International Journal of
Financial Studies

MDPI

Article

The Impact of Lending Relationships on the Lead Arrangers' Retained Share

Alemu Tulu Chala [1,2]

[1] Economics Unit, Dalarna University, 791 88 Falun, Sweden; alch@du.se
[2] School of Economics and Management, Department of Economics, Lund University, P.O. Box 7080, 220 07 Lund, Sweden

Abstract: The lead arrangers of syndicated loans often have lending relationships with the borrowers, while other lenders participating in the syndicate largely engage in an arm's length transaction. Relatively little is known about how these relationships affect the shares of syndicated loans that the lead arrangers retain in their portfolio. Using a random sample of 10,328 syndicated loans made to 7316 nonfinancial U.S. firms over the period 1987 to 2013, this paper investigates the impact of lending relationships on the shares of loans retained. The results show that lending relationships are associated with a significant reduction in retained shares. These results are robust to alternative estimation techniques, such as propensity score matching and binary endogenous treatment models, which are employed to address endogeneity concerns. Furthermore, the results provide additional evidence that the existence and strength of lending relationships lead to decreased retained shares, particularly for non-top-tier lead arrangers. Moreover, the findings also demonstrate that when lead arrangers have lending relationships with borrowers, they retain significantly smaller shares whether the loans are made to informationally opaque, small, or speculative-grade-rating firms. Overall, the findings of this paper have important implications for lenders seeking to reduce their risk exposure in syndicated loans.

Keywords: lending relationships; retained share; syndicated lending

check for updates

Citation: Chala, Alemu Tulu. 2023. The Impact of Lending Relationships on the Lead Arrangers' Retained Share. *International Journal of Financial Studies* 11: 119. https://doi.org/10.3390/ijfs11040119

Academic Editor: Zied Ftiti

Received: 17 July 2023
Revised: 15 September 2023
Accepted: 22 September 2023
Published: 4 October 2023

1. Introduction

Retention theories suggest that lead arrangers of syndicated loans need to hold substantial portions of the loans they originate (Gryglewicz et al. 2021). The argument is that lead arrangers, assigned with screening responsibilities (Adamuz and Hernández Cortés 2015) and monitoring tasks (Gustafson et al. 2021), enjoy an information advantage over other syndicate participants. This advantage may lead to adverse selection and moral hazard problems, as the lead arrangers' screening and monitoring efforts are unobservable to other participants. Thus, to enhance incentives for diligent screening and monitoring and thereby address adverse selection and the moral hazard concerns of less informed participants, lead arrangers need to retain larger shares of the loans.

In line with the prediction of retention theories, empirical studies investigating the determinants of retained shares show that lead arrangers hold larger shares when intensive screening and closer monitoring are required (Sufi 2007; Lim et al. 2014). Research also indicates that the allocation of loan shares among syndicate members depends on lead arrangers' reputations, with reputable lead arrangers retaining smaller shares (Chaudhry and Kleimeier 2015; Winton and Yerramilli 2021). Another factor influencing the division of loan shares is the information availability of borrowers; lead arrangers retain larger shares when borrowers are informationally opaque (Sufi 2007; Balasubramanyan et al. 2019). However, it is less clear how lending relationships between lead arrangers and borrowers, which exacerbate information asymmetries between lead arrangers and other participants, affect lead arrangers' retained loan shares.

In this paper, I investigate the impact of lead arrangers' lending relationships with borrowers on the proportion of syndicated loans they retain. The existing literature indicates that two opposing forces come into play when considering the impact of lending relationships on retained loan shares. Bharath et al. (2007) and Gadanecz et al. (2012) show that lead arrangers often establish lending relationships with borrowers, while other participants primarily engage in arm's-length transactions. Through these relationships, lead arrangers gain access to the firm's inside information that may not be available to other lenders. As shown by Down et al. (2022), lead arrangers might exploit their information advantage by originating riskier loans. While arranging riskier loans can entail reputation risks, lead arrangers aiming to capture borrowers in long-term relationships and extract associated relationship benefits (Donker et al. 2020) may originate riskier loans for their borrowers. In line with this argument, a zombie lending model developed by Hu and Varas (2021) illustrates that lenders continue to extend credit to distressed relationship borrowers even after learning unfavorable news. Additionally, evidence presented by Aramonte et al. (2022) indicates that bank lead arrangers originate riskier loans and subsequently sell them to institutional participants. Thus, with less information about the firm, other lenders are unwilling to buy a higher share of loans, anticipating that lead arrangers might syndicate lower-quality loans.

On the other hand, there may also be effects that work in the opposite direction. Financial intermediation theories suggest that firms require some level of monitoring for the information compatibility constraints to be satisfied (Diamond 1984; Baliga 1999). However, monitoring borrowers involves non-zero costs, implying that the quality of lead arrangers' monitoring is a function of costly investments made in monitoring. As delegated monitors, lead arrangers bear monitoring costs, while only a fraction of the benefits accrue to them. Thus, for lead arrangers to choose optimal monitoring efforts, monitoring must be cheap. As described by Boot (2000) and Carrasco and De Mello (2010), lending relationships enhance monitoring efforts by reducing the costs of producing firm-specific information. With increased monitoring activities, participants become more willing to buy a higher share of loans.

Based on these arguments, the net impact of lending relationships on retained shares depends on the relative dominance of these two opposing effects. To determine which effects are dominant, I conduct an empirical analysis of how lead arrangers' relationships with borrowers affect their retained loan shares. This analysis is based on 10,328 syndicated loans made to 7316 nonfinancial U.S. firms over the period from 1987 to 2013. Before conducting the empirical analysis, I construct relationship measures that capture the existence and strength of lending relationships by tracking the history of lending interactions between lead arrangers and borrowers, using a method similar to that employed by Bharath et al. (2007, 2011).

