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Abstract

We challenge theories that lead arrangers retain shares of syndicated loans to overcome information asymmetries. Lead arrangers frequently sell their entire loan stake—in over 50 percent of term and 70 percent of institutional loans. These selloffs usually occur days after origination, with lead arrangers retaining no other borrower exposure in 37 percent of selloff cases. Counter to theories, sold loans perform better than retained loans. Our results imply that information asymmetries could be lower than commonly assumed or mitigated by alternative mechanisms such as underwriting risk. We also provide guidance for Dealscan users on how to approximate loan ownership after origination.

Key words: syndicated lending, loan sales, lead arranger

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1 Introduction

According to classical theories on the role of banks in lending contracts, lead arrangers should retain a significant share of the loans they help syndicate. This follows from the argument that they possess an informational advantage, relative to other lenders, and are typically tasked with loan monitoring. The retention argument therefore relies on two motives: the avoidance of adverse selection (Leland and Pyle (1977)) and the mitigation of moral hazard (Gorton and Pennacchi (1995), Holmstrom and Tirole (1997)). Consistent with these theories, prior studies have found empirical evidence suggesting that the loan stake of the lead arranger – the lead share – serves as a mechanism to overcome these asymmetric information problems in the syndicated loan market (Sufi (2007), Ivashina (2009), Benmelech et al. (2012)). This has led to the conventional wisdom that lead arrangers do not sell their lead share.

However, most prior studies have relied on loan origination data from Dealscan. Using Dealscan data presents researchers with two issues. First, lender shares at origination are only reported for a very small set of loans. Moreover, the reporting of lender shares is non-random, leading to a potential sampling bias. Second, almost no institutional investors participate in the loan syndicate at origination. Instead, they purchase loan shares in prearranged transactions within days of origination. As institutional investors have become a major force in this market (Irani et al. (2021), Fleckenstein et al. (2020)), the lender composition as observed at origination is often not representative of the actual loan ownership a few days after origination. These observations lead us to revisit the role of the lead share using both Dealscan data for the loan ownership at origination and the Shared National Credit Registry (SNC) data, which is maintained by the three bank supervising institutions in the US (The FDIC, OCC and FRB), and tracks the loan ownership over time.

How can researchers, who only have access to Dealscan data, approximate lending by syndicate members? First, we show that the reported shares for loans are fairly accurate for loans that are more targeted at banks, such as credit lines and Term A loans, and therefore see less turnover after origination. Second, for loans that have no lender shares reported or are targeted at institutional investors, we propose approximating the lender shares of syndicate members after origination with various loan characteristics available in Dealscan, based on a regression that we fit with SNC holdings data. We show that this method vastly outperforms commonly used methods in the literature such as imputing lender shares based on the syndicate structure (e.g., Chodorow-Reich (2014)).

We then turn to the role of the lead arranger's share in syndicated loan transactions. We formulate and test three hypotheses about the lead arranger's share implied by information asymmetry theories. First, the lead arranger should rarely sell its stake because of the issues resulting from moral hazard and adverse selection. Second, the lead arranger should be less likely to sell its loan share than other banks that are also part of the loan syndicate. This follows from information advantage of the lead arranger and its delegated task of screening and monitoring the firm. Third, loans that are entirely sold by the lead arranger should perform worse, on average. After all, without exposure to the firm, the lead arranger has no incentive to monitor the firm. In addition, it should prefer to sell loans that it privately knows are of worse quality.

Inconsistent with the first hypothesis, we find that the lead arranger frequently sells its entire loan share. The lead arranger sells its entire share for 13% of all loans and for 32% of all term loans prior to loan maturity. Moreover, lead share sales are most frequent (61%) for loans preferred by institutional investors, such as Term B loans. Weighting loans by their outstanding dollar amounts reinforces that picture: over 50% of the outstanding term loan dollars are part of a loan in which the lead arranger has no stake at some point over the loan duration. This number is even higher (73%) for institutional term loans.

Importantly, we find that the lead arranger typically sells its entire exposure within days of origination. Because many of these transactions are pre-arranged prior to origination, the lead arranger never has any post-origination exposure to these loans. Potentially, the lead arranger could retain sufficient skin-in-the-game by investing in other loans of the same borrower. However, we find that this is often not the case. For 37% of the loans in which the lead arranger sells its stake, it has no other loan exposure to the same borrower.

Inconsistent with the second hypothesis, the lead arranger is as likely to sell off its entire share as any other bank lender that participates in the syndicate.

Finally, inconsistent with the third hypothesis, we find no evidence that sell-offs by lead arrangers induce issues of averse selection and moral hazard. We find that loans in which the lead bank retains its share are more – not less, as predicted by theory – likely to become non-accruing (i.e., miss a payment) in the future. Our baseline results show that a sale of the entire lead share by the arranger is associated with an approximately 1% lower probability that the loan becomes non-accruing in the future. This coefficient is economically large, considering that the unconditional probability of a loan being classified as non-accruing in the SNC data is only 3.4%. The relationship holds when controlling for ex-ante default risk with three different measures: (a) the all-in-drawn spread at origination, (b) the lead arranger's internal risk rating of the loan, and (c) external ratings from rating agencies. The result is also robust to various other specifications. For example, it holds when limiting the sample to loans that we observe immediately after origination, such that our covariate only picks up immediate (or pre-arranged) loan sales by the lead arranger.

We view these results as evidence that the loan share retained by the lead arranger does not play the role emphasized in the prior literature. What does this imply for any potential information asymmetries between lenders in the syndicated loan market? One possibility is that the degree of information asymmetry between the lead arranger and other lenders is lower than previously assumed. For one, a large part of institutional investment vehicles in the syndicated loan market, e.g., collateralized loan obligations (CLOs), are actively managed and presumably conduct their own due diligence. These investors can collect soft information about the borrower through access to its management during the syndication process and obtain outside opinions through public ratings. Accordingly, there might be less need for an incentive mechanism – such as the lead share – to signal the quality of the loan. Another possibility is that information asymmetries are mitigated by other mechanisms that incentivize the lead arranger to perform the screening or monitoring it was delegated to do. Importantly, these two explanations are not mutually exclusive but might even be interlinked as weaker information asymmetries might allow for other incentive mechanisms (especially if they are less costly than retention). We propose two incentive mechanisms that could be at work in the loan market.

First, the lead arranger's commitment to underwrite loans entails the risk that (bad) loans end up on its balance sheet, i.e., the lead arranger is exposed to a form of "pipeline risk" (Bruche et al. (2020)).¹ Facing the prospect of holding a (bad) loan on its balance sheet incentivizes the lead arranger to conduct due diligence before agreeing to underwrite a loan.² This can be tested, for instance, by looking at shocks to the borrower or the economy during the syndication process. Second, repeated interactions between the lead arranger and other lenders in the loan market entail reputation risks for the lead arranger when syndicating bad loans (Gopalan et al. (2011), Hartman-Glaser (2017), Winton and Yerramilli (2021)). The potential loss of underwriting revenue as a result of underwriting bad loans could give the lead arranger faces the risk that underwriting bad loans leads to negative consequences. We therefore use the term "underwriting risk" to describe them.

We conduct a number of tests suggesting that pipeline and reputation risks are present in the syndicated loan market and might therefore function as alternative incentive mechanisms. First, we show that the lead arranger is less likely to sell its share when negative information about the borrower arises during the syndication process, consistent with pipeline risk. Pipeline risk can also explain part of the differential performance of retained and sold loans

¹Pipeline risk has recently made headlines in the financial press, because the ECB is concerned about the risks to major banks arising from their loan underwriting business (see FT article "ECB threatens banks with capital 'add-ons' over leveraged loan risks."). For example, Deutsche Bank suffered multimillion-dollar losses after it struggled to offload two risky corporate loans that it agreed to underwrite for private equity clients (see FT article "Deutsche Bank rebuffed ECB over call for action on leveraged finance.").

²The argument is similar in spirit to Hartman-Glaser et al. (2012). They argue that temporary retention can suffice to induce proper due diligence. We argue that retention with some probability (i.e., when pipeline risk materializes) might suffice to induce proper due diligence.

conditional on the loan spread. We find that the differential performance between sold and retained loans significantly widens following a negative shock to the borrower's prospects during the syndication process. After all, the lead arranger is often bound by the underwriting commitment not to increase the loan spread beyond some upper limit. Second, we find that when loans that the lead arranger underwrote turn sour, the lead arranger's market share in loan underwriting drops subsequently, consistent with a loss in reputation. This implies a fall in underwriting fees collected by the lead arranger. These results indicate that loan underwriting is a risky business, but one that is also rewarded with high fee revenue. We perform a series of quantification exercises to show that both are economically meaningful.³

Literature review. We contribute to a large literature that studies the role of information asymmetry problems in lending markets. Seminal papers argue that the two issues resulting from asymmetric information, adverse selection and moral hazard, are mitigated when the lead bank retains part of the loan on its balance sheet (Leland and Pyle (1977), Gorton and Pennacchi (1995), Holmstrom and Tirole (1997)).⁴ Hartman-Glaser et al. (2012) and Gryglewicz et al. (2021) show theoretically that lead arrangers do not need to retain their share permanently, but merely for a sufficiently long time to induce screening and monitoring. Several empirical studies have applied these theories to the syndicated loan market, typically using Dealscan data. Sufi (2007) shows that the lead arranger has a larger syndicate share for loans with stronger monitoring requirements, consistent with information asymmetry theories of the lead share. Similarly, Ivashina (2009) finds that a larger share held by a lead bank at origination reduces the spread demanded by investors. To the best of our knowledge, we are the first to test these theories using actual loan holdings shortly after origination as observed in the SNC data, and our results question the importance of the lead share in

 $^{^{3}}$ According to Bloomberg estimates, the top 10 lead arrangers earned underwriting revenues of more than 9 billion USD in 2021 (enter "LEAG @USLOAN" into the Bloomberg terminal).

⁴The theoretical result of Hébert (2018) suggests that if the lead arranger needs to retain a share to overcome moral hazard, it would optimally retain an "equity" slice of the loan it originates.

mitigating information asymmetry problems in syndicated loans.⁵

Retention theories apply not only to syndicated loans but more generally to all loans originated by an intermediary. A large literature has studied banks' incentives in mortgage origination following the large number of mortgage defaults during the global financial crisis. In contrast to our findings, this literature finds loan retention by the originating bank to have a strong positive effect on loan quality. For instance, Keys et al. (2010) and Keys et al. (2012) find that loans that were more likely and took less time to be securitized and for which the originating bank consequently retained less or even no economic exposure were substantially more likely to default, conditional on observable risk. Purnanandam (2011) finds similar results on the bank level. Moreover, Begley and Purnanandam (2017) provide evidence that residential mortgage-backed securities with a larger equity tranche – and thus more retention by the originating bank – invested in loan pools that performed better ex-post. One reason for the differing result could be that information asymmetries between the originating bank and ultimate investors are weaker in the syndicated loan than in the mortgage market. Most funds investing in syndicated loans are actively managed, obtain detailed financial information about the borrower and can collect soft information through access to its top management during the syndication process. Consequently, the information asymmetry between lenders might be weaker than previously assumed. Alternatively, mechanisms other than retention might suffice to induce proper screening by the originating bank.

Our findings support the theories proposed by Hartman-Glaser (2017) and Winton and Yerramilli (2021). They study asset sales in which the originating agent can build reputation, which allows for an equilibrium without adverse selection and moral hazard, despite no or very little retention. In particular, our finding that lead banks experiencing defaults with the loans they originated are punished, supports the prediction by Winton and Yerramilli (2021), and confirms findings by Gopalan et al. (2011) using Dealscan.

⁵Other notable studies that use the lead share as reported in the SNC data are Bord and Santos (2012, 2015), Bruche et al. (2020), Gustafson et al. (2021), Paligorova and Santos (2018), Santos and Shao (2018), Irani et al. (2021), and Balasubramanyan et al. (2019) though they do not analyze the question we work on here.

Our study contributes to the literature that has examined loan sales of banks without focusing on the lead bank.⁶ It also connects to a growing literature that focuses on the "originate-to-distribute" practice in the syndicated loan market and its implications Bord and Santos (2012).⁷ Finally, our study is also related to Gustafson et al. (2021) who find that directly measured monitoring efforts by the lead bank are positively correlated with its retained share, consistent with the theory proposed by Holmstrom and Tirole (1997). However, they also find that loans with a higher lead share are more likely to violate covenants, consistent with our finding that loans with positive lead share perform worse.

The rest of the paper is organized as follows. Section 2 describes the data and provides some institutional background on loan syndications. Section 3 discusses theories on asymmetric information and derives testable hypotheses. Section 4 empirically tests these hypotheses. Section 5 provides evidence for alternative incentive mechanisms. Section 6 concludes.

2 Data & Institutional Background

2.1 Data

SNC. Our primary data is loan-lender-time-level data from the Shared National Credit (SNC) registry, which is maintained by the Board of Governors of the Federal Reserve Sys-

⁶Several papers have examined corporate loan sales banks without specifically focusing on the lead bank. For instance, Drucker and Puri (2009) find that loans which trade in the secondary market have more covenants and firms whose loans are traded benefit from increased debt availability. Similarly, Gande and Saunders (2012) find a positive stock price reaction when a firm's loan is first traded in the secondary market, consistent with the alleviation of the firm's financial constraints. In contrast, Dahiya et al. (2003) using a small sample of seasoned loan sales find a negative price reaction consistent with an informational advantage by banks compared to equity market investors.

⁷Lee et al. (2019a) show that for leveraged term loans the average share retained by the lead agent declines from about 20% to only 2% within 90 days after origination. More generally, Lee et al. (2019b) show that for leveraged term loans the average share held by banks drops from over 80% to under 20% in the same period after origination. Hu and Varas (2020) study theoretically the credit market dynamics and banks' financing when arranging banks can sell their share. Bruche et al. (2020) focus on one important aspect of the originate-to-distribute business model: pipeline risk. They show that the lead share is larger for loans that experience lower than expected demand, consistent with pipeline risk. We also find evidence that supports this theory.

tem, the Federal Deposit Insurance Corporation, and the Office of the Comptroller of the Currency. The data encompasses information for all syndicated loans with a minimum aggregate commitment of USD 20 million⁸ which are held by at least three federally supervised institutions.⁹ The administrative agent of a qualifying loan – usually the lead arranger – is obliged to report detailed information about the loan as well as the commitment held by each loan participant. The reporting frequency is annual before 2015, quarterly in 2015, and semi-annual in the years 2016 to 2018.

Crucially, for our purposes, the lead bank must report details on the loan, even if they are no longer in the syndicate. Thus, the SNC data allows us to observe the lead arranger's share and the share held by other lenders at the end of every reporting period over the entire loan duration. We want to stress that the SNC data does not allow us to observe the lead share at loan origination, but only at each of the SNC report dates. In addition to loan holdings, the SNC contains information on loan characteristics such as the loan's size, lead banks' internal loan ratings, whether a loan is non-accruing, and whether parts of a loan are rated non-pass by Federal Reserve Examiners.

The SNC data reports the facility of each loan deal separately. Thus, when a loan deal consist of a credit line and a term loan, we obtain separate information on the two loans and can therefore observe the lead arranger's stake in each facility. We treat such loans as distinct throughout our analyses, but track such commitments for the purpose of assessing aggregate lead agent exposure to a borrower. We are additionally able to distinguish between newly originated and renegotiated loans. For the purpose of cleanly identifying the effects in question, we focus only on newly originated loans in the analyses below.

We aggregate loan holdings to the holding company level. For bank entities, we therefore aggregate up to the bank holding company level. While aggregating, we exclude funds that

 $^{^{8}}$ We end our data in 2018, to avoid an issue with sample selection. The threshold for loans captured by the SNC was raised to USD 100 million effective January 1, 2018.

⁹This also encompasses loan facilities that are part of a loan agreement that includes another loan facility that is held by at least three federally supervised institutions. A detailed description of the reporting requirements can be found under https://www.kansascityfed.org/banking/bankerresources/complete-and-file-reports/shared-national-credit.

are managed by bank holding companies, which do not invest the bank's money.¹⁰ We allow for bank mergers in our sample, aggregating the holdings of individual banks in the reporting period in which the merger occurs. However, the majority of our analyses are focused on the period directly following loan origination. These are largely unaffected by merger considerations.

Our sample starts in 1993 and ends in 2018. In order to have a consistent panel, in which we observe each loan shortly after origination, we exclude loans that are first observed in the SNC more than 400 days after their origination. This mostly excludes loans that were originated before 1993 or loans that meet the SNC requirements at a later date, after their origination.¹¹ After dropping these loans, our final sample contains 71,007 loans.

Dealscan. We obtain further loan information from Refinitiv Dealscan LPC. Most of this data is self-reported by lead arranging banks to Refinitiv. The purpose of this self-reporting is for banks to better their standing in the 'league table' of arrangers. Refinitiv requires the lead arranger to report any loan deal within 15 days of its closing date and to provide some deal details.¹² The lead arranger sometimes report the lenders' individual shares in the origination syndicate, though this information is frequently not available.

We limit the sample to loans for which the all-in-drawn spread and the loan purpose are available. We then merge the Dealscan data with the SNC data on the loan-level using a fuzzy match algorithm similar to Cohen et al. (2018), based on the borrower name and a conservative definition of common loan variables. In total, we are able to match 21,180 Dealscan loans to the SNC loan sample. We then also match lenders in both data sets to

¹⁰This has no impact on the results as most asset managers of loan mutual funds or CLOs are not affiliated with any bank.

¹¹In total, we drop 21,171 loans due to this requirement.

¹²The lead arranger needs to provide the borrower name; the total deal and individual facility (tranche) types and amounts; new or incremental amount (if upsizing, add-on or meets Refinitiv LPC definition of "new money"); the deal purpose; the financial close/closing date; the tenor or maturity date of individual tranches; the full-titled lender group including bookrunners, lead arrangers, agents, arrangers, and any non-titled lenders; sponsor name; base rate; margin and fees at close; identification of all second lien ABL, PIK, Green, ESG, or unitranche facilities; borrower sales and EBITDA (if requested by Refinitiv); borrower industry and SIC or NAIC code (if requested by Refinitiv); and borrower state and country.

get a loan-lender match based on lender names. Given the manual nature of this match, we focus on the lenders with the largest (cumulative) exposure to the syndicated loan market. We merge well over 80% of lenders in our joint loan sample.

The combined data is ideal for our study. We observe the syndicate structure at loan origination (from Dealscan) as well as the loan's true owners once a loan has been originated (from SNC). This allows us to see the degree to which the lender composition changes over time – and when the most pronounced changes occur.

Summary statistics. Columns 1-3 of Table 1 show summary statistics for the main variables used throughout the paper. The remaining columns of the table are discussed further in Section 4. 21% of the loans are term loans. The average loan in the data has a loan size of USD 296 million and a maturity of 4.43 years. The average all-in-drawn spread is 225 basis points. 3.4% of the loans in our sample became non-accruing over their life, which means that there was some form of payment default for the lender.¹³ The fraction of loans that were rated non-pass and therefore considered at risk of suffering a payment default is higher at 16.45%. We use these two variables to measure the ex-post performance of loans. The correlation between the two variables is 43%. Term loans are slightly more likely to become non-accruing or be rated non-pass, at 3.9% and 17.9% respectively.

2.2 Institutional Background

Syndication process. In this section, we describe the syndication process with an emphasis on (1) when different types of lenders join the syndicate, and (2) their respective roles.¹⁴ A firm that decides to raise syndicated loan financing solicits bids from several potential arranging banks, which outline their syndication strategy, qualifications, and preliminary arrangement terms. Before submitting their bids, banks often have only a few days to con-

¹³This is reported in Table 4.

 $^{^{14}}$ For details on the syndication process with an emphasis on the risk-sharing between firms and banks we refer to the excellent description by Bruche et al. (2020).

