Pipeline Risk in Leveraged Loan Syndication*

Max Bruche†
Cass Business School and FMG, LSE

Frederic Malherbe‡
London Business School and CEPR

Ralf R. Meisenzahl§
Federal Reserve Board

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Abstract

Leveraged term loans are typically arranged by banks but distributed to institutional investors. Using novel data, we find that to elicit investors' willingness to pay, arrangers expose themselves to *pipeline risk*: They have to retain larger shares when investors are willing to pay less than expected. We argue that the retention of such problematic loans creates a debt overhang problem. Consistent with this, we find that the materialization of pipeline risk for an arranger reduces its subsequent arranging and lending activity. Aggregate time series exhibit a similar pattern, which suggests that the informational friction we identify could amplify the credit cycle.

JEL classifications: G23, G24, G30
Keywords: syndicated loans, leveraged loans, pipeline risk, lead arranger share, debt overhang

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†Email: max.bruche.1@city.ac.uk
‡Email: fmalherbe@london.edu
§Email: ralf.r.meisenzahl@frb.gov

1 Introduction

Leveraged loans — syndicated loans with high credit risk — make up a large part of the overall syndicated loan market. According to Thomson Reuters LPC, total U.S. syndicated loan issuance in 2013 was about 2.1 trillion, of which more than half, about \$1.1 trillion, was classified as leveraged. In turn, a large part of all leveraged term loans are classified as *institutional* (more than \$600 billion in 2013), meaning that they are meant to be distributed by arranging banks to institutional investors such as hedge funds, mutual funds, and CLOs.

What are the economic problems that arrangers have to solve in such an originate-to-distribute model and, consequently, what are the risks they face? Do these risks matter for prudential regulation and ultimately for aggregate credit provision? To address these questions, we use novel data to examine the syndication process for such loans and obtain three main results.

First, we show that arrangers face a demand discovery problem: They need to ascertain how much institutional investors are willing to pay for the loans. To do so, they use a process that resembles the one described by bookbuilding theory (Benveniste and Spindt, 1989).

Second, in this process, incentive compatibility requires that arrangers allocate smaller amounts to investors who indicate a low willingness to pay. But with syndicated term loans, issuers often have limited flexibility on the amount. As a consequence, arrangers often give guarantees that they will make up for any shortfall in funds. Arrangers therefore face the risk that they must retain larger shares in those loans for which investors are willing to pay less than expected. We show that this is the case in the data. Because this risk arises on the loans in arrangers' syndication pipelines, we refer to it as *pipeline risk*.

Third, when banks have to retain such problematic loans, they potentially face a form of debt overhang. We show that when arrangers face lower willingness to pay than expected, they subsequently reduce the number and dollar volume of leveraged term loans that they arrange,

as well as their participations in newly-syndicated credit lines. The behavior of aggregate time series furthermore suggests that pipeline-risk-induced debt overhang could amplify credit cycle fluctuations.

In our empirical analysis we use the S& P Capital IQ's Leveraged Commentary and Data (LCD).[1] The terms of the loans are frequently adjusted during the syndication process or, in market parlance, "flexed." LCD contains information on leveraged loan syndication from 1999 to 2015, including information on secondary market prices and also on flex, which makes the dataset unique. We combine the LCD data with lender share data from the Shared National Credit Program (SNC), an annual survey of syndicated loans carried out by U.S. financial regulators.

We first focus on the nature of the economic problem, then on the consequences at the bank level, and finally on the consequences at the aggregate level. To structure the first two steps, we draw on the literature on bookbuilding.

Bookbuilding is generally described as a means for the arranger to elicit private information from market participants about their willingness to pay for the asset being sold. To illustrate the theory, consider an example in which a borrower wants to finance a leveraged buyout bid of a given size. We can represent this by a fixed supply of the loan, as indicated by the vertical supply curve in the left panel of Figure 1. The arranging bank does not know whether investors have a high or a low willingness to pay, as indicated by the (perfectly elastic) demand schedules D_h and D_l in the left panel of Figure 1.

To obtain the best terms for the loan, the arranging bank must make it incentive compatible for investors to reveal their true willingness to pay. To achieve this, the arranging bank must do two

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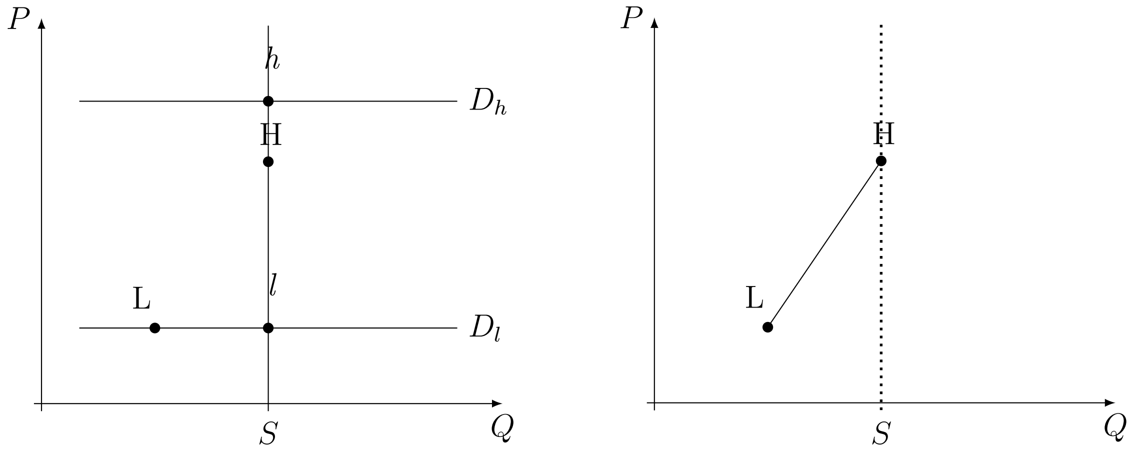


Figure 1. Price, quantity, and incentive compatibility
A borrower wants to raise a fixed amount of financing by placing a loan of size S. The willingness of investors to pay for the loan can be either high or low, as indicated by the demand schedules D_h and D_l. To preserve incentives for investors to reveal their willingness to pay, the arranger needs to underprice when investors reveal high demand (point H) and ration investors when they reveal low demand (point L).

things. First, it must reward investors when they reveal a high willingness to pay, by underpricing the issue (setting the price to that at point H rather than the full price at point h) and by giving investors large quantities. Second, the arranging bank must punish investors by not underpricing the issue and rationing quantities when they reveal a low willingness to pay: the total quantity placed shrinks from that at point l to that at point L. The logic of incentive compatibility implies that even when the underlying supply curve is vertical, the effective supply curve that investors face in equilibrium must be upward-sloping, as indicated in the right panel of Figure 1.

In practice, building on the empirical literature on underpricing, we can identify situations in which investors reveal a high willingness to pay as those in which the arranger increases price during syndication or, in our case, decreases spreads, and vice versa. We then have several testable implications of the theory. First, underpricing should on average be positive. Also, because prices only partially adjust to revealed information, underpricing should be higher when investors indicate a high willingness to pay and spreads are flexed down. Second, when investors indicate a low will-

ingness to pay and spreads are flexed up, the arranger is likely to retain a larger share. Third, when this happens, this can generate a debt overhang problem, which reduces the arranger's willingness to arrange and participate in loans going forward.

We find empirical support for these three hypotheses. First, according to the pricing information in LCD, the leveraged term loans are on average underpriced in the primary market and pricing is adjusted only partially.[2]

Second, when spreads are flexed up, the share retained by the lead arranger is larger. The point estimates imply that a 100 bps upward flex in spread is associated with an increase in the lead arranger share of around 1.06 to 1.36 percent. This is substantial, given an average lead share of only about 5.3 percent in our data.

Third, arrangers who face a lower willingness to pay than expected in a given quarter reduce the number and dollar volume of loans they arrange in the following quarter. The point estimates imply that an arranging bank which has to increase spreads on an additional $1,000m of loans arranges roughly 0.7 fewer loans and $450m less in the following quarter. We also find a negative effect on the total amount of their subsequent participations in other syndicated loans (i.e., as a lender and not necessarily as an arranger). Here, raising spreads on an additional $1000m of loans leads to a $150m decline in lending for that institution, in the following quarter.

Regulators are concerned about pipeline risk.[3] However, to the best of our knowledge, no systematic information exists which would allow an assessment of the extent of guarantees given by

[2]We find that the median loan is underpriced by 75bps relative to the mid-point of the bid-ask spread in the secondary market. Given the bid-ask spreads prevalent in secondary markets, this would suggest that the median loan is underpriced by about 30-40 bps relative to the bid price in the secondary market. This level of underpricing is comparable to the 47bps reported by Cai, Helwege, and Warga (2007) for high-yield bonds. It is much lower than the underpricing for stocks (Jenkinson and Ljungqvist (2001) report an average of around 19 percent over four decades in the US).

[3]See, e.g., "Interagency Guide on Leveraged Lending," 21 March 2013, Board of Governors of the Federal Reserve System, Federal Deposit Insurance Corporation, Office of the Comptroller of the Currency and "Draft Guidance on Leveraged Transactions," 23 November 2016, European Central Bank.

arrangers to borrowers and, hence, of arrangers' risk exposures. In addition, exposure to pipeline risk does not carry a capital charge, which is only imposed once the risk has materialized and leveraged loans are on the balance sheet.

The behavior of aggregate time series suggests that pipeline risk could amplify fluctuations in the credit cycle. In particular, we find that a proxy for the aggregate overhang is associated with a subsequent significant (both statistically and economically) decline in aggregate arranging and lending activity in various lending markets. Two recent episodes of market wide adverse realization of pipeline risk, the first quarter of 2008 and the last quarter of 2015 (see Appendix A) highlight that pipeline risk is potentially a macroprudential concern.

Our paper contributes to the literature in a number of ways. We provide strong evidence that demand discovery is a key economic function of arrangers. We establish that demand discovery gives rise to pipeline risk, which in turn is a key determinant of the share retained by lead arrangers and, hence, syndicate structure. Pipeline risk matters at the bank level, not just for microprudential reasons, but also because its materialization affects the bank's arranging and lending activity going forward. We also provide suggestive evidence that pipeline risk could matter at the aggregate level and amplify fluctuations in the credit cycle.

Related Literature Few papers have examined how shocks to institutional investor demand affect the syndication process. Ivashina and Sun (2011) look at the time a loan spends in syndication as a proxy for demand and show how it relates to spreads. Ivashina and Scharfstein (2010) provide evidence that on average, lead shares are higher in times in which investors' aggregate demand is low. We provide empirical evidence that a similar relationship arises, at the arranger level, as the outcome of an incentive-compatible demand discovery process.

Ivashina and Scharfstein (2010) also posit that if banks are financially constrained, then the larger shares retained in downturns will reduce the amount of loans that arrangers are willing to originate, which could amplify the credit cycle. Consistent with this hypothesis, we show that, at the level of an individual arranger, the realization of pipeline risk reduces arranging and lending activity. Our interpretation is that the retention of larger shares of problematic loans create a debt overhang problem (Myers, 1977): The presence on a firms' balance sheet of debt-financed, problematic assets decreases the firm willingness to invest. (Admati, DeMarzo, Hellwig, and Pfleiderer (2016) and Bahaj and Malherbe (2016) propose recent applications of debt overhang to banks.) We also find that pipeline risk is correlated across arrangers, and can be associated with subsequent contraction in aggregate arranging and lending activity. This suggests that the information problem we highlight is a possible root of the amplification mechanism described by Ivashina and Sharfstein.

Our paper speaks to the literature on the determinants of loan syndicate structure. We highlight that the loan share retained by arrangers is driven by the revelation of private information of investors during the demand discovery process. In contrast, following Sufi (2007) most of the literature notes that lead arrangers hold larger initial shares in loans to informationally opaque borrowers and interprets such shares as a commitment to monitor the borrower.[4] Ivashina (2009) documents that such larger lead shares are also associated with lower spreads. Our paper also differs from most of the literature on syndicate structure in that we focus on leveraged term loans, using lender shares from SNC. In contrast, the literature that examines syndicate structure has so far relied on lender share data from Thomson Reuters LPC DealScan, in which investment-grade credit lines are overrepresented (see Appendix D for details).

[4]An arranger clearly will have greater incentives to monitor if it holds a larger share (Gustafson, Ivanov, and Meisenzahl, 2016). However, when it comes to leveraged term loans, arrangers can typically sell their initial shares in opaque over-the-counter secondary markets (Bord and Santos, 2012). Therefore, it is not clear whether, for such loans, the share initially retained by the lead arranger can serve as a reliable *commitment* to monitor. Monitoring incentives could also be ensured by non-loan exposures (Neuhann and Saidi, 2016).

Other aspects of syndicated lending examined in the literature include the propensity to syndicate a loan (Dennis and Mullineaux, 2000), final spreads and fees (Angbazo, Mei, and Saunders, 1998; Berg, Saunders, and Steffen, 2016; Cai, Saunders, and Steffen, 2016), covenants (Drucker and Puri, 2009), and final syndicate composition (Cai, Saunders, and Steffen, 2016; Benmelech, Dlugosz, and Ivashina, 2012).

Finally, we draw on the bookbuilding literature. Benveniste and Spindt (1989) establish the underpricing and partial adjustment results explained above. Biais and Faugeron-Crouzet (2002) show that the French *Mise en Vente* can also be seen as a demand discovery mechanism and leads to similar outcomes as bookbuilding. A series of studies have tested the bookbuilding hypothesis and its implications in the context of stock IPOs. Examples include Hanley (1993), Cornelli and Goldreich (2001), and Cornelli and Goldreich (2003).

As such, leveraged loan pipeline risk is related to underwriting risk in public security offerings, e.g., stock IPOs. However, while arrangers of leveraged loans typically need to provide guarantees before demand discovery takes place, equity underwriters effectively only offer guarantees after demand discovery has taken place and restrict the formal risk to minimal (overnight) exposure (Lowry, Michaely, and Volkova, 2017).[5] Also, mortgage securitizers face the risk that loans can become delinquent while still in the pipeline. While this mortgage securitization risk has also been referred to as "pipeline risk" (Brunnermeier, 2009), or as "warehousing risk" (Keys, Seru, and Vig, 2012), it is not related to demand discovery.

[5] There is evidence that IPO underwriters buy substantial numbers of shares in less successful IPOs in after-market price stabilization. However, it seems that they eliminate much of the risk associated with this activity via overallotment options (Ellis, Roni, and O'Hara, 2000, see section 3).

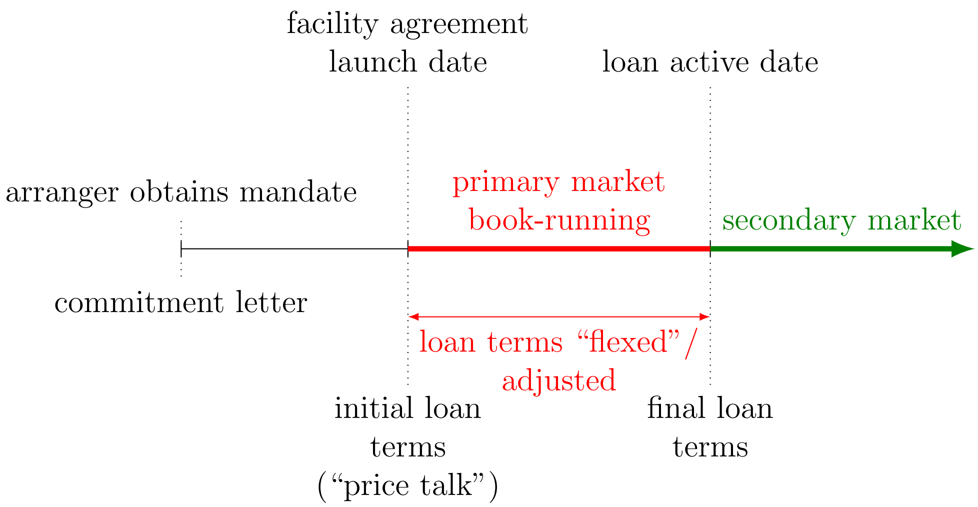


Figure 2. Syndication timeline
Timeline for the leveraged term loan syndication process.

2 Overview of the syndication process

This section is based on a series of interviews with market participants and summarizes how they described the practice of the leveraged loan syndication process, especially as it relates to term loans. We first give a general overview and then provide more details on each of the separate stages.

The overall process is structured as follows: First, the borrower awards the mandate to a lead arranger. If the borrower requires guarantees, the lead arranger often provides these via a "commitment letter" just after obtaining the mandate. Second, after an initial meeting with potential investors, the arranger draws up a proposed loan document (the facility agreement) which serves as the basis for marketing the deal. Third, book-running commences. Depending on demand for the loan, the terms might be adjusted in several rounds. Finally, syndication closes and a final loan document is signed by all lenders. The borrower receives the funds and trading in the secondary market can commence. The timing of the stages is depicted in Figure 2. We now describe each of

them in more detail.

Mandate Issuers typically solicit bids from several potential arrangers. Bidders perform an initial credit analysis and then compete on two main dimensions: pricing and syndication strategy. Key elements of pricing include the spread ("the margin") over a base rate such as LIBOR, an original issue discount ("OID") (described in more detail in the next section), and fees. The strategy consists of how the loan will be tranched, what share of the loan the arranger intends to retain in the primary market (the "sell down target"), how baseline prices and fees can be adjusted ("flexed") in the process, and who bears the cost of such flex. For instance, loans can either be "underwritten," in which case formal guarantees on the terms of the loan are given to the borrower, or can be "best-efforts," in which case no such guarantees are offered. When formal guarantees are offered, it is often the case that two or more arrangers co-underwrite the loans (that is, share the risk associated with giving guarantees).