The empirical results show that lending relationships are negatively and significantly related to the loan shares retained by lead arrangers. This finding suggests that lending relationships are a significant determinant of retained shares; lead arrangers retain smaller loan shares when syndicated loans are extended to borrowers with whom they have prior relationships. This indicates that other participants do not require relationship lead arrangers to hold larger loan shares to prevent leniency in their screening and monitoring tasks. Building on this baseline result, I next investigate whether there is a heterogeneous effect of lending relationships based on the degree of lead arrangers' reputation. The results indicate that lending relationships lead to a significant reduction in retained loan shares only for non-top-tier lead arrangers. Finally, I investigate the impact of borrower characteristics on the association between lending relationships and retained loan shares. The evidence suggests that the negative effect of lending relationships on retained loan shares is at work whether loans are extended to informationally opaque, small, or speculative-grade-rating firms.

The baseline result is robust to a range of sensitivity analysis performed in this study to address potential concerns. One concern is related to endogeneity, which could arise from the possible nonrandom match between a lead arranger and a borrower. To address this concern, I employ propensity score matching (Rubin 1973; Rosenbaum and Rubin 1983; Heckman et al. 1998). The evidence indicates that relationship loans have lower retained shares compared to similar nonrelationship loans.

To further address endogeneity concerns, I also estimate binary endogenous treatment models (Heckman 1978). The findings show that the baseline result remains robust to the control of unobservable factors that could affect the formation of lending relationships. In addition to endogeneity concerns, there may also be concerns related to the presence of multiple lead arrangers in a loan facility. Having multiple lead arrangers could increase the likelihood that the loan is initiated by a lead arranger with prior lending relationships with the borrower. To address this concern, I restrict the sample to loan facilities with a single lead arranger. The findings reinforce the baseline result that lending relationships lead to a significant reduction in retained loan shares. While this study is based on data spanning from 1987 to 2013, the findings remain particularly relevant for lenders under regulatory pressure to reduce riskier loans from their portfolios.

The remaining part of this paper is organized as follows. Section 2 presents a selective review of the literature on the determinants of the lead arrangers' retained loan shares. Section 3 describes the data and presents the econometric model used to estimate the impact of lending relationships on retained loan shares. Section 4 discusses the empirical results, and Section 5 presents the conclusion.

2. Literature Review

This paper contributes to the literature on the determinants of syndicated loan shares retained by lead arrangers. According to the informed–uninformed investor theory, a key theoretical framework employed in empirical studies, uninformed lenders invest in loans only after informed lenders, who monitor the firm, have retained substantial shares of the loans (Leland and Pyle 1977; Holmstrom and Tirole 1997). In line with this theory, a recent model developed by Gryglewicz et al. (2021) relates retained loan shares to lead arrangers' screening and monitoring efforts. The argument is that screening and monitoring efforts are unobservable to other participants, giving rise to adverse selection and moral hazard problems. Consequently, to mitigate such problems, syndicate participants request lead arrangers to retain larger loan shares than they would otherwise prefer to hold for optimal risk diversification.

Empirical literature has extensively explored the predictions of retention theories. For example, Dennis and Mullineaux (2000) and Jones et al. (2005) show that loan marketability increases as information about the borrower becomes more transparent, suggesting that lead arrangers hold larger shares of informationally problematic loans. Panyagometh and Roberts (2010) suggest that lead arrangers syndicate larger proportions of loans that subsequently do not experience lower Altman (1968) Z-scores, indicating that lead arrangers do not exploit syndicate participants. Balasubramanyan et al. (2019) find that favorable private information is associated with a higher loan retention by lead arrangers. In contrast, Down et al. (2022) show that lead arrangers retain smaller loan shares when they withhold negative information from syndicate participants.

Several empirical studies also establish a link between retained loan shares and lead arrangers' monitoring activities. For instance, Sufi (2007) shows that lead arrangers retain larger loan shares when borrowers require more intense monitoring. Mora (2015) reinforces the monitoring perspective by showing that borrower performance improves as the loan shares retained by lead arrangers increase. While Plosser and Santos (2016) do not detect differential monitoring activities based on retained loan shares, Gustafson et al. (2021) establish a positive association between larger retained loan shares and increased monitoring incentives. Beatty et al. (2019) find that loans shares retained by lead arrangers decrease when participants learn about lead lenders' monitoring quality.

However, certain empirical studies challenge retention theories. For instance, Bruche et al. (2020) argue that lead arrangers retain larger loan shares to ration investors when the demand for loans is low; this motive is different from the monitoring motive suggested by retention theories. In contrast to the monitoring perspective, Blickle et al. (2022) provide evidence that lead arrangers frequently sell their shares, with sold loans outperforming retained ones. However, while lead arrangers frequently sell term loans, credit lines are much less frequently traded (Aramonte et al. 2022; Lee et al. 2022). Thus, lead arrangers still retain exposure to borrowers, potentially motivating them to engage in costly screening and monitoring.

As discussed in the introduction, a large body of research argues that soft information accumulated through relationships with borrowers reduces the costs associated with screening and monitoring (Boot 2000; Carrasco and De Mello 2010). However, previous empirical work generally provides little formal evidence on how lending relationships affect the loan shares retained by lead arrangers. Existing studies primarily investigate the impact of lending relationships on syndicated loan amount, maturity, and price (Bharath et al. 2011; Gadanecz et al. 2012; Alexandre et al. 2014; Even-Tov et al. 2023; Shen et al. 2023; Zhang et al. 2023). This paper fills this gap and contributes to the literature on the determinants of retained shares by providing direct empirical evidence on how lending relationships affect syndicated loan retention.

Previous empirical studies on syndicated lending have also investigated the role of the lead arrangers' reputation. They argue that the reputation of lead arrangers mitigates conflicts of interest within syndicate members (Gatti et al. 2013; Chaudhry and Kleimeier 2015; Winton and Yerramilli 2021). In this light, this paper further extends the literature on retained shares by investigating whether the empirical association between lending relationships and retained loan shares depends on the degree of the lead arrangers' reputation. Moreover, building on the findings of previous studies by Dennis and Mullineaux (2000), Sufi (2007), and Gatev and Strahan (2009), this paper contributes to the retained share literature by investigating whether relationships with borrowers reduce the financial stake lead arrangers must hold when borrowers are informationally opaque, small firms, or have speculative-grade ratings.