	Ν	Mean	SD	Mean sold	Mean not-sold	Diff.	R^2
Loan Characteristics							
Maturity (in years)	71,007	4.43	2.20	5.78	4.29	1.50^{***}	0.04
Loan size (in million USD)	71,007	296	651	378	287	93***	0.00
Term loan	71,007	0.21	0.41	0.55	0.17	0.38^{***}	0.07
Term loan B	71,007	0.03	0.16	0.13	0.02	0.12^{***}	0.05
All-in-drawn spread (in %)	21,182	2.25	1.53	3.88	2.07	1.80^{***}	0.12
Pro-rata loan	21,182	0.74	0.44	0.24	0.80	-0.56^{***}	0.21
Asset-backed loan	71,007	0.07	0.29	0.12	0.09	0.03^{***}	0.03
M&A purpose	71,007	0.06	0.23	0.17	0.04	0.12^{***}	0.00
General corporate purpose	71,007	0.11	0.31	0.14	0.11	0.03^{***}	0.00
Working capital purpose	71,007	0.35	0.48	0.17	0.37	-0.20***	0.00
Agent with no other exposure	71,007	0.05	0.21	0.37	0.01	-0.36***	0.24
Market Segment							
Covenant-lite	21,182	0.06	0.24	0.37	0.03	0.34^{***}	0.16
Leveraged loan	$21,\!182$	0.14	0.35	0.40	0.11	0.29^{***}	0.06
Buyout loan	21,182	0.23	0.42	0.53	0.20	0.34^{***}	0.06
Middle-market loan	21,182	0.27	0.45	0.21	0.28	-0.07***	0.00
Club-deal	$21,\!182$	0.02	0.13	0.01	0.02	-0.01***	0.00
Borrower Characteristics							
Public firm	21,182	0.36	0.48	0.20	0.38	-0.17***	0.01
Loan or firm rating observed	21,182	0.35	0.48	0.81	0.30	0.51***	0.02
No. of loans by firm in SNC	71,007	17.7	16.4	21.0	17.3	3.7^{***}	0.00
Syndicate Characteristics							
No. of syndicate members	21,182	8.43	7.50	6.14	8.67	-2.54^{***}	0.01
No. of agents/arrangers	21,182	3.88	3.47	3.21	3.95	-0.74***	0.00
Share of funds at first SNC obs.	71,007	0.14	0.27	0.59	0.09	0.50***	0.31
No. of lenders at first SNC obs.	71,007	24.7	76.9	113.1	15.7	97.4***	0.14

Table 1: Summary Statistics of Loans

Note: This table presents (a) summary statistics for all loans in the first three columns. Included in the sample are loans which are first observed in the SNC data within 400 days of origination. Variables with only 21,182 observations are obtained from Dealscan; all other variables are from SNC. The remaining columns compare loans for which the lead arranger sells its stake by the time the loan is first observed in SNC with the loans for which it does not. The significance levels for the difference in means are: *(p<0.10), **(p<0.05), ***(p<0.01). The R-squared reported in the last column is obtained from a univariate regression in which a dummy for a lead arranger sale is regressed on the respective variable.

duct due diligence on the borrower. Once the firm awards the mandate to a lead arranger (who often forms a consortium with several co-agents), all parties sign a commitment letter, which specifies the arrangement fees and the preliminary loan terms. The lead arranger is the main point of contact for the firm, the driver of the syndication process, and will later become the administrative agent who is responsible for maintaining the list of lenders and coordinating the flow of funds during the life of the loan.¹⁵ The main motivation for including co-agents at the origination stage is to share the commitment across several banks. This is particularly important for so-called underwritten deals, where the agent banks guarantee that the borrower will receive the committed funds at a maximum interest rate spread and hence would have to provide any remaining loan amount if investors' demand for the loan falls short.

Once the commitment letter is signed, the lead arranger and co-agents conduct a more thorough due diligence on the borrower, draft the marketing material, and – in the case of loans marketed to institutional investors – work with rating agencies to obtain a rating for the loan. On the launch date, the lead arranger and co-agents start the book running based on a preliminary credit agreement. The credit agreement governs the terms of the loan deal such as the collateral, covenants, loan amount and the loan spread. During this process, the deal is marketed to other banks as well as to institutional investors such as collateralized loan obligations (CLOs), loan mutual funds, insurance companies, and pension funds. These investors then conduct their own due diligence, and engage in discussions with the borrower's management during the roadshow. Based on the interest in the deal, the loan terms are adjusted during this book running process until the deal closes with a final credit agreement that is signed by the agent banks. Non-banks typically do not directly participate in the syndicate at this stage. Instead, they commit to purchase loan shares on a "whenissued basis" on the secondary market from agent banks (so-called "primary assignments")

¹⁵This list of lenders is important because the administrative agent manages not only the flow of money, i.e., the coupon and principal payments, from the firm to the lenders, but often also the information exchange between the borrower and the lenders. The administrative agent's knowledge of all current holders of the loan makes it the main market maker for the loan, once the loan starts trading in the secondary market.

as soon as the loan starts trading in the secondary market, i.e., when the loan "breaks to trade". While these final commitments are made typically shortly after the closing date, the ownership is transferred after the loan deal becomes active and the agent banks transfer the entire loan amount to the borrower.

There are two main reasons for primary assignments. First, CLOs, which are the main non-bank investors in the loan market, are typically situated off-shore for tax purposes. Usually, non-US entities are required to pay US taxes on US income (called "Effectively Connected Income" (ECI)). However, under the Internal Revenue Code section 864(b)(2)trading in securities is excluded from this requirement (called the "Securities Safe Harbor"), which is the basis on which off-shore investment funds can avoid paying US taxes. Lending into the US, i.e., original issue participation, is not considered to fall under the "Securities Safe Harbor" (Sicular and Sobol (2003)). Hence, primary syndicate participation would risk a CLO's status of being exempt from US taxes. CLOs therefore choose to participate through primary assignments as opposed to participating in the origination syndicate. Second, the settlement process in the loan market is rudimentary compared to - for example - the bond market.¹⁶ Hence, it is more practical – and better for the borrowers – if the agent banks transfer the entirety of the funds to the firm and then collect the payments from all institutional investors (often numbering in the hundreds). For this reason, domestic mutual funds typically do not participate in the primary market either, but purchase loans as soon as the loan "breaks to trade", based on the commitments made during the book running process.¹⁷

We highlight the changes in the syndicate in Figure 1 where we compare the lender composition at origination (as observed in Dealscan) with the lender composition for loans

¹⁶There is no equivalent to the Depository Trust Company (DTC) in the syndicated loan market that could act as a central clearing house and custodian. The settlement process in the syndicated loan market is therefore less standardized, involves a lot of information exchange, and takes much longer.

¹⁷Another potential reason why loan mutual funds will avoid participating in the syndication process is their common requirement to hold active loans for which they can easily determine market prices. This is not possible for loans that are not trading actively in the secondary market and as such it is more difficult for the fund to determine its net asset value (NAV). Furthermore, the risks, effort, and time associated with underwriting are beyond the scope of their business interests.

that we observe within 10 days after origination (in SNC).

Panel A depicts the average share of a loan that is held by the lead arranger, other banks and funds. It shows that the average lead share drops in the days after origination. The sell-off coincides with a large increase in the average share of the loan held by funds such as CLOs and loan mutual funds. This shift in lender composition is the strongest for Term B loans, which are most commonly marketed to institutional investors. In fact, the median share held by the lead arranger for a Term B loan at the first observation in SNC is zero. Because most of the sales are arranged prior to the active date of the loan, the shift in lender composition happens within days of origination (see also Internet Appendix Section B).

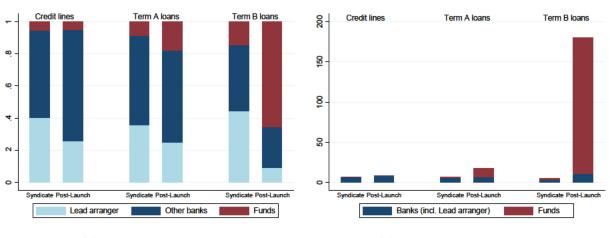


Figure 1: Syndicate Composition at and after Origination

(a) Mean lender shares

(b) Mean number of lenders

Note: This figure shows the change in the lender structure after loan origination for different types of loans. Panel A shows the average shares held by each lender group. The first bar ("Syndicate") is obtained by using lender shares as reported by Dealscan. If missing, we interpolate the lender shares based on the syndicate structure (e.g., Chodorow-Reich (2014)). The second bar ("Post-Launch") is obtained by computing the lender shares at the first observation in SNC. We focus here on loans that we observe within 10 days of origination, i.e., loans that were originated shortly before an SNC report date. The sample contains all USD-denominated loans in Dealscan and all loans in SNC. Panel B shows the average number of each lender type in a loan.

The change in the lender composition after origination is also evident when looking at the average number of lenders by type in the syndicate (Panel B of Figure 1). It shows that the number of lenders is stable for credit lines, but jumps for term loans. For Term B loans, the average number of lenders explodes from 5 syndicate members to around 175 lenders after origination. This increase in the number of lenders is strongly driven by funds. It is also worth noting that almost no funds participate in the original syndicate. The lender increase is still pronounced for Term A loans, for which the average number of lenders rises from 6 to 20. This is the result of a few Term A loans seeing a large influx of fund investors. By contrast, the median Term A loan has almost exclusively bank lenders and the number of lenders is quite stable (see Internet Appendix Figure B.2).

Comparison to other markets. The other two markets where large firms obtain funds from investors are the bond and the equity market. The role of the lead arranger in the syndication process for institutional loans is very similar to the role of the underwriter in an initial public offering or in a debt issue in terms of due diligence and marketing of the deal. This is underlined by the facts that (a) the most-active underwriters are the same across the bond and the loan market, and (b) the debt underwriting desks are connected and often the same. For example, the leveraged finance desk is responsible for both the leveraged loan underwriting and the high-yield bond underwriting. Moreover, underwriters typically form a syndicate when underwriting a debt or equity security, similar to a loan syndicate.

2.3 Syndicate Shares Reported in Dealscan

The fact that originating banks often sell their shares immediately after origination, based on pre-arranged transactions, questions the usefulness of lender shares at origination in Dealscan for studying bank lending. As we show in the Internet Appendix Section A, two additional problems arise with lender shares in Dealscan: first, lender shares are only reported for a small number of loans (about 10% in recent years), and second, the loans for which lender shares are available are not randomly selected, leading to sampling bias. More specifically, lender shares are mostly available for loans that are not sold to institutional investors. The fact that reported loans are not representative for non-reported loans, biases any imputation of lending shares from reported to unreported loans as is popular in the literature (e.g.,

Chodorow-Reich (2014)).

Despite these shortcomings, the literature approximating bank lending using Dealscan information is large and growing. We therefore provide guidance to researchers that have access to Dealscan and are interested in the actual loan holdings of the lead arranger and other bank lenders after origination. We only outline this guidance briefly here and refer the interested reader to Internet Appendix Section A for more information. First, we distinguish two cases: (a) when syndicate shares are reported in Dealscan, and (b) when lender shares are not reported. In the case of reported syndicate shares, we suggest researchers scale the Dealscan-reported lender shares. We obtain these scaling coefficients by regressing loan holdings, as observed in SNC, on lender shares at origination that we observe in Dealscan. When syndicate shares are not reported in Dealscan, we suggest researchers use a regression model that makes use of only those loan characteristics observed in Dealscan, which we have estimated with SNC holdings data. As we show, this method vastly outperforms existing methods such as imputation based on reported loans or equal allocation to all syndicate members when predicting actual loan holdings post origination. We also provide code that performs this task on our website.

3 Theory & Hypothesis Development

In this section we outline the theoretical motivations behind the conventional wisdom that the lead arranger retains a large stake in the loan it syndicates. We formulate testable hypotheses based on the existing theoretical literature.

Moral hazard. Standard banking theory argues that banks are informed intermediaries, which have the delegated role to screen and monitor in order to mitigate the information asymmetry problem between borrowers and lenders (Diamond (1984), Gorton and Pennacchi (1995), Holmstrom and Tirole (1997)). However, monitoring and screening efforts by banks are assumed to be costly and unobservable in these models, which gives rise to a moral

hazard problem. The solution to this moral hazard problem, as argued by Gorton and Pennacchi (1995) and Holmstrom and Tirole (1997), is that the monitoring bank does not sell the entire loan to other lenders, but retains a sufficiently large loan stake on its balance sheet. The resulting economic exposure induces the bank to exercise sufficient effort to screen and monitor the borrower. More recent studies argue that the loan retention need not be permanent in order to overcome the moral hazard of screening and monitoring (Hartman-Glaser et al. (2012), Gryglewicz et al. (2021)). If the uninformed investors learn about the quality of the loan (and therefore the lead bank's screening efforts) through information revealed at a later date, there is no need for loan retention by the lead bank past this point in time. As such, temporary retention may provide sufficient incentives for the lead bank to properly screen the borrower before originating the loan.

Adverse selection. In addition to the moral hazard problem of monitoring, the banking literature has argued that the retained share solves the problem of information asymmetry between the bank and investors (Leland and Pyle (1977)). Through its delegated role of screening and prior relationship with the borrower, the lead bank may obtain superior information about the borrower. This gives rise to an adverse selection problem between the bank and other lenders. The bank could profit by selling bad and keeping good loans, while both seem identical to investors. Wary of this lemons problem, investors would only be willing to pay for the value of a bad loan and the market for good loans would collapse. Retaining a large stake in the loan can overcome this adverse selection problem, because it allows the bank to provide a signal of the borrower's quality.

It is commonly assumed that these asymmetric information theories can be applied to the syndicated loan market. It is assumed that the lead arranger conducts the delegated monitoring and screening, while selling parts of the loan to other lenders. Consequently, it is the conventional wisdom that the lead arranger needs to retain a large stake in a syndicated loan – the so-called lead share – for at least some time after origination in order to overcome the adverse selection and moral hazard concerns. Using Dealscan data, the prior literature has found evidence supporting this interpretation of the lead share. Sufi (2007) documents that the lead arranger's share is larger for loans to firms that are more opaque which therefore requires more intensive monitoring and due diligence. Ivashina (2009) documents that the lead share is correlated with the loan spread. The argument goes that the higher lead share assuages asymmetric information concerns, leading to lower borrowing costs for the borrower. However, the observation from Section 2.2 that lender shares at origination are often not representative of holdings days after origination leads us to revisit the role of the lead share.

We do so by testing three hypotheses that are implied by theory. First, the lead arranger should rarely sell its entire loan share for at least some time after origination, because, in such a case, one would expect lax monitoring and adverse selection. In other words, it would make the intermediary redundant because it does not contribute to the resolution of information asymmetry between the firm and lenders:

Hypothesis 1. The lead arranger rarely sells its loan share (immediately) following origination because the resulting moral hazard in monitoring and the adverse selection would lead to a market collapse.

Second, the share held by the lead arranger is special. The lead arranger conducts the due diligence, typically has a prior relationship with the borrower, and is tasked with monitoring. Therefore, the lead arranger should be less likely to sell its loan stake compared to other banks participating in the primary syndicate. After all, none of the other participants have a special role:

Hypothesis 2. The lead arranger is less likely to sell its loan share than other banks in the syndicate.

Third, in case the lead arranger sells its loan stake, those loans should perform worse than retained loans with the same observable ex-ante risk. From the perspective of the moral hazard theory of the lead share, the differential performance of loans with and without retained lead share reflects the gain from monitoring. In the adverse selection theory, the differential performance after controlling for observable risk reflects the difference in the ex-ante quality of the loans that was only observable to the informed lead arranger:

Hypothesis 3. Loans that are entirely sold by the lead arranger immediately following origination perform worse, on average (conditional on ex-ante observable risk).

We test these three hypotheses in the following section. To take into account more recent theories arguing that temporary retention of the lead share is sufficient to resolve information asymmetry problems (e.g., Hartman-Glaser et al. (2012)), we specifically conduct variants of our empirical tests focusing on the period immediately following origination.

4 Main Empirical Results

4.1 H1: Does the Lead Arranger Ever Sell Its Share?

In contrast to Hypothesis 1, we find that the lead arranger often sells its stake. We define a loan as sold by the lead arranger when its share is less than 0.5% of the outstanding loan amount and distinguish two cases of lead share sales: (a) the lead arranger sold its stake at the first SNC report date after origination, and (b) the lead arranger sold its stake at some report date at which the loan is observed in the SNC data. The interpretation of the first case is that the lead arranger sold its share of the loan shortly after loan origination, while in the second case, the lead arranger has no loan exposure at some time over the life of the loan.

We plot the frequency of lead shares sales according to both definitions in Figure 2. Panel A gives equal weight to all loans, while Panel B weights loans by the utilized (i.e., drawn) loan amount.¹⁸ Panel B therefore shows the frequency of lead shares sales as a fraction of

¹⁸As a result, undrawn credit commitments receive zero weight in Panel B, while large Term B loans are given more weight.

the outstanding credit exposure in the syndicated loan market. The figure shows that the frequency of lead share sales is surprisingly high. The lead arranger sells its stake for 9% of loans directly after origination and for 13% of loans at some point over the loan's life. When we weight loans by their outstanding loan amount these numbers rise to 25% and 35%, respectively. This reflects the fact that lead arrangers are less likely to retain any stake in loans that have a larger outstanding loan amount.

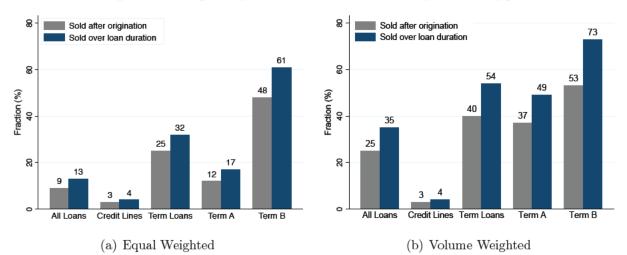


Figure 2: Frequency of Lead Share Sales by Loan Type

Note: This figure shows the fraction of loans for which the lead arranger has sold its entire loan share. We classify a loan as (i) sold after origination if the lead share is less than 0.5% at the first report date after origination, or as (ii) sold over the loan duration if the lead share is less than 0.5% at any SNC report date. Panel A weights loans equally, while Panel B weights loans by the outstanding loan amount. We include only loans which are first observed in the SNC data within 400 days of origination. The sample contains 71,007 loans, 14,867 term loans, 37,946 credit lines, 12,987 Term A loans, 1,880 Term B loans, and 18,194 other loans (not shown).

The figure also documents that the lead arranger sells its entire loan share more often for term loans than for credit lines. 40% of term-loans (if weighted by loan amount) see no lead agent exposure after origination. Furthermore, the lead share is zero at first observation for around 53% (weighted by loan amount, or 48% when weighted equally) of loans that cater to institutional investors such as Term B loans.

The propensity of lead share sales has been rising over time. This can be seen in Figure 4 which plots the likelihood that a loan has been completely sold off by the lead agent directly following origination (i.e., at first observation in SNC). This trend is consistent with the rise



Figure 3: Frequency of Lead Share Sales over Time

Note: This figure shows the fraction of loans for which the lead arranger has sold its entire stake at the time the loan is first observed in the SNC data, plotted over time. We define a loan as sold by the lead arranger when the lead share is less than 0.5%. The blue line plots the unweighted fraction, while the red line weights loans by the outstanding amount. We include only loans which are first observed in the SNC data within 400 days of origination. The figure is based on 71,019 loans from the SNC data.

of the originate-to-distribute business model of banks (Bord and Santos (2012)).

Residual borrower exposure. While the lead arranger frequently has no loan-specific exposure, it might retain exposure to the borrower through other loans. This could ensure that the lead arranger still has the incentive to engage in costly screening and monitoring efforts. In particular, the lead bank might sell-off the Term B tranche of a loan deal but still have exposure to the borrower by retaining the credit line of the same loan deal, which often contains more covenants (Berlin et al. (2020)). We therefore analyze how often the lead arranger maintains other loan exposures to a borrower when it has sold its entire loan stake.

To do so, we compute the aggregate exposure of the lead arranger to the borrower through all other loans in the SNC data at a given report date.¹⁹ We further categorize the lead

¹⁹We want to caution here that we do not observe the entire loan universe, as some loans might not fulfill the SNC requirements. The exposure of the lead arranger might therefore be larger than what we observe. However, loans that do not fulfill the requirement are either (a) small loans with an outstanding amount of less than 20 million or (b) held by less than two reporting institutions and therefore more likely to be held outside of the banking sector. Both requirements make us believe that the bias in our analysis is likely to be small. In addition, these other loans would likely be secured by different collateral. Gustafson et al. (2021) point to the fact that collateral valuation and verification is a core component of monitoring activity. Thus, it is unclear whether the lead arranger has sufficient monitoring incentives in such a case.

arranger's residual loan exposures to the borrower into three categories: (a) the lead arranger has no other loan exposure to the borrower, (b) the lead arranger has exposure through other loans in which it is a syndicate member but not a lead arranger (*participant exposure*), and (c) the lead arranger has exposure through at least one other loan for which it acts as the lead arranger (*agent exposure*).

Table 2 shows that a large number of lead arrangers have no exposure to borrowers whose loans they sell. The lead agent maintains no other exposure over the course of a loan's life in 37% of all cases in which the loan is sold. In a quarter of all Term B loans which are sold off by the lead arranger, the lead agent retains no other exposure to the borrower.

	Fraction of loans for which the lead agent sold its share			
	All loans	Term loans	Term B loans	
Lead agent has no other exposure	37%	30%	25%	
Lead agent has other "participant exposure"	29%	39%	39%	
Lead agent has other "agent exposure"	34%	31%	36%	
Number of loans	6,733	3,712	897	

Table 2: Retained Borrower Exposure After Lead Share Sales

Note: This table examines the residual exposure of the lead arranger to a borrower when it has sold its lead share. For each loan sold by the arranger, we aggregate the exposure of this arranger to the same borrower (at the level of the holding company) through all other loans in the SNC data to determine whether the agent has other exposure to the borrower. We distinguish between whether the arranger acts as the lead arranger (*agent exposure*) for at least one other loan or as a mere syndicate participant (*participant exposure*) for all other loans. Loans are weighted equally.

Several further observations speak against the hypothesis that the lead arranger's screening and monitoring occurs through other loan exposure. First, whenever the lead arranger retains residual loan exposure, the exposure often comes in the form of *participant exposure* (26%). It is unclear whether this ensures sufficient monitoring incentives as it potentially gives rise to a free-rider problem, where a lead arranger relies on another lead arranger to conduct the monitoring. We find that the lead arranger has *agent exposure* for only 34% of the loans for which it has sold its lead share. This share is similar when considering only term loans (31%) or Term B loans (36%).

Second, market participants are generally not able to observe the stake the lead arranger holds in other loans. After all, adverse selection is only mitigated if exposure to the borrower can be credibly signaled. The fact that a lead arranger participates in another loan of the same borrower may be unobserved and therefore meaningless to other market participants.