It is important to note that in contrast to traditional equity IPOs, guarantees are given to issuers *before* book-running starts and the arranger can gauge market demand for the issue. As a result, underwriting loan issues can be much more risky. The reason for this difference in timing is that borrowers who require guarantees often do not want the market to know that they are seeking financing. A typical example would be an LBO: the acquirer needs to present a debt commitment letter to the board of the target to show that financing is in place for the bid. At the same time, the acquirer does not want information about the bid to leak out to the market ahead of time and, hence, does not want the arranger to start book-running before the target receives the bid.

The proposed loan structure and baseline pricing are summarized in a "term sheet," which can later be shown to investors. The specifics of the mandate, fees, and guarantees and the flex permitted to the arranger are described in a "mandate letter," a "fee letter," and a "commitment

letter." The mandate and fee letters are kept confidential. In acquisitions and LBOs, commitment letters are shown to the sellers of the shares or assets.

Facility agreement After an initial meeting with potential investors, the arranger draws up a "facility agreement" which describes all of the proposed terms of the deal, including pricing, structure, the set of covenants and their tightness, as well early repayment conditions.[6] Price variables as set in the facility agreement are referred to as the "talk price."

Book-running Once the facility agreement is finalized, the deal is "launched" and a "book runner," often an entity linked to the lead arranger, starts marketing the deal to investors. Information about deals currently being marketed is provided to investors by platforms such as Thomson Reuter LPC's LoanConnector or S&P Capital IQ's Leveraged Commentary and Data. As part of the marketing, information about the deal is shared with potential investors, who are given time to go through their risk analysis and, ultimately, obtain the green light from their credit committees. If the right amount of demand exists to meet the selldown target at the talk price, the deal is successful and is closed. If the deal is under- or over-subscribed, the arranger uses feedback from investors to flex the price (and/or covenants, lock-ins, etc.). In such a case, the marketing process is re-iterated at the new terms. If syndication is still unsuccessful, there could be additional flex and subsequent marketing rounds. At some point, even though the selldown targets are not met, the arranger could decide not to decrease the price any further. If the deal is underwritten, this means that the underwriters have to retain a larger share than expected. Sometimes, the underwriters prefer to pull the deal out of the market altogether, issue a bridge loan instead, and defer further marketing attempts.

[6] If investors appetite is not as expected at this initial meeting, some flex activity can take place before the facility agreement is produced. That is, the terms in the facility agreement could differ from those initially specified in the term sheet.

The book-running process typically takes several weeks (46 days on average in our sample). Because formal guarantees need to be made before book-running starts, underwriters are exposed during at least this period.

Secondary market Once the arranger has established which investors will participate in the deal, the final loan document can be signed and the deal is closed and becomes "active." The borrower receives the funds and trading of the loan in the secondary market can commence.

3 Data

We first describe how we construct a sample from the LCD data and then describe loan characteristics and the adjustments to loan terms (flexes) in our sample. We delay the discussion of how we construct a sample with information on the share retained by lead arrangers using the Shared National Credit data to Section 5.

3.1 Sample construction

We use loan-level data on the syndication process provided by S&P Capital IQ's Leveraged Commentary and Data (LCD). LCD covers the syndication of leveraged loans, which S&P defines as any syndicated loan with either a non-investment-grade rating, or with a first or second lien and a spread of at least 125bps over LIBOR. The data set contains information on 12,071 deals from January 1, 1999 until October 15, 2015. (As we explain below, however, for our formal analysis we mostly focus on deals from November 2008 onwards.) Each deal consists of one or more facilities, classified either as "pro-rata" facilities or "institutional" facilities. The pro-rata facilities are revolving credit facilities (i.e., credit lines) or amortizing term loans, traditionally bought by banks, and the institutional facilities are bullet term loans, traditionally bought by institutional investors.

To better understand the coverage of the LCD data, we compare LCD with Thomson Reuters

LPC DealScan, a syndicated loan origination database that has been extensively used in the literature.[7] Figure 3 shows the total number of loans in DealScan, the number of U.S. leveraged loan deals with institutional term loans in DealScan, and the number of U.S. leveraged loan deals with institutional term loans in LCD, per year. The coverage of U.S. leveraged loans in DealScan is somewhat wider before 2007, however the LCD and DealScan data have roughly similar number of observations after 2007. We provide a more detailed discussion in Appendix D.

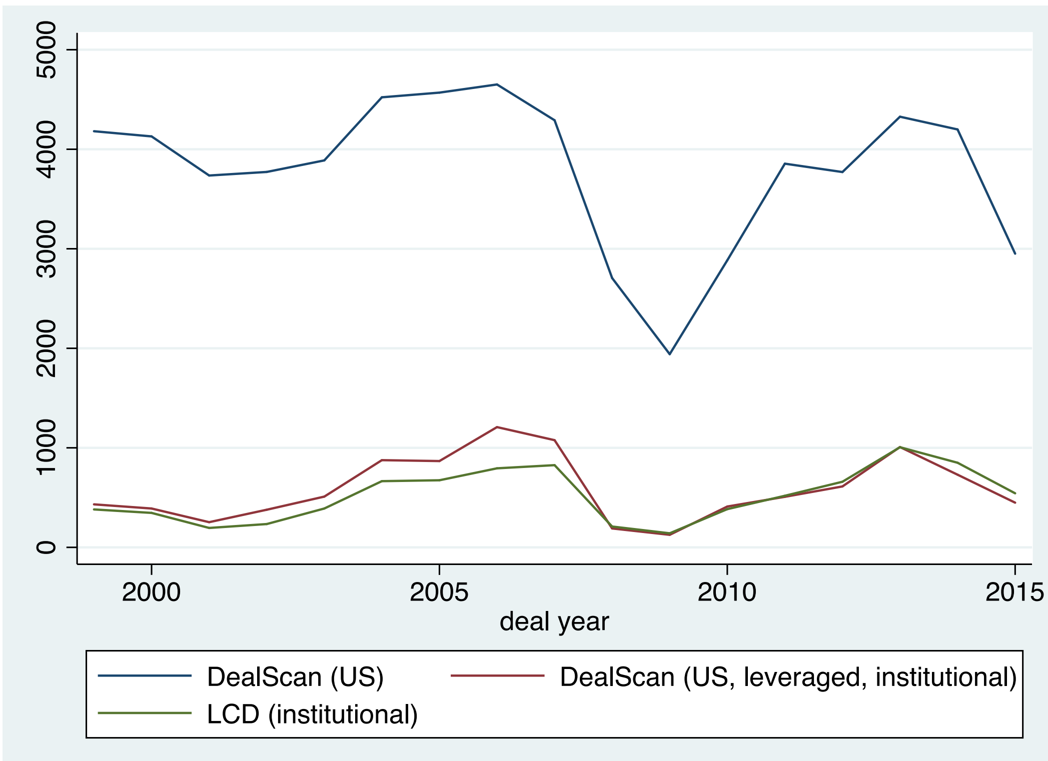


Figure 3. Number of deals in DealScan and LCD over time
Number of deals in Thomson Reuters LPC DealScan and S&P Capital IQ LCD over time. DealScan (US) are all deals syndicated in the USA and in USD. DealScan (US, leveraged, institutional) are deals that contain at least one leveraged institutional facility. LCD (institutional) are all deals with at least one institutional facility in LCD.

[7] Thomson Reuters LPC DealScan, Wharton Research Data Services (WRDS), `wrds-web.wharton.upenn.edu/wrds/about/databaselist.cfm`

At the deal level, the available information always includes the overall deal size, issuer name and issuer industry, a launch date and a closing month for the deal,[8] and an issuer rating (if the issuer is rated). LCD also records whether the deal is sponsored, for instance by a private equity firm.

At the facility level, LCD records a rating, if available, whether the facility is a first-lien or second-lien and whether it has covenant-light (cov-lite) status or full covenant status, a purpose, and the lead arranger. LCD also provides information on amounts, maturities, spreads, and potentially information on how these variables were adjusted during the syndication process. The main independent variables of interest to us are these pricing adjustments. Furthermore, for some facilities, there is information on the initial secondary market price.

We restrict our analysis to deals which contain at least one institutional facility for two reasons. First, pro-rata facilities (especially credit lines) are much less likely to be traded in secondary markets and, hence, there are next to no secondary market prices for such facilities. Second, one of the main aims of LCD is to inform institutional investors about deals that they can buy into and, hence, it has better coverage of flex for institutional facilities. We will need information both on the first secondary market price as well as on flex. Hence, we drop all deals that consist only of lines of credit and amortizing term loans, leaving 8,816 deals. Furthermore, we consider only the institutional facilities within these deals. Finally, we exclude a small number of deals that have facilities with different purposes or lead arrangers, leaving 8,716 deals.

We aggregate information across all institutional facilities within a deal and conduct our analysis at the deal level. The mean number of institutional facilities per deal is 1.14 and more than 75% of deals only have a single institutional facility, indicating that the way in which we aggregate data is unlikely to have a large impact on our results.

[8] The launch date is the day the arranger starts marketing the deal to primary market participants. The closing date is the day the syndicate composition is finalized and the loan documents are signed.

In Section 4 and part of Section 5, we further restrict our sample to loans with information about pricing and drop all deals for which we do not have the initially proposed yield (the "talk yield"). If the talk yield is observed in the data then all other pricing information is usually also present. This restriction reduces the sample to 3,711 deals, as talk yield information become available starting with deals in November 2008.[9]

In Section 5, we also match the LCD data with data from the Shared National Credit (SNC) database. We defer a description of our matched sample to Section 5.

3.2 Description of loan characteristics

Table 1 provides the summary statistics for our sample of leveraged loan deals that includes pricing information. The median deal size (including pro-rata facilities, e.g., undrawn commitments on credit lines) is \$400m. The median total institutional amount lent per deal is \$350m. The distribution of deal sizes and institutional amounts is highly skewed, with a small number of very large deals.

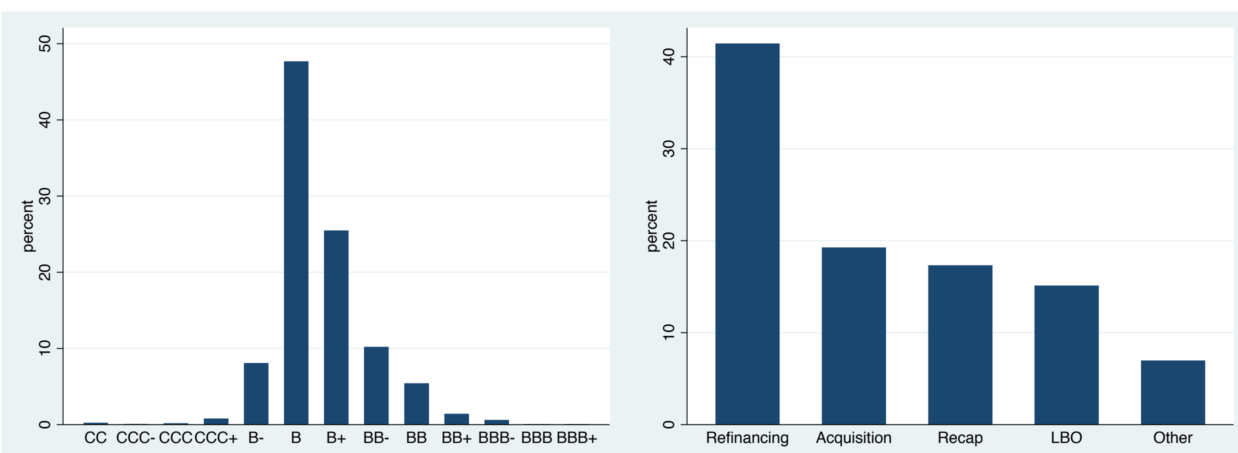
It takes on average 46 days from the launch date until the loan becomes active. About 90% of the deals involve some rating, 68% involve a sponsor, and 40% involve at least one cov-lite facility. If the issuers in these deals have a rating, they are practically always non-investment grade, as illustrated in Figure 4a. Figure 4b also illustrates that given the low interest rates over our sample period, deals that refinance existing debt are the most common (41%), followed by deals that finance transactions — acquisitions or LBOs — which together represent about 34% of our deals.

[9] This sample does not include the early phase of the financial crisis or the pre-crisis period. This distinguishes it from many other samples of syndicated deals used in the literature. For example, there is no overlap with the sample of Ivashina and Sun (2011). Although we do not report results here, we have run all of our analysis on the larger sample that also includes the pre-crisis deals for which sufficient pricing information is available. The main results are unchanged. If the analysis is run only on pre-crisis deals, coefficients in general show the same sign, but tend to be statistically insignificant, probably due to a small sample size.

Table 1
Summary statistics

This table displays summary statistics for the basic variables at the deal level, as used in our analysis. Total Deal Size is the sum of amounts and commitments across all pro-rata and institutional facilities in a deal. Institutional Amt. is the sum of amounts only across institutional facilities in a deal. Both Total Deal Size and Institutional Amt. are reported in millions of USD. Rated, Sponsored, and Cov- lite are dummies that indicate whether at least one facility within a deal is rated, sponsored, or classified as cov-lite, respectively. Spread and OID (original issue discount) are calculated as averages across the spreads and OIDs of institutional facilities in each deal, and are reported in percentage points of par. Effective spread is computed as spread + OID/4, also reported as percentage points of par. Break Price is the average first secondary market price of institutional facilities in a deal, reported reported in percentage points of par. Source: Authors' calculations based on S&P Capital IQ LCD.

	Total Deal Size	Institutional amt.	Rated	Sponsored	Cov-lite	Spread	OID	Eff. Spread	Break Price
mean	663	552	.895	.678	.395	4.65	1.03	4.90	99.843
sd	775	617				1.59	1.35	1.77	1.299
min	10	10				1.75	-2.50	2.00	78.375
25%	225	200				3.50	0.25	3.50	99.500
median	400	350				4.25	0.75	4.50	100.125
75%	775	660				5.50	1.38	5.88	100.500
max	9,500	7,600				15.00	22.50	16.50	104.250
N	3,711	3,711	3,711	3,711	3,711	3,709	3,686	3,686	3,087



(a) Rating **(b) Purpose**

Figure 4. Ratings and purpose for deals in our sample
Histogram of (a) issuer ratings and (b) most common purposes for the deals in our sample. Source: S&P Capital IQ LCD.

A first component of pricing, the spread, measured in basis points over LIBOR, is available for all facilities. The median deal spread is 425 bps. For most facilities, we also observe a second pricing component: the original issue discount (OID). In our terminology, an OID of $x\%$ indicates that the lenders have to hand over only $(100 - x)\%$ of face value at origination, while spreads and principal repayments are calculated on the basis of the full face value. Note that our use of the term OID differs from the way some market participants use this term, who confusingly use OID to refer to the fraction of face value that lenders have to hand over, the $(100 - x)\%$. As opposed to upfront fees in other syndicated loans, OIDs in leveraged institutional facilities are typically not tiered by commitments, so that all lenders who participate in the primary market receive the same OID. When aggregating by averaging across the facility OIDs in a deal, the median OID at the deal level is 75 bps, with substantial variation across deals.

To compare loans with different OIDs and spreads along a single dimension, by convention, market participants in the US compute the yield on a loan as follows:

$$yield = LIBOR + spread + \frac{OID}{4}. \tag{1}$$

The idea behind this calculation is that the OID is amortized over an effective maturity of (on average) 4 years. Following this convention, we define the effective spread as

$$effective\ spread \equiv spread + \frac{OID}{4}. \tag{2}$$

Over all deals for which we observe OIDs in our sample, the effective spread as defined in Equation (2) is on average 25bps higher than the spread. Taking only the deals in 2009, it is on average 80bps higher than the spread. While OIDs do not necessarily have a large impact on the cost of debt in every deal, they clearly had a substantial impact during the height of the crisis in 2009.[10]

[10]Berg, Saunders, and Steffen (2016) argue that fees are an important part of the cost of debt, focussing mostly on credit lines. They report an average up-front fee of about 80bp in their Table 1, which is similar to our OID.

As we discuss below in detail, OIDs are also crucial for computing measures of underpricing in the syndicated loan market.

For many facilities we also observe a third piece of information on pricing, the break price. The break price is defined as the first price observed in the secondary market after the deal is completed. LCD collects this from market participants as the average mid-point between bids and offers, where the bids and offers are required to have "reasonable" depth.[11] As indicated in Table 1, when aggregating by averaging across the facility break prices in a deal, the median break price at the deal level is slightly above par.

3.3 Description of adjustments (flexes)

Our main set of independent variables of interest relate to flex information: At launch, the arranger initially proposes a spread and OID. Depending on the level of demand, the arranger may then adjust spreads and the OID, in order to allocate the facility. In some instances, the arranger may also increase or decrease the amount borrowed between launch and close. Market participants refer to the changes that have been made to the initially proposed quantities by the close as spread flex, OID flex, and amount flex, respectively. One of the key advantages of the LCD data is that it provides this flex information.[12]

We have 2,453 deals (out of 3,711) in our sample in which at least one of the spread, OID, or amount of an institutional facility was flexed. We have 325 deals in which more than one institutional facility is flexed. When aggregating to the deal level, we take the average of spread flex and OID flex and sum the amount flex across all facilities within a deal. Table 2 reports summary statistics on the distribution of flexes in our sample, at the deal level. Spreads are

[11] Although we are told that no formal criteria are used, it was indicated to us that, e.g., quotes with a depth of $3m on either side would be considered "reasonable."

[12] When the initially proposed quantity is a range, the flex is defined as the difference between the final quantity and the edge of the range. E.g., if the initial spread range is 525-550 bps and the final spread is 600 bps, the spread flex would be reported as 600 - 550 = 50 bps.

flexed frequently (in 1,626 deals), OIDs and amounts slightly less often (1,389 and 1,153 deals, respectively).