3. Data and Econometric Methodology

3.1. Data

For the empirical analysis, I merge data collected from different sources. The syndicated loan data are collected from the DealScan database. This database provides information on the loan amount, maturity, type, purpose, and the facility origination date. DealScan also provides information on the identity of the lenders and some information on the identity of the borrowers, including the borrower's name, geographic location, and standard industrial classification (SIC). For borrowers and lead arrangers with missing addresses, I hand-collect their addresses from the Securities and Exchange Commission (SEC) 10-k filings and the National Information Center (NIC). To facilitate the hand-collection of addresses, I exclude lead arrangers whose headquarters are located outside of North America from the analysis. The borrowers' financial information is extracted from Compustat, and the information from the two databases is merged using the DealScan–Compustat link table constructed by Chava and Roberts (2008).

The construction of the sample begins with all loan facilities in the combined data file. Following previous empirical studies, I exclude loans made to firms in the financial industry (i.e., firms with SIC code between 6000 and 6999) from the sample. Since the focus of this study is syndicated loans, I remove loan facilities distributed by non-syndication methods and those lacking information on the lead arrangers. Furthermore, I require that the loans should be made to U.S. firms and initiated between 1987 and 2013. This sample period is determined by data availability. This process of data cleaning yields a sample containing 10,328 syndicated loan facilities borrowed by 7316 nonfinancial U.S. firms.

3.1.1. Measures of Retained Shares

The dependent variable, denoted by *Retained share*, is the proportion of syndicated loans retained by lead arrangers. While DealScan provides information on the allocation made by some lenders, it is important to determine the roles of the lenders before using this information. DealScan contains a field called *Lead Arranger Credit*, which describes the lenders' role. This field takes values *Yes* or *No* for each lender. I use this field to classify a lender as a lead arranger if the *Lead Arranger Credit* field takes the value *Yes* and as a participant lender if it takes the value *No*. For loans originated by multiple lead arrangers, the *Retained share* is calculated as the average of the proportion held by each lead arranger.

3.1.2. Measures of Lending Relationships

The main independent variable of interest is the lending relationships between lead arrangers and borrowers. To construct lending relationship measures, I follow a similar approach employed by Bharath et al. (2007, 2011). To this end, I track the history of previous lending interactions between the lead arranger and the borrower of a current loan using a five-year history window.[1] It is important to note that the sample is left-tail trimmed, i.e., the first loan facility of any borrower has no prior loan experience. Thus, to avoid erroneously sorting the first loan into a relationship or non-relationship group, I exclude the first loan of each borrower from the analysis.

Following the method outlined above, I construct three measures of lending relationships. The first measure, denoted by *Prior relationship*, identifies whether a lending relationship exists between a lead arranger i and borrower j through loan facility l. This dummy variable takes the value of one if the lead arranger and the borrower of the current loan have engaged in lending interactions in the past, and zero otherwise. For loans involving multiple lead arrangers, *Prior relationship* takes the value of one if at least one lead arranger has interacted with the borrower in the past.

The second measure, denoted by *Relationship intensity* (#), captures the intensity of lending interactions. This measure is constructed by dividing the number of loans arranged by a lead arranger i of loan facility l for a borrower j in the last five years by the total number of loans taken by borrower j over the same period. To show this concept mathematically, let $(N)_{l,t}^{i\rightarrow j}$ denote the number of times the lead arranger i of loan facility l has organized loans for the borrower j at time t. Similarly, let $(N)_{t}^{all\rightarrow j}$ denote the number of times all lead arrangers have lent to the borrower j at time t. Then, the value of *Relationship intensity* (#) between the lead arranger i and borrower j as of loan facility l is expressed as follows:

$$Relationship\ intensity\ (\#)_{i,j,l} = \sum_{t-1}^{t-5}(N)_{l,t}^{i\rightarrow j} \Bigg/ \sum_{t-1}^{t-5}(N)_{t}^{all\rightarrow j} \tag{1}$$

The third measure is denoted by *Relationship depth* (\$). To construct this measure, I divide the total amount of loans that a lead arranger i of loan facility l has lent to a borrower j in the last five years by the total amount of loans borrowed by the borrower j during the same period. To express this concept mathematically, let $(A)_{l,t}^{i\rightarrow j}$ represent the amount that a lead arranger i of loan facility l has lent to a borrower j at time t. Similarly, let $(A)_{t}^{all\rightarrow j}$ represent the total amount borrowed by the borrower j from all lenders in the same period. The amount-based measure of lending relationships between a lead arranger i and borrower j through loan facility l is given as follows:

$$Relationship\ depth\ (\$)_{i,j,l} = \sum_{t-1}^{t-5}(A)_{l,t}^{i\rightarrow j} \Bigg/ \sum_{t-1}^{t-5}(A)_{t}^{all\rightarrow j} \tag{2}$$

For loans involving multiple lead arrangers, I allow *Relationship intensity* (#) and *Relationship depth* (\$) to take the largest value.

3.1.3. Other Control Variables

To control the effects of other factors that could influence retained loan shares, I include a set of independent variables in a regression model. One such variable is the lead arrangers' reputation. Following prior studies by Bharath et al. (2007) and Sufi (2007), I use the lead arrangers' previous market shares in the syndicated loan market to construct the measure of reputation. To this end, I compute the market share by dividing the total amount of syndicated loans arranged by a lead arranger at a given time by the total amount of syndicated loans arranged by all lead arrangers in the same period. When a loan is organized by more than one lead arranger, the loan amount is divided equally among the lead arrangers before calculating the market share. To show this concept mathematically, let $(A)^i_{lt}$ represent the amount of the syndicated loan l arranged by the lead arranger i at time t. The market share for the lead arranger i at time t is then calculated as follows:

$$Market\ share_{i,t} = \sum_{l}^{L}(A)^i_{lt} \Big/ \sum_{i}^{I}\sum_{l}^{L}(A)^i_{lt} \tag{3}$$

The numerator sums the dollar value of syndicated loans (where $l = 1, \ldots, L$) arranged by the lead arranger i at time t, while the denominator aggregates the dollar amount of all syndicated loans organized by all lead arrangers (where $i = 1, \ldots, I$) at time t. To capture the idea that top-tier arrangers have more reputational concerns than less prestigious lead arrangers, I construct the *Top 3 arranger* and *Top 10 arranger* variables, following McCahery and Schwienbacher (2010) and Ross (2010). These variables identify lead arrangers in the top 3 and top 10 percentiles of market shares, respectively. When a facility is arranged by multiple lead arrangers, a loan is classified as arranged by a dominant lead arranger if at least one lead arranger is a top-tier arranger. Godlewski et al. (2012) argues that arrangers can gain experience by participating in the syndicated loan market with higher stakes. Thus, the reputation variable constructed above potentially captures the experience of lead arrangers.