Third, it is unclear to what extent investors of sold loans benefit from monitoring through covenants in other loans. Covenant violations are typically used by lenders to accelerate repayments or renegotiate loan terms (Chava and Roberts (2008), Roberts and Sufi (2009), Nini et al. (2012)). This, however, applies only to the loans with violated covenants. Lenders in Term B loans, which are mostly sold off by the lead arranger and have different covenants, would not benefit from covenant violations in a credit line.²⁰

Fourth, one may assume that retaining parts of other loans of the same deal – that are all backed by the same collateral – may be sufficient incentives for the lead arranger to monitor the loan. In practice, we actually find that different loans arranged by the same lead arranger – including different tranches of the same loan package – are often secured with different collateral. Using collateral data that is available for a subset of about 30% of SNC loans,²¹ we find that only around 24% of loans to a borrower – that are made by the same arranger on the same day – share a collateral type. If we include "business assets" as a single broad collateral category, which simply implies that the loan is secured by the firm's cash flows, this figure rises somewhat to 40%. Importantly, for the loans that are sold by the lead arranger.

Fifth, the lead arranger is much less likely to hold other borrower exposure when it sells off the entire loan than when it retains a loan (see Table 1). We conclude that – while it

²⁰In the appendix we explore the types of monitoring activities which are supposed to prevent covenant violations, a little more. Less than 10% of loans appear to involve any form of "active monitoring" by the arranging bank. Most appear to rely instead on the activities of third parties, including financial audit firms. While we are careful not to interpret these results to mean a bank is not engaged in monitoring, they do speak to the danger of assuming bank engagement with the borrower over the life of the loan.

²¹Collateral data is based on SNC-examiner data, which is the result of Federal Reserve examiners taking a more detailed look at certain loans. Data includes information on collateral types and covenants.

is possible for some loans – it seems unlikely that the lead arranger generally retains the necessary skin-in-the-game through other loans.

When does the lead arranger sell? The next important question we consider is when exactly lead share sales occur. Here, we make use of the fact that we observe loans at fixed dates in the SNC. This implies that we observe some loans immediately after origination. Using this information, we can show how quickly – after origination – the lead arranger sells off its stake on average.

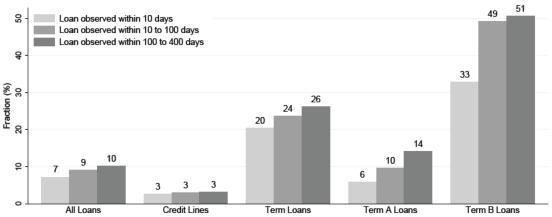


Figure 4: Timing of Lead Share Sales

Note: This figure shows that lead share sales happen swiftly after origination. It shows the fraction of all loans observed in SNC within a certain number of days (e.g., 10 days) after origination that are sold by the lead arranger. We define a loan as sold by the lead arranger when the lead share is less than 0.5%. Loans are weighted equally.

Figure 4 demonstrates that most lead share sell-offs typically occur in the first few weeks after origination. As discussed in Section 2, above, most of these loan sales are pre-arranged, but executed after loan origination. The long settlement period in the loan market means that it likely takes some time to transfer the loan ownership.

Given that most sales are pre-arranged and executed in the first weeks after origination, it is unlikely that there is any meaningful information about the borrower's quality that can be revealed between the loan origination and loan sale dates. Thus, it seems implausible that lead share sales only occur after enough information about the borrower has been revealed such that any information asymmetry is dissolved. We further confirm this by showing in Internet Appendix Table C.2 that loans sold by the lead arranger are not more likely to have experienced a major news publication, for instance through earnings announcement. This is different from the mortgage market for which Keys et al. (2012) provide evidence that a longer retention period is associated with better loan outcomes. This is consistent with the originating bank screening with more effort when retaining exposure for a longer period as proposed by Hartman-Glaser et al. (2012).

Nonetheless, it is possible that information is revealed at later dates, which can impact the propensity that loans are *ever* sold off. As such, we focus only on loans sold by the time they are first observed, in subsequent analyses below.

Which loans does the lead arranger sell? In Table 1 we compare the means of various characteristics across loans for which the lead arranger sold its entire share by the time the loan is first observed in the SNC data and loans in which the lead arranger still holds a stake. We find that loans that are sold by lead arrangers are larger, have a longer maturity, have a higher loan spread at origination, and are more likely to be covenant-lite. By contrast, loans that are smaller and more targeted to banks, such as club deals and pro-rata loans, are more frequent among the loans that are not sold by lead arranger.

We also find some significant differences for the loan purpose and borrower characteristics across the two groups. Loans sold by lead arrangers are more likely to finance M&A deals or be used for general corporate purposes. They are also more likely to be backed by assets and less likely to finance working capital. In addition, we find that firms whose loans are sold are more likely to be private. This speaks against the hypothesis that lead arrangers need to retain more of opaque and therefore harder to monitor firms as argued by Sufi (2007). Firms whose loans are sold by the lead arranger tend to have a higher number of issued loans (as observed in the SNC data). Loans that are sold are also more likely to come with a loan or borrower rating. As above, this indicates that the lead arranger sells its stake in loans targeted to nonbank investors who often require loans to be rated (e.g., CLOS). Finally, we compare the syndicate structure across the two loan groups. We find that loans that are sold have fewer syndicate members and fewer lenders that are classified as "arrangers" in Dealscan. However, when we look at the number of lenders after origination, i.e., at the first SNC observation, then these numbers reverse. The mean number of lenders increases dramatically to 113 for loans that are sold, while it is much lower at 16 for loans that are not sold. In addition, the loan share held by funds at first observation in SNC is much higher (59% vs. 9%) for loans that are sold by the lead arranger.

The differences are somewhat indicative of a segmented market in which some loans are pre-ordained for institutional investors. These loans, it seems, are somewhat more likely to be sold off by the lead arranger. The final column in Table 1 depicts the R-squared of a regression that relates the characteristic in question to the likelihood that the loan is sold off by the lead arranger. Variables that proxy for the appeal of the loan to institutional investors, such as their risk (measured through the all-in-drawn spread), whether the loan is covenant-lite, and the share of funds at the first SNC observation, have the greatest explanatory power.

4.2 H2: Do Lead Agents Sell Less Often Than Other Lenders?

In this section we document that lead agents are, on average, as likely to sell their stakes in a loan – both after origination and over the course of a loan's life – as other banks that participate in the same loan syndicate. This provides evidence against Hypothesis 2.

We test this hypothesis by comparing the likelihood that the lead bank and non-lead banks which participate in a syndicate sell their entire loan stake immediately following origination. According to prior theories on the lead share, one would expect that the lead arranger is less likely to sell its share than other lenders for two reasons: First, the lead arranger needs to retain skin-in-the-game to maintain the incentive to monitor, which is not required for other loan participants. Second, because the lead arranger possesses superior information about the borrower, any loan investor would be less willing to purchase a loan from the lead agent. To test this formally, we estimate the following regression

$$LoanShareSold_{i,l} = \beta_0 + \beta_1 LeadAgent_{i,l} + \beta_2 ShareAtOrigination_{i,l} + \delta_l + \delta_{i,t} + \epsilon_{i,l}, \quad (1)$$

where the dependent variable LoanShareSold_{*i*,*l*} is 1 if a lender *i* (which can be either a syndicate participant or the lead arranger) sold its entire stake in loan l at the first observation in SNC. The unit of observation is therefore a loan-bank tuple. The main explanatory variable LeadAgent_{i,l} is a dummy variable that is 1 if lender i acts as the lead arranger for loan land 0 otherwise; the main coefficient of interest is therefore β_1 which determines whether lead arrangers behave differently from other bank participants. We control for the syndicate share $\text{ShareAtOrigination}_{i,l}$ in the regression, since it takes longer to sell off the entire loan share if the original syndicate share was larger. We additionally include a set of fixed effects to address potential alternative mechanisms driving our results. For example, one might be worried that a bank is more likely to accept the title of lead arranger whenever the institutional investors with which it has a strong relationship experience strong inflows. As a result, the lead arranger might be more likely to sell its share in a loan than a bank syndicate member whose associated investors had no inflows. We control for this alternative hypothesis by including bank \times report date fixed effects, $\delta_{i,t}$, which measure the average propensity of bank lender i to sell loans at a given point in time, independent of whether it acts as lead arranger or not. This coefficient would also absorb any selling pressure that a bank faces, for example due to regulatory pressure (Irani et al. (2021)). In some specifications we also include loan fixed effects, δ_l , which capture the general propensity of all lenders to sell a given loan after origination. For example, these fixed effects would be much higher for loans intended for institutional investors from the outset.

We perform our regression on a matched sample of bank lenders that we observe both in Dealscan and SNC. Here, we limit the lender sample to banks that we are ever able to match across the two data sets. We therefore exclude funds and other non-bank lenders which infrequently participate in the primary syndicate in any case. If a lender is in this pool of matched banks and is a syndicate member for a given loan at origination (observed in Dealscan) but is not observed at the first loan observation in SNC, then we assume that the lender has sold its stake.²² We then compare lead agents with lenders that are classified as "Participants" in Dealscan.²³ That is, we ignore co-syndication agents because their role is less clear theoretically.

	Share sold off by lender					
	(1)	(2)	(3)	(4)	(5)	(6)
Lead arranger	0.001 (0.007)	$0.005 \\ (0.009)$	$0.012 \\ (0.019)$	-0.006 (0.023)	-0.023 (0.022)	-0.023 (0.035)
Syndicate share	-0.001^{**} (0.000)	-0.002^{**} (0.001)	-0.002^{**} (0.001)	-0.005^{**} (0.002)	-0.002^{***} (0.001)	-0.012^{*} (0.006)
Lender x report date FE	Yes	Yes	Yes	Yes	Yes	Yes
Loan FE	No	Yes	No	Yes	No	Yes
Mean of dependent variable	0.08	0.08	0.11	0.11	0.18	0.18
\mathbb{R}^2	0.51	0.70	0.55	0.74	0.35	0.83
Ν	22,050	22,050	2,031	2,031	10,113	10,113
Loan sample	All loans	All loans	Term loans	Term loans	Term loans	Term loans
Syndicate shares	Observed	Observed	Observed	Observed	Imputed	Imputed

Table 3: Loan Share Sales: Lead Arranger vs. Non-Lead Banks

Note: This table shows the results of regression (1). The dependent variable is a dummy variable that is 1 if a syndicate bank sold its loan share at the first observation in SNC and 0 otherwise. The unit of observation is a bank-loan observation. We include only syndicate banks that are either classified as "Lead Agents" or as "Participants" in Dealscan. Columns (1) to (4) focus on loans for which we observe the syndicate shares in Dealscan. Columns (5) and (6) focus on loans for which we do not observe the shares. For this sample we use syndicate structures to impute syndicate shares (e.g., Chodorow-Reich (2014)). Standard errors are clustered by bank lender and by SNC report date. Significance levels: *(p<0.10), **(p<0.05), ***(p<0.01).

Table 3 shows that lead arrangers are not more or less likely to sell their stake in a given loan than any other bank-participant. The coefficient of the lead arranger dummy in

 $^{^{22}}$ This is necessary as we cannot identify participants that have sold stakes from SNC data alone – unlike with lead arrangers that we can identify from SNC data regardless of their stake at any given point in time.

²³For the purpose of this section, we define lead agents following the prior literature (Sufi (2007)): We assign the lead agent role first to the "admin agent". If there is no "admin agent" in the syndicate, we choose any lender with the title "Agent", "Bookrunner", "Joint arranger", "Lead bank", "Lead manager", "Mandated Lead arranger". If there is also no lender with such title, then we assign any of the lenders with the title "Co-agent", "Co-arranger", "Collateral agent", "Coordinating arranger", "Documentation agent", "Managing agent", "Syndications agent". If there are several agents with the same title, then we choose the one with the highest lender share at origination, otherwise we randomly draw the lead agent. Our results are unchanged if we use the lead agent classification from SNC (not reported).

column (1) is statistically indistinguishable from zero. We find a similar result in column (2) where we include loan fixed effects that capture the propensity of the syndicate to sell the loan. Columns (3) and (4) focus on the sample of term loans. The message is the same. Lead arrangers are not less likely to sell than other banks that participate in the same loan syndicate after syndication – no matter the loan type.

The prior analysis has one caveat: it relies on a small and selected sample for which we observe the lender shares at origination. We can therefore not be certain that our results are generally valid in the loan market. To address this concern, we conduct two additional tests. First, we re-run the above regressions using term loans for which Dealscan does not report syndicate shares in columns (5) and (6). Our results remain the same. Second, we compare the selling propensity of lead agents and other lenders between the first and the second observation in SNC in Internet Appendix Section C.2. We focus on loans which we observe at most one month after origination and which therefore exhibit a higher probability that lenders have not sold off their entire stake already. The results broadly confirm our main conclusion – lead agents are not less likely to sell their entire loan stake than non-agent lenders.

4.3 H3: Do Loans Sold by the Lead Arranger Perform Worse?

In this section, we provide evidence against Hypothesis 3 – loans sold by arranging banks do not perform worse, as predicted by theory. Instead they perform better. We test this hypothesis by regressing the ex-post performance of a loan on a dummy that indicates whether the lead share was sold by the lead arranger by the time the loan is first observed in SNC:

 $ProblemAfterLoanSold_{l,t\to T} = \beta_0 + \beta_1 LeadShareSold_{l,t} + \beta_2 LoanRisk_l + \beta_3 X_{l,t} + \epsilon_{l,t}, \quad (2)$

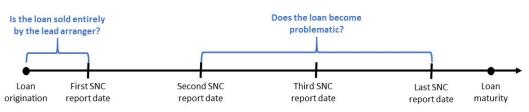


Figure 5: Illustration of the Timing of Equation 2

Note: This figure illustrates the timing of regression 2. LeadShareSold_{*l*,*t*} is an indicator that is 1 if the lead arranger of loan *l* has sold its entire loan share at the first SNC report date *t* after origination and 0 otherwise. ProblemAfterLoanSold_{*l*,*t*→*T*} is a dummy variable that is 1 if loan *l* incurs a credit problem at any SNC report date after the report date *t* and 0 otherwise.

where ProblemAfterLoanSold_{$l,t\to T$} is a dummy variable that is 1 if loan l becomes nonaccruing at any SNC report date *after* the first report date t. The main explanatory variable LeadShareSold_{l,t} is an indicator that is 1 if the lead arranger of loan l sold its entire loan commitment at the report date t at which the loan is first observed in SNC and 0 otherwise. The timing of our empirical design is further illustrated in Figure 5. We exclude loans that are already non-accruing at the first report date.²⁴ This eliminates any potential cases where the lead arranger sold its share after – and perhaps because – a problem with the loan occurred.

In order to capture adverse selection on unobservable risk and lax monitoring after the loan sale, we need to condition on the ex-ante observable risk of the loan. We do this with two main risk measures: (a) the all-in-drawn spread of the loan and (b) the internal risk rating of the lead arranger. Additionally, we control for loan characteristics such as dummies for term loans, Term B loans, and leveraged loans as well as the logarithm of the total loan amount, the time since origination, and the loan maturity. In some specifications, we also include either industry \times date fixed effects, which absorb any time variation in industry-specific loan market stress. These fixed effects would for example capture stress in oil-producing industries during the oil price crash of 2014. One might also be concerned that other bank-specific explanations affect our results. For example, a lead arranger wanting to boost its

²⁴Note that this drops only 75 observations from the sample containing all loan types, and 40 observations from the term loan sample. Our results are unchanged if we include these loans.

market share might offer a spread to its borrowers that is too low relative to the default risk. This might make it harder to sell off these loans. We therefore include lead arranger \times report date fixed effects to compare the performance of sold loans with retained loans that are arranged by the same lead arranger at the same time.

As outlined in Section 3, the existing theory on the role of the lead arranger's share predicts a positive relationship between the lead share sales and future credit problems. Instead, Table 4 reports a negative relationship in the data. The regression coefficient in column (1) implies that a lead share sale is associated with a 1.5 percentage point lower probability that the loan becomes non-accruing in the future. The unconditional probability of a loan becoming non-accruing is 2.4% in the matched data sample. Thus, the coefficient is economically meaningful, implying that a lead share sale coincides with a 60 percent lower probability of the loan becoming non-accruing, relative to the unconditional probability. The results remain similar when including lead arranger \times date fixed effects (column (2)).

We use bank internal risk ratings of the loan as risk controls in column (3). We are therefore comparing loans the lead arranger considers to be equally risky. Given that not all banks apply the same risk-metrics, we include arranger-specific ratings, so that the regression is not biased by some arrangers giving systematically better scores than others. We again find a negative relationship between lead share sales and future loan performance. Loans sold by the lead arranger are nearly 50% less likely to become non-accruing over their duration, holding the internal risk rating constant. As we further discuss in Section 5, this result even suggests – under the assumption that internal ratings fully capture lead banks' information set – that the lead bank knows less about the quality of the loan than other investors (combined).

Finally, in column (4) we change the main explanatory variable to a dummy variable that denotes whether the arranger has no other loan exposure to the borrower. If the arranger is incentivized to monitor by having other borrower exposure, then having no exposure should correlate with worse loan performance. We find that the opposite is true. Loans for which

Table 4: Performance: Sold vs. Retained Loans

(A) All loans

	Loan becomes non-accruing				
	(1)	(2)	(3)	(4)	
Lead share sold	-0.015^{**} (0.006)	-0.013^{**} (0.006)	-0.011^{***} (0.003)		
Lead agent retains no borrower exposure				-0.019^{***} (0.007)	
All-in-drawn spread	0.013^{***} (0.002)	0.012^{***} (0.001)			
Loan controls	Yes	Yes	Yes	Yes	
Industry x report date FE	Yes	No	No	No	
Lead agent x report date FE	No	Yes	Yes	Yes	
Bank internal loan rating	No	No	Yes	Yes	
Mean of dependent variable	0.024	0.024	0.023	0.023	
\mathbb{R}^2	0.048	0.162	0.283	0.283	
Ν	$21,\!280$	$21,\!280$	29,075	29,075	

(B) Term loans

	Loan becomes non-accruing			
	(1)	(2)	(3)	(4)
Lead share sold	-0.012^{*} (0.007)	-0.008 (0.007)	-0.007^{*} (0.004)	
Lead agent retains no borrower exposure				-0.011^{*} (0.007)
All-in-drawn spread	0.010^{***} (0.002)	0.009^{***} (0.001)		
Loan controls	Yes	Yes	Yes	Yes
Industry x report date FE	Yes	No	No	No
Lead agent x report date FE	No	Yes	Yes	Yes
Bank internal loan rating	No	No	Yes	Yes
Mean of dependent variable	0.027	0.027	0.024	0.024
\mathbb{R}^2	0.065	0.235	0.341	0.341
N	5,566	5,566	11,737	11,737

Note: This table shows the results of regression 2. The unit of observation is a loan (i.e., every loan is included only once in the analysis). The dependent variable is a dummy variable that is 1 if the loan becomes non-accruing at any SNC report date after the report date that follows the loan origination date and 0 otherwise. The main independent variable *Lead share sold* is a dummy variable that is 1 if the lead arranger has sold its entire loan share at the first SNC report date and 0 otherwise. The sample is restricted to loans for which the first observation in the SNC data is within 400 days of the origination of the loan. We exclude any loan for which the dependent variable already takes the value of 1 at the first observation, i.e., the loan is already non-accruing. This drops 75 loans of all types, and 40 term loans. Included as loan controls are a term loan dummy, a Term B loan dummy, a leveraged loan dummy, the logarithm of the total loan amount, the time since origination, the loan maturity and the all-in-drawn spread (in percent). The all-in-drawn spread is obtained from Dealscan. Standard errors are clustered by lead agent and by SNC report date. Significance levels: *(p<0.10), **(p<0.05), ***(p<0.01).

the arranger holds no other loan exposure to the borrower perform better than loans for which the arranger holds exposure.

In Panel B we confirm that the negative relationship remains when we focus on term loans. Term loans are up to 50 percent less likely to become non accruing – relative to the unconditional mean – if the agent retains no stake in the loan. To further ensure the robustness of our results, we also perform a series of additional tests in Internet Appendix Section C.3. First, we change our definition of non-performing loans; namely we use an indicator of whether parts of the loan are classified as "non-pass" by the bank and Federal Reserve examiners. Second, we vary our controls for ex-ante riskiness of the loan. We use external risk ratings from rating agencies, make use of non-linear as well as non-parametric spread controls, and forego risk ratings entirely. We continue to find a negative relationship between lead sales and loan performance. Third, we limit our set of loans to those observed within 90 days of origination. As such, we can be sure that the sale we observe occurred immediately after origination, without significant information being released post-origination. Finally, we examine how our results vary for the cross-section of firms. We find that even when we focus on smaller and more opaque firms, the relationship between lead share sales and performance remains negative. We also examine how loan prices react to lead arranger sales. To do so, we match secondary market loan prices as reported by LSTA to our data set. This matched sample contains mostly large term loans. We then use the price closest in date to the SNC date at which we observe the loan for the first time. As can be seen in Internet Appendix Table C.18, the secondary market prices are uncorrelated with whether the lead arranging bank has sold its stake. This result is independent of how we control for loan risk. To conclude, we do not find a negative relationship between loan performance – as measured by loan prices or future credit problems – and lead arranger sales as predicted by Hypothesis 3.