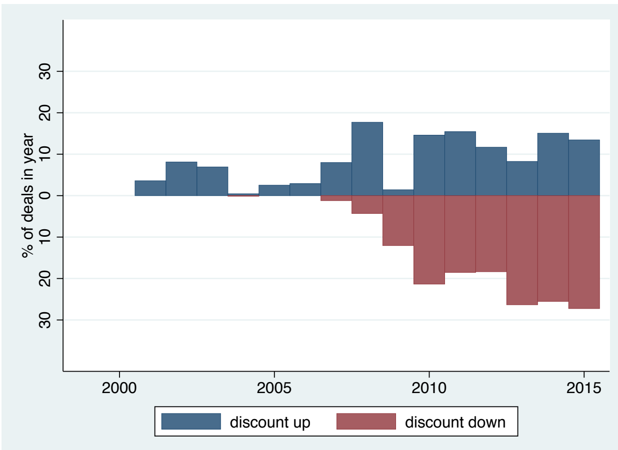
Table 2
Summary statistics - flex

Summary statistics at the deal level on the flex of amounts, spread, OID, and effective spread of institutional term loans in our sample. We calculate the deal-level amount flex by summing the amount flexes for all institutional loans in a deal. We calculate the deal-level spread flex and OID flex by taking averages over all institutional spread flexes and institutional OID flexes within a deal, respectively. We calculate the deal-level effective spread flex as the deal-level spread flex plus the deal-level OID flex divided by 4. Amounts are in million USD. Spread flex, discount flex, and effective spread flex are in bps of face value. Source: Authors' calculations based on S&P Capital IQ LCD.

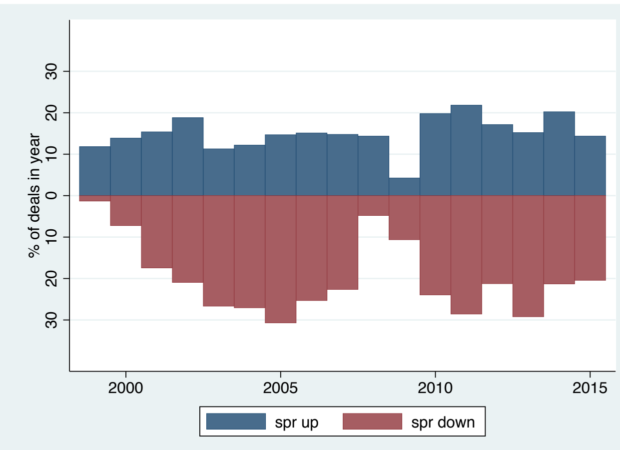
	Institutional amt. flex	Spread flex	OID flex	Eff. spread flex
mean	28	8	13	8
sd	273	64	132	67
min	-3,900	-200	-450	-200
25%.	-25	-25	-50	-37.5
median	10	-25	-25	-12.5
75%	50	50	50	50
max	2,600	325	1,700	425
N	1,153	1,626	1,389	2,103

We plot the fraction of deals for which spreads, OIDs, and amounts are flexed up or down by year in Figure 5. Comparing panel (a) and (b) shows that there has been a shift in the use of flex. While spread flex has been common practice for a long time (30-50 percent of deals per year), flexes in OIDs were uncommon before 2007. Moreover, if the OID was flexed before the financial crisis, it was only flexed up (and not down). Since the financial crisis, flexes in the OIDs (up and down) have become as frequent as flexes in the spreads. Flexes in amounts also became common practice since the financial crisis.

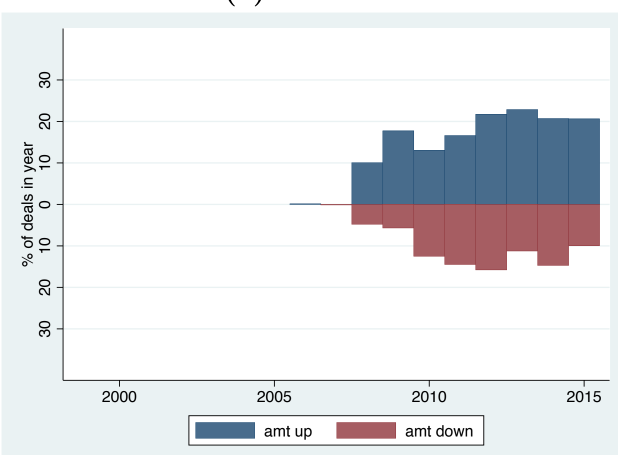
Flexing an OID up or flexing a spread up both make a loan more attractive to investors. Do arrangers tend to flex OID and spread in the same direction or in opposite directions? Table 3 indicates that they are much more likely to be flexed in the same direction. According to



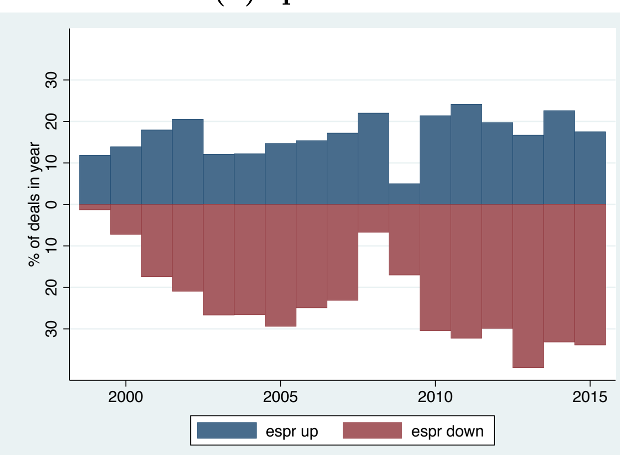
(a) OID flex



(b) spread flex



(c) amount flex



(d) effective spread flex

Figure 5. Average up and down flex by year

Fraction of deals in our sample in a given year for which OIDs/ spreads/ amounts/ effective spreads are flexed up or down. OIDs were not flexed down before the financial crisis and amounts were not flexed at all before the financial crisis, but are flexed both up and down now, reflecting a change in market practice. Source: S&P Capital IQ LCD.

practitioners, arrangers primarily flex in order to meet investors' demand for yield (as defined in Equation (1)). However, in situations in which the spread has been increased already but yield needs to be increased further, arrangers often increase the discount rather than further increasing the spread. This is because a very high spread can generate substantial prepayment risk.[13]

Table 3
Relation between discount and spread flex

Fraction of deals in our sample in which we observe spreads/ discounts being flexed down (↓) / not being flexed (=)/ being flexed up (↑), in percentage points.

	discount ↓	discount =	discount ↑	Total
spread ↓	13.74	11.37	0.16	25.28
spread =	10.46	43.38	2.51	56.35
spread ↑	0.49	7.81	10.08	18.38
	24.68	62.57	12.75	100.00

We briefly describe when and whether loans are flexed here and provide a more detailed description in Appendix B. In our sample, loans with a high talk yield, or loans that finance acquisitions or LBOs as opposed to refinancing existing loans, or that contain a revolving credit facility, are more likely to experience spread flex. A possible interpretation is that for such more complex loans, the arranger finds it harder to anticipate the true demand for the loan and, hence, adjustments occur more frequently. Also, the likely direction in which spreads are flexed relates to net inflows into high yield mutual funds and CLOs. (These flows occur after the arranger has launched the deal and, hence, are not known to the arranger at launch.) Net outflows, indicating low aggregate demand, are more likely to be associated with spreads being flexed up. Flexes in discounts exhibit a similar pattern. Finally, amounts are much more likely to be flexed when the loan is issued to finance a dividend or a share repurchase.

[13]We were also told that accounting reasons (both on part of the lender or the borrower) could also influence the choice between providing yield via discount or spread.

4 Demand discovery

In this section we provide evidence that a key economic function of the arranger in leveraged loan syndication is to engage in demand discovery. Specifically, we use the LCD data to test implications of bookbuilding theory which relate to loan underpricing.

As mentioned in the introduction, bookbuilding theory describes how underwriters or arrangers elicit information from market participants about their willingness to pay for the security being issued (Benveniste and Spindt, 1989). An implication is that investors receive, on average, information rents in the form of underpricing.

In the context of leveraged loans, underpricing can be calculated as the difference between the secondary market price and the primary market price:

$$\text{underpricing} = \underbrace{\text{break price}}_{\text{secondary market price}} - \underbrace{(\text{par} - \text{original issue discount})}_{\text{primary market price}}$$

To illustrate the importance of accounting for original issue discounts, consider that in 2009, in our data, break prices were on average about 130 bps below par. With these numbers, if market participants had bought the loan at par, they would have suffered an immediate mark-to-market loss of 130 bps. However, primary market prices include a discount. In 2009, on average, this discount was above 300 bps. So actually, on average, market participants enjoyed a potential mark-to-market gain of more than 170 bps. As is evident, the original issue discount plays a crucial role in the pricing of syndicated loans and cannot be ignored.

For 3,079 deals in our sample, we have at least one facility for which we have both a break price and a discount and so can calculate a deal-level underpricing variable by taking the average underpricing across all facilities within the deal. The resulting distribution of our deal-level underpricing variable is described in Table 4.

Table 4
Summary statistics - underpricing

Summary statistics for deal-level underpricing in our sample. We first calculate underpricing at the facility level as break price – (par – discount), and then aggregate to the deal level by taking the average across all institutional facilities in a deal. Source: Authors' calculations based on S&P Capital IQ LCD.

	underpricing
mean	84.836
sd	48.89
min	-150
25%	50
median	75
75%	100
max	450
N	3,079

The median underpricing is 75 bps of par. Because the break price that we have is a midpoint and bid-ask spreads are substantial, the actual profit that a primary market participant could make by buying in the primary market and selling at the bid is going to be lower. With a typical bid-ask spread of about 75 bps, the profit would be about 37.5 bps. This number is lower than the 19% underpricing found for stocks (Jenkinson and Ljungqvist, 2001), is similar to the 47 bps underpricing found for speculative-grade bonds and higher than the zero underpricing found for investment-grade bonds (Cai, Helwege, and Warga, 2007).

To illustrate the cyclical nature of underpricing, Figure 6 plots the time series of our underpricing measure. The LCD data starts reporting break prices for deals in 2002. Initially, break prices are only reported for a small fraction of the deals, so it is possible that some of the apparent early volatility in underpricing reflects data availability issues rather than cyclical variation. However, coverage improves over time. From the end of 2008 and on, break prices are reported for more than 80% of all deals. It can be seen that underpricing peaked at over 170 bps during the financial crisis in 2008-09. With the sharp increase in deals after the financial crisis, shown in Figure 3,

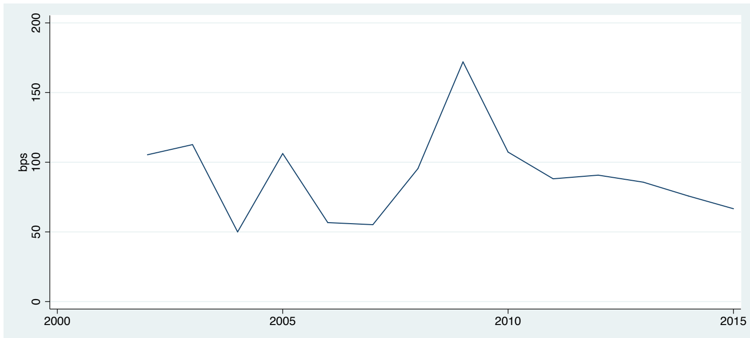


Figure 6. Underpricing
Average deal underpricing by year. We first calculate underpricing at the facility level as break price − (par − discount) and then aggregate to the deal level by taking the average across all institutional facilities in a deal. In the early part of the sample, few break prices are reported, so that we can only calculate underpricing for a small fraction of the deals. Coverage improves over time. By the end of 2008, when our sample starts, we can calculate underpricing for more than 80% of all deals. Source: Authors' calculation based on S&P Capital IQ LCD.

underpricing has also fallen substantially since the crisis.

A key implication of bookbuilding theory is that pricing should only adjust partially to revealed information: If potential syndicate members reveal that they find the loan terms very attractive, then the lead arranger can decrease the spread or discount, but must do so in a way that leaves a larger underpricing rent to investors as a reward for revealing that they find the loan terms attractive. The following hypothesis summarizes the testable implication.

Hypothesis 1. *The flex in the spread or discount is negatively related to underpricing.*

We test Hypotheses 1 by estimating the following equation at the deal level:

$$Underpricing_i = c + \beta_1 Spread\ Flex_i + \gamma X_i + \epsilon_i. \tag{3}$$

We control for additional loan characteristics (X_i) including the loan amount, maturity, talk yield, and dummies for whether the deal is rated, is sponsored, includes a covenant-lite facility, or a second lien. We include fixed effects for loan purpose, borrower industry, and deal month-year.

Table 5 shows the results of estimating Equation (3).

Column (1) shows our baseline regression. Consistent with Hypothesis 1, flexes in the spread have a negative and statistically significant effect on underpricing. The point estimate implies that a negative effective spread flex of 100 bps is associated with an increase in underpricing by about 10 bps. This "partial adjustment" is strong evidence that arrangers of leveraged loans engage in demand discovery, as do underwriters in equity IPOs (Hanley, 1993). In our baseline specification, we follow Ivashina and Sun (2011) and control for institutional demand and overall risk appetite by including *Fund Flows*, defined as the sum of net inflows to high yield mutual funds (obtained from the financial accounts of the United States) and CLO issuance (obtained from Lipper).

In column (2), we drop arranger fixed effects and add an indicator variable that is equal to 1 if a deal was arranged by one of the three lead arrangers with the largest market share and 0 otherwise. We can see that deals arranged by one of the top three lead arrangers exhibit about 8 bps less underpricing. This is consistent with the interpretation of Benveniste and Spindt (1989) that a potential substitute for underpricing in the current deal is the promise of additional underpricing in the future. In our context, lead arrangers with higher deal flow could be able to reduce underpricing in the current deal by rewarding potential syndicate members also with access to future deal flow. Because other theories offer alternative interpretations of this finding, it should be seen only as complementary evidence in favor of demand discovery.

Next, in column (3)-(5), we drop the top three dummy and include arranger fixed effects and more importantly also replace Fund Flows with syndication-month fixed effects. While the coefficients on spread flex are smaller than in column (1), the estimate remains highly statistically significant. The effect of flexes in the effective spread on underpricing implies that a negative effective spread flex of 100 bps is associated with an increase in underpricing by about 7 to 8 bps. Ivashina and Sun (2011) argue that time-to-syndication provides a plausible measure of demand

Table 5
Underpricing and Spread Flex: Partial Adjustment

Regressions of underpricing measures on spread flex, discount flex, and deal flow proxies, at the deal level. Underpricing is calculated as break price − (par − OID) at the facility level and aggregated to the deal level by taking averages across all institutional facilities in a deal. Top Three is a dummy that indicates whether the lead arranger for a deal is one of the top three lead arrangers in terms of number of deals. Eff. Spread Flex, Spread Flex and Discount Flex represent changes in spreads and discounts, respectively, over the syndication period, and assume that when no change is reported, this is because there is no change. Fund Flows are net inflows into high yield mutual funds and CLO issuances measured in billions of dollars. Log Synd. Time is the log of the time between launch date and close date, in days. Rated, Sponsored, Cov-lite, and Second lien are dummies that indicate whether at least one facility within a deal is rated, sponsored, or classified as cov-lite or second lien, respectively. Log Maturity is the log of the average maturity of institutional facilities. Log Talk Amount is the log of the initially proposed total institutional loan amount. Log Talk Yield is log of the initially offered all-in yield to maturity. Time fixed-effects are at the syndication month-year. (See Tables 1, 2, and 4 for relevant summary statistics).

	(1) underpricing	(2) underpricing	(3) underpricing	(4) underpricing	(5) underpricing
Top Three	-7.658***				
	(2.006)				
Eff. Spread Flex	-0.0936***	-0.100***	-0.0653***	-0.0638***	
	(0.0177)	(0.0182)	(0.0181)	(0.0175)	
Spread Flex					-0.0837***
					(0.0245)
Discount Flex					-0.00368
					(0.00991)
Fund Flows	0.827**	0.802**			
	(0.335)	(0.326)			
Log Synd. Time				9.136**	
				(4.473)	
Rated	12.80***	8.615**	9.492**	9.152**	9.542**
	(4.017)	(3.990)	(3.966)	(3.992)	(3.958)
Sponsored	-13.29***	-11.00***	-10.12***	-10.05***	-9.994***
	(2.063)	(2.126)	(2.171)	(2.135)	(2.169)
Cov-lite	-2.171	-2.719	3.304*	3.212*	3.197*
	(2.087)	(1.926)	(1.829)	(1.829)	(1.818)
Second Lien	-13.84***	-12.76***	-6.239*	-6.049*	-6.297*
	(3.536)	(3.317)	(3.307)	(3.254)	(3.309)
Log Maturity (Years)	3.399	0.162	4.225	4.121	4.224
	(4.302)	(4.033)	(4.010)	(4.027)	(3.993)
Log Talk Amount	5.842***	5.281***	4.169***	4.220***	4.113***
	(1.173)	(1.089)	(1.029)	(1.041)	(1.042)
Log Talk Yield	94.09***	98.16***	80.17***	79.66***	80.09***
	(6.402)	(6.519)	(5.871)	(5.787)	(5.884)
Arranger FE	No	Yes	Yes	Yes	Yes
Purpose FE	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes
Time FE	No	No	Yes	Yes	Yes
Observations	3078	3075	3075	3075	3075
R^2	0.264	0.308	0.409	0.410	0.409

Standard errors in parentheses
SEs clustered by syndication month
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

for a specific loan.[14] We add time-to-syndication in column (4) and find that our point estimate on spread flex remains unchanged. Loans that take longer to syndicate exhibit significantly higher underpricing, possibly because complicated loans take longer to evaluate, and because for such loans, it is optimal to pay higher information rents in order to extract information about demand.

In column (5), we include spread flex and discount flex separately, but find no significant effect of discount flexes on underpricing. This could be the result of low power (due to a lower number of observations in which the discount is flexed), or could suggest that the relevant margin of adjustment during the syndication process is the spread.