The next set of control variables corresponds to loan characteristics. The loan size, denoted by *Ln(Amount)*, is measured by the natural logarithm of the facility amount in dollars. Loan maturity, denoted by *Ln(Maturity)*, is measured by the natural logarithm of the number of months from the facility start date to the facility end date. A dummy variable, *Sponsor*, is used to identify whether a loan is sponsored. Another variable, *Covenant*, captures the number of financial covenants in a loan facility. A categorical variable, *Loan type*, is used to distinguish whether a facility is a revolver, term loan, 364-day facility, or other type. Similarly, a categorical variable, *Loan purpose*, is used to categorize the loan's intended use, whether for corporate purposes, working capital, debt repayment, takeover, or other purposes.

The last set of control variables corresponds to firm-specific characteristics. The firm size, denoted by *Firm size*, is measured by the natural logarithm of total assets. To account for limited information about a firm, I construct a dummy variable, *Opacity*, that takes the value of one for firms without S&P long-term issuer ratings, and zero otherwise. As firms repeatedly access the syndicated market, they become more known to syndicate participants. This reduces information asymmetry between lead arrangers and other participants. Following Sufi (2007), I control for this by using the natural logarithm of one plus the number of times the firm has previously borrowed in the syndicated loan market, denoted by *Ln*(1 + *#prev. borrow*). *Profitability* is measured by EBITDA scaled by total assets. The predominant view in the corporate finance literature, influenced by the seminal work of Jensen and Meckling (1976), is that leverage increases the incentive to engage in risk-shifting activities. As this affects previous and current loan outcomes, I control for firm leverage using the ratio of total debt to total assets. *Tangibility* is measured by the ratio of property, plant, and equipment to total assets. Following Aktas et al. (2012), I control for the quality of investment projects using the Altman (1968) *Z*-score. To this end, I construct a dummy variable, *Financial distress*, that takes the value of one for Altman

(1968) Z-scores less than or equal to 1.81, and zero otherwise. All the variables used in this study are formally defined in Table A1 in Appendix A.

3.1.4. Descriptive Statistics and Univariate Analysis

Table 1 reports the descriptive statistics of the variables used in the empirical analysis. As some firms appear more than once in the sample, I calculate the descriptive statistics of borrowers at the firm-year level. For the remaining variables, their descriptive statistics are computed at the loan facility level.

Table 1. Descriptive statistics of the sample.

	N	Mean	SD	Min	50th	Max
Prior relationship	10,328	0.59	0.49	0.00	1.00	1.00
Relationship intensity (#)	10,328	0.40	0.41	0.00	0.33	1.00
Relationship depth ($)	10,328	0.36	0.40	0.00	0.21	1.00
Retained share	10,328	27.83	23.26	0.00	20.00	100.00
Total lead arrangers	10,328	1.61	1.97	1.00	1.00	38.00
Top 3 arranger	10,328	0.30	0.46	0.00	0.00	1.00
Top 10 arranger	10,328	0.51	0.50	0.00	1.00	1.00
Loan amount (million USD)	10,328	438.99	1205.66	0.02	150.00	36,498.43
Maturity	10,328	45.34	24.03	1.00	48.00	276.00
Term loan	10,328	0.20	0.40	0.00	0.00	1.00
Revolver	10,328	0.61	0.49	0.00	1.00	1.00
360-day facility	10,328	0.11	0.31	0.00	0.00	1.00
Corporate purposes	10,328	0.29	0.46	0.00	0.00	1.00
Working capital	10,328	0.19	0.39	0.00	0.00	1.00
Takeover	10,328	0.11	0.31	0.00	0.00	1.00
Debt repayment	10,328	0.22	0.41	0.00	0.00	1.00
Sponsor	10,328	0.06	0.24	0.00	0.00	1.00
Covenant	10,328	1.89	2.08	0.00	2.00	12.00
Total asset (billion USD)	7316	6.42	20.43	0.00	1.02	340.65
Profitability	7316	0.14	0.10	−3.03	0.13	1.14
Tangibility	7316	0.38	0.25	0.00	0.33	0.97
Leverage	7316	0.32	0.23	0.00	0.30	3.74
Opacity	7316	0.56	0.50	0.00	1.00	1.00
Financial distress	7316	0.32	0.47	0.00	0.00	1.00

Note: Descriptive statistics are calculated at the loan facility level except descriptive statistics of the borrowers, which are calculated at the firm-year level.

The mean value of *Prior relationship* indicates that 59% of syndicated loans are organized by lead arrangers with whom the borrowers have had prior lending interactions. Regarding the proportions of loans held by lead arrangers, the mean value of *Retained share* shows that, on average, lead arrangers retain 27.83% of the loans. The distribution of this variable demonstrates considerable variations among lead arrangers. The minimum value implies that certain lead arrangers syndicate out the entire loans (i.e., 0% retained share), while the maximum value indicates that others retain the full amount (i.e., 100% retained share). Regarding lead arranger reputation, the mean value of *Top 3 arranger* (and *Top 10 arranger*) suggests that 30% (and 51%, respectively) of syndicated loans are organized by lead arrangers whose market shares are in the top 3 (or top 10) percentiles.

Moving on to loan size, the average amount is USD 438.99 million, with a standard deviation of USD 1205.66 million. Loan facilities have an average maturity of 45.34 months and a median maturity of 48 months. Turning to loan types, the line of credit (revolver) is the most common, accounting for 61% of the facilities in the sample. These facilities are typically used to fund corporate purposes, which constitutes 29% of the loans in the sample.