5 Alternative Incentive Mechanisms

The prior literature has argued, based on classical banking theories, that the lead share serves as the incentive device to overcome information asymmetries between the lead arranger and other syndicated loan investors. This has also led to the conventional wisdom that the lead arranger never sells its share in order to maintain skin-in-the-game.

We have presented three pieces of evidence that challenge this view. What does this imply for the information asymmetry in the syndicated loan market? Our findings raise the following possibilities: The information asymmetry between the lead arranger and other lenders is not as material as previously thought, or incentive mechanisms other than loan retention help avoid information asymmetry problems. These two arguments might be related: A low level of information asymmetry between lenders might give rise to cheaper (given banks' likely disadvantage at holding risky loans), but less effective incentive mechanisms.

5.1 Weak Information Asymmetry

Several institutional details question whether the information asymmetry between the lead arranger and other lenders is as severe as in other markets – say, the mortgage market. In particular, most nonbank investment vehicles are actively managed (see, e.g., Fleckenstein (2022)). Moreover, managers of CLOs and other loan funds are often affiliated with hedge funds and private equity firms and therefore have the expertise and resources to conduct their own due diligence.²⁵ Moreover, lenders other than the lead bank can collect soft information about the borrower by interacting with the borrowing firm's management during the roadshow and can obtain a separate opinion on the borrower through external ratings, both of which are not the case in the mortgage market. Importantly, not all investors must

²⁵For instance, private equity firms, such as Blackstone and Carlyle, are among the largest CLO managers and have developed large debt divisions. Moreover, many of the institutional investors now arrange loans on their own, either in the syndicated loan market or through their direct lending platforms (Chernenko et al. (2022)). Moreover, Blickle et al. (2021) show that even small banks and funds can specialize in industries, reducing potential informational asymmetries.

be informed for an equilibrium without retention to be sustainable as theoretically shown by Chemla and Hennessy (2014).

The evidence from Table 4 that conditional on bank internal ratings, retained loans perform worse than sold loans, is consistent with notion that the lead arranger is not better informed about the borrower than other lenders. If the lead arranger reports its information truthfully, then internal risk ratings would capture the private knowledge of the lead arranger. We would therefore expect that if the lead arranger had superior knowledge about the loan, then the inclusion of the internal risk rating would have driven out the relationship between loan sales and performance. The fact that we still find a negative coefficient on lead share sales might indicate that other lenders in the market could have superior information compared to the lead arranger. After all, the lead arranger is up against the entire market of loan investors which might be able to aggregate some information about a firm more efficiently. However, there is one caveat to this interpretation of our results: lead arrangers might not report their internal ratings truthfully in order to reduce their required capital (Behn et al. (2022)).

Nonetheless, it is still plausible that the lead bank possesses some private information that no other lender can acquire. For example, the lead bank might obtain information through its other business relations with the borrower, for instance, when it provides hedging services to the borrower. Moreover, the involvement of the lead bank might serve as a certification of the loan and the borrower, similar to situations arising in an IPO. In the following we discuss and test two incentive mechanisms that could overcome any remaining information asymmetry: pipeline risk and reputation concerns.

5.2 Pipeline Risk

One mechanism incentivizing the lead arranger to conduct proper due diligence is pipeline risk. Pipeline risk typically materializes during the loan syndication process when investor

demand falls sharply as a result of new information about the borrower and the economy.²⁶ In a syndicated loan deal, the lead arranger often guarantees an upper limit in the loan spread to the borrower before promoting the deal to investors.²⁷ When, during the syndication process (which takes about 45 days on average, see Bruche et al. (2020)), investors' loan demand crumbles, the lead arranger has to step in and retain the residual amount of the loan, i.e., the part that could not be sold at the promised spread limit. In principle, the lead arranger could take an immediate loss and sell the retained part to investors at a lower price. However, in the pipeline risk model proposed by Bruche et al. (2020), the lead arranger optimally chooses not to do so if it cannot perfectly observe investors' true demand for the loan. In this case, it needs to ration investors by retaining a part of the loan when investors express little demand in oder to induce truth telling by them. Of course, if the lead arranger is stuck with a loan on its balance sheet, it would prefer to hold a good loan over a bad one. Hence, the prospect of pipeline risk might suffice to incentivize the lead arranger to properly screen the borrower ex-ante and to only originate creditworthy loans. This argument is similar in flavor to the argument made by Hartman-Glaser et al. (2012) who propose that temporary exposure to the borrower can induce screening by the originating bank. Similarly, we argue that loan exposure which the lead arranger might have with some probability – when pipeline risk materializes – might induce the necessary screening effort ex-ante.²⁸

We start testing for pipeline risk by examining whether the lead arranger is less likely to

²⁶Pipeline risk was also discussed in a recent Financial Times article "Deutsche faces big hits on US leveraged-loan losses" which appeared on June 25, 2019. The article discusses the losses of Deutsche Bank related to its leveraged loan underwriting. More explicitly, the article says, "The bank was forced to take a loss on a \$340m loan backing the leveraged buyout of Smart & Final after investors refused to buy the debt under the original terms offered," and, "A second, much bigger deal – a EUR 1.5bn loan funding the buyout by Advent International, a private equity group, of a plastics business owned by Evonik – also faced a lukewarm reception from investors. They were worried about global growth prospect [..]."

 $^{^{27}}$ Note that this is the case in an *underwritten syndication*, but not in a *best-efforts syndication*. See Bruche et al. (2020) for a detailed description of the syndication process and the pipeline risk faced by the lead arranger.

²⁸Bruche et al. (2020) speak of the underwriting agreement specifying the risk sharing between the borrower and the arranging banks regarding loan demand. In this sense, one can think of the lead arranger providing the borrower insurance against changes in loan demand in underwritten deals, and as any insurance provider has an incentive to conduct due diligence on the policyholder, the arranger has an incentive to screen the borrowing firm.

sell when loan conditions in the loan market deteriorate. We estimate the regression

LeadShareSold_{*l*,*t*} =
$$\beta_0 + \beta_1$$
Borrower Information_{*l*,*t*-45 \to *t*} + β_2 Spread_{*l*,*t*} + $\beta_3 X_{l,t} + \epsilon_{l,t}$, (3)

where LeadShareSold_{l,t} is an indicator of whether the lead arranger of loan l sold its share, and the explanatory variable Borrower Information_{l,t-45 \to t} serves as a measure of shocks to investor demand in the 45 days prior to origination. We use (i) changes in the average price of the borrower's *other* outstanding loans, (ii) changes in aggregate loan prices (as measured by the S&P/LSTA US Leveraged Loan Index) and (iii) the idiosyncratic volatility in the borrower's stock price. While the first and last variable directly measure a change in the borrower's fundamentals and its effect on loans, the second reflects aggregate changes in the economy. $X_{l,t}$ is a vector of other loan and borrower information. We also include lead arranger × report date fixed effects capturing the tendency of a lead arranger to sell off its loans at a given point in time.

Column (1) in Table 5 shows that a negative price change in the firm's other outstanding loans during the syndication process is associated with a lower probability of the lead arranger selling off the entire loan, consistent with pipeline risk. A fall of one cent per dollar of face value in the price of other loans by the borrower is correlated with a one percentage point drop in the likelihood that an arranger is able to fully sell off a loan. Column (2) documents a similar, albeit statistically insignificant, relationship between lead share sales and aggregate loan market conditions. A fall of one cent per dollar of face value fall in aggregate loan prices is associated with a 0.3 percentage point fall in the probability that a loan is sold. Column (3) documents that a 1 percentage point higher idiosyncratic volatility during the syndication is associated with 0.9 percentage point lower probability that the loan is sold. This is consistent with new information about the firm making it less likely that the lead arranger sells off the loan.²⁹ We view this as suggestive evidence for pipeline risk complementing the anecdotal and

²⁹In Internet Appendix Section D we show that the results are very similar when using the continuous lead share as dependent variable, i.e., when not only considering the extensive margin.

systematic evidence in Bruche et al. (2020). The revelation of new information can change the ability of an arranger to sell off the loan, therefore incentivizing good and safe ex-ante selection. Is this incentive sufficiently large to induce costly screening? While a precise costbenefit comparison, necessary to answer this question, is difficult (in part because banks' monitoring/screening costs are not observable), we can nonetheless calculate banks' benefit from lower default rates and assess whether this is large. If one takes the probability of a lead arranger being unable to fully sell an institutional term loan at origination – which is 47% based on Panel B of Figure 2 – then the average bank would suffer losses of \$60 million when it shirks from screening such that the default probability of its borrower pool increases by 10 percentage points.³⁰

While these results are consistent with pipeline risk, they are also consistent with a classical retention argument, i.e., when there is a shock to the borrower then lead arranger retention becomes more important. To distinguish between the information asymmetry and pipeline risk hypotheses we add an interaction term to the regression:

ProblemAfterLoanSold_{*l*,*t*→*T*} =
$$\beta_0 + \beta_1$$
Borrower Information_{*l*,*t*-45→*t*} + β_2 LeadShareSold_{*l*,*t*}
+ β_3 Borrower Information_{*l*,*t*-45→*t*} × LeadShareSold_{*l*,*t*} + $\beta_4 X_{l,t} + \epsilon_{l,t}$.
(4)

If the lead arranger's prior commitment to the firm prevents it from fully adjusting the loan spread when bad information about the borrower's fundamentals arises during the syndication process, then these loans are overpriced (i.e., have a too low spread) given the updated information about the firm. We would expect that loans which are not sold by the lead arranger but that experience a deterioration in borrower quality during the syndication process, should perform worse. In other words, when there is bad information about the borrower, the relationship between loan retention and performance becomes more negative

 $^{^{30}}$ We multiply the average volume of institutional loans from 2018-2020 (\$333 billion), the average market share of a Top20 bank in 2020 (4.3%), a typical recovery rate for institutional term loans of 50%, and the average lead share in institutional term loans conditional on a materialization of pipeline risk (18%).

	Lo	oan share so	old	Loan be	comes non-a	accruing
	(1)	(2)	(3)	(4)	(5)	(6)
Δ Borrower's loan price	0.011^{*} (0.006)			-0.005^{***} (0.001)		
$\Delta \mathrm{LSTA}$ Leveraged Loan Index		$\begin{array}{c} 0.003 \\ (0.003) \end{array}$			-0.002 (0.003)	
Borrower's stock volatility			-0.009^{*} (0.005)			0.008^{***} (0.001)
Lead share sold \times $\Delta Borrower's loan price$				0.005^{**} (0.002)		
Lead share sold \times $\Delta \mathrm{LSTA}$ Lev. Loan Index					0.011^{*} (0.006)	
Lead share sold \times Borrower's stock volatility						-0.009^{**} (0.003)
Lead share sold				-0.038^{**} (0.014)	-0.013 (0.008)	$\begin{array}{c} 0.010 \\ (0.007) \end{array}$
Loan controls	Yes	Yes	Yes	Yes	Yes	Yes
Lead agent \times report date FE	Yes	Yes	Yes	Yes	Yes	Yes
All-in-drawn spread	Yes	Yes	Yes	Yes	Yes	Yes
\mathbb{R}^2	0.487	0.484	0.528	0.308	0.236	0.662
Ν	619	9,883	2,103	614	9,848	2,099
Loan sample	All loans	All loans	All loans	All loans	All loans	All loans

Note: This table shows the results of regression (3) in columns (1)-(3) and regression (4) in columns (4)-(6). The unit of observation is a loan. Δ Borrower's loan price is the 45-day price change in other outstanding loans of the borrower prior to origination. Δ LSTA Leveraged Loan Index is the 45-day change in the S&P/LSTA US Leveraged Loan Index prior to origination. Borrower's stock volatility is computed using daily equity returns in excess of predicted returns in a 45-day window prior to origination, measured in percent. Predicted returns are based on beta estimated with daily returns prior to the syndication process. The sample is restricted to loans for which the first observation in the SNC data is within 90 days of the origination of the loan, in order to focus on loans that are immediately observed after origination. The loan controls are the time since origination, the loan maturity, the logarithm of the loan amount, a leveraged loan dummy, a Term B dummy and the all-in-drawn spread. The standard errors are clustered by lead arranger and by SNC report date. Significance levels: *(p<0.10), **(p<0.05), ***(p<0.01).

under pipeline risk. The retention theory makes the opposite prediction, i.e., it predicts the relationship to become more positive because skin-in-the-game should matter more for high-risk borrowers.

Columns (4) to (6) of Table 5 document that the difference in performance between sold and retained loans widens when there is a negative shock to the borrower. Specifically, when the prices of the borrower's other loans drop by 1 cent during the syndication process, the difference in the probability of becoming non-accruing between sold and retained loans widens by an additional 0.5 percentage points. Similarly, the differential probability of becoming non-accruing – between sold and retained loans – widens if aggregate market conditions deteriorate or the standard deviation of returns rises. The empirical results are consistent with pipeline risk, but go in the opposite direction of what we expect from an argument relying on skin-in-the-game.

While these results indicate that pipeline risk helps explain why lead arrangers on average end up holding worse loans than other investors, this still leaves open the question of why the lead bank is willing to participate in this equilibrium. An obvious explanation is that underwriting loans is a lucrative business. Though lead banks risk ending up holding loans that pay a spread that is too low for the loan risk, they receive compensation through underwriting fees. These fees are typically 2-3% of the loan volume for underwritten loan deals (Bruche et al. (2020)). Assuming a recovery rate of 50% for non-accruing loans, our results from Table 4 suggest that about one fifth of the underwriting fees are compensation for retaining worse loans.³¹

5.3 Reputation Risk

A second possible motivating factor for a lead arranger to carefully select loans, besides the likelihood of accidentally having to retain a large part of them, is its reputation (e.g.,

³¹The cost of retaining worse loans is the average recovery rate of 50% multiplied by the difference in the probability of becoming non-accruing for retained vs. sold loans of 1 percent from Column 2 of Table 4.

Hartman-Glaser (2017), Winton and Yerramilli (2021)). In the repeated game model of Winton and Yerramilli (2021), defaults of previously arranged loans (imperfectly) signal to outside lenders the arranger's past monitoring efforts. Following defaults, lenders punish the arranging bank by purchasing less from it, which is costly for the arranger due to high capital costs.³² This incentivizes the arranging bank to monitor the borrower and therefore reduce the probability of default. The model predicts that following defaults in loans it has arranged, the lead arranger is less likely to (be able to) sell its loan stake. Wary of this punishment, it might be optimal for the lead arranger to arrange fewer loans, giving up market share.

We test this hypothesis by regressing either (a) the lead arranger's market share or (b) the share of originated loans it sold off in a given year, on the share of outstanding loans arranged by the same bank which have turned non-accruing. For this, we collapse the SNC data to the lead arranger-report date level. We estimate the following regressions:

$$Y_{i,t+1} = \beta_0 + \beta_1 \text{Share Non-Accruing Loans}_{l,t} + \beta_2 X_{l,t} + \epsilon_{l,t}.$$
(5)

Here, $Y_{i,t+1}$ is a variable that measures either (a) the market share of lead arranger *i* or (b) the share of loans that are sold off by arranger *i* at report date t + 1. We obtain a lead arranger's market share from the league table on US institutional loans which is available on Bloomberg for the years after 2005. In the regression focusing on market shares, we concentrate on banks that appeared at least once in the top 20 of the league table.³³

³²The costs of having to retain a loan that was designed to be sold off – because the arranger failed to accurately gauge market appetite for a loan – is non-trivial for the arranging bank. The risk weights for a Term B loan typically lie between 100 and 150%. This implies that a bank which holds onto a 100 million USD leveraged Term B loan and faces a minimum common equity tier 1 (CET1) capital ratio of 10% would have to raise around 15 million USD of additional CET1 capital. The CET1 ratio is a measure of the minimum equity (and similarly valued capital) a bank must hold, relative to its risk-weighted-assets. Risky loans receive higher risk weights. 10% is a reasonable assumption for a GSIB bank, considering the GSIB surcharges (for more details, see: https://www.federalreserve.gov/publications/large-bank-capital-requirements-20210805.html). Given that banks are extremely averse to raising such capital, the inability to sell a large and risky loan entails significant risk to the arranger.

³³This sample criterion ensures that we observe a sufficient number of loans for each lead arranger-year pair. In the end, we have information on 14 years and the 23 largest lead arrangers yielding 225 observations. Some of these lead arrangers are not observed for the entire period due to entries/exits from the syndicated

When constructing the explanatory variables we focus on term loans. The main explanatory variable Share Non-Accruing $\text{Loans}_{i,t}$ measures the fraction of term loans originated by lead arranger *i* that become non-accruing at report date *t*. We also include controls $X_{i,t}$ that capture the average riskiness of loans that lead agent *i* arranges. This is measured by the average all-in-drawn spread and the fraction of loans that are either Term B or leveraged loans.

	Marke	t share	Marke	t share	Fraction o	f loans sold	
	in curr	ent year	in follow	ving year	off in folle	owing year	
	(1)	(2)	(3)	(4)	(5)	(6)	
Fraction of non-accruing loans	-0.076**		-0.050*		-0.064**		
	(0.031)		(0.027)		(0.022)		
Fraction of problematic loans		-0.108**		-0.032		-0.041*	
-		(0.044)		(0.044)		(0.023)	
Sample		Top 20 a	rrangers		All ar	rangers	
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	
Lead agent FE	Yes	Yes	Yes	Yes	Yes	Yes	
Loan riskiness controls	Yes	Yes	Yes	Yes	Yes	Yes	
\mathbb{R}^2	0.76	0.76	0.77	0.77	0.53	0.53	
Ν	225	225	206	206	1556	1556	

Table 6: Reputation Damage of Underwriting Bad Loans

Note: This table shows the results of regression (5). The unit of observation is an arranger-year observation. The dependent variable is the arranger's contemporaneous market shares in columns (1) and (2), the market shares in the following year in columns (3) and (4), and the fraction of loans that the lead arranger sells off in the following year in columns (5) and (6). The market share is taken from the league table for US institutional loans available on Bloomberg since 2005. Additionally, we focus in columns (1)-(4) only on underwriters that were ranked in the top 20 at least once during our sample period. Problematic loans are loans that have received a non-pass rating. All regressions include controls for the average riskiness of loans originated by a lead arranger measured by the average all-in-drawn spread as well as the share that are Term B or leveraged loans. We additionally include year and lead arranger fixed effects. Standard errors are clustered by the lead arranger and by year level. Significance levels: *(p<0.10), **(p<0.05), ***(p<0.01).

Table 6 shows that a 10 percentage point share of outstanding loans that become nonaccruing is associated with a reduction in the lead arranger's market share in the same year by 0.76 percentage points. This is consistent with the lead arranger being punished if its arranged loans default. The relationship is slightly stronger when we look at the fraction loan business giving us an unbalanced panel. of arranged loans that receives a non-pass rating. A 10 percentage point share of arranged loans becoming problematic is correlated with a 1.08 percentage point lower market share for the lead arranger in the same year. The coefficients are slightly smaller when the market share is measured in the following year. When the lead arranger is punished by less demand for its loans by investors, it might still decide to originate loans but be forced to keep them on its books rather than being able to sell them off. The evidence presented in columns (5) and (6) is consistent with this. A 10 percentage point higher share of outstanding loans becoming non-accruing is associated with a 0.6 percentage point higher share of loans that the lead arranger will need to retain in the following year.

The results that we document are consistent with the theoretical framework proposed by Winton and Yerramilli (2021). However, there are also other potential explanations for the documented relationship. One such story might be that lead arrangers specialize in different industries. If the loan demand and the loan performance of borrowers is positively correlated across industries, then this might explain the correlation between loan performance and market share. However, loan demand less plausibly explains the finding that the lead arranger is less likely to be able to sell its stake after its arranged loans become non-accruing.

Is the potential loss in market share sufficiently large to induce the bank to screen and monitor the borrower? We can try to quantify lead arrangers' reputational costs when shirking from monitoring such that default rates rise by 10 percentage points and assess whether these costs are large. The coefficient of 0.076 in column (1) is large relative to the average arranger's market share of 2.74%. It suggests that a 10 percentage point rise in the share of non-accruing loans would cost the average bank almost one third of its syndication business. This represents a significant loss of fees.³⁴ Based on Bloomberg estimates, a large US syndicating bank earned on average 1% of its league table allocation in fees. Applying this fee to the average total issuance volume of institutional loans of 546 billion USD across the years 2018-2020, a bank would stand to miss out on about 42 million USD in fees following

 $^{^{34}}$ In fact, the market share differences, between individual league table ranks, is less than 0.4%, meaning a slight increase in non-accruing loans can already be costly from a rank-perspective.

a 10 percentage point rise in the fraction of non-accruing loans.³⁵ This is substantial and could plausibly suffice to induce proper screening by the lead arranger.

6 Conclusion

In this paper, we make use of Shared National Credit Registry (SNC) data to analyze the role of the lead arranger's stake – the lead share – in the syndicated loan market. Our findings that the lead arranger often sells its share and this does not lead to adverse selection and moral hazard problems, challenge classic banking theories assigning the loan retention by the originating bank a special role to overcome information asymmetry problems.

In part, past researchers studying lead shares have primarily used Dealscan data. Given the self-reported nature of the data and the pace with which loan ownership changes after origination, the data may be less well-suited for such analyses. To remedy this issue, we offer researchers a guide to working with Dealscan.