Benveniste and Spindt (1989) suggest that lower valuation uncertainty should produce lower underpricing. Some of the control variables that can be interpreted as proxies for valuation uncertainty merit discussion. We find that in times of high demand, measured by net inflows in high yield mutual funds and CLO issuances, underpricing is higher. Similarly, more risky loans, measured by the talk spread, are likely to be harder to value and indeed exhibit more underpricing. Some deals are sponsored by private equity groups. We interpret the presence of a sponsor as proxy for lower valuation uncertainty for the loan because not only the credit quality of the relatively unknown borrower, but also the credit quality of the presumably better known sponsor matters for the repayment probabilities. Consistent with this prediction, sponsored deals are associated with lower underpricing by about 12 bps. However, almost all theories predict that valuation uncertainty should be positively related to underpricing. Unlike the evidence on partial adjustment, these complementary finding cannot be seen as evidence in favor of a particular theory.

A potential sample selection issue could affect our estimate of the relationship between underpricing and spread flex. It is possible that when investors indicate a low willingness to pay in the primary market, such that the arranger needs to flex spread up substantially, they also show little

[14] In Appendix C.1, we show that riskier loans and loans with downward flexes have longer time-to-syndication.

interest in the secondary market, so that the loans are less likely to trade in the secondary market. In terms of numbers, we observe a break price for 588 (86%) of the 682 deals with positive spread flex. This compares to 874 (93%) of the 938 deals with negative spread flex. A simple test of difference of proportions suggests that this difference is significant. However, a multiple regression shows that once we control for the fact that a break price is more likely to be observed for larger, rated loans, with a longer maturity and a lower talk yield, the difference becomes statistically insignificant. (See Appendix C.2 for details.)

This selection issue, if present, would mean that we are less likely to observe a break price and, hence, underpricing on deals with positive spread flex. Bookbuilding theory suggests that if underpricing were observed for such deals, it should be low. If we are missing such observations, then this should bias us against finding a significant and negative relationship between underpricing and spread flex. The fact that we do find a significant and negative relationship indicates that the bias, if it exists, is not very strong. However, we cannot rule out that we overestimate the level of underpricing due to this selection issue.

5 Pipeline Risk

Having established that the syndication of leveraged term loans is essentially a demand discovery exercise, we now turn to the risks that arrangers face during such a process and to the consequences that arise when these risks materialize.

5.1 Lead share retention

We argue that arrangers facing lower-than-expected demand must retain larger shares of the loans for reasons relating to incentive compatibility. To see this, consider an arranger who announces that large quantities in the loan will be allocated to investors who express a high willingness to

pay, and small quantities (or zero) to investors who express a low willingness to pay. The arranger will also increase the final price (decrease the spread or discount) if most investors express a high willingness to pay, and decrease the price (increase the spread or discount) if most investors express a low willingness to pay. Then, investors have no incentive to lie: If an investor pretends to have low willingness to pay in the loan, that will lower the final price, but this is unattractive precisely because the investor will then only obtain a small allocation. To preserve incentives, it is crucial that when prices are decreased (spreads or discounts are increased), less of the loan is allocated to investors. In the context of leveraged term loans, it is often the case that the total amount that is borrowed cannot easily be flexed, such as in an LBO or an acquisition. In such situations, the arranger often gives guarantees and then must then make up for any shortfall of funds provided by investors by increasing its retained share. This argument produces the empirical prediction in Hypothesis 2.

Hypothesis 2. *The flex in the effective spread is positively associated with the share retained by the arranger.*

To test this hypothesis, we match the LCD data with the Shared National Credit Program (SNC) to obtain the shares of lead arrangers (or simply the *lead shares*). The SNC is an annual survey of syndicated loans carried out by the Board of Governors of the Federal Reserve System, the Federal Deposit Insurance Corporation (FDIC), the Office of the Comptroller of the Currency, and, until recently, the Office of Thrift Supervision. The program obtains confidential information from administrative agent banks on all loan commitments exceeding $20 million and shared by three or more unaffiliated federally supervised institutions, or a portion of which is sold to two or more such institutions. Information on new and existing loans that meet these criteria is collected as of December 31 of each year.[15]

[15] Information on the purpose of the SNC is provided at `www.federalreserve.gov/bankinforeg/snc.htm`

In the LCD sample that we have used so far, we restricted ourselves to the deals for which we had information on the initially proposed yield (the "talk yield"). Matching this sample with SNC leaves us with very few observations. This is why here we also consider all deals from LCD which contain at least one institutional facility, which have a single lead arranger and a single stated purpose (8,716 deals).

We only retain term loans in SNC and match those to LCD on borrower name, origination date, and deal amounts. This yields a final matched sample of 1,848 loans. The average lead share in our sample is 5.3 percent. This number is low when compared with lead shares in DealScan but is consistent with the magnitudes of and general decline in lead shares for term loans in SNC (Bord and Santos, 2012). Another potential reason for the discrepancy relates to so-called "primary assignments," which are pre-arranged loan purchases on the origination date and at the primary market price, but which are structured as secondary market transactions. These allow off-shore investors, such as CLOs, to avoid the tax implications of direct participation in the primary market. A portion of what DealScan reports as the share of the arranger will typically be sold immediately upon close via such primary assignments. From that point of view, the lead share reported in SNC appears to be the more appropriate measure.[16]

We test Hypothesis 2 by estimating the following regression:

$$Lead\ Share_i = c + \beta_1 Effective\ Spread\ Flex_i + \gamma X_i + \epsilon_i, \tag{4}$$

According to Hypothesis 2, we expect coefficient β_1 to be positive.

Table 6 shows the estimation results. We control for market-wide fluctuations in demand by

and inclusion criteria at `www.newyorkfed.org/banking/reportingforms/guidelines.pdf`.

[16]In addition, while DealScan contains lender shares for about 18 percent of all deals in DealScan, it contains lender shares for only about 4 percent of the leveraged loan deals that we consider here. This means that using DealScan as a source of lead share information when matching with LCD would result in only in a very small set of deals with both lead share and flex information and is therefore not useful. (See Appendix D for details.)

Table 6
Lead Share - all deals

Regressions of lead arranger share on spread flex and deal flow proxies, at the deal level. Lead Share is taken from the Shared National Credit Program and matched with deals in LCD. (Lead Share is expressed as a fraction between 0 and 1.) Eff. Spread Flex, Spread Flex and Discount Flex represent changes in spread and discount over the syndication period and assume that when no change is reported, this is because there is no change. Fund Flows are net inflows into high yield mutual funds and CLO issuances measured in billions of dollars. Log Synd. Time is the log of the time between launch date and close date, in days. Rated, Sponsored, Cov-lite, and Second lien are dummies that indicate whether at least one facility within a deal is rated, sponsored, or classified as cov-lite or second lien, respectively. Log Maturity is the log of the average maturity of institutional facilities. Log Talk Amount is the log of the initially proposed total institutional loan amount. Log Talk Yield is log of the initially offered all-in yield to maturity. Time fixed-effects are at the syndication month-year.

	(1) Lead Share	(2) Lead Share	(3) Lead Share	(4) Lead Share	(5) Lead Share	(6) Lead Share	(7) Lead Share
Eff. Spread Flex	0.000123***	0.000136***	0.000106**	0.000116**	0.000116**		0.000134*
	(0.0000468)	(0.0000508)	(0.0000511)	(0.0000523)	(0.0000523)		(0.0000715)
Spread Flex						0.000129*	
						(0.0000690)	
Discount Flex						0.0000138	
						(0.0000573)	
Fund Flows	-0.0000310						
	(0.000529)						
Log Synd. Time					-0.00418		
					(0.0103)		
Rated	-0.0283***	-0.0276***	-0.0183***	-0.0165***	-0.0165***	-0.0165***	-0.0206
	(0.00521)	(0.00521)	(0.00541)	(0.00630)	(0.00630)	(0.00630)	(0.0147)
Sponsored	-0.00681	-0.00967*	-0.00867*	-0.00865	-0.00867	-0.00878	-0.0174
	(0.00460)	(0.00539)	(0.00517)	(0.00587)	(0.00587)	(0.00589)	(0.0134)
Cov-lite	0.00904	0.00151	0.00319	0.00348	0.00352	0.00357	0.000563
	(0.00616)	(0.00666)	(0.00656)	(0.00699)	(0.00700)	(0.00692)	(0.0111)
Second Lien	-0.00543	-0.00138	0.00186	0.000565	0.000444	0.000525	-0.000429
	(0.00566)	(0.00565)	(0.00547)	(0.00600)	(0.00600)	(0.00597)	(0.0156)
Log Maturity (Years)	-0.0122	-0.00671	-0.0105	-0.0140	-0.0139	-0.0141	-0.0263
	(0.0112)	(0.0124)	(0.0119)	(0.0125)	(0.0125)	(0.0125)	(0.0242)
Log Talk Amount	-0.0214***	-0.0238***	-0.0193***	-0.0174***	-0.0174***	-0.0174***	-0.0118**
	(0.00241)	(0.00267)	(0.00266)	(0.00275)	(0.00274)	(0.00275)	(0.00497)
Log Talk Yield							-0.00377
							(0.0274)
Purpose FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	No	Yes	Yes	Yes	Yes	Yes	Yes
Arranger FE	No	No	Yes	No	No	No	No
Arranger-Year FE	No	No	No	Yes	Yes	Yes	Yes
Observations	1750	1864	1860	1860	1860	1860	638
R^2	0.166	0.352	0.463	0.595	0.595	0.595	0.520

Standard errors in parentheses
SEs clustered by syndication month
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

including high yield & CLO fund flows in column (1) and by including syndication-month fixed effects in columns (2) to (7). We find a positive and statistically significant coefficient on effective spread flex (β_1). Because the conditions at the arranger could be correlated with effective spread flex and also matter for the retained lead share, we control for these first by including time-invariant arranger fixed effects in column (3) and then by including time-varying arranger-year fixed effects in columns (4) to (6).[17] The point estimates are not substantially affected by the inclusion of these controls. In terms of magnitudes, a 100 bps upward flex in the spread is associated with an increase in the lead share of between 1.1 - 1.4 percent of face value, a 20-26 percent increase relative to the average lead share of 5.3 percent of face value. This result is also robust to the inclusion of log syndication time (column (5)). In column (6), we also control for the talk yield, which reduces the sample size by almost two-thirds. Even so, the coefficient on net flex is still (marginally) significant.

We also replicate a result of the prior literature: arrangers tend to keep a higher share (of about 1.5-3%) of unrated loans as opposed to rated loans (Sufi, 2007): the coefficient on the rated dummy is negative in columns (1)-(6) and statistically significant in columns (1) and (2). In studies that did not specifically focus on leveraged term loans, this has been interpreted as evidence that the share retained by the arranger is used as a commitment to monitor. In our case, the fact that the arranger can sell the leveraged term loans in an opaque over-the-counter secondary market casts some doubt on this interpretation. An alternative interpretation would be that for unrated loans, arrangers attempt to signal quality through higher initial retention. Finally, the lead share is also significantly negatively related to the amount being borrowed (all columns), as arrangers take smaller shares in larger loans.

The SNC lead share is observed on December 31. Given the existence of an active secondary

[17] Irani and Meisenzahl (forthcoming) document that lenders conditions mattered for loan sales during the financial crisis. Specifically, they find that lenders that relied heavily on wholesale funding pre-crisis sold more loan shares.

market, our observations may not accurately reflect the share initially retained by the lead arranger. In particular Aramonte, Lee, and Stebunovs (2015) document that banks sell substantial parts of their term loan shares in the first quarter after origination.

For this reason, our results are likely to underestimate the effect of flexes on lead shares. To get a sense of the bias, we run the same set of regressions as in Table 6 but on a sample restricted to only those deal that take place in the final quarter of each year. The idea is that the bias must be smaller if banks had less time to sell down their positions. The results are displayed in Table 18 in Appendix C.3. In short, we lose power due to the drastic decrease in the number of observations, but the point estimates for β_1 are larger. Compared with the 20-26 percent relative increase in the lead share in the full sample, an 100 upward flex is now associated with a 28-43 percent increase.

In some deals, the total amount that is issued can be flexed to match the amount that can be allocated to investors. This can be the case for instance when the loan is meant to finance a dividend to shareholders or a share repurchase. One should therefore also observe that if amounts can be flexed, they are flexed down when prices are flexed down (spreads or discounts are flexed up) and they are flexed up when prices are flexed up (spreads or discounts are flexed down).[18] We run the corresponding regression and find that this is indeed the case. The relevant results are discussed in Appendix C.4.

In sum, the results in this subsection indicate that arrangers face the risk that they end up with larger shares when investors indicate a lower willingness to pay. Because this risk arises from the loans in an arrangers pipeline, we refer to this risk as pipeline risk.

[18] Hanley (1993) conducts a similar test in the context of equity IPOs.

5.2 Debt overhang

Having established that lead arrangers retain a larger share precisely in the loans which investors find less attractive, we now ask whether the unexpected retention of these loans affects the subsequent behavior of arrangers. Theory suggests that when banks retain problematic loans, this is likely to generate a debt overhang problem (Myers, 1977), which in turn reduces the banks' willingness to raise capital to fund new lending (Admati, DeMarzo, Hellwig, and Pfleiderer, 2016; Bahaj and Malherbe, 2016). We would therefore expect that when many loans get stuck in an arranger's pipeline simultaneously, this could induce the arranger to reduce arranging activity and scale back lending in other markets. In practice, decision makers would likely complain about larger-than-expected lead shares tying down additional regulatory capital, or triggering risk management limits. In this subsection, we provide empirical support for this hypothesis.

Arranging activity Debt overhang theory suggests that an arranger might lend (or arrange) less than planned whenever actual retention exceeded planned retention. Because positive flex implies higher than anticipated retention, while negative flex implies lower than anticipated retention, we can construct a proxy of "pipeline overhang" for arranger i as the difference between total amount of loans with positive flexes and the total amount loans with negative flexes over a given quarter t ($net\ flex_{it}$).

We start by examining the effects of pipeline overhang on the arranging of leveraged term loans. We aggregate all loans arranged by a given lead arranger in the LCD data in each quarter. Quarters with no arranging activity are included with both $Net\ flex_{it}$ on $Lending_{it}$ set to 0 for those quarters.[19] We study two outcomes at the arranger-quarter level: the number of arranged loans and total arranged loan amounts. Like our proxy for pipeline overhang, both outcomes

[19] We only fill in quarters between the first and the last arranging activity. Fully balancing the panel does not change the results. Dropping quarters with no lending yields similar results.

($Lending_{it}$) are measured in levels. Pipeline overhang is expected to reduce an arranger's willingness to arrange *new* loans in the current quarter—that is, we expect a negative coefficient on *Net* $Flex_{it-1}$ when regressing *Net* $Flex_{it-1}$ on $lending_t$. In our empirical model, we include lead arranger fixed effect (θ_i) and time fixed effect (γ_t) and later also arranger-time fixed effects, to control for unobserved arranger characteristics and macroeconomic conditions and time-varying arranger conditions, respectively.

$$Lending_{it} = \beta_1 Net\ Flex_{it-1} + \beta_2 Lending_{it-1} + \theta_i + \gamma_t + \epsilon_{it} \quad (5)$$

Table 7
Effective spread flex and arranging activity (number of loans)

Bank-level regressions of total number of term loan arranged (# TL Arranged) on net amount with positive flexes (Net Flex), in millions of dollars. Both quantities are calculated from the S & P Capital IQ LCD data. Net Flex is the difference of loan amounts of loans with positive and negative effective spread flexes in a quarter in the LCD data. Time fixed-effects are at the syndication-quarter level. Arranger trend is a linear time trend. Arranger post-crisis trend is a linear trend starting in 2009Q3.

	(1)	(2)	(3)	(4)	(5)
	# TL Arranged	# TL Arranged	# TL Arranged	# TL Arranged	# TL Arranged
Net Flex$_{t=1}$	-0.000728***	-0.000728***	-0.000761***	-0.000864***	-0.000642**
	(0.000171)	(0.000162)	(0.000171)	(0.000212)	(0.000241)
# TL Arranged$_{t-1}$	0.527***	0.406***	0.371***	-0.124	0.366***
	(0.0517)	(0.0586)	(0.0595)	(0.109)	(0.0887)
Arranger FE	Yes	Yes	Yes	No	Yes
Time FE	Yes	Yes	Yes	Yes	Yes
Arranger Trend	No	Yes	Yes	No	No
Arranger Post-crisis Trend	No	No	Yes	No	No
Arranger-Year FE	No	No	No	Yes	No
Observations	2912	2912	2912	2912	966
R^2	0.800	0.817	0.821	0.892	0.846

Standard errors in parentheses
SEs clustered by quarter
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 7 shows the results of estimating Equation (5) with the number of arranged term loans as outcome. Consistent with pipeline overhang reducing the willingness to arrange loans, the coefficient on *Net Flex* is negative and statistically significant at the 1 percent level (column (1)). One potential concern with this specification is that arranger fixed-effects do not sufficiently control

for different trajectories of arrangers' economic conditions. We therefore include arranger-specific trends in column (2) and find that the estimated coefficient remains basically unchanged. To address concerns about trend breaks during the 2008-09 financial crisis, we add a separate, linear post-crisis trend, which increases the size of the coefficient slightly. To more flexibly control for the arrangers' economic conditions, we use arranger-year fixed effects in column (4). The estimated coefficient is again only very slightly bigger and still statistically significant at the 1 percent level, suggesting that unobserved arranger economic conditions do not play a large role. Finally, in column (5) we restrict the sample to the post-crisis period (from 2009Q3) and find that in this shorter panel the point estimate, while slightly smaller, remains close to that in the baseline specification. In terms of economic significance, an arranger who flexes spreads up on an additional $1,000m of term loans will arrange about 0.7 loans less in the subsequent quarter. For comparison, the standard deviation of *Net Flex* is $914.36m and the average number of loans arranged per quarter is 2.78.

