 0.094 | 0.098 | 0.108 | 0.130 | 0.134 |