Our study ultimately sheds new light on the intermediation role of banks. While a well-established literature shows that retention by the arranging bank is important in the mortgage market to ensure proper functioning of banks' intermediation role, we find that this is not the case for syndicated loans. The question of why the intermediation role of banks is so different in these two markets and whether the difference lies in the type of borrowers (e.g., firms being less opaque than homeowners) or the type of investors (e.g., CLOs and other loan investors being more sophisticated) remains open.

³⁵This is calculated as: $10\% \times 0.076\% \times 546$ billion USD $\times 1\% = 42$ million USD.

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INTERNET APPENDIX FOR "THE MYTH OF THE LEAD ARRANGER'S SHARE"

Kristian Blickle Quirin Fleckenstein Sebastian Hillenbrand Anthony Saunders

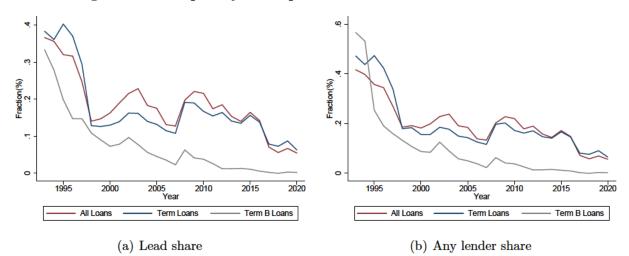
A Guide for Dealscan Users

Lender shares in Dealscan. The information for most loans in Dealscan is self-reported by the lead arrangers. For a very small subset of loans the lead arrangers also report the syndicate shares at origination. These syndicate shares have often been used by researcher to approximate loan ownership (e.g., Sufi (2007), Chodorow-Reich (2014)). However, as we demonstrate in this paper, the lender composition changes – most importantly for loans that are sold to institutional lenders – substantially after origination. Given these challenges how should researchers that have only access to Dealscan proceed? In this section we offer a guide for researchers looking to compute estimates of loan shares that lead arranger and other loan syndicate participants may hold following origination using only Dealscan information, for instance to study on-balance sheet lending volumes and spreads of banks.³⁶ While we want to caution that this does not yield perfect estimates, we feel that it is significant improvement over how the prior literature has used Dealscan.

Frequency of reported lender shares. As discussed in the paper, lenders report loan origination data to Dealscan in order to get credit for the syndicated loan league tables. The lender shares at syndication are not among the information that lead arrangers are required to provide. As a result, only a small fraction of loans include shares at origination. The share of loans for which the lead share at syndication is observed has declined over time, as shown in Panel A of Figure A.1. In recent years, lead shares are reported for less than 10% of loans. This is consistent with the increased tendency of lead arranger to sell their shares

³⁶While SNC directly reports a unique lead agent (administrative agent) per loan, Dealscan does not always do so. To identify the "main" lead agent in Dealscan we follow the prior literature (e.g., Sufi (2007)). We assign the lead agent role first to the "admin agent". If there is no "admin agent" in the syndicate, we choose any lender with the title "Agent", "Bookrunner", "Joint arranger", "Lead bank", "Lead manager", "Mandated Lead arranger". If there is also no lender with such title, then we assign any of the lenders with the title "Co-agent", "Co-arranger", "Collateral agent", "Coordinating arranger", "Documentation agent", "Managing agent", "Syndications agent". If there are several agents with the same title, then we choose the one with the highest lender share at origination, and otherwise we randomly draw the lead agent.





Note: This figure shows the fraction of loans for which we observe (a) the lead share at origination or (b) at least one lender share at origination in Dealscan. The sample contains the entire sample of USD-denominated syndicated loans in Dealscan since 1993.

following increased institutional participation in the market. As we show in the paper, the loan holdings composition changes most starkly for loans tailored to institutional investors – implying syndicate shares for these loans are least likely to reflect actual loan holdings after origination. Panel B shows that not just the reporting of the lead shares has declined, but also the reporting of the shares of other syndicate members.

Selection bias in reporting. More importantly, the reporting of lender shares to Dealscan is non-random. Table A.1 documents that the reporting of lender shares can be predicted fairly well with several loan characteristics. In other words, the sample for which we observe lender shares is non-random and biased. Conducting analysis only with this subset of loans can therefore be problematic and might not allow conclusions to be drawn for the entire set of loans. One way to overcome this bias is to include loans for which we do not observe lender shares into any analysis. We show below how this can be done.

Informativeness of syndicate shares for loan ownership. We start by analyzing the loans for which we observe the lender shares at syndication. Specifically, we analyze whether these shares are reflective of the ultimate holdings of syndicate members after origination. For this, we use a matched data set at the loan-lender level that merges Dealscan and SNC. We focus here on banks as non-banks typically do not participate in the syndicate.

First, we find that if a share is reported as being smaller than 0.5% of the loan, then this is highly likely either an error or a share that will be immediately sold off. It is therefore

	Nonmissing	g lead share	Any nonmiss	sing lender share
	(1)	(2)	(3)	(4)
Year of origination	-0.75***		-0.90^{***}	
	(0.13)		(0.12)	
Maturity	-0.42^{***}	-1.01^{***}	-0.37^{***}	-1.09^{***}
	(0.09)	(0.12)	(0.10)	(0.13)
All-in-drawn spread	-0.02^{***}	-0.03^{***}	-0.02^{***}	-0.03^{***}
	(0.00)	(0.00)	(0.00)	(0.00)
$\log(\text{Loan amount})$	-0.09	0.13	-0.54	-0.27
	(0.44)	(0.37)	(0.54)	(0.43)
Number of lenders in syndicate	1.05***	0.97***	1.17***	1.08***
	(0.09)	(0.09)	(0.09)	(0.09)
Dummy: Fund in syndicate	-6.48^{***}		-5.77^{***}	
	(1.22)		(1.68)	
Term B loan	-9.02^{***}		-8.92^{***}	
	(0.93)		(1.04)	
Origination year FE		Yes		Yes
Loan purpose FE		Yes		Yes
Loan type FE		Yes		Yes
Mean of dependent variable	0.20	0.20	0.21	0.21
\mathbb{R}^2	0.11	0.17	0.13	0.19
N	$136,\!833$	136,829	$136,\!833$	136,829

Table A.1: Selection of Reported Lender Shares in Dealscan

Note: This table shows that the reporting of lender shares in Dealscan is non-random, i.e., can be predicted with observable variables. The regression model is $\mathbb{I}(\text{Reported Lead Share})_l = \beta' \cdot \text{Loan Characteristics}_l + \epsilon_l$. The unit of observation is a loan l. The dependent variable is a dummy that indicates whether Dealscan reports a lender share for the lead arranger in column (1)-(2) or for any lender in the syndicate in column (3)-(4) (multiplied with 100). The sample contains all USD-denominated syndicated loans in Dealscan that are originated between 1993 and 2018. The standard errors are clustered by the origination year. The significance levels are: *(p<0.10), **(p<0.05), ***(p<0.01).

advisable to approximate the ultimate loan holdings of the lender with a zero.

Second, to analyze the predictive power of the remaining shares for actual loan holdings, we run the following regression:

Share at first observation $(SNC)_{i,l} = \beta_0 + \beta_1 \cdot Share at syndication (Dealscan)_{i,l} + \epsilon_{i,l}$ (A.1)

for loan l and lender i. Regarding the different lenders, we distinguish between lead agents (defined following the literature (Sufi (2007))) and other lenders (e.g., other co-agents and participants in Dealscan).

Figure A.2 documents the relationship between the syndicated share in Dealscan and the lending share at the first SNC observation graphically in the form of binscatter plots. The figure shows that when the syndicate shares at origination are reported in Dealscan, then they can serve as decent predictors of the ultimate loan ownership of the agent. Because the linear relationship flattens when the Dealscan share is high, the regression interacts the Dealscan share with a dummy when the Dealscan share is above 30%.

Table A.2 shows the regression results. The coefficient in column 1 (credit lines) suggest that the reported lead shares in Dealscan should be scaled (down) with a factor of 0.936 when the share is below 30%. When the share is above 30%, then the lead share in the syndicate should be multiplied with a factor 0.347, but a constant of 24.65% should be added. The fitted value explains 80% of the variation of the true loan ownership for Credit Lines (column 1), 64% of the variation in Term A loans (column 3) and 56% of the variation in other loans (column 5). However, the term A analysis is based on a much smaller sample. Similarly, we cannot run the regression analysis for Term B loans as we simply do not have enough observations where the lead/lender shares are reported. We obtain similar results when we look at the loan holdings of other syndicate members (columns 2, 4, and 6).

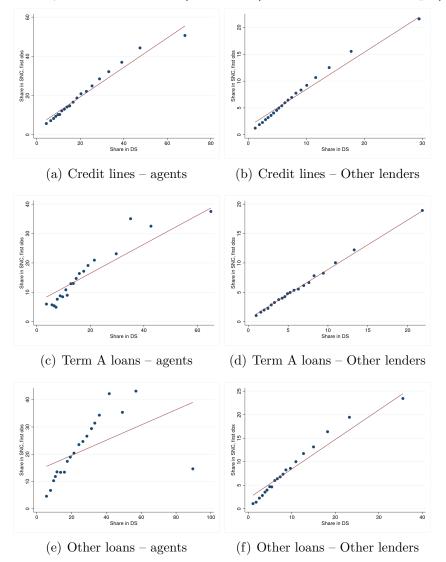


Figure A.2: Syndicate Shares (Dealscan) vs. Loan Ownership (SNC)

Note: This figure show binscatter plots of the syndicate share (as reported in Dealscan) and the loan ownership after origination (as observed at the first observation in SNC). Panel (a), (c) and (e) focus on lead agents, while panels (b), (d) and (f) focus on all other syndicate members (e.g., co-agents or participants).

		S	share at first o	bservation (SNC	3)	
	(1)	(2)	(3)	(4)	(5)	(6)
Share at origination (Dealscan)	$\begin{array}{c} (1) \\ 0.936^{***} \\ (0.015) \end{array}$	$\begin{array}{c} (2) \\ 0.854^{***} \\ (0.029) \end{array}$	$\begin{array}{c} (0) \\ 0.979^{***} \\ (0.074) \end{array}$	$\begin{array}{c} (1) \\ 0.891^{***} \\ (0.037) \end{array}$	$\begin{array}{c} (0) \\ 0.918^{***} \\ (0.061) \end{array}$	$\begin{array}{c} (0) \\ 0.871^{***} \\ (0.024) \end{array}$
Share at origination x Large share	-0.589^{***} (0.068)	-1.080^{***} (0.136)	-1.221^{***} (0.344)	-1.265 (2.188)	-1.258^{***} (0.061)	-1.255^{***} (0.083)
Large share	$23.462^{***} \\ (2.697)$	32.440^{***} (5.064)	$\begin{array}{c} 43.382^{***} \\ (13.891) \end{array}$	41.131 (86.340)	$\begin{array}{c} 48.425^{***} \\ (3.224) \end{array}$	36.625^{***} (4.108)
Constant	1.188^{***} (0.289)	$\begin{array}{c} 0.424^{***} \\ (0.119) \end{array}$	$\begin{array}{c} 0.071 \\ (1.334) \end{array}$	0.201 (0.140)	$0.786 \\ (0.930)$	$0.262 \\ (0.163)$
Loan sample	Credit lines	Credit lines	Term A	Term A	Other loans	Other loans
Lender sample	Lead agent	Other lenders	Lead agent	Other lenders	Lead agent	Other lenders
Mean of dependent variable	19.986	6.865	15.294	5.714	21.564	8.037
\mathbb{R}^2	0.801	0.648	0.625	0.747	0.554	0.662
Ν	2,417	26,888	90	1,569	308	2,112

Table A.2: Syndicate Shares (Dealscan) vs. Loan Ownership (SNC)

Note: This table reports the results of regression (A.1). The unit of observation is a loan-lender pair. We also repeat the analysis for other lenders (e.g., co-agents and participants) that do not function as lead agents in columns (2), (4) and (6). Lender shares are in percent. The sample is a matched SNC-Dealscan sample for which we observe the lender shares at origination. *Large share* is a dummy variable that is 1 if the share at origination is larger than 30% and 0 otherwise. Standard errors are clustered by lender. The significance levels are: *(p<0.10), **(p<0.05), ***(p<0.01).

How to approximate loan ownership when lender shares are not reported. As Figure A.1 shows, the lead share (or any lender share for that matter) is missing for the vast majority of loans in Dealscan. The question that arises for Dealscan users: how can the actual loan ownership share be inferred for syndicate participants that are observed in Dealscan? This is an important question for anyone who is interested in how much lending is provided not only by the lead agent but also by other bank lenders. This is all the more important considering (a) the low number of reporting and (b) the selection in reporting.

One common procedure to approximate loan holdings is to use the sample of loans with reported lender shares to impute lender share for loans with missing ones. For example, one could use the syndicate structure to infer missing lender shares (e.g., Chodorow-Reich (2014)). This approach relies on the assumption that (1) syndicate shares at Dealscan are reflective of the ultimate loan holdings and (2) that the correlation between syndicate structure and lenders shares is similar across loans with and without reported lender shares. However, as the reporting of the syndicate shares is non-random, this can potentially lead to a large bias. For example, projecting lender shares at origination from credit lines (which frequently come with lender shares) onto the syndicate participants in a Term B loan (which almost never come with lender shares) is unlikely to yield the ultimate holders of the loan.

A second widely-used method is to apply equal weights to all syndicate members. While this method is simple to apply, it does not take into account that many loan investors only participate after origination. Thus, the loan share held by syndicate members drops mechanically after origination.

In this paper we propose an alternative way to approximate loan holdings. More concretely, we use the loan information available from Dealscan to directly predict the lender shares observed at the first observation in SNC. We fit the regression

Share at first observation
$$(SNC)_{i,l} = \beta_0 + \beta_1 \cdot X_{i,l} + \beta_2 \cdot X_l + \epsilon_{i,l},$$
 (A.2)

where X_{il} and X_l are vectors of lender-loan characteristics and loan characteristics that are observable in Dealscan for almost every loan. We show the results of this predictive exercise in Table A.3. This regression of course cannot be run by researchers having only access to Dealscan. However, researchers can use our reported regression coefficients to get a rough approximation of the loan holdings of syndicate participants for almost every loan in Dealscan.

	Share at first observation (SNC)					
	(1)	(2)	(3)	(4)	(5)	
Lender role "agent"	7.326^{***}	-4.401	-0.984	-0.077	25.761^{***}	
	(1.173)	(6.425)	(5.850)	(3.483)	(7.003)	
Interaction: Lender role "agent" * Facility amount	-0.744^{***}	1.143	1.175	-0.140	-4.000^{***}	
	(0.197)	(1.164)	(0.939)	(0.539)	(1.230)	
Interaction: Lender role "agent" * Facility amount * Inv. numb. lenders	4.273^{**}	-31.113^{**}	-78.712^{***}	-30.085^{**}	11.570	
	(2.082)	(13.471)	(16.838)	(12.314)	(9.447)	
Interaction: Lender role "agent" * Inv. numb. lenders	-24.978^{***} (8.919)	165.967^{***} (61.496)	$296.914^{***} \\ (81.868)$	139.451^{**} (61.766)	-68.838 (48.809)	
Lender role "adm. agent"	8.918^{***}	6.260	-3.995	-2.112	27.473^{***}	
	(1.148)	(5.947)	(5.468)	(3.139)	(6.886)	
Lender role "adm. agent" * Facility amount	-1.427^{***}	-0.749	0.783	0.441	-4.331^{***}	
	(0.190)	(1.070)	(0.879)	(0.474)	(1.158)	
Interaction: Lender role "adm. agent" * Facility amount * Inv. numb. lenders	27.369^{***}	-1.073	-27.147^{**}	-4.430	18.663^{**}	
	(2.242)	(12.983)	(13.345)	(15.001)	(8.455)	
Interaction: Lender role "adm. agent" \ast Inv. numb. lenders	-194.884^{***}	-53.453	142.337^{**}	-12.896	-151.133^{***}	
	(10.106)	(63.454)	(71.485)	(76.248)	(47.315)	
Lender role "Co- X"	2.064	-4.735	-9.204	-6.954	28.035^{***}	
	(1.370)	(7.922)	(7.358)	(4.882)	(8.495)	
Lender role "Co- X" * Facility amount	-0.057	1.181	2.301^{**}	0.891	-4.582^{***}	
	(0.225)	(1.412)	(1.155)	(0.733)	(1.454)	
Lender role "Co- X" * Facility amount * Inv. numb. lenders	-11.108^{***}	-31.952^{*}	-93.312^{***}	-52.549^{**}	9.890	
	(2.791)	(18.203)	(23.728)	(24.235)	(12.464)	
Lender role "Co- X" * Inv. numb. lenders	43.615^{***}	127.296	366.579^{***}	215.113	-78.961	
	(13.243)	(89.179)	(125.472)	(130.862)	(65.224)	
Lender role "Participant"	2.010	-9.733	-6.370	-2.409	26.028^{***}	
	(1.227)	(6.483)	(5.960)	(3.743)	(7.192)	
Lender role "Participant" * Facility amount	-0.210	1.761	1.705^{*}	0.118	-4.337^{***}	
	(0.204)	(1.173)	(0.956)	(0.582)	(1.257)	
Lender role "Participant" \ast Facility amount \ast Inv. numb. lenders	-6.101^{***}	-37.349^{***}	-84.806^{***}	-35.385^{***}	4.669	
	(2.203)	(13.713)	(17.049)	(12.599)	(9.932)	
Lender role "Participant" * Inv. numb. lenders	-1.198	161.808^{***}	283.420^{***}	135.558^{**}	-74.293	
	(9.687)	(62.510)	(82.719)	(63.168)	(51.330)	
Agent Lead (Ds def.)	4.686^{***}	0.893	4.178^{***}	0.628	2.399	
	(0.319)	(1.092)	(1.583)	(0.542)	(1.524)	
Agent Lead (Ds def.) * Facility amount * Inv. numb. lenders	-31.215^{***}	-20.794^{**}	-35.469^{**}	-11.341	-11.205^{**}	
	(1.640)	(9.704)	(14.014)	(14.113)	(5.619)	
Agent Lead (Ds def.) * Inv. numb. lenders	253.833^{***} (6.341)	$206.687^{***} \\ (39.727)$	149.097^{**} (68.423)	146.162^{**} (66.229)	146.801^{***} (26.713)	
Lender role "Other"	5.200^{***}	-17.945^{***}	-4.790	-10.962^{***}	14.739^{**}	
	(1.409)	(6.214)	(6.314)	(3.365)	(6.996)	
Lender role "Other" * Facility amount	-0.630^{***} (0.229)	3.279^{***} (1.142)	1.455 (1.008)	1.507^{***} (0.523)	-2.629^{**} (1.227)	
Lender role "Other" * Facility amount * Inv. numb. lenders	2.111	-48.644^{***}	-82.094^{***}	-29.995^{***}	-15.107	
	(2.429)	(13.474)	(17.105)	(10.497)	(9.420)	

Table A.3: Prediction of Loan Holdings with Dealscan Variables

Lender role "Other" * Inv. numb. lenders	-20.921^{*}	256.491***	326.073***	152.069***	73.941
	(11.151)	(60.704)	(82.507)	(52.315)	(48.310)
Log. (Number of lenders)	1.618^{***}	-0.868	2.491**	0.136	0.547
	(0.365)	(1.198)	(1.000)	(0.598)	(1.056)
	0.010	0.157	0 179	0.007	0.000
Log. (Number of lenders) * Facility amount	0.012 (0.059)	0.157 (0.205)	-0.173 (0.153)	-0.087 (0.090)	-0.089 (0.163)
	(0.003)	(0.200)	(0.100)	(0.050)	· · ·
Log (Facility Amt.)	0.406	-1.481	0.631	-0.854	4.416***
	(0.304)	(1.438)	(1.426)	(1.118)	(1.437)
Inv. numb. lenders	122.984***	-41.039	-148.473^{*}	55.865	181.213***
	(10.570)	(63.506)	(82.952)	(63.066)	(52.675)
Inv. numb. lenders * Facility amount	5.822**	34.279**	77.131***	6.428	-8.421
	(2.336)	(13.804)	(17.072)	(12.548)	(10.048)
	101.000			10.05	F 01 005
Inv. numb. "adm. agents"	184.863	9923.877**	-1.6e+05	$1.9e+05^{***}$	561.367
	(162.651)	(4471.133)	(1.1e+05)	(7.2e+04)	(1517.806)
Inv. numb. "adm. agents" *Facility amt.	-30.897	$-1.2e+03^{*}$	$2.9e{+}04$	$-2.4e+04^{**}$	-138.572
	(25.759)	(664.634)	(2.1e+04)	(1.2e+04)	(308.933)
Inv. numb. "Participants"	-1.4e+03	$-2.5e+05^{***}$	6.3e + 05	$-1.3e+06^{***}$	-2.6e+04
*	(3632.118)	(8.4e+04)	(5.8e+05)	(4.0e+05)	(3.1e+04)
Inv. numb. "Participants" *Facility amt.	327.364	2.8e+04**	-1.3e+05	$1.3e+05^{**}$	6114.818
	(571.423)	(1.2e+04)	(1.0e+05)	(6.0e+04)	(5417.990)
· · · · · ·					
Inv. numb. "Agents"	8.097***	13.760***	17.536***	6.480***	6.416***
	(0.382)	(1.843)	(1.527)	(1.884)	(1.900)
Inv. numb. "Participants" * Faciliy amt.	-0.900^{***}	-2.048^{***}	-2.321^{***}	-0.982^{***}	-0.533
	(0.066)	(0.341)	(0.273)	(0.294)	(0.346)
"Has bankallocation" * Facility amt.	-0.219^{***}	-0.685^{***}	-0.243	-1.083^{*}	-0.009
	(0.035)	(0.223)	(0.172)	(0.653)	(0.226)
Constant	-11.444^{***}	7.026	-11.769	16.404**	-28.230^{***}
Constant	(1.821)	(8.145)	(8.878)	(7.256)	(8.402)
Year FE	Yes	Yes	Yes	Yes	Yes
Dummy(Reported Shares) x Year FE	Yes	Yes	Yes	Yes	Yes
Mean of dependent variable					
\mathbb{R}^2	0.683	0.676	0.676	0.336	0.615
N	72,978	5,536	7,386	$6,\!652$	3,539
Sample	CL	TL	TLA	TLB	All Other Loans

Note: This table shows the results of regression A.2. The unit of observation is a loan-lender pair. Lender shares are in percent. The significance levels are: *(p<0.10), **(p<0.05), ***(p<0.01).