While the findings for the number of loans as outcome are consistent with pipeline overhang, arrangers could just refrain from arranging some small loans, with little effect on their overall arranging activity. We therefore show the results of estimating Equation (5) with the total arranged loan amount as outcome in Table 8. In the baseline specification (column (1)), the coefficient on *Net Flex* is negative and statistically significant at the 1 percent level. In terms of economic significance, an arranger who flexes spreads up on an additional $1,000 million worth of loans decreases the arranged loan amount in the subsequent quarter by about $450 million, so that the estimated effect for amounts is similar to the estimated effect for numbers. For comparison, the standard deviation of *Net Flex* is $914.36 million and the average amount arranged per quarter is $1,232 million.

To ensure the robustness of these results, we include a linear arranger-specific trend in column (2), a separate post-crisis trend in column (3), and bank-year fixed effects in column (4) and find

Table 8
Effective spread flex and arranging activity (dollar value)

Bank-level regressions of total arranged loan amounts ($ TL Arranged) on net amount with positive flexes (Net Flex), both in millions of dollars. Number of loans arranged on the quarterly level is calculated from the S&P Capital IQ LCD data. Net amount with positive flexes is the difference of loan amounts of loans with positive and negative effective spread flexes in a quarter in the LCD data. Time fixed-effects are at the syndication-quarter level. Arranger trend is a linear time trend. Arranger post-crisis trend is a linear trend starting in 2009Q3.

	(1)	(2)	(3)	(4)	(5)
	$ TL Arranged	$ TL Arranged	$ TL Arranged	$ TL Arranged	$ TL Arranged
Net Flex$_{t-1}$	-0.450***	-0.407***	-0.443***	-0.582***	-0.492**
	(0.148)	(0.151)	(0.160)	(0.209)	(0.227)
$ TL Arranged$_{t-1}$	0.504***	0.381***	0.344***	-0.109	0.327***
	(0.0565)	(0.0644)	(0.0648)	(0.108)	(0.104)
Arranger FE	Yes	Yes	Yes	No	Yes
Time FE	Yes	Yes	Yes	Yes	Yes
Arranger Trend	No	Yes	Yes	No	No
Arranger Post-Crisis Trend	No	No	Yes	No	No
Arranger-Year FE	No	No	No	Yes	No
Observations	2912	2912	2912	2912	966
R^2	0.727	0.750	0.756	0.851	0.795

Standard errors in parentheses

SEs clustered by quarter

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

similar results. When looking only at the post-crisis sample, we find a comparable coefficient (column (5)). In sum, we find a robust, negative relationship between net flex and loan origination.

Spillovers The results are consistent with our interpretation that when arrangers have to retain larger-than-expected shares in less successful syndications, they subsequently have less capacity to arrange loans. An alternative interpretation would be that it is borrowers who do not want their loans to be arranged by arrangers who have just had to flex spreads up (perhaps reflecting a lack of ability or of diligence). Under either interpretation, the arranging banks are affected, so both raise prudential concerns. Under the second interpretation, however, borrowers themselves would be less likely to be affected directly.

Based on our interviews with market participants, the second interpretation appears less plausible. For instance, many practitioners mentioned that a widely accepted measure of success are the so-called league tables. These are used to attract customers and are based on the number and amounts of arranged loans, which are meant to reflect experience and expertise. Information on flex is not used in the construction of league tables.

To alleviate the potential concerns, we assess whether net flex is related to participations in unrelated syndications, rather than arranging activity. Under the pipeline overhang interpretation, the retention of problematic loans should also reduce the willingness of affected arrangers to hold participations in unrelated syndications. Under the borrower-choice interpretation, while borrowers may not want the less successful arrangers to arrange their loans, there is no reason why they would be reluctant to have institutions, whose arranging desk they perceive as less able or diligent, hold participations in their loans.

To construct a sample that contains information on participations, we first restrict ourselves to the more active arrangers. We define these as arrangers who arranged loans in at least half of all

quarters in the LCD data. We hand-match these to the SNC data. This leaves us with the 18 active arrangers who together account for 88 percent of the leveraged term loan market.[20] In the SNC data, we use all participations of these arrangers and not just the participations in which the arranger is the lead bank, to construct an arranger-quarter panel of total *new lending* based on the origination date.[21] Note that here, we also includes participations in investment grade term loans and credit lines. As noted above, one caveat is that the SNC only reports loan shares as of December 31st of the reporting year. We assign that year-end loan share to the respective origination quarter. While this assignment introduces measurement error in term loan lending because of secondary market activity, the assignment should be reasonably accurate for credit lines, which are rarely traded.

Table 9 shows the results of estimating Equation (5) with the following outcome variables: new term loan participations, new credit line participations, and new total participations. The results relating to total participations are in columns (1) and (2). The coefficient on *Net Amount with Positive Flexes* is negative and statistically significant in the baseline specification (column (1)) and when including arranger-specific time trends (column (2)). The estimated coefficient implies that an arranger who raises spreads on an additional $1,000 million of loans in one quarter reduces participations by about $150 million in the following quarter. For comparison, the standard deviation of *Net Flex* for this subsample of more active arrangers is $1661.9 million and the average amount arranged is $4,400 million (out of which $3,500 million would be credit lines and the rest term loans).

Further inspection suggests that the total effect is mostly driven by that on credit lines. In particular, we can find in columns (3) and (4) a negative and significant coefficient on *Net Flex*, suggesting that a clogged pipeline in the leveraged term loan market negatively affects lending in

[20]The result shown above also hold when using only this subsample of arrangers.

[21]We do this only for the first time a loan is observed in the SNC. We double-check that the origination year and reporting year line up.

Table 9
Effective spread flex and participation in new syndications

Bank-level regressions of new total, credit line, and term loan lending (Total Lending, CL Lending, TL Lending, respectively) on net amount with positive flexes (Net Flex), all measured in millions of dollars. New total, credit line, and term loan lending arranged on the quarterly level is calculated from the SNC data. For details, see text. Net amount with positive flexes is the difference of loan amounts of loans with positive and negative effective spread flexes in a quarter in the S&P Capital IQ LCD data. Time fixed-effects are at the syndication-quarter level. Arranger trend is a linear time trend. Arranger post-crisis trend is a linear trend starting in 2009Q3.

	(1)	(2)	(3)	(4)	(5)	(6)
	Total Lending	Total Lending	CL Lending	CL Lending	TL Lending	TL Lending
Net Flex$_{t-1}$	-0.147*	-0.166**	-0.137**	-0.149**	-0.00524	-0.0132
	(0.0760)	(0.0828)	(0.0583)	(0.0654)	(0.0237)	(0.0258)
Total Lending$_{t-1}$	0.594***	0.371***				
	(0.0750)	(0.0984)				
CL Lending$_{t-1}$			0.597***	0.382***		
			(0.0624)	(0.0813)		
TL Lending$_{t-1}$					0.401***	0.248***
					(0.0852)	(0.0934)
Arranger FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Arranger Trend	No	Yes	No	Yes	No	Yes
Arranger Post-Crisis Trend	No	Yes	No	Yes	No	Yes
Observations	1035	1035	1035	1035	1035	1035
R^2	0.869	0.889	0.878	0.895	0.718	0.752

Standard errors in parentheses

SEs clustered by quarter.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

the syndicated credit line market. (Column 4 includes arranger-specific linear time trends for the pre- and post-crisis period). The magnitudes of the effect for credit lines and the effect for total participations differ only very slightly. In contrast, we find no effect of our pipeline overhang proxy on new term loan lending, whether we include arranger-specific time trends (columns (6)) or not (column (5)). That the total effect seems driven by credit lines should not be too surprising since, as already noted, banks tend to sell down their positions in term loans in the secondary market over time (Aramonte, Lee, and Stebunovs (2015)).

To sum up, in this section, we have shown that when realized demand for term loan is lower than expected, such that spreads need to be flexed up, arrangers end up holding a larger-than-expected shares of the loan. Our findings suggest that when such problematic loans clog the pipeline, this decreases an arrangers' willingness to arrange new loans. The economic effects of such clogs are not contained to the leveraged loan markets. Sizeable spillovers to the shares held in new credit lines suggests that pipeline overhang can hamper other activities of the bank.

6 Aggregate pipeline risk and lending activity

Ivashina and Scharfstein (2010) posit that if banks are financially constrained, then the retention of larger shares of syndicated loans in downturns could amplify the credit cycle, and show that average shares are indeed larger in times in which credit is tightened. In this section, we explore whether this relationship could possibly be driven by the realization of pipeline risk.

The bank-level lending regressions of the previous section show that when investors indicate a lower willingness to pay than expected, the arranger retains larger share of the loan and subsequently arranges fewer loans and lends less. We have interpreted this as evidence of pipeline-induced debt overhang, which would imply that the arranger passes up on positive net-present-value opportunities to arrange and to lend. This invites the question as to whether other financial institutions

can pick up the resulting slack or not. In situations in which many arrangers simultaneously suffer from clogged syndication pipelines, substitution between lenders may not be possible and aggregate credit supply could contract. There are stories in the financial press which suggest that, e.g., around the start of 2008 and also towards the end of 2015 many arrangers were simultaneously sitting on a very large numbers of loans that had turned out to be difficult to syndicate (see Appendix A) and that the aggregate supply of credit was affected.

To explore this question, we relate aggregate flex activity to aggregate lending and lending standards. Our measure of aggregate net flex is the sum of the loan amounts with positive effective spread flexes minus the sum of the loan amounts with negative effective spread flexes, across all arrangers in a given quarter. This market-wide measure is large and positive when many arrangers flex spreads up and, hence, retain larger shares. If there are aggregate consequences, we would expect a positive net flex amount to be associated with a reduction in aggregate lending and a tightening of lending standards. To test whether this is the case, we estimate the following time-series regression on quarterly data:

$$Aggregate\ lending_t = c + \alpha aggregate\ lending_{t-1} + \beta net\ flex\ _{t-1} + \text{linear time trend} + \varepsilon_t \qquad (6)$$

As aggregate lending variables, we use aggregated versions of the dependent variable in the previous sections: The total amount of leveraged term loans arranged in a given quarter (as reported in LCD) and the new shares the 18 most active arrangers buy into as reported in SNC (we again break this down into new total lending, term loan lending, and credit line lending). To control for the supply of credit by institutional investors, we also include inflows into high yield funds and CLO issuances (Fund Flows). (Doing so reduces the number of observations very slightly, as we only have data on fund flows starting in 2001.)

Table 10 shows the results of estimating equation (6). The negative coefficient on net flex in

Table 10
Aggregate effective spread flex, arranging, and participations

Quarterly time-series regressions of aggregate new lending variables on aggregate net amount flex. TL Arranged is the total amount of leveraged term loans that are arranged in a given quarter, computed from S&P Capital IQ LCD, in millions of dollars. Total Lending, CL Lending, and TL Lending represents new participations in both credit lines and term loans, in credit lines only, and in term loans only, respectively, as calculated from SNC, in millions of dollars. (For details, see text.) Net Flex is the total loan amount of all deals with positive flexes minus the total loan amount of all deals with negative flexes in the respective quarter, in millions of dollars. Fund Flows are net inflows into high yield mutual funds and CLO issuances, in millions of dollars.

	(1) TL Arranged	(2) TL Arranged	(3) Total Lending	(4) Total Lending	(5) CL Lending	(6) CL Lending	(7) TL Lending	(8) TL Lending
Net Amount with Positive Flexes$_{t-1}$	-0.974***	-0.694**	-0.891**	-0.964**	-0.831***	-0.991***	-0.0379	0.0887
	(0.300)	(0.305)	(0.363)	(0.445)	(0.239)	(0.307)	(0.137)	(0.146)
TL Arranged$_{t-1}$	0.401***	0.104						
	(0.0911)	(0.103)						
Total Lending$_{t-1}$			0.511***	0.531***				
			(0.139)	(0.162)				
CL Lending$_{t-1}$					0.585***	0.632***		
					(0.127)	(0.143)		
TL Lending$_{t-1}$							0.230	0.126
							(0.176)	(0.155)
Fund Flows$_{t-1}$		6146.3***		-544.9		-1284.3		990.3**
		(1471.1)		(1836.1)		(1415.6)		(428.7)
Observations	65	61	65	61	65	61	65	61
R^2	0.605	0.699	0.493	0.461	0.564	0.548	0.196	0.232

Standard errors in parentheses
Robust standard errors in parentheses. All regressions include a linear time trend
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

columns (1) and (2) indicates that when spreads are flexed up, the aggregate amount of leveraged term loans arranged in the subsequent quarter drops. Furthermore, as indicated by columns (3) and (4), arrangers reduce their participations in new syndications. As in the bank-level results, we can see that this is driven by a decrease in the participations in credit lines (columns (5) and (6)) rather than in term loans (columns (7) and (8)). These results are consistent with the interpretation that when many arrangers simultaneously end up with larger shares in the some loans on which they have to flex up spreads, there are too few unencumbered arrangers to take up the resulting slack and arranging activity and lending activity therefore decreases in the aggregate.

Following Ivashina and Scharfstein (2010), we also consider loan terms and lending standards as outcome variables, as reported in the Federal Reserve's Senior Loan Officer Opinion Survey.

Table 11 shows the results of estimating equation (6) with loan terms as the dependent variable,

Table 11
Aggregate loan terms and aggregate net flex

Quarterly time-series regressions of changes in loan terms on aggregate net amount flex. The left-hand-side variables are the percentage points of respondents in the Federal Reserve's Senior Loan Officer Opinion Survey who report a change in loan terms offered to borrowers as indicated by the various column headings. (For details, see text.) Net Flex (scaled) is the total loan amount of all deals with positive flexes minus the total loan amount of all deals with negative flexes in the respective quarter, in billions of dollars. Fund Flows are net inflows into high yield mutual funds and CLO issuances, in millions of dollars.

	(1) Decrease in credit line limits	(2) Increase in cost of credit lines	(3) Tightening covenants	(4) Increase in collateral
Net Amount with Positive Flexes(scaled)$_{t-1}$	0.0981*	0.399***	0.224***	0.182***
	(0.0559)	(0.0995)	(0.0780)	(0.0506)
Increase in cost of credit lines$_{t-1}$	0.589***			
	(0.0499)			
Tightening covenants$_{t-1}$		1.218***		
		(0.0944)		
Decrease in credit line limits$_{t-1}$			0.927***	
			(0.0655)	
Increase in collateral$_{t-1}$				0.855***
				(0.0791)
Fund Flows$_{t-1}$	0.333	0.753	-0.370	0.0342
	(0.353)	(0.524)	(0.315)	(0.261)
Observations	61	61	61	61
R^2	0.863	0.842	0.864	0.839

Standard errors in parentheses
Robust standard errors in parentheses. All regressions include a linear time trend
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 12
Aggregate lending standards and aggregate net flex

Quarterly time-series regressions of changes in loan terms on aggregate net amount flex. The left-hand-side variables are the percentage points of respondents in the Federal Reserve's Senior Loan Officer Opinion Survey who report a change in lending standards as indicated by the various column headings. (For details, see text.) Net Flex (scaled) is the total loan amount of all deals with positive flexes minus the total loan amount of all deals with negative flexes in the respective quarter, in billions of dollars. Fund Flows are net inflows into high yield mutual funds and CLO issuances, in millions of dollars.

	(1) Tightening Standards - large firms	(2) Increase in premiums - large firms	(3) Tightening Standards - small firms	(4) Decrease in credit card limits
Net Amount with Positive Flexes(scaled)$_{t-1}$	0.227***	0.370***	0.183***	0.174***
	(0.0567)	(0.0854)	(0.0638)	(0.0604)
Tightening Standards - large firms$_{t-1}$	0.894***			
	(0.0708)			
Increase in premiums - large firms$_{t-1}$		0.904***		
		(0.0520)		
Tightening Standards - small firms$_{t-1}$			0.856***	
			(0.0823)	
Decrease in credit card limits$_{t-1}$				0.872***
				(0.0887)
Fund Flows$_{t-1}$	0.414	0.471	0.00374	-0.0109
	(0.298)	(0.392)	(0.294)	(0.388)
Observations	61	61	61	61
R^2	0.869	0.912	0.829	0.840

Standard errors in parentheses
Robust standard errors in parentheses. All regressions include a linear time trend
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

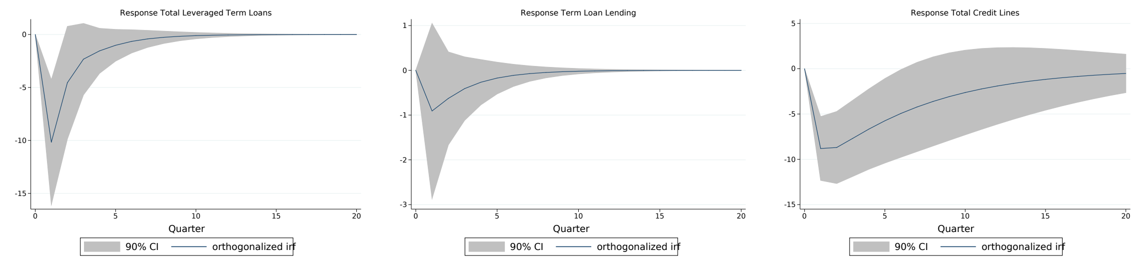
while Table 12 uses lending standards as the dependent variable. Overall, we can see that positive aggregate net flex is associated with a tightening of both loan terms and lending standards. Pipeline risk is therefore a possible explanation for the aggregate relationship between retained shares and lending standards observed by Ivashina and Scharfstein (2010).