Regarding firm characteristics, borrowers have an average total assets value of USD 6.42 billion, and 56% of them do not have S&P credit ratings. According to Altman (1968)'s Z-Scores, 32% of firms in the sample are financially distressed. Overall, the descriptive statistics highlight the heterogeneous characteristics of the borrowers, lead arrangers, and syndicated loan facilities in the sample.

Before turning to the regression analysis, I conduct a univariate test to obtain preliminary results about the impact of lending relationships on retained shares. The results of the univariate analysis are presented in Table 2. To perform the univariate test, I categorize syndicated loans into relationship loans (when *Prior relationship* = 1) and non-relationship loans (when *Prior relationship* = 0). The means and standard deviations for relationship and non-relationship loans are reported in Panel A and Panel B, respectively. The differences of these means are displayed in Panel C.

Table 2. Univariate analysis by prior relationship.

	Panel A		**Panel B**		**Panel C**	
	***Prior Relationship* = 1**		***Prior Relationship* = 0**		***Difference***	
	Mean	**SD**	**Mean**	**SD**	**Mean**	**SD**
Retained share	25.08	(21.70)	31.77	(24.81)	−6.69 ***	(0.46)
Top 3 arranger	0.35	(0.48)	0.23	(0.42)	0.12 ***	(0.01)
Total asset (billion USD)	7.75	(22.71)	4.48	(14.86)	3.27 ***	(0.40)
Profitability	0.14	(0.09)	0.13	(0.11)	0.00	(0.00)
Tangibility	0.38	(0.25)	0.37	(0.24)	0.02 **	(0.00)
Leverage	0.34	(0.23)	0.33	(0.24)	0.00	(0.00)
Opacity	0.54	(0.50)	0.62	(0.48)	−0.09 ***	(0.01)
Financial distress	0.34	(0.47)	0.31	(0.46)	0.02 *	(0.01)
Loan amount (million USD)	517.79	(1369.51)	326.42	(910.85)	191.37 ***	(24.03)
Maturity	45.04	(24.19)	45.76	(23.80)	−0.72	(0.48)
Term loan	0.18	(0.39)	0.21	(0.41)	−0.03 ***	(0.01)
Revolver	0.61	(0.49)	0.62	(0.49)	−0.00	(0.01)
360-day facility	0.12	(0.33)	0.09	(0.28)	0.04 ***	(0.01)
Corporate purposes	0.31	(0.46)	0.27	(0.45)	0.03 ***	(0.01)
Working capital	0.18	(0.38)	0.20	(0.40)	−0.02 **	(0.01)
Takeover	0.10	(0.30)	0.11	(0.32)	−0.01	(0.01)
Debt repayment	0.23	(0.42)	0.21	(0.41)	0.02	(0.01)
Sponsor	0.05	(0.22)	0.07	(0.26)	−0.02 ***	(0.00)
Covenant	1.74	(2.00)	2.10	(2.17)	−0.36 ***	(0.04)

Note: The *t*-test of significance is represented as: *** significant at the 1% level, ** significant at the 5% level, and * significant at the 10% level.

The univariate evidence suggests that the retained shares for relationship loans are significantly lower than the retained shares for non-relationship loans (25.08% vs. 31.77%). The difference in retained shares is −6.69% and it is statistically significant at the 1% level. The univariate analysis also reveals significant differences between relationship and non-relationship loans in terms of lead arranger, borrower, and loan characteristics. As the failure to account for these differences could bias the results, I control for these characteristics in a regression framework.

3.2. Econometric Model

To examine the impact of lending relationships on retained shares, I estimate the following baseline regression model:

$$Retained\ share_{i,j,l} = \alpha + \beta Relationship_{i,j,l} + X'\gamma + \eta_{\kappa} + \lambda_t + \varepsilon_{i,j,l} \quad (4)$$

where $Retained\ share_{i,j,l}$ represents the proportion of a syndicated loan retained by a lead arranger i on a loan facility l made to a borrower j. The key independent variable of interest, indicated by $Relationship_{i,j,l}$, is the lending relationship between lead arranger

i and borrower j through loan facility l. I use *Prior relationship*, *Relationship intensity* (#), and *Relationship depth* ($) as measures of lending relationships. The coefficient of interest is β, and it measures the net effect of lending relationships. As discussed earlier, when lending relationships enhance the lead arrangers' monitoring activities, this effect should be reflected in decreased retained shares. In contrast, when informed lead arrangers take advantage of their superior information to exploit less informed participants, this should be reflected in increased retained shares. Thus, if the first effect dominates the second, β is negatively estimated.

The variable X controls for a set of borrower, lead arranger, and loan characteristics discussed in Section 3.1.3. In the model, η_κ controls for the borrower's industry fixed effect, where I define industry using a one-digit Standard Industrial Classification (SIC). λ_t controls for the facility start year fixed effects. $\varepsilon_{i,j,l}$ is an error term, and the standard errors are robust to heteroskedasticity and clustered at the firm level.

4. Empirical Results

In the first part of the empirical analysis, I present and discuss the baseline estimation results and then turn to issues related to the endogeneity of lending relationships. In the second part, I conduct an additional analysis by including interaction terms between lending relationships and other variables.

4.1. Baseline Regression Results

The empirical results of the baseline regression Model (4) are reported in Table 3. In Column (1), I estimate the baseline regression using *Prior relationship* as a measure of lending relationships. As can be seen from the results reported in this column, the coefficient of *Prior relationship* is negative and statistically significant at the 1% level. This result indicates that lead arrangers who were previously involved in lending relationships with borrowers retain 2.58% less of the syndicated loans they subsequently arrange for those borrowers.

Table 3. The impact of lending relationships and on retained shares.