We use the R-squared

$$R^{2} = 1 - \frac{\sum_{l} \sum_{i} (\text{SNC share}_{i,l} - \text{Predicted share}_{i,l})^{2}}{\sum_{l} \sum_{i} (\text{SNC share}_{i,l} - \overline{\text{SNC share}}_{i,l})^{2}},$$
(A.3)

for loan l and lender i, to compare the performance of the different methods. Table A.4 shows that our approach leads to much smaller prediction errors compared to the interpolated shares based on the syndicate structure and the equal-weighted shares. The difference in prediction errors is particularly stark for loans that are later sold to institutional investors, i.e., Term B loans, where the error for the interpolated shares are very large. Here, the interpolation based on the syndicate structure constantly overpredicts the loan holdings leading to negative R-squareds. This makes sense, given that it is hardly possibly to project from lender shares at origination for loans that are held by banks onto lender shares after origination for loans that are predominantly held by institutional investors. Equal weighting also performs poorly which is not surprising given that many lenders, such as CLOs, only participate in the loan after origination. By contrast, our method avoids these issues and performs much better. This new method is able to explain between 27% (Term B loans) and 64% (credit lines) of the variation in ultimate loan holdings.

								-		
		Prediction Accuracy (R-squared)								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)		
Method 1: Syndicate structure	-0.14	0.10	0.43	0.43	-9.42	-8.28	-0.62	-0.35		
Method 2: Equal shares	-0.11	-0.05	0.50	0.19	-8.10	-9.60	-0.84	-0.53		
Method 3: Direct SNC prediction	0.64	0.56	0.66	0.59	0.28	0.34	0.57	0.49		
Loan sample	Credit lines	Credit lines	Term A loans	Term A loans	Term B loans	Term B loans	Other loans	Other loans		
Lender sample	Lead Agent	Other Lenders	Lead Agent	Other Lenders	Lead Agent	Other Lenders	Lead Agent	Other Lenders		

Table A.4: Comparison of Methods to Approximate Loan Ownership

Note: This table compares different methods that can be used to predict actual loan holdings in SNC when Dealscan shares are missing. The method "Syndicate Structure" uses the syndicate structure and the reported syndicate shares (from Dealscan) to infer loan holding shares (e.g., Chodorow-Reich (2014)). The method "Equal Shares" gives equal loan holdings to all syndicate members in Dealscan. The method "Direct Prediction" is based on our regression of actual loan holding shares (as observed in SNC) on various Dealscan variables (see Table A.3). The R-squared shows the goodness of fit when predicting actual lender shares as observed at the first SNC observation of the two methods and is computed as $R^2 = 1 - \frac{\sum_l \sum_i (\text{SNC share}_{i,l} - \text{Predicted share}_{i,l})^2}{\sum_l \sum_i (\text{SNC share}_{i,l} - \frac{\text{SNC share}_{i,l}}{2} \text{ for loan } l \text{ and lender } i. A negative R-squared typically arises because a method "overpredicts" loan holdings shares.$

Guidance for Dealscan users. We conclude this section by summarizing our guidance for researchers who have only access to Dealscan but are interested in the actual loan holdings of lead arrangers and other bank lenders after origination. We distinguish two cases: (a) when lender shares are reported in Dealscan, and (b) when lender shares are not reported. Regarding (a), we suggest researchers to use the regression coefficients from Panel A of Table A.2 to scale the Dealscan-reported lender shares at origination after removing 'outlier observations', i.e., observations with a share smaller than 0.5%. Regarding (b), we suggest researchers use our predictive regression (reported in Table A.3) that uses only Dealscan variables which are available for almost all loans. We also provide code that performs this task on our website. Of course, our method does not yield the loan ownership of lenders that do not participate in syndicate such as the majority of institutional lenders such as CLOs and loan mutual funds. As such, the method is most suited to approximate syndicate lending by banks.

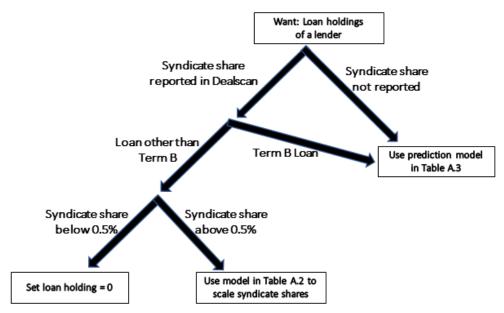


Figure A.3: Dealscan Guide: Decision Tree

Note: This figures provides the decision tree when researchers want to approximate loan holdings of banks using only Dealscan data.

B Lender Composition at and after Origination

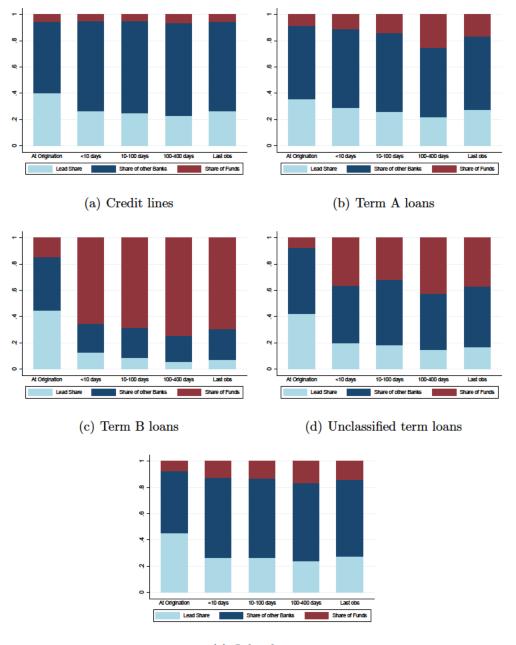


Figure B.1: Timeline of lender shares

(e) Other loans

Note: This figure shows the change in the lender structure after loan origination for different types of loans. It shows the average share of a loan held by each lender group across loans. The first bar ("At Origination") is obtained by using lender shares as reported by Dealscan. If missing we interpolate the lender shares based on the syndicate structure (e.g., Chodorow-Reich (2014)). The second bar is based on lender shares for loans observed within 10 days of origination in SNC, the third and fourth bar are computed accordingly. The fifth bar is based on lender shares at the last observation in SNC.

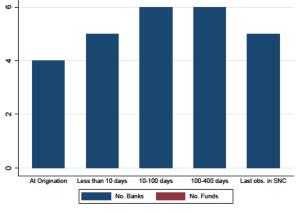
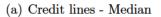
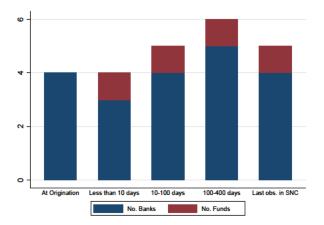
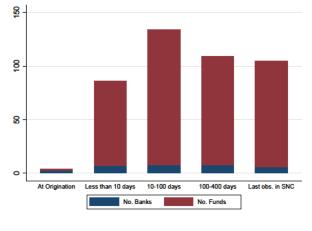


Figure B.2: Timeline of number of lenders

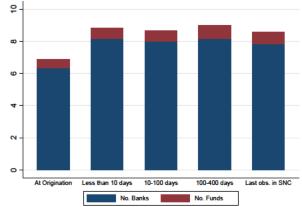




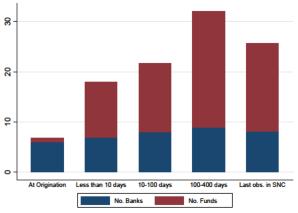
(c) Term A loans - Median



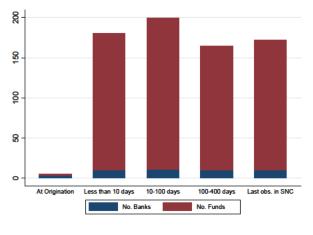
(e) Term B loans - Median



(b) Credit lines - Average



(d) Term A loans - Average



(f) Term B loans - Average

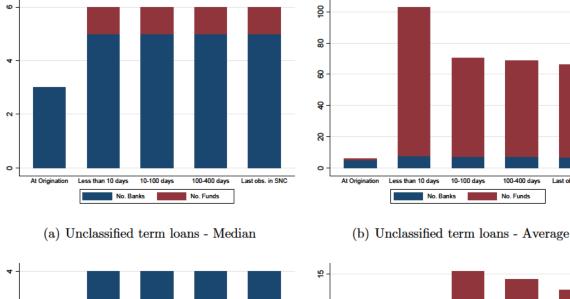
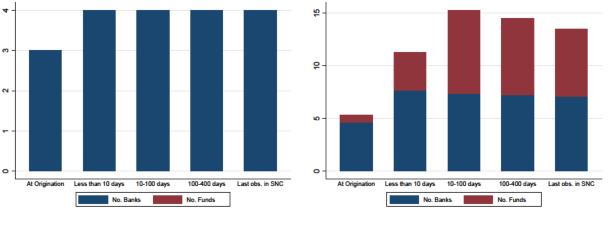


Figure B.3: Continued. Timeline of number of lenders



(c) Other loans - Median

(d) Other loans - Average

10-100 days

No. Banks

100-400 days

No. Funds

Last obs. in SNC

Note: This figure shows the change in the lender structure after loan origination for different types of loans. It shows the average or median number of lenders of each lender type (banks or funds) across all loans. The first bar ("At Origination") is obtained by using the number of syndicate members in Dealscan. The second bar is based on loans observed within 10 days of origination in SNC, the third and fourth bar are computed accordingly. The fifth bar is based on the number of lenders observed at the last observation in SNC.

C Main Empirical Results – Robustness

C.1 H1: Does the lead arranger ever sell its share?

Residual borrower exposure. In Table C.1 we show the residual exposure of the lead arranger to the borrower when the lead arranger has sold its share. We also distinguish here where the exposure comes in the form of term loans or drawn credit lines or merely in the form of "passive", i.e., undrawn, credit lines. Typically, the borrower only needs to comply with credit line covenants if at least 30% of the credit line is drawn.

Table C.1: Retained Borrower Exposure – Drawn vs. undrawn loan commitments

	Fraction of loans for which the lead share is sold after origination				
	All loans	Term loans	Term B loans		
Lead agent has no exposure	37%	30%	25%		
Lead agent has participant exposure through					
• Undrawn credit lines	12%	17%	15%		
• Drawn credit lines or term loans	17%	22%	24%		
Lead agent has agent exposure through					
• Undrawn credit lines	10%	6%	4%		
• Drawn credit lines or term loans	24%	25%	32%		
Number of loans	6,733	3,712	897		

Note: This table examines the residual exposure of the lead arranger to a borrower when its lead share is zero. For each loan sold by the arranger, we aggregate the exposure of this arranger to the same borrower (at the level of the holding company) through all other loans in the SNC data. At the same time, we distinguish between whether the lender acts a lead arranger (*agent exposure*) for at least one other loan or as a participant (*participant exposure*) for all other loans. Second, we also distinguish whether the residual exposure comes exclusively from undrawn credit lines, or from at least one drawn credit line or term loan.

When does the lead arranger sell? Table C.2 reports results from tests of the hypothesis that the lead arranger can only sell its share after sufficient information about the borrower has become public, so that investors can infer the lead arranger's screening effort and information asymmetries are dissolved. Specifically, we test whether loans sold by the lead arranger experienced more information release than retained loans. As proxies for information releases we use indicator variables for whether the borrower (a) has a CUSIP code

and therefore has publicly-trading stocks (which makes information retrieval easier), (b) had an earnings announcement according to the IBES database between the origination date and the first SNC report date, (c) had an earnings announcement according to Compustat between the origination date and the first SNC report date, and (d) had a highly volatile stock prices as measured by the standard deviation of the firm's stock return between the origination date and the first SNC report date. We do not find that retained and sold loans differ in the amount of information that was revealed. This holds for all loans and only term loans.

				Lea	d share sold			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Public firm	$0.009 \\ (0.005)$				$\begin{array}{c} 0.023\\ (0.018) \end{array}$			
Earnings announcement (IBES)		-0.013 (0.014)				-0.028 (0.040)		
Earnings announcement (Compustat)			-0.018 (0.015)				$0.069 \\ (0.050)$	
Stock price volatility				-0.005 (0.005)				$0.005 \\ (0.020)$
Lead agent x report date FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
All-in-drawn spread	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Loan controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Mean of dependent variable	0.069	0.090	0.058	0.046	0.218	0.267	0.208	0.181
\mathbb{R}^2	0.361	0.444	0.392	0.393	0.409	0.501	0.547	0.651
Ν	12,043	4,594	2,329	1,997	3,268	1,377	538	392
Loan sample	All loans	All loans	All loans	All loans	Term loans	Term loans	Term loans	Term loans

Table C.2: Lead Share Sales and Information Revelation

Note: This table reports results from the following regression:

LeadShareSold_l =
$$\beta_0 + \beta_1$$
Information Release_l + $\beta_2 X_l + \epsilon_l$, (C.1)

where LeadShareSold_l is an indicator that is 1 if the lead arranger of loan l has sold its entire share at the first SNC report date after loan origination and zero otherwise. We limit ourselves to loans we observe within 90 days of origination. Our variables of interest are various measures of whether information is released (or could have been released) during the period after origination and a potential loan sale. Public firm denotes whether the borrowing firm has a cusip code, which makes information retrieval easier. Earnings Announcement (IBES) denotes whether the borrower had an earnings announcement reported in IBES between origination and the first SNC report date past origination. Earnings Announcement (Compustat) denotes whether the borrower had an earnings announcement reported in Ocmpustat between origination and the first SNC report date past origination. X_l is a vector of controls and includes the time since origination, the loan maturity, the logarithm of the loan amount, a leveraged loan dummy, a term loan dummy, and a Term B dummy. Standard errors are clustered by lead arranger and by SNC report date.

Which loans does the lead arranger sell? The main paper compares the characteristics of loans that are sold by the lead arranger with the characteristics of loans that are not sold by the lead arranger. For example, we document that the lead arranger has no other borrower

exposure for 37% of the loans which the lead arranger sells, while the lead arranger has no other borrower for only 1% of the loans which the lead arranger does *not* sell. Here, we want to ask a related, but slightly different question. Which loan characteristics predict lead share sales? To do so, we estimate the regression specification

$$LeadShareSold_l = \beta_0 + \beta_1 X_l + \epsilon_l, \tag{C.2}$$

where LeadShareSold_l is an indicator that is 1 if the lead arranger of loan l has sold its entire share at the first SNC report date after loan origination and zero otherwise. When interpreting the regression coefficients it is important to keep in mind that loan contract terms are an endogenous choice by the borrower and the lead arranger. In other words, the loan characteristics could be chosen after the lead arranger decides on whether to keep or sell a loan. As such, X_l do not present the causal effect of a change in the loan characteristics on the likelihood of the lead arranger selling the loan, but they merely document the observed correlation between endogenous variables. It is nevertheless interesting to examine how well we can explain the likelihood of lead share sales with various loan characteristics.

The regression results are reported in Table C.3 and C.4. In sum, the table indicates that lead banks tend to sell loans that are generally less attractive for banks, such as risky loans with higher shares of nonbanks in the syndicate and Term B loans. Inconsistent with exposure to other loans of the same firm alleviating information asymmetry problems and thus facilitating the loan sale in the first place, the lead bank is more likely to sell a loan if it does not hold any other loan of the firm, including the credit line that is part of the same loan deal. Figure C.1 plots the coefficients from the same regression as specified in equation C.2 for each characteristic individually, conditional on a standard set of controls. Each covariate of interest is standardized to facility comparability.

			Leac	l share sold		
	(1)	(2)	(3)	(4)	(5)	(6)
Time since origination	0.030^{***} (0.006)	0.050^{***} (0.009)	0.027^{***} (0.008)	0.098^{***} (0.018)	0.186^{***} (0.027)	0.120^{***} (0.025)
Loan maturity	0.022^{***} (0.001)	0.014^{***} (0.002)	0.004^{***} (0.001)	0.033^{***} (0.003)	0.031^{***} (0.005)	0.010^{***} (0.003)
Log(Loan amount)	0.004 (0.002)	0.028^{***} (0.003)	-0.008^{***} (0.002)	0.055^{***} (0.006)	0.050^{***} (0.007)	-0.016^{***} (0.005)
Term B loan	0.325^{***} (0.023)	0.189^{***} (0.026)	0.022 (0.026)	0.194^{***} (0.024)	0.103^{***} (0.027)	$0.005 \\ (0.025)$
$\operatorname{count}_b orrower$	0.004^{***} (0.001)	0.002^{***} (0.001)	0.001 (0.001)	0.005^{***} (0.001)	0.004^{***} (0.001)	-0.001 (0.002)
All-in-drawn spread		0.047^{***} (0.004)			0.059^{***} (0.005)	
Pro-rata		-0.047^{***} (0.005)			-0.105^{***} (0.013)	
Rated as high-risk by Fed examiners		$0.003 \\ (0.015)$			$\begin{array}{c} 0.002\\ (0.030) \end{array}$	
Loan package includes credit line		$\begin{array}{c} 0.047^{***} \\ (0.009) \end{array}$			-0.070^{***} (0.014)	
Covenant-lite loan		$\begin{array}{c} 0.270^{***} \\ (0.023) \end{array}$			0.173^{***} (0.026)	
Club deal		-0.059^{***} (0.014)			-0.129^{***} (0.035)	
Buyout loan		0.011 (0.007)			0.035^{**} (0.015)	
Middle-market loan		-0.028^{***} (0.006)			-0.060^{***} (0.016)	
Leveraged loan		0.026^{*} (0.014)			0.053^{**} (0.021)	
Share of participants that are funds			0.492^{***} (0.028)			$\begin{array}{c} 0.436^{***} \\ (0.032) \end{array}$
Log(1+Borrower-arranger interactions)			0.007^{***} (0.002)			0.021^{***} (0.005)
Log(1+Participant-arranger interactions)			-0.014^{***} (0.002)			$\begin{array}{c} -0.021^{***} \\ (0.004) \end{array}$
Lead agent is investment bank			$\begin{array}{c} 0.212^{***} \\ (0.043) \end{array}$			$\begin{array}{c} 0.160^{***} \\ (0.050) \end{array}$
lead agent retains no other exposure			0.038^{***} (0.006)			$\begin{array}{c} 0.165^{***} \\ (0.017) \end{array}$
Fraction of investment banks in syndicate			$\begin{array}{c} 0.030 \\ (0.020) \end{array}$			0.092^{**} (0.042)
Number of syndicate members			0.019^{***} (0.004)			0.010^{**} (0.004)
Log(1 + Numb. times borrower appeared in SNC)			$\begin{array}{c} 0.003 \\ (0.003) \end{array}$			$\begin{array}{c} 0.017^{**} \\ (0.009) \end{array}$
Constant	-0.104^{**} (0.043)	-0.637^{***} (0.071)	0.168^{***} (0.035)	-1.040^{***} (0.110)	-1.104^{***} (0.132)	0.229^{**} (0.106)
R ² N	$0.098 \\ 71,007$	$\begin{array}{c} 0.301 \\ 21,355 \end{array}$	$0.439 \\ 21,163$	$0.148 \\ 14,867$	$0.304 \\ 5,606$	$0.419 \\ 5,485$
Loans sample	All loans	All loans	All loans	Term loans	Term Loans	Term Loans

Table C.3: Lead Share Sales and Loan Covariates

Note: This table reports results from regression (C.2). Time since origination and loan maturity are measured in years. Loan amount is measured in USD. The remaining variables are either fractions, integers, or indicator variables as inferable from their names. The standard errors are clustered by lead arranger and by SNC report date.