Finally, we ask how persistent the effect of net flex on aggregate new lending is. For this purpose, we estimate quarterly tri-variate VARs of aggregate lending, net flex, and fund flows. We include an exogenous linear time trend and seasonal dummies for each quarter and one lag for the dependent variables.[22] To identify the effect of shocks to this system, we order the variables from most endogenous to least endogenous (lending, net flex, and fund flows) and use a Cholesky factorization of the variance-covariance matrix of error terms. That is, contemporaneous shocks to lending affect net flex and fund flows but not vice versa, and contemporaneous shocks to net flex affect fund flows but not vice versa. We estimate three sets of VARs, one each for our three lending variables: amount of leveraged term loans arranged in a given quarter, as computed from LCD, and new participations in term loans and new participations in credit lines, as computed from SNC.

For the sake of brevity, we omit reporting parameter estimates for the VARs, and plot only a subset of the resulting impulse-response functions in Figure 7. Sub-figure 7a shows the response in the amount of leveraged term loans arranged (from LCD) to an orthogonalized shock in net flex. We can see that a one-standard-deviation innovation in net flex leads to a significant reduction in the amount of arranged loans up to two quarters after the shock. This reduction approaches zero after five quarters. (In unreported results, we have confirmed that a VAR at monthly frequency produces similar results.)

7b and 7c show the response of new participations in term loans (TL Lending) and in credit lines (CL Lending), respectively, to an orthogonalized shock to net. While this shock has no significant

[22]The final prediction error and the Hannan and Quinn information criterion suggest one lag.



(a) TL Arranged **(b) TL Lending** **(c) CL Lending**

Figure 7. Impulse-response functions of lending, net flex, and fund flows
Impulse-response functions as implied by tri-variate VAR of lending, net flex, and fund flows, for three different lending variables: amount of leveraged term loans arranged in a given quarter, as computed from S&P Capital IQ LCD (subfigure 7a), and new participations in term loans (subfigure 7b) and in credit lines (subfigure 7c), as computed from SNC. We order variables from most to least endogenous as lending, net flex, and fund flows. Impulse-reponses show response of the relevant lending variable to a one-standard deviation shock to the innovation in net flex.

effect on new participations in term loans, a one-standard-deviation innovation in net flex reduces participations in term loans significantly for up to 6 quarters. The fact that, also in the aggregate, net flex is strongly related to subsequent arranging and credit line lending is consistent with the bank-level results in Table 9.

While the results from the VARs do not provide any insight about the origins of the shocks to net flex per se, they are consistent with the interpretation that the materialization of pipeline risk that produces debt overhang has a significant and large effect on credit line lending, and that this effect persists over time.

7 Conclusion

We use novel data to study the syndication of leveraged term loans. The data allows us to draw conclusions about the relevant informational frictions and the nature of the economic problem arrangers face. In particular, we show that arrangers need to uncover investors' willingness to pay for the loan. Arrangers often need to give guarantees to borrowers at an early stage of the process.

Together with incentive compatibility concerns, this implies that arrangers run the risk of having to retain a larger share when investors reveal a lower willingness to pay than expected. We document that this is the case. Because this risk arises from arrangers' syndication pipelines, we refer to it as *pipeline risk*.

When pipeline risk materializes, the retention by arrangers of larger shares of problematic loans can cause debt overhang problems. Consistent with this, we find that when an arranger faces an overall lower willingness to pay in a given quarter, it reduces the number and dollar volume of loans it arranges in the following quarter, as well its participations in other syndications.

We also examine aggregate time series and find that quarters during which market-wide willingness to pay is lower than expected are followed by a tightening of lending standards and a market-wide reduction in arranging activity and arrangers' participations in syndications.

Ivashina and Scharfstein (2010) have documented the counter-cyclicality of shares retained by arrangers. The materialization of pipeline risk is correlated across arrangers in our sample. Hence our analysis suggests that pipeline risk is a potential driver of the aggregate relationship between the lead share and credit activity. If this is the case, this raises macroprudential concerns: excessive pipeline risk taking could result in sector-wide debt overhangs, associated with an inefficient contraction of credit.

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Appendix

A Anecdotal Evidence on Pipeline Risk

In this appendix, we present some anecdotal evidence on pipeline risk.

- In February 2008 the syndication of $14 billion debt used to finance the buy-out of Harrah's Entertainment by Apollo Management and Texas Pacific Group collapsed. The group of banks syndicating the loan were not able to sell the leveraged buy-out debt to third parties. The unsold debt remained on the banks' books, which in turn led to a sizable loss at a time when banks were already holding more than $150 billion of unsyndicated, mostly LBO-related debt.[23]

- At the beginning of the financial crisis, concerns about syndicated bridge loans financing LBOs emerged, since selling off these loans became virtually impossible. As such, banks were on the hook for billions in bridge loans. Citi's Chief Financial Officer, Gary Crittenden, told participants of a conference call on July 20, 2008 that Citi was involved in four LBO financings that could not be sold and that other such deals would occur in the future.[24]

- The financing for the largest private-equity deal until 2008, the $41 billion leveraged buy-out of BCE Inc. by a consortium of Ontario Teacher's Pension Plan, Providence Equity Partners LLC, Madison Dearborn partners LLC, and Merrill Lynch Global Private Equity, was supposed to be arranged by Citigroup Inc., Deutsche Bank AG, Royal Bank of Scotland PLC and Toronto Dominion Bank. The banks underwrote $34 billion debt to fund the deal.

[23] "Loan market in 'disarray' after Harrah's upset" Financial Times, February 4, 2008, available at http://www.ft.com/cms/s/0/645de070-d2c3-11dc-8636-0000779fd2ac.html.

[24] "Bridge Loans Put Banks in a Bind" Bloomberg Business, August 13, 2007, available at http://www.bloomberg.com/bw/stories/2007-08-13/bridge-loans-put-banks-in-a-bindbusinessweek-business-news-stock-market-and-financial-advice.

Overall demand for the debt turned out to be so weak that the four banks would have been on the hook for losses of as much as $12 billion. However, the LBO collapsed after KPMG expressed concerns about the financial condition of BCE and delivered a preliminary opinion that it could not provide a certificate of solvency.[25]

- In November 2010, Sports Authority refinanced a $275 million bullet term loan that paid LIBOR + 225bps and had no LIBOR floor with a new, $300m bullet term loan. The arranger, BofA Merrill Lynch, originally priced the loan at LIBOR + 525bps-550bps along with a 1.5% LIBOR floor and a discount of 1-2%. However, due to low demand the terms had to be adjusted to LIBOR + 600bps with a discount of 3%. Concurrently, the cell phone insurance provider Asurion had to sell debt with a discount of 4%, substantially higher than the initially proposed discount of 1%, and also higher than underwritten discount limit of the Barclays-led syndicate.[26]

- In 2013, arrangers for the loan financing the buyout of Rue21 were on the hook for $780 million and stood to lose up to $100 million due to having to slash prices to place the underwritten loan with institutional investors.[27]

- With spreads on high-yield bonds increasing in late 2015, banks found it harder to sell syndicated loans financing LBOs. In the fall of 2015, six deals failed to attracted enough investor interest. Consequently, financing for new deals became much harder to obtain. By January 21, 2016, banks had still not managed to complete the syndication of 20 of the LBOs

[25] "BCE Leveraged Buyout Deal Collapses" Wall Street Journal, Dec 11, 2008, available at `http://www.wsj.com/articles/SB122896949125997537`.

[26] "Covenant-lite loans are back but investors hope to limit mistakes of the past" Financial Times, November 24, 2010, available at `http://www.ft.com/cms/s/2/a242e5d0-f812-11df-8d91-00144feab49a.html`.

[27] "Banks Seeking to Sell Rue21 Debt at a Discount; Three Banks on Hook for $780 million in Buyout Financing," Wall Street Journal, 25 September 2013.

initiated in 2015, with a total value of $40 billion.[28]

- In October 2015, arrangers for the $1.2 billion loan financing the buyout of FullBeauty were struggling to sell it.[29] According to the LCD data, placing this loan required an increase in the discount of 7.5% of face value.

- In November 2015, Carlyle Group's buyout of Veritas collapsed when the arrangers, Bank of America Merrill Lynch and Morgan Stanley, could not place the LBO debt. One of the first adjustments the banks offered was to cut the size of the term loan B to $1.5 billion from $2.45 billion - moving $ 250 million to bonds and retaining $700 million themselves. With the new spreads well outside the initial range, investors knew the banks were on the hook. However, this offer did not sway investors. The underwriters then tried to sweeten the deal by raising the spread and offering a steeper discount of 5%. When even these terms did not attract investors, the banks bumped up the discount to 10%. After these efforts failed, the financing was subsequently pulled.[30]

[28] "Buyout firms lose leverage with backers" Financial Times, January 21, 2016, available at `http://www.ft.com/cms/s/0/3ace5424-bfdc-11e5-9fdb-87b8d15baec2.html`.

[29] "Warning for M&A: Another Debt Deal Struggles; Goldman, J.P. Morgan run up against wary investors in attempt to shed leveraged loans," Wall Street Journal, 6 Oct 2015.

[30] "Underwriters on the hook after botch" Reuters, November 20, 2015, available at `http://www.reuters.com/article/veritas-ma-carlyle-group-debt-idUSL8N13D3Z620151120`.

B When are loans flexed?

What determines when and whether loan terms are flexed? If the underlying reason is that the arranger does not know the ultimate demand for the loan, then we should probably observe more or bigger flexes, up and down, for loans for which demand should be harder to judge. Whether demand for a loan is harder to judge could relate to loan characteristics such as the riskiness or purpose of the loan.

We first examine flexes in spreads. To describe how in our data, the probability and direction of spread flex relate to loan characteristics, we estimate a linear probability model, in which the dependent variable is either a dummy variable that is equal to 1 if the spread was flexed, or equal to 1 if the spread was flexed up only, or equal to 1 if it was flexed down only. Explanatory variables include the log talk yield (the initial all-in yield to maturity at the beginning of the syndication process, see also Equation (1)) and dummies that indicate whether the loan is made to finance an LBO or Acquisition. We control for time-varying and market-wide institutional demand and overall risk appetite, by either including time fixed effects, or fund and CLO flows. We also control for additional loan characteristics including a polynomial of the loan amount, whether the deal contains a revolving credit facility, is rated, is sponsored, includes a covenant-lite facility, or includes a second lien as well as fixed effects for loan purpose, borrower industry, and lead arranger.

Table 13 shows the results from this estimation. In columns (1) and (2), it can be seen that loans with a high talk yield, or loans that finance Acquisitions or LBOs as opposed to refinancing existing loans, or that contain a revolving credit facility, are more likely to experience spread flex. A possible interpretation is that for such more complex loans, the arranger finds it harder to anticipate the true demand for the loan and, hence, adjustments occur more frequently. In columns (3) to (6), we examine the direction of spread flex, by using as dependent variables dummies which are 1

Table 13
Incidence and direction of spread flex

Regressions of institutional spread flex dummies on loan characteristics at the deal level. Spr Flex (d) is equal to 1 if the spread was flexed. Spr Flex Up (d) and Spr Flex Down (d) are equal to 1 if the spread was flexed up or down, respectively. Log Talk Yield is the initially offered all-in yield to maturity. Acquisition and LBO are indicator variables for the respective loan purpose. (Refinancing is the omitted purpose category.) Fund Flows are net inflows into high yield mutual funds and CLO issuances, measured in millions. Rated, Sponsored, Cov-lite, and Second Lien are dummies that indicate whether at least one facility within a deal is rated, sponsored, or classified as cov-lite or second lien, respectively. Log Maturity is the log of the average maturity of institutional facilities. Log Talk Amount is the log of the initially offered loan amount. Time fixed-effects are at the syndication month-year. (See Tables 1 and 2 for relevant summary statistics).

	(1) Spr Flex (d)	(2) Spr Flex (d)	(3) Spr Flex Down (d)	(4) Spr Flex Up (d)	(5) Spr Flex Down (d)	(6) Spr Flex Up (d)
Log Talk Yield	0.197***	0.173***	0.0161	0.183***	0.0733*	0.101***
	(0.0390)	(0.0396)	(0.0353)	(0.0374)	(0.0381)	(0.0356)
Acq.	0.148***	0.137***	0.104***	0.0457**	0.0857***	0.0526***
	(0.0229)	(0.0217)	(0.0223)	(0.0211)	(0.0220)	(0.0200)
LBO	0.204***	0.199***	0.152***	0.0585**	0.133***	0.0710**
	(0.0276)	(0.0256)	(0.0284)	(0.0280)	(0.0284)	(0.0280)
Fund Flows		0.00158			0.0101***	-0.00838***
		(0.00217)			(0.00247)	(0.00218)
RC dummy	0.173***	0.175***	0.0944***	0.0796***	0.0942***	0.0816***
	(0.0190)	(0.0188)	(0.0214)	(0.0140)	(0.0194)	(0.0148)
Rated	0.0296	0.0244	0.00780	0.0237	0.0113	0.0144
	(0.0327)	(0.0313)	(0.0289)	(0.0247)	(0.0284)	(0.0235)
Sponsored	-0.0527***	-0.0425**	-0.0666***	0.0122	-0.0511***	0.00708
	(0.0199)	(0.0206)	(0.0156)	(0.0167)	(0.0171)	(0.0168)
Cov-lite	-0.00473	-0.0210	0.0476***	-0.0505***	0.0152	-0.0345**
	(0.0208)	(0.0200)	(0.0163)	(0.0184)	(0.0193)	(0.0170)
Second Lien	-0.00117	0.00298	0.00356	0.00552	-0.0440	0.0567**
	(0.0282)	(0.0265)	(0.0267)	(0.0276)	(0.0271)	(0.0276)
Log Maturity (Years)	0.156***	0.202***	0.152***	0.00246	0.169***	0.0325
	(0.0377)	(0.0356)	(0.0351)	(0.0310)	(0.0353)	(0.0315)
Log Synd. Time	-0.0109	-0.0509	0.0480	-0.0580	-0.0296	-0.0226
	(0.0364)	(0.0360)	(0.0449)	(0.0372)	(0.0407)	(0.0331)
Amount Polynomial	Yes	Yes	Yes	Yes	Yes	Yes
Arranger FE	Yes	Yes	Yes	Yes	Yes	Yes
Purpose FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	No	Yes	Yes	No	No
Observations	3693	3693	3693	3693	3693	3693
R^2	0.252	0.212	0.193	0.184	0.125	0.122

Standard errors in parentheses
SEs clustered by syndication month.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

when the spread is flexed up only (flexed down only) and show that these are related to net inflows into high yield mutual funds and CLOs: In column (4), we can see that net inflows, indicating high demand, are more likely to be associated with spreads being flexed down. In column (6), we can see that net outflows, indicating low demand, are more likely to be associated with spreads being flexed up. It is important to note that such inflows and outflows are contemporaneous and therefore not known to the lead arranger at launch.

We now turn to flexes in discounts. We first estimate a linear probability model in which the dependent variable is either a dummy variable that is equal to 1 if the discount was flexed, or equal to 1 if the discount was flexed up only, or equal to 1 if it was flexed down only. Table 14 shows the results of these estimations. As in the case of spread flex, we find that discounts are more likely to be flexed for loans with a high talk yield, or loans that finance Acquisitions or LBOs as opposed to refinancing existing loans. Again, a possible interpretation is that for such more complex loans, the arranger finds it harder to anticipate the true demand for the loan and, hence, adjustments occur more frequently. We can also see that discounts are more likely to be decreased when there are inflows into high yield mutual funds and CLOs and more likely to be increased when there are outflows. Even though the results for the discount flexes are less statistically significant, they are similar to those for spread flexes.

Finally, we examine flexes in amounts. We estimate a linear probability model in which the dependent variable is either a dummy variable that is equal to 1 if the institutional amount was flexed, or equal to 1 if the amount was flexed up only, or equal to 1 if it was flexed down only. Table 15 shows the results of these estimations. Here, we report an additional fixed effect related to the purpose of the deals: Eq. Payout is a dummy that is one if the purpose of the loan is to finance a dividend or share repurchase. It can be seen that in particular in the syndication of such

Table 14
Incidence and direction of discount flex

Regressions of institutional discount flex dummies on loan characteristics at the deal level. Disc Flex (d) is equal to 1 if the discount was flexed. Disc Flex Up (d) and Disc Flex Down (d) are equal to 1 if the discount was flexed up or down, respectively. Log Talk Yield is the initially offered all-in yield to maturity. Acquisition and LBO are indicator variables for the respective loan purpose. (Refinancing is the omitted purpose category.) Fund Flows are net inflows into high yield mutual funds and CLO issuances measured in millions. Rated, Sponsored, Cov-lite, and Second Lien are dummies that indicate whether at least one facility within a deal is rated, sponsored, or classified as cov-lite or second lien, respectively. Log Maturity is the log of the average maturity of institutional facilities. Amount Polynomial is a 4th-order polynomial in the log of the initially offered loan amount. Time fixed-effects are at the syndication month-year. (See Tables 1 and 2 for relevant summary statistics).