	(1)	(2)	(3)	(4)	(5)	(6)
Prior relationship	−2.577 *** (0.48)			−2.315 *** (0.48)		
Relationship intensity		−2.372 *** (0.56)			−2.041 *** (0.56)	
Relationship depth			−1.889 *** (0.60)			−1.604 *** (0.60)
Top 3 arranger	−3.929 *** (0.47)	−4.030 *** (0.47)	−4.074 *** (0.47)			
Top 10 arranger				−5.412 *** (0.53)	−5.500 *** (0.53)	−5.563 *** (0.53)
Opacity	−0.127 (0.84)	−0.0924 (0.84)	−0.094 (0.84)	−0.214 (0.83)	−0.181 (0.83)	−0.184 (0.83)
Ln(1 + #prev. borrow)	−0.117 (0.59)	−0.649 (0.59)	−0.589 (0.59)	−0.163 (0.58)	−0.636 (0.59)	−0.584 (0.59)
Firm size	−3.937 *** (0.37)	−3.952 *** (0.37)	−3.989 *** (0.37)	−3.824 *** (0.36)	−3.837 *** (0.36)	−3.867 *** (0.37)
Profitability	−0.869 (3.42)	−0.722 (3.43)	−0.796 (3.44)	−0.346 (3.36)	−0.216 (3.37)	−0.275 (3.37)
Tangibility	−2.002 (1.44)	−2.087 (1.44)	−2.050 (1.45)	−2.204 (1.43)	−2.279 (1.43)	−2.250 (1.44)
Leverage	−2.436 (1.51)	−2.382 (1.52)	−2.444 (1.52)	−2.279 (1.50)	−2.229 (1.50)	−2.280 (1.50)
Financial distress	2.613 *** (0.71)	2.649 *** (0.71)	2.613 *** (0.71)	2.712 *** (0.71)	2.744 *** (0.71)	2.714 *** (0.71)
Ln(Amount)	−4.703 *** (0.38)	−4.712 *** (0.38)	−4.713 *** (0.38)	−4.496 *** (0.37)	−4.503 *** (0.37)	−4.501 *** (0.37)
Ln(Maturity)	−4.500 *** (0.49)	−4.485 *** (0.49)	−4.491 *** (0.49)	−4.413 *** (0.49)	−4.399 *** (0.49)	−4.402 *** (0.49)

Table 3. *Cont.*

	(1)	(2)	(3)	(4)	(5)	(6)
Sponsor	−3.085 **	−3.023 **	−2.988 **	−2.627 **	−2.561 **	−2.524 **
	(1.26)	(1.26)	(1.26)	(1.26)	(1.26)	(1.27)
Covenant	−0.412 **	−0.418 **	−0.409 **	−0.397 **	−0.401 **	−0.393 **
	(0.17)	(0.17)	(0.17)	(0.17)	(0.17)	(0.17)
Lon type FE	Yes	Yes	Yes	Yes	Yes	Yes
Loan purpose FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.382	0.381	0.381	0.388	0.387	0.387
N	10,328	10,328	10,328	10,328	10,328	10,328

Note: The *t*-test of significance is: *** significant at the 1% level and ** significant at the 5% level. Heteroskedasticity robust standard errors are in parentheses.

The reduction in retained loan shares is economically nonnegligible. For example, consider lead arrangers holding the sample average share of 27.83%. For these lead arrangers, the existence of lending relationships leads to a 9.27% decrease in retained shares (−2.58/27.83 × 100). This implies that lead arrangers organizing a syndicated loan with the sample average amount of USD 438.99 million will contribute USD 11.33 million (438.99 × 27.83% × 9.27%) less than they would otherwise have to contribute if they had not established a lending relationship with the borrowers.

In Column (2), I investigate whether the impact of lending relationships depends on the frequency of lending interactions between the lead arranger and the borrower. I perform this by estimating Regression Model (4) using *Relationship intensity* (#) as the main independent variable of interest. The finding shows that *Relationship intensity* (#) is negatively and significantly (at the 1% level) related to retained loan shares. This suggests that the effect of lending relationships depends on the intensity of lending interactions; as these interactions become more frequent, lead arrangers retain smaller shares.

One possible explanation is that repeated interactions enable lead arrangers to access more proprietary information about the borrower (Von Thadden 1995). This signals the lead arrangers' monitoring cost advantage to other participants. Another possible explanation is that repeated interactions allow lead arrangers to impute premiums in the form of higher interest rates on future loans (Stiglitz and Weiss 1983). Additionally, it can be argued that repeated interactions allow lead arrangers to establish a credible termination threat (Stiglitz and Weiss 1983; Bolton and Scharfstein 1990). Thus, borrowers that value future relationships would exercise self-restraint. This solves one layer of agency conflicts, i.e., conflicts between borrowers and lenders, enabling lead arrangers to retain smaller loan shares.

In Column (3), I repeat the estimation in Column (2) by replacing *Relationship intensity* (#) with *Relationship depth* ($) to investigate whether the effect of lending relationships also depends on the proportion of dollar amounts that the lead arranger has previously organized for the firm. As can be seen from the results, the coefficient of *Relationship depth* ($) is negative and significant. This suggests that an increase in the strength of lending relationships, as measured by the relationship depth, is associated with a decrease in retained loan shares. Taken together, these results support the hypothesis that the monitoring cost advantage of lending relationships dominates the information exploitation aspect in the syndicated loan market. Hence, participants do not require relationship lead arrangers to retain larger loan shares.

The remaining columns of Table 3 rerun the analysis conducted in the first three columns, replacing *Top 3 arranger* with *Top 10 arranger*. As expected, all coefficients of lending relationships are negative and statistically significant. Thus, apart from a small decrease in the estimated magnitudes, the conclusion drawn above remains unchanged. Overall, the findings of this study have important implications for lenders seeking to reduce their risk exposure in syndicated loans.

Regarding the control variables, most have the expected signs. For instance, more reputable lead arrangers retain smaller shares. Lead arrangers organizing loans for financially distressed firms retain a larger portion of the loans. For larger borrowers, lead arrangers retain a smaller portion of the loans. In line with the prediction of agency-based theory (Jensen and Meckling 1976; Myers 1977) and the shift of control rights on a state-contingent basis (Gârleanu and Zwiebel 2009), the retained shares of lead arrangers decrease with loan size, maturity, and covenant.