Table C.4: Lead S	snare Sale	es and Loa	in Covai	$r_{1}ates - Pa$	art 2	
			Lead sha	re sold		
	(1)	(2)	(3)	(4)	(5)	(6)
Purpose: M&A	0.136^{***}			0.123^{**}		
	(0.037)			(0.044)		
Purpose: Asset securitization	0.038^{*}			0.038		
	(0.019)			(0.041)		
Purpose: CAPEX	0.019			-0.041		
	(0.021)			(0.037)		
Purpose: General corporate	-0.001			0.050^{*}		
	(0.013)			(0.027)		
Purpose: Working capital	-0.023^{**}			-0.042		
	(0.009)			(0.026)		
Purpose: Real estate	-0.033^{*}			-0.091^{***}		
	(0.017)			(0.028)		
Purpose: Debt refinancing	0.149***			0.176^{***}		
	(0.042)			(0.051)		
All-in-drawn spread		0.184^{***}			0.118^{*}	
		(0.046)			(0.068)	
All-in-drawn spread ²		-0.006^{**}			-0.006	
		(0.003)			(0.004)	
Log(All-in-drawn spread)		-0.274^{***}			0.072	
		(0.084)			(0.189)	
SNC report date FE	Yes	Yes	Yes	Yes	Yes	Yes
Borrower FE	No	No	Yes	No	No	Yes
R ² N	0.121	0.249	0.481	0.176	0.266	0.618
11	71,007	21,355	59,452	14,867	$5,\!606$	9,833

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Note: This table reports results from regression (C.2). The standard errors are clustered by lead arranger and by SNC report date.

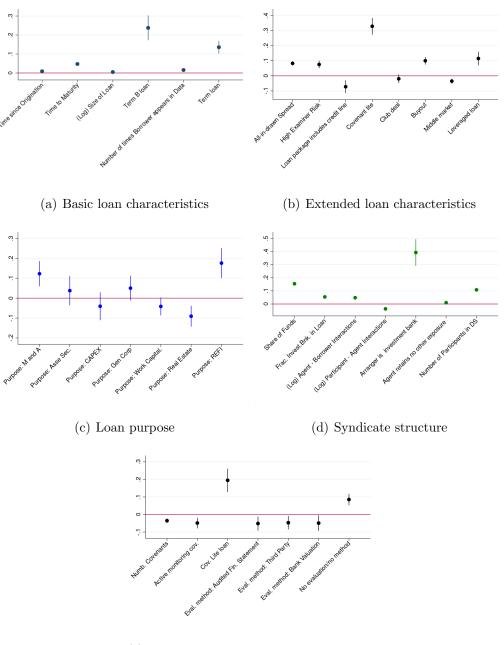


Figure C.1: Lead Shares Sales and Loan characteristics

(e) Covenant intensity and collateral monitoring

Note: This figure reports the coefficients from regression (C.2) for a subset of loan characteristics. All variables are standardized. To get the coefficients we run regression (C.2) and include as the right-hand-side variables the variable of interest plus a standard set of co-variates, which are the time since origination, the loan maturity, the logarithm of the loan size, and a Term B loan dummy. In Panel (e), we additionally include fixed effects for broad categories of collateral type. Not all samples are the same, as not all information is available for the entire sample.

C.2 H2: Do lead agents sell less often than other lenders?

We extend the analysis from the main text whether a difference in the behaviour of lead arrangers and other banks exists shortly after origination, now using only data from SNC. We condition on loans that were originated within a month prior to the first SNC report date and ask whether the lead arranger is more or less likely to sell the loan until the next report date.³⁷ This implies that the second observation is at most 1 year and 1 month after origination.

We report the results in the Appendix in Table .³⁸ In column 1, we consider all loan types. We differentiate between credit line and all other types of loans by including the interaction of the lead arranger and a dummy denoting whether the loan is a credit line. The main coefficient of interest, β_1 , is not significantly different from zero in column 1 suggesting that lead arrangers do not behave differently than other lenders in the year after origination. However, the credit line interaction term is significantly negative and also larger in absolute magnitude than the baseline coefficient, indicating that lead arrangers are less likely to sell credit lines than other lenders after origination. This could be due to stronger restrictions on sales for credit lines by the lead arranger to mitigate the counter-party risk for the borrower.

In columns 2 to 4, we focus specifically on term loans. We again find that lead banks are as likely to sell their loan stake as any other bank lender. This is also the case when we distinguish between institutional term loans (Term B loans) and term loans held by banks in column 3. Finally, we examine whether lead arrangers behave differently in term loans which have a credit line in the same package. One might expect this if lead arrangers preferably hold exposure in the form of credit lines. As one might expect, given our earlier results, we do not find any evidence for any difference in behavior when we look at term loans with an accompanying credit line (Column 4). Overall, our finding, that the lead arranger does not sell term-loan exposures less frequently than other banks, indicates that the lead arranger's share does not have the role typically assumed in the literature. As such, we offer a strong refutation of hypothesis 2. The lead arranger is not special – at least in regards to their propensity to sell off loans.

 $^{^{37}\}mathrm{Our}$ results are unaffected if we drop this time-requirement.

³⁸Note that Irani et al. (2021) and Irani and Meisenzahl (2017) conduct similar analyses, albeit with a very different motivation. The motivation in these studies is to examine whether wholesale funding pressure (Irani and Meisenzahl (2017)) or regulatory capital (Irani et al. (2021)) had an effect on banks' loan sales. These studies also include a Lead Agent dummy as a control. The conclusions we draw are different from these studies for two reasons: First, we focus exclusively on loan sales after origination and second, we differentiate between credit lines and term loans.

	Share sold by lender			
	(1)	(2)	(3)	(4)
Lead agent	-0.002	-0.009***	0.013	0.003
	(0.003)	(0.003)	(0.013)	(0.012)
Lender share at first observation	-0.142***	-0.121***	-0.372***	-0.138***
	(0.010)	(0.019)	(0.038)	(0.052)
Loan x report date FE	No	Yes	No	Yes
Lender x report date FE	Yes	Yes	Yes	Yes
Mean of dependent variable	0.2	0.2	0.25	0.24
\mathbb{R}^2	0.52	0.65	0.47	0.63
Ν	$216,\!964$	$216,\!964$	$124,\!306$	124,306
Sample	SNC	SNC	SNC	SNC
Loan sample	All loans	All loans	Term loans	Term loans
Time since origination less than	1 month	1 month	1 month	1 month

Table C.5: Selling Propensity between First and Second SNC Observation

Note: This table shows results of the following regression:

 $\text{LoanShareSold}_{i,l,t} = \beta_0 + \beta_1 \text{LeadAgent}_{i,l} + \beta_2 \text{LoanShare}_{i,l,t-1} + \delta_l + \delta_{i,t} + \epsilon_{i,l}, \tag{C.3}$

The dependent variable LoanShareSold is a dummy variable that is one if lender *i* sold its share of loan *l* between the first SNC report date and the second report date after origination. The unit of observation is therefore a lender-loan-time observation. LeadAgent indicates whether the lender is the lead arranger, and LoanShare is the lender's loan share at the first report date. Only loans that are observed at most one month after origination are included to condition on newly originated loans. Standard errors are clustered by lender and by SNC report date. Significance levels: *(p<0.10), **(p<0.05), ***(p<0.01).

C.3 H3: Do loans sold by the lead arranger perform worse?

In order to showcase the robustness of these results we perform a series of additional tests for regression specification 2.

First, we change our definition of non-performing loans (Table C.6). We use an indicator for whether part of the loan is classified as "non-pass" by the bank and Federal Reserve examiners. Again, we find a economically and statistically significant negative relationship between loan performance and the sale of the lead arranger's share at first observation.

Secondly, one might be worried that loan performance is not lineary related to the all-indrawn spread. To eliminate this concern, the binscatter plot shown in Figure C.2 documents a linear relationship. Nevertheless, Table C.7 shows that our main result is robust to using different functional forms for the all-in-drawn spread, such as the logarithm of the spread and 10 quantile groups for the spread. Thirdly, we use a number of alternate measures to quantify ex-ante loan riskiness. As such, we first run the baseline regression – relating loan performance to whether a lead arranger has sold its stake – on our full sample without accounting for ex-ante loan riskiness, such as the all-in-drawn spread or internal risk ratings. We find that our results hold even without accounting for any measure of ex-ante loan riskiness. Secondly, we control for loan ratings from external rating agencies as observed in Dealscan LoanConnector (Table C.9). Table C.10 then also replaces loan ratings with available firm ratings when loan ratings are missing. It should be noted that our sample is reduced substantially for these analyses, as rating data exists for only a subset of loans. Even so, our main results continue to hold.

Fourthly, we limit our sample to those loans we observe for the first time between 1 and 90 days after origination (Table C.11). The results remain fairly similar – although many of the coefficients are not statistically significant due to the smaller sample size.

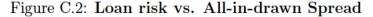
Fifth, we additionally cluster the standard errors at the borrower level to take into account any account any correlation at the firm level (Table C.13).

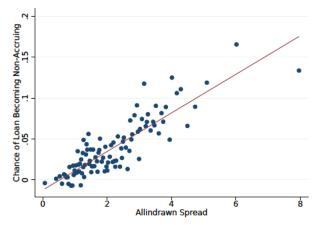
Finally, we examine how the results vary when we look at the heterogeneity of borrowers and the loan syndicate. Table C.15 documents that the relationship between loan performance and lead share sales is fairly similar for different borrower group. For example, the baseline coefficient remains almost unchanged when we look at middle-market or private firms where information asymmetry is supposed to be larger. Table C.16 finds a similar results when we compare loans based on their syndicate structure.

				Loan receiv	ves 'non-pass'	rating		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Lead share sold	-0.035***	-0.042***	-0.018***		-0.015	-0.024**	-0.002	
	(0.009)	(0.008)	(0.006)		(0.011)	(0.011)	(0.009)	
Lead agent retains no borrower exposure				-0.026*				-0.002
				(0.016)				(0.020)
All-in-drawn spread	0.040***	0.041***			0.022***	0.023***		
	(0.004)	(0.004)			(0.003)	(0.004)		
Loan controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry x report date FE	Yes	No	No	No	Yes	No	No	No
Lead agent x report date FE	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Bank internal loan rating	No	No	Yes	Yes	No	No	Yes	Yes
Mean of dependent variable	0.099	0.099	0.082	0.082	0.090	0.090	0.079	0.079
\mathbb{R}^2	0.086	0.199	0.272	0.272	0.093	0.263	0.341	0.341
N	20,027	20,027	26,959	26,959	5,036	5,036	10,589	10,589
Loan sample	All loans	All loans	All loans	All loans	Term loans	Term loans	Term loans	Term loans

Table C.6: Performance Regression – Alternate Definition of Performance

Note: This table shows the results of regression 2 using a different definition to measure loan performance. The unit of observation is a loan. The dependent variable is a dummy variable that is 1 if the loan receives a 'non-pass' rating at any SNC report date after the report date that follows the loan origination date and 0 otherwise. The main independent variable *Lead agent sold its stake* is a dummy variable that is 1 if the lead arranger has sold its entire loan share at the first SNC report date and 0 otherwise. The sample is restricted to loans for which the first observation in the SNC data is within 400 days of the origination of the loan. We exclude any loan for which the dependent variable already takes the value of 1 at the first observation, i.e., the loan already receives a non-pass rating. Included as loan controls are a term loan dummy, a Term B loan dummy, a leveraged loan dummy, the logarithm of the total loan amount, the time since origination, the loan maturity and the all-in-drawn spread (in percent). The all-in-drawn spread is obtained from Dealscan. Standard errors are clustered by lead agent and by SNC report date. Significance levels: *(p<0.10), **(p<0.05), ***(p<0.01).





Note: The figures show binscatter plots of the ex-post loan risk - as measured by whether a loan became accruing – and our main measure for the ex-ante risk of the loan – the all-in-drawn spread (in percent).

tormatice negression		lerent .	runction	
		Loan becon	nes non-accrui	ng
	(1)	(2)	(3)	(4)
Lead share sold	-0.010*	-0.012**	-0.012^{*}	-0.011*
	(0.006)	(0.006)	(0.007)	(0.006)
Log(All-in-drawn spread)	0.023***		0.034***	
	(0.003)		(0.005)	
All-in-drawn spread quantile 2		0.008**		-0.003
		(0.004)		(0.032)
All-in-drawn spread quantile 3		0.015***		0.012
		(0.004)		(0.032)
All-in-drawn spread quantile 4		0.019***		0.028
		(0.004)		(0.033)
All-in-drawn spread quantile 5		0.022***		0.012
		(0.004)		(0.033)
All-in-drawn spread quantile 6		0.026***		0.030
		(0.006)		(0.033)
All-in-drawn spread quantile 7		0.043***		0.041
		(0.005)		(0.034)
All-in-drawn spread quantile 8		0.049***		0.037
		(0.007)		(0.036)
All-in-drawn spread quantile 9		0.053***		0.047
		(0.007)		(0.033)
All-in-drawn spread quantile 10		0.065***		0.064**
		(0.008)		(0.032)
Loan controls	Yes	Yes	Yes	Yes
Industry x report date FE	Yes	Yes	Yes	Yes
Mean of dependent variable	0.024	0.024	0.027	0.027
\mathbb{R}^2	0.048	0.049	0.066	0.067
N	$21,\!280$	21,280	5,566	5,566
Loan sample	All loans	All loans	Term loans	Term loans

Table C.7: Performance Regression – Different Functional Forms for Spread

Note: This table shows the results of regression 2 using different functional forms to control for the ex-ante loan risk. In columns (1) and (3) we use the logarithm of the all-in-drawn spread as a control, and in columns (2) and (4) we include 10 quantiles of the all-in-drawn spread. The unit of observation is a loan. The dependent variable is a dummy variable that is 1 if the loan becomes non-accruing at any SNC report date after the report date that follows the loan origination date and 0 otherwise. The main independent variable *Lead agent sold its stake* is a dummy variable that is 1 if the lead arranger has sold its entire loan share at the first SNC report date and 0 otherwise. The sample is restricted to loans for which the first observation in the SNC data is within 400 days of the origination of the loan. We exclude any loan for which the dependent variable already takes the value of 1 at the first observation, i.e., the loan is already non-accruing. This drops 75 loans of all types, and 40 term loans. Included as loan controls are a term loan dummy, a Term B loan dummy, a leveraged loan dummy, the logarithm of the total loan amount, the time since origination, the loan maturity. The all-in-drawn spread is obtained from Dealscan. Standard errors are clustered by lead agent and by SNC report date. Significance levels: *(p<0.10), **(p<0.05), ***(p<0.01).

			Loan beco	mes non-accru	iing	
	(1)	(2)	(3)	(4)	(5)	(6)
Lead share sold	-0.010^{***} (0.002)	-0.010^{***} (0.002)		-0.005 (0.004)	-0.005 (0.004)	
Lead agent retains no borrower exposure			-0.019^{***} (0.007)			-0.011 (0.008)
Loan controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry x report date FE	No	Yes	Yes	No	No	No
Lead agent x report date FE	Yes	Yes	Yes	Yes	Yes	Yes
Mean of dependent variable	0.026	0.026	0.026	0.024	0.024	0.024
\mathbb{R}^2	0.120	0.131	0.131	0.168	0.187	0.187
Ν	70,464	70,464	70,464	14,641	14,641	14,641
Loan sample	All loans	All loans	All loans	Term loans	Term loans	Term loans

Table C.8: Performance Regression – No Risk Controls

Note: This table shows the results of regression 2 using no direct controls for the ex-ante risk of the loan. The unit of observation is a loan. The dependent variable is a dummy variable that is 1 if the loan becomes non-accruing at any SNC report date after the report date that follows the loan origination date and 0 otherwise. The main independent variable *Lead agent sold its stake* is a dummy variable that is 1 if the lead arranger has sold its entire loan share at the first SNC report date and 0 otherwise. The sample is restricted to loans for which the first observation in the SNC data is within 400 days of the origination of the loan. We exclude any loan for which the dependent variable already takes the value of 1 at the first observation, i.e., the loan is already non-accruing. Included as loan controls are a term loan dummy, a Term B loan dummy, a leveraged loan dummy, the logarithm of the total loan amount, the time since origination, the loan maturity. Standard errors are clustered by lead agent and by SNC report date. Significance levels: *(p<0.10), **(p<0.05), ***(p<0.01).

			Loan beco	mes non-accru	uing	
	(1)	(2)	(3)	(4)	(5)	(6)
Lead share sold	-0.008 (0.005)	-0.009^{*} (0.005)		-0.005 (0.005)	-0.005 (0.006)	
Lead agent retains no borrower exposure			0.004 (0.011)			0.010 (0.013)
Loan controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry x report date FE	Yes	No	No	Yes	No	No
Lead agent x report date FE	No	Yes	Yes	No	Yes	Yes
External loan rating	Yes	Yes	Yes	Yes	Yes	Yes
Mean of dependent variable	0.020	0.020	0.020	0.016	0.016	0.016
\mathbb{R}^2	0.224	0.309	0.309	0.181	0.294	0.295
Ν	3,820	3,820	3,820	$2,\!153$	$2,\!153$	$2,\!153$
Loan sample	All loans	All loans	All loans	Term loans	Term loans	Term loans

Table C.9: Performance Regression – Loan Ratings

Note: This table shows the results of regression 2 using external loan ratings as risk controls. The unit of observation is a loan (i.e., every loan is included only once in the analysis). The dependent variable is a dummy variable that is 1 if the loan becomes non-accruing at any SNC report date after the report date that follows the loan origination date and 0 otherwise. The main independent variable *Lead agent sold its stake* is a dummy variable that is 1 if the lead arranger has sold its entire loan share at the first SNC report date and 0 otherwise. The sample is restricted to loans for which the first observation in the SNC data is within 400 days of the origination of the loan. We exclude any loan for which the dependent variable already takes the value of 1 at the first observation, i.e., the loan is already non-accruing. Included as loan controls are a term loan dummy, a Term B loan dummy, a leveraged loan dummy, the logarithm of the total loan amount, the time since origination, the loan maturity. The loan ratings are obtained from LPC LoanConnector. Standard errors are clustered by lead agent and by SNC report date. Significance levels: *(p<0.10), **(p<0.05), ***(p<0.01).

			Loan beco	mes non-accru	uing	
	(1)	(2)	(3)	(4)	(5)	(6)
Lead share sold	-0.016^{***} (0.005)	-0.014^{**} (0.005)		-0.008 (0.007)	-0.005 (0.008)	
Lead agent retains no borrower exposure			-0.003 (0.010)			0.011 (0.013)
Loan controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry x report date FE	Yes	No	No	Yes	No	No
Lead agent x report date FE	No	Yes	Yes	No	Yes	Yes
External loan rating	Yes	Yes	Yes	Yes	Yes	Yes
Mean of dependent variable	0.027	0.027	0.027	0.030	0.030	0.030
\mathbb{R}^2	0.173	0.250	0.250	0.208	0.275	0.275
Ν	8,013	8,013	8,013	3,242	3,242	3,242
Loan sample	All loans	All loans	All loans	Term loans	Term loans	Term loans

Table C.10: Performance Regression – Loan or Firm Ratings

Note: This table shows the results of regression 2 using external loan ratings or firm ratings as risk controls. The unit of observation is a loan (i.e., every loan is included only once in the analysis). The dependent variable is a dummy variable that is 1 if the loan becomes non-accruing at any SNC report date after the report date that follows the loan origination date and 0 otherwise. The main independent variable *Lead agent sold its stake* is a dummy variable that is 1 if the lead arranger has sold its entire loan share at the first SNC report date and 0 otherwise. The sample is restricted to loans for which the first observation in the SNC data is within 400 days of the origination of the loan. We exclude any loan for which the dependent variable already takes the value of 1 at the first observation, i.e., the loan is already non-accruing. Included as loan controls are a term loan dummy, a Term B loan dummy, a leveraged loan dummy, the logarithm of the total loan amount, the time since origination, the loan maturity. The loan and firm ratings are obtained from LPC LoanConnector. When both are available we use the loan rating. Standard errors are clustered by lead agent and by SNC report date. Significance levels: *(p<0.10), **(p<0.05), ***(p<0.01).

				Loan bec	omes non-acci	uing		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Lead share sold	-0.012	-0.008	-0.004		-0.005	-0.006	0.002	
	(0.009)	(0.010)	(0.005)		(0.009)	(0.011)	(0.010)	
Lead agent retains no borrower exposure				-0.032*				-0.018**
				(0.016)				(0.009)
All-in-drawn spread	0.013***	0.013***			0.011***	0.011***		
-	(0.003)	(0.003)			(0.003)	(0.003)		
Loan controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry x report date FE	Yes	No	No	No	Yes	No	No	No
Lead agent x report date FE	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Bank internal loan rating	No	No	Yes	Yes	No	No	Yes	Yes
Mean of dependent variable	0.021	0.021	0.016	0.016	0.020	0.020	0.017	0.017
\mathbb{R}^2	0.080	0.340	0.420	0.421	0.163	0.438	0.543	0.543
Ν	6,573	6,573	9,229	9,229	1,938	1,938	3,787	3,787
Loan sample	All loans	All loans	All loans	All loans	Term loans	Term loans	Term loans	Term loans

Table C.11: Performance Regression – Loans observed within 90 Days

Note: This table shows the results of regression 2 focusing on loans that are observed between 1 and 90 days after origination. The unit of observation is a loan. The dependent variable is a dummy variable that is 1 if the loan becomes non-accruing at any SNC report date after the report date that follows the loan origination date and 0 otherwise. The main independent variable *Lead agent sold its stake* is a dummy variable that is 1 if the lead arranger has sold its entire loan share at the first SNC report date and 0 otherwise. The sample is restricted to loans for which the first observation in the SNC data is within 400 days of the origination of the loan. We exclude any loan for which the dependent variable already takes the value of 1 at the first observation, i.e., the loan is already non-accruing. Included as loan controls are a term loan dummy, a Term B loan dummy, a leveraged loan dummy, the logarithm of the total loan amount, the time since origination, the loan maturity and the all-in-drawn spread (in percent). The all-in-drawn spread is obtained from Dealscan. Standard errors are clustered by lead agent and by SNC report date. Significance levels: *(p<0.10), **(p<0.05), ***(p<0.01).