	(1) Disc Flex (d)	(2) Disc Flex (d)	(3) Disc Flex Down (d)	(4) Disc Flex Up (d)	(5) Disc Flex Down (d)	(6) Disc Flex Up (d)
Log Talk Yield	0.205***	0.161***	-0.00112	0.209***	0.0252	0.138***
	(0.0447)	(0.0369)	(0.0400)	(0.0325)	(0.0374)	(0.0311)
Acq.	0.218***	0.226***	0.174***	0.0428*	0.167***	0.0571***
	(0.0229)	(0.0221)	(0.0225)	(0.0216)	(0.0220)	(0.0185)
LBO	0.250***	0.256***	0.180***	0.0699***	0.166***	0.0883***
	(0.0282)	(0.0287)	(0.0260)	(0.0232)	(0.0279)	(0.0242)
Fund Flows		0.00369**			0.0114***	-0.00774***
		(0.00185)			(0.00197)	(0.00177)
RC dummy	0.105***	0.100***	0.0654***	0.0410***	0.0633***	0.0382***
	(0.0191)	(0.0182)	(0.0157)	(0.0122)	(0.0152)	(0.0132)
Rated	0.0918***	0.0962***	0.0621**	0.0305	0.0700***	0.0269
	(0.0329)	(0.0314)	(0.0259)	(0.0251)	(0.0242)	(0.0248)
Sponsored	-0.0233	-0.0159	-0.00522	-0.0199	0.00422	-0.0216*
	(0.0179)	(0.0185)	(0.0175)	(0.0134)	(0.0171)	(0.0129)
Cov-lite	0.0310*	0.0406**	0.0619***	-0.0283**	0.0539***	-0.0108
	(0.0175)	(0.0175)	(0.0165)	(0.0121)	(0.0184)	(0.0110)
Second Lien	0.0316	0.0402	0.0358	0.00289	0.00484	0.0420
	(0.0325)	(0.0293)	(0.0260)	(0.0253)	(0.0257)	(0.0263)
Log Maturity (Years)	0.0437	0.0735	0.0963**	-0.0524*	0.0932**	-0.0193
	(0.0498)	(0.0478)	(0.0431)	(0.0305)	(0.0410)	(0.0321)
Log Synd. Time	0.0364	-0.00646	0.0911**	-0.0584**	0.0324	-0.0418*
	(0.0365)	(0.0316)	(0.0359)	(0.0278)	(0.0293)	(0.0241)
Amount Polynommial	Yes	Yes	Yes	Yes	Yes	Yes
Arranger FE	Yes	Yes	Yes	Yes	Yes	Yes
Purpose FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	No	Yes	Yes	No	No
Observations	3693	3693	3693	3693	3693	3693
R^2	0.178	0.144	0.160	0.166	0.102	0.109

Standard errors in parentheses
SEs clustered by syndication month.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 15
Incidence and direction of amount flex

Regressions of institutional amount flex dummies on loan characteristics at the deal level. Amt Flex (d) is equal to 1 if the amount was flexed. Amt Flex Up (d) and Amt Flex Down (d) are equal to 1 if the spread was flexed up or down, respectively. Log Talk Yield is the initially offered all-in yield to maturity. Acquisition, LBO, and Eq. Payout are indicator variables for the loan purpose, where Eq. Payout indicates a Recapitalization to finance a dividend or a share repurchase. (Refinancing is the omitted purpose category.) Fund Flows are net inflows into high yield mutual funds and CLO issuances measured in millions. Rated, Sponsored, Cov-lite, and Second Lien are dummies that indicate whether at least one facility within a deal is rated, sponsored, or classified as cov-lite or second lien, respectively. Log Maturity is the log of the average maturity of institutional facilities. Amount Polynomial is a 4th-order polynomial in the log of the initially offered loan amount. Time fixed-effects are at the syndication month-year. (See Tables 1 and 2 for relevant summary statistics).

	(1)	(2)	(3)	(4)	(5)	(6)
	Amt Flex (d)	Amt Flex (d)	Amt Flex Down (d)	Amt Flex Up (d)	Amt Flex Down (d)	Amt Flex Up (d)
Log Talk Yield	0.138***	0.162***	0.00476	0.132***	0.0153	0.146***
	(0.0468)	(0.0383)	(0.0295)	(0.0416)	(0.0268)	(0.0331)
Acq.	0.0801***	0.0668***	0.0467**	0.0395*	0.0440**	0.0292
	(0.0228)	(0.0222)	(0.0189)	(0.0206)	(0.0185)	(0.0201)
LBO	0.0610*	0.0497	-0.0485**	0.104***	-0.0473**	0.0912***
	(0.0322)	(0.0310)	(0.0225)	(0.0279)	(0.0213)	(0.0262)
Eq. Payout	0.211***	0.192***	0.160***	0.0899	0.160***	0.0682
	(0.0587)	(0.0604)	(0.0508)	(0.0584)	(0.0505)	(0.0598)
Fund Flows		0.00285			-0.00324***	0.00579***
		(0.00191)			(0.00116)	(0.00171)
RC dummy	0.0921***	0.0888***	0.0896***	0.0267*	0.0933***	0.0194
	(0.0167)	(0.0165)	(0.0147)	(0.0152)	(0.0144)	(0.0149)
Rated	0.0615***	0.0630***	0.00813	0.0520**	0.00633	0.0566**
	(0.0227)	(0.0225)	(0.0201)	(0.0240)	(0.0201)	(0.0235)
Sponsored	-0.0480**	-0.0433**	-0.0281**	-0.0187	-0.0310**	-0.0106
	(0.0194)	(0.0194)	(0.0136)	(0.0161)	(0.0137)	(0.0163)
Cov-lite	0.0165	0.0110	-0.00900	0.0327*	-0.0147	0.0346**
	(0.0178)	(0.0173)	(0.0144)	(0.0166)	(0.0137)	(0.0158)
Second Lien	0.0861***	0.0732**	0.186***	0.131***	0.186***	0.116***
	(0.0305)	(0.0279)	(0.0258)	(0.0292)	(0.0255)	(0.0259)
Log Maturity (Years)	0.101**	0.0932**	0.0216	0.0699**	0.0312	0.0520*
	(0.0396)	(0.0381)	(0.0253)	(0.0316)	(0.0247)	(0.0309)
Log Synd. Time	0.0248	0.0119	-0.0303	0.0630**	-0.0118	0.0298
	(0.0349)	(0.0319)	(0.0249)	(0.0269)	(0.0226)	(0.0245)
Amount Polynomial	Yes	Yes	Yes	Yes	Yes	Yes
Arranger FE	Yes	Yes	Yes	Yes	Yes	Yes
Purpose FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	No	Yes	Yes	No	No
Observations	3693	3693	3693	3693	3693	3693
R^2	0.128	0.095	0.142	0.127	0.117	0.091

Standard errors in parentheses
SEs clustered by syndication month.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

loans, amounts tend to be adjusted. (The omitted purpose category is Refinancing.)

C Robustness Tests

C.1 Time to Syndication

One important question in the syndication process is how fast the arranging bank can sell the loan to institutional investors. The faster the loan is sold—that is, earlier the loan leaves the pipeline, the earlier the arranging bank has free capacity to take on new mandates and originate new loans. It is plausible that certain loan characteristics, such as high credit risk, lengthen the syndication process. Similarly, the flexes in the loan terms could lengthen the syndication process if demand needs to be re-assessed. Moreover, Ivashina and Sun (2011) argue that time-to-syndication contains information about demand of institutional investors for a loan. Hence, understanding the determinants of time-to-syndication sheds light on which loan characteristic or macroeconomic developments increase pipeline risk. We therefore estimate the following equation:

$$\begin{aligned} \textit{Time to Syndication}_i = & c + \beta_1 \textit{Effective Spread Up}_i + \beta_1 \textit{Effective Spread Down}_i \\ & + \beta_3 \textit{Log Talk Yield}_i + \beta_4 \textit{LBO}_i + \gamma X_i + \epsilon_i, \end{aligned} \tag{7}$$

where time to syndication is the log of number of days between the launch date and the date the loan becomes active. Effective Spread Up (Down) is a dummy variable that is equal to 1 if the effective spread was flexed up (down). Log Talk Yield is the initial all-in yield to maturity at the beginning of the syndication process. LBO is a dummy variable indicating the respective loan purpose (refinancing is the omitted loan purpose category). We control for additional loan characteristics (X_i) including a polynomial of the loan amount, whether the deal is rated, is sponsored, includes a covenant-lite facility, or includes a second lien as well as fixed effects for loan purpose, borrower industry, lead arranger, and deal month-year.

Table 16 shows the results of estimating Equation (7). In column (1), we omit deal month-year fixed effect and find no significant relationship between the explanatory variables and time-to-syndication except for net inflows to high yield mutual fund and CLO issuances, the channel stressed by Ivashina and Sun (2011). When including deal month-year fixed effect, we find that within a deal month-year riskier loans take longer to syndication (column (2)). Perhaps surprisingly, we also find a positive and weakly significant relationship between time-to-syndication and the effective spread being flexed down. This finding suggests that arranging banks needs more time for loans with unexpectedly high demand but not for loans with unexpectedly low demand. One possible reason for this pattern is that formal agreements in mandate-, fee-, and commitment letters are more likely to describe how to split a deficit when demand is low than how to split a surplus when demand is high. Renegotiation between the arranger and borrower might therefore be more lengthy when there is a surplus to split. Another plausible reason is that when the effective spread is flexed up, the arranger always has the option of simply retaining a larger share of the loan instead of trying to find additional buyers.

C.2 Availability of break prices

As mentioned in Section 4, a potential sample selection issue could bias us against finding a significant negative relationship between underpricing and spread flex: It is possible that when investors show little interest in a deal in the primary market, such that the arranger needs to flex spread up substantially, they also show little interest in the secondary market, so we are less likely to observe a break price. Bookbuilding theory suggests that if underpricing were observed for such deals, it should be low. If true, this would mean that we are less likely to observe a break price for deals with low underpricing and positive spread flex. If we are missing such observations, then this should bias us against finding a significant and negative relationship between underpricing and

Table 16
Time-to-Syndication

Regressions of log time-to-syndication on loan characteristics at the deal level. Eff. Spr Flex Up (d) and Eff. Spr Flex Down (d) are equal to 1 if the effective spread was flexed up or down, respectively. Fund Flows are net flows into high yield mutual funds and CLO issuances measured in millions. Rated, Sponsored, Cov- lite, and Second Lien are dummies that indicate whether at least one facility within a deal is rated, sponsored, or classified as cov-lite or second lien, respectively. Log Talk Amount is the initially offered loan amount. Log Talk Yield is the initially offered all-in yield to maturity. Time fixed-effects are at the syndication month-year. (See Tables 1 and 2 for relevant summary statistics).

	(1)	(2)
	Log Synd. Time	Log Synd. Time
Eff. Spr Flex Up (d)	-0.00507	-0.00782
	(0.0132)	(0.0125)
Eff. Spr Flex Down (d)	0.00753	0.0272**
	(0.0128)	(0.0131)
Fund Flows	-0.00338	
	(0.00210)	
Rated	0.0163	0.0200
	(0.0161)	(0.0150)
Sponsored	-0.00782	-0.00627
	(0.0114)	(0.00868)
Cov-lite	0.0174*	0.0116
	(0.00953)	(0.00894)
Second Lien	-0.00945	-0.0260**
	(0.0153)	(0.0128)
Log Talk Amount	-0.00512	0.00306
	(0.00672)	(0.00686)
Log Talk Yield	0.0268	0.0651**
	(0.0296)	(0.0270)
Arranger FE	Yes	Yes
Purpose FE	Yes	Yes
Industry FE	Yes	Yes
Time FE	No	Yes
Observations	3693	3693
R^2	0.048	0.176

Standard errors in parentheses
SEs clustered by syndication month
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

spread flex.

To assess whether are less likely to observe a break price in cases in which the spread is flexed up, we estimate the following equation:

$$\textit{Break Price Dummy}_i = c + \alpha\, \textit{Log Talk Yield}_i + \beta_1 \textit{Spread Flex} + \beta_2 \textit{Discount Flex} + \gamma X_i + \epsilon_i, \quad (8)$$

Break Price Dummy is a variable that is 1 if there is a break price available for the deal. *Spread Flex* and *Discount Flex* assume that deals for which no spread flex (no discount flex) is observed represent deals with no spread flex (no discount flex). *Log Talk Yield* is the initial all-in yield to maturity at the beginning of the syndication process. We also control for additional loan characteristics (X_i) including in particular a dummy that indicates whether the loan is rated, the log maturity of the loan, and the log amount of the loan.

We also control for time-varying and market-wide institutional demand and overall risk appetite in three out of the four specifications, by including either time fixed effects or fund and CLO flows.

The results in Table 17 indicate that a break price is more likely to be available for larger, rated loans with a longer maturity. It is plausible that such loans are more likely to trade in a secondary market. A break price is also less likely to be available when the talk yield is higher. Possibly, the causality here is reversed: For loans that are unlikely to trade in the secondary market, investors demand a higher yield.

Once we control for all these effects, there is no significant relationship between spread flex (or discount flex) and the availability of a break price, whether or not we control for time-varying market-wide conditions with time fixed -effects or fund and CLO flows.

C.3

The SNC lead share is observed only on December 31. Given that deals take place throughout the year, the shares that we observe in SNC may not accurately reflect the share initially retained by

Table 17
Availability of break prices

Regressions of a dummy indicating the availability of the break price, Break Price (d), on loan characteristics at the deal level, and on spread flex and discount flex as a proxy of demand. Spread Flex and Discount Flex represent changes in the spread and discount over the syndication period and assume that if no change is reported, this is because there is no change. Fund Flows are net flows to high yield mutual funds and CLO issuances measured in millions. Rated, Sponsored, Cov- lite, and Second Lien are dummies that indicate whether at least one facility within a deal is rated, sponsored, or classified as cov-lite or second lien, respectively. Log Maturity is the log of the average maturity of institutional facilities. Log Talk Yield is the initially offered all-in yield to maturity. Log Amount is the log of the institutional loan amount. (See Tables 1 and 2 for relevant summary statistics).

	(1) Break Price (d)	(2) Break Price (d)	(3) Break Price (d)	(4) Break Price (d)
Log Talk Yield	-0.120***	-0.119***	-0.0869***	-0.0975***
	(0.0256)	(0.0254)	(0.0238)	(0.0251)
Spread Flex	-0.0000102	0.0000565	0.0000657	0.0000345
	(0.000126)	(0.000133)	(0.000120)	(0.000127)
Discount Flex		-0.0000892	-0.0000917	-0.0000981
		(0.0000859)	(0.0000808)	(0.0000822)
Fund Flows				-0.00240
				(0.00139)
Rated	0.144***	0.144***	0.145***	0.146***
	(0.0278)	(0.0277)	(0.0274)	(0.0275)
Sponsored	-0.00759	-0.00813	-0.00232	-0.000810
	(0.0117)	(0.0118)	(0.0132)	(0.0134)
Cov-lite	0.0158	0.0162	0.000938	0.00340
	(0.0124)	(0.0124)	(0.0115)	(0.0113)
Second Lien	0.0102	0.0107	-0.00172	0.00315
	(0.0174)	(0.0176)	(0.0166)	(0.0168)
Log Maturity (Years)	0.144***	0.143***	0.140***	0.136***
	(0.0361)	(0.0363)	(0.0358)	(0.0359)
Log Talk Amount	0.100***	0.100***	0.0992***	0.0990***
	(0.00889)	(0.00886)	(0.00916)	(0.00916)
Arranger FE	Yes	Yes	Yes	Yes
Purpose FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	No	No
Observations	3693	3693	3693	3693
R^2	0.368	0.368	0.316	0.317

Standard errors in parentheses
SEs clustered by syndication month
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

the lead arranger. In particular Aramonte, Lee, and Stebunovs (2015) document that banks sell substantial parts of their term loan shares in the first quarter after origination.

For this reason, the results in Table 6 are likely to underestimate the effect of flexes on lead shares. To get a sense of the bias, we run the same set of regressions as in Table 6 but on a sample restricted to only the deals that take place in the final quarter of each year. The idea is that the bias must be smaller if banks had less time to sell down their positions. The results are displayed in Table 18. In short, we lose power due to the drastic decrease in the number of observations, but the point estimates for β_1 are larger. Compared with the 20-26 percent relative increase in the lead share in the full sample, an 100 upward flex is now associated with a 28-43 percent increase.

C.4 Amount flex and spread flex

In some deals, the total amount that is issued can be flexed to match the amount that can be allocated to investors. This can be the case for instance when the loan is meant to finance a dividend to shareholders or a share repurchase. One should therefore observe that if amounts are flexed, they are flexed down when prices are flexed down (spreads or discounts are flexed up), and they are flexed up when prices are flexed up (spreads or discounts are flexed down). To test this, we estimate the following regression at the deal level, using the same sample that we use for our demand discovery tests:

$$\textit{Amount Flex}_i = c + \alpha \, \textit{Effective Spread Flex}_i + \beta X_i + \epsilon_i, \tag{9}$$

where $\textit{Amount Flex}_i$ is the change in the total institutional loan amount of deal i during the syndication process and $\textit{Effective Spread Flex}_i$ is the change in the spread during the syndication process. We control for additional loan characteristics (X_i) including whether the deal is rated, is sponsored, includes a covenant-lite facility, or includes a second lien as well as fixed effects for loan

Table 18
Lead Share - end year deals

Regressions of lead arranger share on spread flex and deal flow proxies, at the deal level. Lead Share is taken from the Shared National Credit Program and matched with deals in LCD with an estimated closing date from October to December, as described in the main text. (Lead Share is expressed as a fraction between 0 and 1.) Eff. Spread Flex, Spread Flex and Discount Flex represent changes in spread and discount over the syndication period and assume that when no change is reported, this is because there is no change. Fund Flows are net inflows into high yield mutual funds and CLO issuances measured in billions of dollars. Log Synd. Time is the log of the time between launch date and close date, in days. Rated, Sponsored, Cov-lite, and Second lien are dummies that indicate whether at least one facility within a deal is rated, sponsored, or classified as cov-lite or second lien, respectively. Log Maturity is the log of the average maturity of institutional facilities. Log Talk Amount is the log of the initially proposed total institutional loan amount. Log Talk Yield is log of the initially offered all-in yield to maturity. Time fixed-effects are at the syndication month-year.