4.2. Endogeneity Concerns

As noted by Bharath et al. (2011), the choice of borrowing from a relationship lead arranger or lending to a relationship borrower may not be made at random but rather endogenously determined. To address this concern, I employ alternative estimation techniques such as propensity score matching (Heckman et al. 1997; Imbens and Wooldridge 2009) and binary endogenous treatment models (Heckman 1978, 1979).

4.2.1. Mahalanobis and Propensity Score Matching

The matching method addresses endogeneity concerns by identifying loan facilities provided by the non-relationship lead arrangers (i.e., the control group) that best match those loan facilities provided by relationship lead arrangers (i.e., the treated group). After identifying the closest comparison group, the matching method computes the difference in retained shares between the matched relationship and non-relationship loans. Since the loans in both the treated and control groups are similar, any difference in retained shares is attributed to lending relationships.

To select loan facilities for the control group, I employ two alternative methods. One approach, proposed by Cochran and Rubin (1973) and Rubin (1980), is based on the Mahalanobis distance between relationship and non-relationship loans. However, Gu and Rosenbaum (1993) show that Mahalanobis metric-based matching may be susceptible to bias when many covariates are used. To address this concern, I also employ propensity score matching (PSM), proposed by Rosenbaum and Rubin (1983), to select control subjects. PSM mitigates bias by matching on a function of the covariates (i.e., a similar propensity score) rather than on the covariates themselves.

To implement PSM, I first estimate the probability of a loan being a relationship loan. This probability is estimated as follows:

$$Pr\Big(Prior\ relationship_{i,j,l} = 1\Big) = \Phi(\alpha_0 + X'\psi + \eta_\kappa + \lambda_t) \quad (5)$$

where $Pr(.)$ denotes a probit model. $Prior\ relationship_{i,j,l}$ takes the value of one if a loan is organized by a relationship lead arranger, and zero otherwise. Φ represents the cumulative standard normal distribution function. The variable X controls for the lead arranger, borrower, and loan characteristics discussed in Section 3.1.3. η_κ stands for the borrowers' one-digit SIC, and λ_t is the year fixed effect.

Table 4 presents the matching results. The results from the nearest neighbor estimator based on Mahalanobis metric-matching are reported in Panel A. The nearest neighbor estimators calculate the difference in retained shares between a relationship loan and n non-relationship loans for which the Mahalanobis distance metric is at its minimum. To obtain correct standard errors, I use the Abadie and Imbens (2006) variance estimator. Column (3) of this table reports the difference in retained shares. As can be seen, the *one-to-one* estimator yields an average treatment effect on the treated (ATT) of −2.722. Qualitatively similar results are obtained when I increase the number of non-relationship loans used in the control group.

Table 4. Mahalanobis and propensity score matching.

	Treated (1)	**Untreated (2)**	**ATT (3)**
Panel A: Mahalanobis metric-matching			
One-to-one	6075	4253	−2.722 ***
			(0.46)
Nearest neighbor (n = 10)	6075	4253	−3.164 ***
			(0.41)
Nearest neighbor (n = 50)	6075	4253	−4.335 ***
			(0.46)
Panel B: Propensity score matching			
One-to-one	6068	4253	−2.865 ***
			(0.61)
Nearest neighbor (n = 10)	6068	4253	−2.959 ***
			(0.49)
Nearest neighbor (n = 50)	6068	4253	−3.023 ***
			(0.49)
Epanechnikov	6020	4253	−2.960 ***
			(0.50)
Gaussian	6068	4253	−3.042 ***
			(0.55)

Note: The *t*-test of significance is: *** significant at the 1% level.

In Panel B, I estimate PSM. With PSM, the nearest neighbor estimators calculate the difference in retained shares between a relationship loan and n non-relationship loans that have the closest propensity scores to the relationship loan. With this matching method, the *one-to-one* estimator yields an ATT of −2.865. Qualitatively similar effects are obtained when I increase the number of non-relationship loans in the control group. For example, with $n = 10$, the *nearest neighbor* estimator reports an ATT of −2.959, and for $n = 50$, the ATT is −3.023.

In addition to the nearest neighbor estimators, I also implement PSM using kernel estimators. These estimators calculate the difference in the retained share between a relationship loan and the weighted average of non-relationship loans. For the *Epanechnikov* kernel, I use a bandwidth of $h = 0.01$ to reduce bias. Correct standard errors are obtained through bootstrapping with 100 replications. As Column (3) shows, the *Epanechnikov* kernel estimator yields an ATT of −2.96. A similar qualitative effect is obtained when I use the *Gaussian* kernel. Overall, the matching results confirm the baseline finding that lending relationships are associated with a reduction in retained loan shares, even after controlling for selection on observables.

4.2.2. Binary Endogenous Treatment Models

Although the matching method addresses bias stemming from selection on observable factors, endogeneity concerns may persist if differences between relationship and non-relationship loans result from unobservable factors. To further address endogeneity concerns, I estimate binary endogenous treatment models (Heckman 1979). The binary endogenous treatment model involves estimating a system of equations in which the retained share equation (i.e., the outcome variable equation) is augmented with a lending relationship equation (i.e., an additional equation for the binary endogenous treatment variable). The model is specified as:

$$Retainedshare_{i,j,l} = \beta_0 + \beta Prior\ relationship_{i,j,l} + X'\gamma + \eta_\kappa + \lambda_t + \varepsilon_{i,j,l} \quad (6)$$

$$Prior\ relationship^*_{i,j,l} = \vartheta_0 + \phi Z + X'\gamma + \eta_\kappa + \lambda_t + \nu_{i,j,l} \quad (7)$$

where $Prior\ relationship^{*}_{i,j,l}$ is a latent variable for lending relationship formation. The variable Z represents the potential instrument, and I use the geographic distance between the lead arranger and the borrower as this instrument. As noted by Petersen and Rajan (2002) and Dass and Massa (2011), geographic proximity reduces the costs associated with the collection and processing of borrower soft information, thereby increasing the likelihood of forming a lending relationship. However, geographic distance is unlikely to directly affect retained loan shares.