				Loan bec	omes non-acci	ruing		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Lead share sold	-0.011	-0.000	-0.010		0.013	0.018	-0.008**	
	(0.009)	(0.011)	(0.007)		(0.013)	(0.017)	(0.003)	
Agent retains no other exposure				-0.126***				-0.037**
				(0.047)				(0.018)
All-in-drawn spread	0.018***	0.018***			0.014*	0.016		
-	(0.006)	(0.006)			(0.008)	(0.010)		
Loan controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry x report date FE	Yes	No	No	No	Yes	No	No	No
Lead agent x report date FE	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Bank internal loan rating	No	No	Yes	Yes	No	No	Yes	Yes
Mean of dependent variable	0.025	0.025	0.017	0.017	0.023	0.023	0.018	0.018
\mathbb{R}^2	0.127	0.546	0.562	0.565	0.233	0.703	0.753	0.753
Ν	2,278	2,278	$3,\!297$	$3,\!297$	655	655	1,362	1,362
Loan sample	All loans	All loans	All loans	All loans	Term loans	Term loans	Term loans	Term loans

Table C.12: Performance Regression – Loans observed within 30 Days

Note: This table shows the results of regression 2 focusing on loans that are observed between 1 and 30 days after origination. The unit of observation is a loan. The dependent variable is a dummy variable that is 1 if the loan becomes non-accruing at any SNC report date after the report date that follows the loan origination date and 0 otherwise. The main independent variable *Lead agent sold its stake* is a dummy variable that is 1 if the lead arranger has sold its entire loan share at the first SNC report date and 0 otherwise. The sample is restricted to loans for which the first observation in the SNC data is within 400 days of the origination of the loan. We exclude any loan for which the dependent variable already takes the value of 1 at the first observation, i.e., the loan is already non-accruing. Included as loan controls are a term loan dummy, a Term B loan dummy, a leveraged loan dummy, the logarithm of the total loan amount, the time since origination, the loan maturity and the all-in-drawn spread (in percent). The all-in-drawn spread is obtained from Dealscan. Standard errors are clustered by lead agent and by SNC report date. Significance levels: *(p<0.10), **(p<0.05), ***(p<0.01).

				Loan bec	omes non-acci	ruing		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Lead share sold	-0.015**	-0.013**	-0.011***		-0.012^{*}	-0.008	-0.007*	
	(0.006)	(0.005)	(0.003)		(0.007)	(0.007)	(0.004)	
Agent retains no other exposure				-0.019***				-0.011*
				(0.007)				(0.007)
All-in-drawn spread	0.013***	0.012***			0.010***	0.009***		
-	(0.002)	(0.001)			(0.002)	(0.001)		
Loan controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry x report date FE	Yes	No	No	No	Yes	No	No	No
Lead agent x report date FE	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Bank internal loan rating	No	No	Yes	Yes	No	No	Yes	Yes
Mean of dependent variable	0.024	0.024	0.023	0.023	0.027	0.027	0.023	0.023
\mathbb{R}^2	0.048	0.162	0.283	0.283	0.065	0.235	0.341	0.341
Ν	$21,\!280$	$21,\!280$	29,075	29,075	5,566	5,566	11,737	11,737
Loan sample	All loans	All loans	All loans	All loans	Term loans	Term loans	Term loans	Term loans

Table C.13: Performance Regression – Additional Clustering at Borrower Level

Note: This table shows the results of regression 2 when clustering the standard errors also at the borrower level. The unit of observation is a loan. The dependent variable is a dummy variable that is 1 if the loan becomes non-accruing at any SNC report date after the report date that follows the loan origination date and 0 otherwise. The main independent variable *Lead agent sold its stake* is a dummy variable that is 1 if the lead arranger has sold its entire loan share at the first SNC report date and 0 otherwise. The sample is restricted to loans for which the first observation in the SNC data is within 400 days of the origination of the loan. We exclude any loan for which the dependent variable already takes the value of 1 at the first observation, i.e., the loan is already non-accruing. Included as loan controls are a term loan dummy, a Term B loan dummy, a leveraged loan dummy, the logarithm of the total loan amount, the time since origination, the loan maturity and the all-in-drawn spread (in percent). The all-in-drawn spread is obtained from Dealscan. Standard errors are clustered by lead agent, by SNC report date and by borrower. Significance levels: *(p<0.10), **(p<0.05), ***(p<0.01).

				Loan bec	omes non-acci	ruing		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Lead share sold	-0.007*	-0.005	-0.007***		-0.005	-0.004	-0.004	
	(0.004)	(0.004)	(0.003)		(0.009)	(0.009)	(0.006)	
Agent retains no other exposure				-0.014				-0.018
				(0.015)				(0.025)
All-in-drawn spread	0.004*	0.003^{*}			0.003	0.001		
Ĩ	(0.002)	(0.002)			(0.003)	(0.003)		
Loan controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry x report date FE	Yes	No	No	No	Yes	No	No	No
Lead agent x report date FE	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Bank internal loan rating	No	No	Yes	Yes	No	No	Yes	Yes
Borrower FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Mean of dependent variable	0.024	0.024	0.023	0.023	0.027	0.027	0.023	0.023
R^2	0.712	0.755	0.810	0.810	0.798	0.832	0.857	0.857
Ν	21,280	21,280	29,075	29,075	5,566	5,566	11,737	11,737
Loan sample	All loans	All loans	All loans	All loans	Term loans	Term loans	Term loans	Term loans

Table C.14: Performance Regression – Including Borrower FE

Note: This table shows the results of regression 2 when also including borrower level fixed effects. The unit of observation is a loan. The dependent variable is a dummy variable that is 1 if the loan becomes non-accruing at any SNC report date after the report date that follows the loan origination date and 0 otherwise. The main independent variable *Lead agent sold its stake* is a dummy variable that is 1 if the lead arranger has sold its entire loan share at the first SNC report date and 0 otherwise. The sample is restricted to loans for which the first observation in the SNC data is within 400 days of the origination of the loan. We exclude any loan for which the dependent variable already takes the value of 1 at the first observation, i.e., the loan is already non-accruing. Included as loan controls are a term loan dummy, a Term B loan dummy, a leveraged loan dummy, the logarithm of the total loan amount, the time since origination, the loan maturity and the all-in-drawn spread (in percent). The all-in-drawn spread is obtained from Dealscan. Standard errors are clustered by lead agent, by SNC report date and by borrower. Significance levels: *(p<0.10), **(p<0.05), ***(p<0.01).

		Lo	an becomes	s non-accrui	ng	
	(1)	(2)	(3)	(4)	(5)	(6)
Lead share sold	0.027 (0.049)	-0.020^{***} (0.007)	-0.013 (0.013)	-0.016^{**} (0.007)	-0.007 (0.016)	-0.014^{**} (0.006)
Lead share sold x log(Sales)	-0.006 (0.007)					
Lead share sold x Firm in Compustat		0.017^{*} (0.010)				
Lead share sold x No. of past loans			-0.001 (0.006)			
Lead share sold x Public firm				0.003 (0.008)		
Lead share sold x Firm has rating					-0.009 (0.017)	
Lead share sold x Middle-market firm						-0.002 (0.018)
All-in-drawn spread	0.010^{***} (0.004)	0.012^{***} (0.002)	0.013^{***} (0.002)	0.012^{***} (0.002)	0.013^{***} (0.002)	0.013^{***} (0.002)
Loan controls	Yes	Yes	Yes	Yes	Yes	Yes
Lead agent x report date FE	Yes	Yes	Yes	Yes	Yes	Yes
Mean of dependent variable	0.013	0.024	0.024	0.024	0.024	0.026
\mathbb{R}^2	0.072	0.049	0.048	0.049	0.048	0.048
Ν	$4,\!127$	$21,\!280$	$21,\!280$	$21,\!280$	$21,\!280$	$19,\!287$
Loans	All loans	All loans	All loans	All loans	All loans	All loans

Table C.15: Performance Regression – Borrower Heterogeneity

Note: This table shows the results of regression 2 with an additional term that interacts borrower characteristics with the main independent variable *Lead agent sold its stake*. The main independent variable *Lead agent sold its stake* is a dummy variable that is 1 if the lead arranger has sold its entire loan share at the first SNC report date and 0 otherwise. The unit of observation is a loan. The dependent variable is a dummy variable that is 1 if the loan becomes non-accruing at any SNC report date after the report date that follows the loan origination date and 0 otherwise. The sample is restricted to loans for which the first observation in the SNC data is within 400 days of the origination of the loan. We exclude any loan for which the dependent variable already takes the value of 1 at the first observation, i.e., the loan is already non-accruing. Included as loan controls are a term loan dummy, a Term B loan dummy, a leveraged loan dummy, the logarithm of the total loan amount, the time since origination, the loan maturity and the all-in-drawn spread (in percent). The all-in-drawn spread is obtained from Dealscan. Standard errors are clustered by lead agent, by SNC report date. Significance levels: *(p<0.10), **(p<0.05), ***(p<0.01).

		Loan be	ecomes non-	accruing	
	(1)	(2)	(3)	(4)	(5)
Lead share sold	-0.012 (0.013)	-0.012 (0.022)	-0.001 (0.012)	-0.025^{*} (0.014)	-0.029^{**} (0.012)
Lead share sold x Number of funds in syndicate	-0.001 (0.003)				
Lead share sold x Number of lenders in syndicate		-0.001 (0.005)			
Lead share sold x Share of funds at first observation			-0.016 (0.016)		
Lead share sold x Syndicate interaction score				0.002 (0.002)	
Lead share sold x Top 5 syndicate member					0.019^{*} (0.010)
All-in-drawn spread	0.013^{***} (0.002)	0.012^{***} (0.002)	0.013^{***} (0.002)	0.013^{***} (0.002)	0.013^{***} (0.002)
Loan controls	Yes	Yes	Yes	Yes	Yes
Industry x report date FE	Yes	Yes	Yes	Yes	Yes
Mean of dependent variable	0.024	0.024	0.024	0.024	0.024
\mathbb{R}^2	0.048	0.048	0.049	0.048	0.049
Ν	$21,\!280$	$21,\!280$	$21,\!280$	$21,\!280$	$21,\!280$
Loan sample	All loans				

Table C.16: Performance Regression – Syndicate Heterogeneity

Note: This table shows the results of regression 2 with an additional term that interacts the main independent variable *Lead agent sold its stake* with syndicate characteristics. The main independent variable *Lead agent sold its stake* is a dummy variable that is 1 if the lead arranger has sold its entire loan share at the first SNC report date and 0 otherwise. The unit of observation is a loan. The dependent variable is a dummy variable that is 1 if the loan becomes non-accruing at any SNC report date after the report date that follows the loan origination date and 0 otherwise. *Syndicate interaction score* is a weighted average of how many interactions the syndicate members had with the lead arranger through prior loans. *Top 5 syndicate member* is a dummy that is one if a syndicate member is among the top 5 syndicate members that have interacted the most with a lead arranger through prior loans. The sample is restricted to loans for which the first observation in the SNC data is within 400 days of the origination of the loan. We exclude any loan for which the dependent variable already takes the value of 1 at the first observation, i.e., the loan is already non-accruing. Included as loan controls are a term loan dummy, a Term B loan dummy, a leveraged loan dummy, the logarithm of the total loan amount, the time since origination, the loan maturity and the all-in-drawn spread (in percent). The all-in-drawn spread is obtained from Dealscan. Standard errors are clustered by lead agent, by SNC report date. Significance levels: *(p<0.10), **(p<0.05), ***(p<0.01).

			Loan beco	mes non-accru	uing	
	(1)	(2)	(3)	(4)	(5)	(6)
Agent retains no other exposure	-0.020***	-0.002	-0.019***	-0.012	-0.001	-0.011*
	(0.007)	(0.012)	(0.007)	(0.008)	(0.012)	(0.007)
All-in-drawn spread		0.012***			0.009***	
		(0.001)			(0.001)	
Loan controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry x report date FE	No	No	No	No	No	No
Lead Agent x report date FE	Yes	Yes	Yes	Yes	Yes	Yes
Bank internal loan rating	No	No	Yes	No	No	Yes
Mean of dependent variable	0.026	0.024	0.023	0.024	0.027	0.023
\mathbb{R}^2	0.120	0.162	0.283	0.168	0.235	0.341
Ν	$70,\!464$	21,280	29,075	14,641	5,566	11,737
Loans	All loans	All loans	All loans	Term loans	Term loans	Term loans

Table C.17: Performance – Alternate "No Other Exposure" Specifications

Note: This table shows the results of regression 2. The main independent variable *No other exposure* is a dummy variable that takes the value of 1 if the lead arranger has sold its entire loan share at the first SNC report date and holds no other exposure of any kind to the borrower and 0 otherwise. The unit of observation is a loan. The dependent variable is a dummy variable that takes the value of 1 if the loan becomes non-accruing at any SNC report date after the report date that follows the loan origination date and 0 otherwise. The sample is restricted to loans for which the first observation in the SNC data is within 400 days of the origination of the loan. We exclude any loan for which the dependent variable already takes the value of 1 at the first observation, i.e., the loan is already non-accruing. Included as loan controls are a term loan dummy, a Term B loan dummy, a leveraged loan dummy, the logarithm of the total loan amount, the time since origination, the loan maturity and the all-in-drawn spread (in percent). The all-in-drawn spread is obtained from Dealscan. Standard errors are clustered by lead agent, by SNC report date. Significance levels: *(p<0.10), **(p<0.05), ***(p<0.01).

	Loan price (in LSTA) at first observation							
	(1)	(2)	(3)	(4)	(5)	(6)		
Lead share sold	-0.026 (0.284)	-0.223 (0.265)	0.046 (0.344)	-0.066 (0.279)				
Agent retains no other exposure					-0.444 (0.603)	0.422 (0.665)		
All-in-drawn spread		-0.253^{*} (0.129)	-0.143^{***} (0.050)		-0.141^{***} (0.047)			
Loan controls	Yes	Yes	Yes	Yes	Yes	Yes		
Industry x report date FE	Yes	Yes	No	No	No	No		
Lead agent x report date FE	No	No	Yes	Yes	Yes	Yes		
Bank internal loan rating	No	No	No	Yes	No	Yes		
Mean of dependent variable	98.9	98.9	98.9	99.0	98.9	99.0		
\mathbb{R}^2	0.480	0.486	0.649	0.735	0.650	0.735		
N	$1,\!602$	1,584	1,584	1,510	$1,\!584$	1,510		
Loan sample	Term loans	Term loans	Term loans	Term loans	Term loans	Term loan		

Table C.18: Performance – Secondary Market Loan Prices

Note: This table shows the results of regression 2. The main independent variable *Lead agent sold its* stake is a dummy variable that takes the value of 1 if the lead arranger has sold its entire loan share at the first SNC report date. The variable *No other exposure* takes the value of 1 if the lead arranger has sold its entire loan share at the first SNC report date. The variable *No other exposure* takes the value of 1 if the lead arranger has sold its entire loan share at the first SNC report date and holds no other exposure of any kind to the borrower. The unit of observation is a loan. The dependent variable is the LSTA secondary market price of the loan at the first observation in SNC (the notional is 100 dollars). The sample is restricted to loans for which the first observation in the SNC data is within 400 days of the origination and to which we can match the LSTA loan pricing data. We exclude any loan that is non-accruing at the first observation. Included as loan controls are a term loan dummy, a Term B loan dummy, a leveraged loan dummy, the logarithm of the total loan amount, the time since origination, the loan maturity and the all-in-drawn spread (in percent). The all-in-drawn spread is obtained from Dealscan. Standard errors are clustered by lead agent, by SNC report date. Significance levels: *(p<0.10), **(p<0.05), ***(p<0.01).

D Robustness – Alternative Mechanisms

Pipeline risk. In the main text we showed that when negative news about the borrower arise during the syndication process, then the lead arranger is less likely to sell off its entire lead share. Here, we show that this holds for the general level of the lead share (i.e., also the intensive margin). Specifically, we estimate the following equation:

LeadShare_{*l,t*} =
$$\beta_0 + \beta_1$$
Borrower Information_{*l,t*-45 \to t} + $\beta_3 X_{l,t} + \epsilon_{l,t}$, (D.1)

where LeadShare_{l,t=0} is a variable between 0 and 1 denoting the share of a loan l held by the lead arranging bank at the first observation.

The results are reported in Table D.1. A 10 cent per dollar of face value decline in borrowers' other loan prices is associated with a 3 percentage points larger lead share (column (1)). The effect reduces to 2 percentage points and becomes statistically indistinguishable from zero for the same fall in aggregate loan prices (column (2)). The coefficient in column (3) implies that a 10 percentage points lower idiosyncratic stock price volatility is associated with a 8 percentage points lower lead share. These results are very similar to the baseline version presented in the main text and suggest that changes in borrowers' fundamentals or general credit demand are associated with a larger loan retention by the lead arranger consistent with pipeline risk.

	Share of the lead agent			
	(1)	(2)	(3)	
Δ Borrower's loan price	-0.003^{**} (0.001)			
$\Delta \mathrm{LSTA}$ Leveraged Loan Index		-0.002 (0.002)		
Borrower's stock volatility			0.008^{*} (0.004)	
Loan controls	Yes	Yes	Yes	
Lead agent x report date FE	Yes	Yes	Yes	
All-in-drawn spread	Yes	Yes	Yes	
\mathbb{R}^2	0.465	0.488	0.616	
Ν	619	9,883	$2,\!103$	
Loan sample	All loans	All loans	All loans	

Table D.1: Pipeline Risk – Continuous Lead Share

Note: This table shows the results of regression (D.1). The unit of observation is a loan. The dependent variable is the share of the lead agent at the first SNC observation. Δ Borrower's loan price is the 45-day price change in other outstanding loans of the borrower prior to origination. Δ LSTA Leveraged Loan Index is the 45-day change in the S&P/LSTA US Leveraged Loan Index prior to origination. Borrower's stock Volatility is computed using daily equity returns in excess of predicted returns in a 45-day window prior to origination, measured in percent. Predicted returns are based on beta estimated with daily returns prior to the syndication process. The loan controls are the time since origination, the loan maturity, the logarithm of the loan amount, a leveraged loan dummy, a term loan dummy, a term b dummy and the all-in-drawn spread. The standard errors are clustered by lead arranger and by SNC report date. Significance levels: *(p<0.10), **(p<0.05), ***(p<0.01).

Reputation. In this section, we extend the baseline analysis of reputation risk. In particular, one would expect that lead arrangers are more strongly punished, i.e., lose more business, when the defaults of the loans they arranged impacted more investors. To test this hypothesis, we follow specification 5, but we weight loans by the number of lenders in the loan when computing the fraction of non-accruing loans.

As reported in Table D.2, we find that lead arrangers lose more market share when the loans it arranged become non-accruing, in particular when these loans were held by many investors. Specifically, the coefficient in column (2) implies that a 1 percentage point rise in a lead arranger's fraction of loans that become non-accruing is associated with a 0.52 percentage point lower market share for each 10 investors that were affected by the default. This result is robust to controlling for whether the loan was sold off completely by the lead arranger and the ex-ante risk using the all-in-drawn spread (columns (3) and (4)).

		Market share			
	(1)	(2)	(3)	(4)	
Fraction of non-accruing loans	-0.076**	0.171^{*}	0.195^{*}	0.193	
	(0.031)	(0.095)	(0.102)	(0.147)	
Fraction of non-accruing loans weighted by number of lenders		-0.043*	-0.041*	-0.043	
		(0.022)	(0.020)	(0.033)	
Number of lenders		-0.000	0.004	0.004	
		(0.003)	(0.004)	(0.006)	
Fraction of non-accruing and sold-off loans			-0.101	-0.147	
Ŭ			(0.128)	(0.140)	
Fraction of sold-off loans			-0.028***	-0.029*	
			(0.007)	(0.016)	
Year FE	Yes	Yes	Yes	Yes	
Lead agent FE	Yes	Yes	Yes	Yes	
All-in-drawn spread	Yes	Yes	No	Yes	
\mathbb{R}^2	0.761	0.765	0.777	0.778	
Ν	225	225	242	225	

Table D.2: **Reputation Risk** – **Robustness**

Note: This table shows the results of regression (5) where we weight each loan by the number of lenders when computing the fraction of non-accruing loans. The unit of observation is an arranger-year observation. The dependent variable is the arranger's contemporaneous market shares. The market share is taken from the league table for US institutional loans available on Bloomberg since 2005. Additionally, we focus only on underwriters that were ranked in the top 20 at least once during our sample period. All regressions include controls for the average riskiness of loan originated by a lead arranger measured by the all-in-drawn spread as well as the share that are Term B or leveraged loans. We compute the share of loans that turn non accruing and are sold off as well as the share of all loans sold off in the given year prior to collapsing the data to the lender-year level. We additionally include year and lead arranger fixed effects. Standard errors are clustered by the lead arranger and by year level. Significance levels: *(p<0.10), **(p<0.05), ***(p<0.01).