	(1) Lead Share	(2) Lead Share	(3) Lead Share	(4) Lead Share	(5) Lead Share	(6) Lead Share	(7) Lead Share
Eff. Spread Flex	0.000151	0.000204**	0.000160*	0.000226	0.000222		0.000328*
	(0.000105)	(0.0000923)	(0.0000920)	(0.000136)	(0.000135)		(0.000163)
Spread Flex						0.000296*	
						(0.000161)	
Discount Flex						-0.0000563	
						(0.000114)	
Fund Flows	0.000461						
	(0.00120)						
Log Synd. Time					-0.0136		
					(0.0277)		
Rated	-0.0246**	-0.0203*	-0.0150	-0.0264	-0.0262	-0.0266	0.00867
	(0.0112)	(0.0118)	(0.0116)	(0.0171)	(0.0173)	(0.0166)	(0.0479)
Sponsored	-0.00687	-0.00269	-0.00754	-0.0207	-0.0198	-0.0212	-0.0524
	(0.0118)	(0.0145)	(0.0132)	(0.0169)	(0.0164)	(0.0169)	(0.0409)
Cov-lite	0.00232	-0.00165	0.00353	0.0118	0.0121	0.0122	0.0162
	(0.0157)	(0.0150)	(0.0160)	(0.0231)	(0.0228)	(0.0225)	(0.0313)
Second Lien	-0.01000	-0.00241	0.00453	0.00456	0.00449	0.00322	0.00914
	(0.0135)	(0.0130)	(0.0115)	(0.0161)	(0.0158)	(0.0160)	(0.0369)
Log Maturity (Years)	-0.0134	0.00205	-0.0254	-0.00833	-0.00873	-0.00891	0.00692
	(0.0227)	(0.0261)	(0.0264)	(0.0349)	(0.0353)	(0.0347)	(0.0893)
Log Talk Amount	-0.0176***	-0.0207***	-0.0146***	-0.0198***	-0.0197***	-0.0194***	-0.0193
	(0.00388)	(0.00536)	(0.00490)	(0.00721)	(0.00719)	(0.00712)	(0.0144)
Log Talk Yield							-0.00949
							(0.0539)
Purpose FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	No	Yes	Yes	Yes	Yes	Yes	Yes
Arranger FE	No	No	Yes	No	No	No	No
Arranger-Year FE	No	No	No	Yes	Yes	Yes	Yes
Observations	456	487	486	486	486	486	195
R^2	0.228	0.385	0.519	0.722	0.723	0.723	0.790

Standard errors in parentheses
SEs clustered by syndication month
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

purpose, borrower industry, lead arranger, and deal month-year.

Table 19 shows the results of estimating Equation (9). We interpret not observing amount, spread, or discount flex as indicating that amounts, spreads, or discounts were not flexed for those deals. In column (1), we omit deal month-year fixed effects and control for net inflows to high yield mutual funds and CLO issuances to control for institutional demand and overall risk appetite. Consistent with our hypothesis, the point estimate on effective spread flexes is negative and highly significant. The coefficient on fund and CLO flows is positive, indicating that in times of inflows, amounts are more likely to be increased.

In column (2), we disaggregate the effective spread flex into its two components, the spread flex and the discount flex. The point estimate on the spread flex is the same magnitude as the coefficient on the effective spread flex in column (1), while the coefficient on the discount flex becomes is considerably smaller and insignificant. This finding suggests that flexes in the spread are the crucial margin of adjustment during the syndication process. In column (3) and (4), we include deal month-year fixed effects. The point estimates remain almost unchanged.

C.5 Effective spread flex, arranging, and participations in times of stress

In subsection 5.2, we show that an arranger who experiences positive net flex is likely to reduce the number and volume of arranged loans and is also likely to reduce participations in new credit lines. Here, we ask whether these effects are stronger in times of bank stress. We proxy for bank stress via a dummy which indicates when the level of the 3-month TED spread (computed as LIBOR minus the corresponding treasury rate) exceeds its 75th percentile over the sample period (High TED). We would expect that the effect of net flex on the outcome variables should be stronger (more negative) in times of stress and, hence, augment our regressions by including an interaction

Table 19
Amount flex, OID flex, and Spread flex

Regressions of total institutional amount flex on effective spread flex, original issue discount flex, and spread flex, at the deal level. Amount Flex, Spread Flex, Effective Spread Flex, and Discount Flex represent changes in amounts, spreads, effective spreads (see Equation (2)), and discounts, respectively, over the syndication period and assume that when no change is reported, this is because there is no change. Rated, Sponsored, Cov- lite, and Second Lien are dummies that indicate whether at least one facility within a deal is rated, sponsored, or classified as cov-lite or second lien, respectively. Log Maturity is the log of the average maturity of institutional facilities. Log Talk Yield is log of the initially offered all-in yield to maturity. Log Talk Amount is the log of the initially offered institutional amount. Fund Flows are net inflows into high yield mutual funds and CLO issuances measured in millions. (See Tables 1 and 2 for relevant summary statistics). Time fixed-effects are at the syndication month-year.

	(1)	(2)	(3)	(4)
	Amount Flex	Amount Flex	Amount Flex	Amount Flex
Eff. Spread Flex	-0.201***		-0.188***	
	(0.0472)		(0.0486)	
Discount Flex		-0.00789		-0.00213
		(0.0270)		(0.0281)
Spread Flex		-0.261***		-0.251***
		(0.0772)		(0.0795)
Fund Flows	0.949**	0.945**		
	(0.429)	(0.431)		
Rated	8.069	8.119	6.722	6.812
	(5.753)	(5.748)	(5.724)	(5.736)
Sponsored	1.672	2.043	0.736	1.152
	(6.902)	(6.949)	(7.195)	(7.258)
Cov-lite	15.73**	15.31**	14.72*	14.30*
	(6.973)	(6.972)	(7.739)	(7.682)
Second Lien	-11.90**	-12.08**	-10.26	-10.48
	(5.721)	(5.753)	(6.456)	(6.465)
Log Maturity (Years)	-4.264	-4.125	2.421	2.689
	(10.73)	(10.72)	(11.72)	(11.75)
Log Talk Yield	27.02***	26.49***	23.29**	22.79**
	(9.907)	(9.839)	(11.01)	(11.04)
Log Talk Amount	0.744	0.579	-0.360	-0.512
	(6.648)	(6.718)	(7.216)	(7.278)
Arranger FE	Yes	Yes	Yes	Yes
Purpose FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Time FE	No	No	Yes	Yes
Observations	3693	3693	3693	3693
R^2	0.043	0.044	0.061	0.061

Standard errors in parentheses
SEs clustered by syndication month
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

of net flex with High TED.

Table 20
Net flex, arranging, and participations in times of stress

Bank-level regressions of number of arranged term loans (# TL Arranged) and amounts of arranged term loans ($ TL Arranged), as calculated from S&P Capital IQ LCD, and of new participations in term loans and credit lines (Total Lending), in term loans only (TL Lending), and in credit lines only (CL Lending), as calculated from SNC. Net loans with positive flexes is the difference of loans with positive and negative effective spread flexes in a quarter in the LCD data. Net amount with positive flexes is the difference of loan amounts of loans with positive and negative effective spread flexes in a quarter in the LCD data. Time fixed-effects are at the syndication-quarter level. High TED is a dummy variable that indicates times in which the level of the TED spread exceeds its 75th percentile over the sample period.

	(1)	(2)	(3)	(4)	(5)
	# TL Arranged	$ TL Arranged	Total Lending	CL Lending	TL Lending
Net Loans with Positive Flexes$_{t-1}$	-0.410*				
	(0.206)				
Net Loans with Positive Flexes$_{t-1}$ × High TED	-0.0419				
	(0.477)				
L.Net Amount with Positive Flexes$_{t-1}$		-0.439**	-0.106	-0.126*	0.00894
		(0.177)	(0.0835)	(0.0702)	(0.0230)
Net Amount with Positive Flexes$_{t-1}$ × High TED		-0.0314	-0.461**	-0.179	-0.170**
		(0.255)	(0.188)	(0.147)	(0.0806)
# TL Arranged$_{t-1}$	0.368***				
	(0.0606)				
$ TL Arranged$_{t-1}$		0.344***			
		(0.0647)			
Total Lending$_{t-1}$			0.372***		
			(0.0958)		
CL Lending$_{t-1}$				0.379***	
				(0.0813)	
TL Lending$_{t-1}$					0.257***
					(0.0917)
Arranger FE	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes
Observations	2912	2912	1035	1035	1035
R^2	0.819	0.756	0.890	0.896	0.755

Standard errors in parentheses
SEs clustered by quarter.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

In Table 20 the interaction terms are all negative, although they are not all significant. While times of stress, as measured by High TED, do not appear to matter significantly for the relationship between net flex and the number or amount of arranged term loans, they do appear to matter for new participations, especially for participations in term loans. We can see that in times of stress, flexing spreads up on an additional $1,000m of term loans suggests a decrease in new term loan participations of about $160m. New participations are also reduced, but not significantly differently

so in times of stress. In times of stress, flexing spreads up on an additional \$1,000m of term loans produces a drop in new total participations of about \$570m — a much larger effect than the average effect over times with and without stress.

D Comparison of the LCD data to DealScan data

In this appendix, we compare the LCD data with the data in Thomson Reuters DealScan, which is more commonly used for research on syndicated loans.

We first show that the number of deals that include leveraged institutional term loans are roughly equal in both datasets. We then try to match up deals in both datasets directly and find that we can match up between about 30-50% directly (depending on the exact matching criteria). Finally, we check that while lead arranger share can be computed for about 18% of all deals in DealScan, this fraction drops to about 4% of deals when considering only deals that contain leveraged institutional loans.

The main conclusions from these comparisons are as follows: For deals that contain leveraged institutional loans, both datasets cover a similar number of deals. Also, while there is a substantial degree of overlap, at the same time there are deals in either dataset that cannot be matched to the other. Finally, the proportion of leveraged institutional deals in DealScan for which a lead share is available is very low. This means that any empirical analysis of such deals that involves lead share can only be conducted on a very small number of deals, but also that there appears to be a systematic difference in the reporting of lead share for leveraged institutional versus other types of deals in DealScan.

D.1 Number of deals in both datasets

Our LCD data describes deals launched in the US leveraged loan market between January 1, 1999 and October 15, 2015. To find the comparable deals within DealScan, we first restrict ourselves to deals that have a "deal active date" in the same range as the "launch date" in LCD.[31] We also restrict ourselves to deals for which the country of syndication was the USA and which were syndicated in USD. We call the resulting set of 64,373 deals "DealScan (US)."

We then define the subset of leveraged deals within DealScan (US), based on the definition used by LCD: LCD defines a leveraged loan as a loan that is either rated non-investment grade, or is secured by a first or second lien and has a spread of 125bps or higher. Because we do not have access to a rating in DealScan, we use the second part of this definition.

First, we compute the spread as the difference between the all-in-drawn spread and the all-in-undrawn spread as reported in DealScan.[32] We then define a facility in DealScan as leveraged if it is secured and has a spread of 125 bps or more. We define a facility as non-leveraged if is either unsecured or has a spread of less than 125 bps.

Our definition is slightly different from that of LCD. Under our definition, all unsecured facilities are non-leveraged, while according to LCD, an unsecured facility could be still be leveraged if it is rated non-investment grade. In practice, given the risk of these loans, lenders will insist on collateral in the vast majority of cases. For instance, in the LCD data, only about 2% of the deals contain facilities that are unsecured, so we are confident that this difference in definitions does not have quantitatively important consequences.

We then classify a deal as leveraged if it contains at least one leveraged facility and non-leveraged

[31] The difference in the dates that we use here will introduce a slight discrepancy as deal typically close 4-6 weeks after being launched.

[32] The all-in-drawn spread includes commitment and annual fees paid for revolvers, which is not part of the spread used by LCD in the definition of a leveraged loan.

if all classified facilities for that deal are non-leveraged. We cannot classify a deal if none of the facilities within the deal can be classified. We have 23,397 leveraged deals, 16,432 unleveraged deals, and 24,544 unclassified deals.

In our analysis, we restrict ourselves to deals which contain at least one institutional term loan, meaning non-amortizing term loans (Term Loan B or higher). In DealScan, we can identify these as loans with loan type "Term Loan B," "Term Loan C," ..., "Term Loan K." There are also some loans labeled simply as "Term Loans." This label is not specific and could designate either loans which are actually amortizing term loans (Term Loan A) but it could also designate additional institutional term loans (Term Loan B and higher). A broader definition could also include these, but we exclude them here.

We can then define a "leveraged institutional deal" as one which has at least one leveraged institutional facility. There are 10,024 such deals. This is slightly higher than our 8,816 deals with at least one institutional facility in LCD. As illustrated in Figure 8, DealScan appears to have slightly more of these deals in the earlier part of the sample, but in the later part of the sample, the number of deals line up well. (With the broader definition alluded to above, we would obtain 13,721 leveraged institutional deals.)

D.2 Matching deals in both datasets

We now examine to what degrees both datasets overlap for leveraged institutional deals. We match deals by borrower name and approximate date, meaning that the "deal active date" in DealScan must be within 3 months of the estimated closing date in LCD. This results in 5,707 matched deals, out of a total of about 12,071 deals in LCD, representing about 47% of the total LCD sample.[33] In

[33] A fraction of these deals have substantially different deal sizes in both datasets, potentially because facilities are missing in either the DealScan or the LCD description of the deal. If we restrict ourselves to deals with reported sizes which are, e.g., within 10% of each other, the number of matched deals is reduced to 4,010.

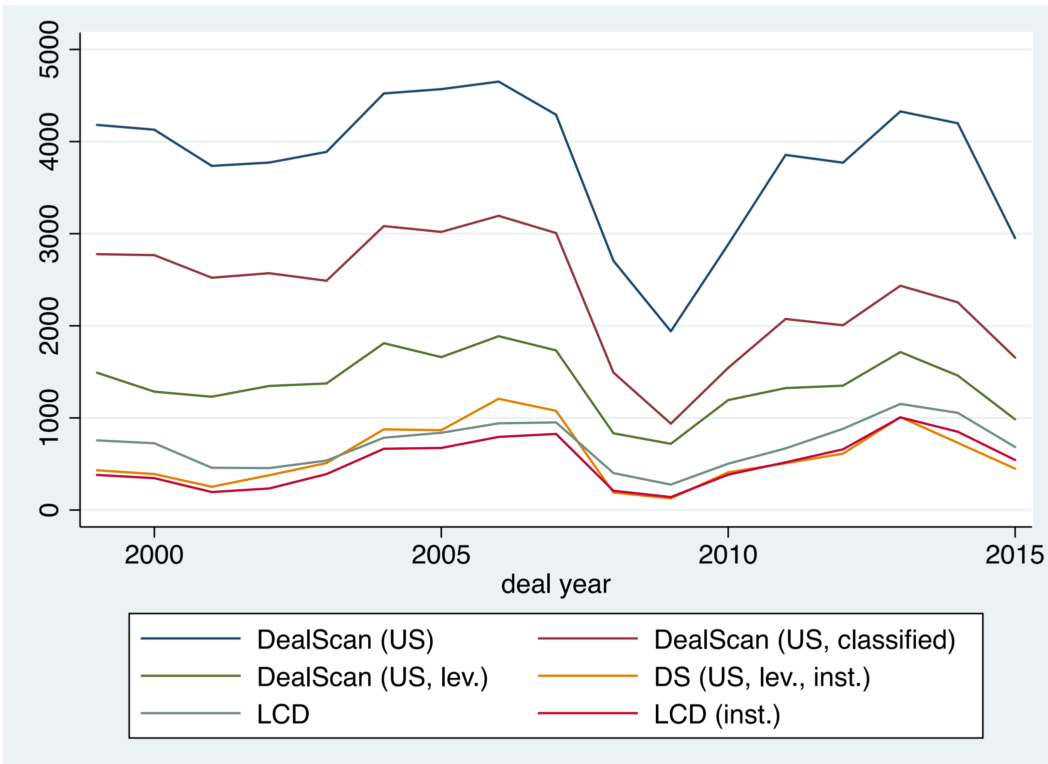

Figure 8. Number of deals in DealScan and LCD over time

Number of deals in Thompson Reuters LPC DealScan and S&P Capital IQ LCD over time. DealScan (US) are all deals syndicated in the USA and in USD. DealScan (US, classified) are deals that can be classified as either leveraged or non-leveraged. DealScan (US, lev.) are deals that can be classified as leveraged, that is, contain at least one leveraged facility. DealScan (US, lev., inst.) are deals that contain at least one leveraged institutional facility. LCD and LCD (inst.) are all deals and all deals with at least one institutional facility in LCD, respectively.

our regressions in the main text, we only consider deals with at least one institutional facility. There are 8,816 of such deals in LCD. Out of this subset, 4,045 deals (or about 46%) can be matched to DealScan.

We can try to evaluate how good our definition of a "leveraged institutional deal" is for predicting whether a deal is in the set of LCD deals with at least one institutional facility: Out of the 4,045 LCD deals with at least one institutional facility that we can match to DealScan, 3,516 fall into our category of "leveraged institutional deals," 297 do not, and 232 cannot be classified. This suggests that the estimated probability of a type II error is $297/(297+3{,}516) \approx 8\%$. (Using the broader definition of "institutional loan" alluded to above, i.e., including all "Term Loans" the estimated type II error would be $\approx$3%.) We do not have any information on false positives and so unfortunately cannot estimate the probability of a type I error. Nevertheless, the low probability of a type II error suggests that our definition of a "leveraged institutional deal" is at least somewhat reasonable at identifying a subset of loans within DealScan that is similar to the LCD deals with institutional facilities.

Overall, we conclude that there is a substantial degree of verifiable overlap between LCD and DealScan. At the same time, there is also a substantial number of deals which cannot be matched up.

D.3 Lead share in leveraged institutional deals in DealScan

From data in DealScan, we compute a deal-level lead arranger share as in Sufi (2007), but using the slightly broader definition of a lead arranger of Bharath, Dahiya, Saunders, and Srinivasan (2011).

We have the lead share for 11,381 out of 64,373 deals in DealScan (US), or about 18%. However, we have the lead share for only 402 out of 10,024 leveraged institutional deals in DealScan (US), or about 4%. Similarly, we have the lead share for 160 out of 4,045 deals that we can match to our

(institutional) LCD deals, or about 4%. We draw two conclusions from these numbers. First, they suggest a potential sample selection issue in DealScan for research that relies on this data. Second, it is difficult to examine how lead share as reported in DealScan relates to flex in leveraged loans due to a small sample size.