To compute the physical distance between a loan's lead arranger and borrower, I adopt the approach proposed by Dass and Massa (2011). To this end, I first manually collect the latitude and longitude of each city where the lead arrangers and borrowers are located. The spherical distance in kilometers is then calculated as follows:

$$Distance_{i,j} = arccos(deg[latlon]) \times r \tag{8}$$

where:

$$\begin{gathered} deg[latlon] = cos(lat_i) \times cos(lon_i) \times cos\left(lat_j\right) \times cos\left(lon_j\right) \\ +cos(lat_i) \times sin(lon_i) \times cos\left(lat_j\right) \times sin\left(lon_j\right) + sin(lat_i) \times sin\left(lat_j\right) \end{gathered}$$

In Equation (8), r is the Earth's radius in kilometers; lat and lon denote the latitude and longitude converted to radians from degrees by multiplying by $\pi/180$. When a loan involves multiple lead arrangers, I select the closest geographic distance between the lead arranger and the borrower.

The binary endogenous treatment models solve the endogeneity problem by allowing the residuals in Equations (6) and (7) to be correlated, i.e., $cov\left(\varepsilon_{i,j,l}, \nu_{i,j,l}\right) = \rho \neq 0$. Since whether a syndicated loan is a relationship or non-relationship loan is observable, the observed relationship is modeled as:

$$Prior\ relationship_{i,j,l} = \begin{cases} 1\ if\ Prior\ relationship^{*}_{i,j,l} > 0 \\ 0\ otherwise \end{cases} \tag{9}$$

To estimate the binary endogenous treatment models, I apply the method developed by Cerulli (2014). Table 5 reports the results. Column (1) contains the results of the first stage regression, in which a probit model of a lending relationship is estimated. As can be seen, the estimated coefficient of geographic distance is negative and significant at the 1% level. Consistent with expectations, this result indicates that firms in closer proximity to lenders are more likely to form a lending relationship.

Column (2) reports *Probit-OLS* estimates. Operationally, *Probit-OLS* involves applying a probit model to the lending relationship equation and obtaining the predicted probability of relationship formation. In the second stage, retained shares are regressed on the predicted probability of forming relationships, along with the control variables, by OLS. The results show that the estimated coefficient of *Prior relationship* is significantly negative, thus qualitatively replicating the evidence presented in Table 3 that lending relationships reduce retained loan shares.

Column (3) presents probit two-stage least squares (*Probit-2SLS*) estimates. Operationally, *Probit-2SLS* involves applying a probit model to the lending relationship equation and obtaining the predicted probability of a lending relationship. This predicted probability is later used as an instrument for relationship formation to obtain a new fitted value. The retained share is then regressed on this new predicted probability of a lending relationship, along with the control variables. As can be seen from the results reported in this column, I obtain quite similar effects as with *Probit-OLS*. The last column contains Heckman two-step regression estimates, and again I obtain qualitatively similar effects.

Overall, these results reinforce the evidence that lending relationships are associated with a significant reduction in retained shares. However, the endogenous treatment model produces relationship coefficients with a larger magnitude compared to the OLS estimates.

As can be seen, these coefficients are approximately six-times larger.[2] This increase might stem from the predicted relationship not being a very good fit for *Prior relationship*, as indicated by the low McFadden (1973)'s pseudo R^2.[3] Since OLS yields conservative estimates, it is used in the remaining sections of this article.

Table 5. Estimation of binary endogenous treatment models.

	First Stage (1)	Probit-OLS (2)	Probit-2SLS (3)	Heckit (4)
Ln(1 + Distance)	−0.103 ***			
	(0.02)			
Prior relationship		−14.916 **	−14.177 **	−12.947 **
		(6.04)	(6.00)	(6.18)
Top 3 arranger	−0.071	−6.493 ***	−6.505 ***	−6.475 ***
	(0.08)	(1.02)	(1.08)	(1.15)
Opacity	0.034	1.650	1.677	1.662
	(0.09)	(1.14)	(1.22)	(1.20)
Ln(1 + #prev. borrw)	0.641 ***	1.245	1.091	0.822
	(0.06)	(1.50)	(1.50)	(1.59)
Firm size	0.013	−3.037 ***	−3.022 ***	−3.027 ***
	(0.04)	(0.60)	(0.60)	(0.55)
Profitability	−0.681 *	−7.832	−7.597	−7.332
	(0.38)	(6.17)	(5.98)	(5.38)
Tangibility	0.206	−3.198	−3.265	−3.349
	(0.16)	(2.21)	(2.34)	(2.24)
Leverage	−0.331 *	1.079	1.200	1.337
	(0.17)	(2.64)	(2.82)	(2.43)
Financial distress	−0.066	4.511 ***	4.532 ***	4.567 ***
	(0.10)	(1.35)	(1.41)	(1.33)
Ln(Amount)	0.053	−5.288 ***	−5.297 ***	−5.319 ***
	(0.04)	(0.69)	(0.70)	(0.58)
Ln(Maturity)	−0.045	−6.856 ***	−6.845 ***	−6.824 ***
	(0.06)	(1.15)	(1.21)	(0.89)
Sponsor	−0.020	−1.701	−1.647	−1.617
	(0.14)	(2.55)	(2.72)	(2.02)
Covenant	0.025	−0.819 ***	−0.818 **	−0.831 ***
	(0.02)	(0.32)	(0.34)	(0.28)
Loan type FE	Yes	Yes	Yes	Yes
Loan purpose FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Lambda				7.132 *
				(3.77)
McFadden's pseudo R^2	0.126			
N	2081	2081	2081	2081

Note: The *t*-test of significance is: *** significant at the 1% level, ** significant at the 5% level, and * significant at the 10% level. Heteroskedasticity robust standard errors are in parentheses.

4.3. Subgroup Analyses

In this second part of the empirical analysis, I present two sets of results. The first set of results investigates whether the effect of lending relationships depends on the degree of the lead arrangers' reputation. The second set of results examines whether the effect varies between informationally opaque and transparent firms, small and large firms, and firms with investment-grade and speculative-grade ratings.

4.3.1. Analysis by Lead Arrangers' Reputation

To examine whether the impact of lending relationships varies depending on the degree of the lead arrangers' reputation, I estimate an extended version of the baseline regression model. The extended regression model is given as follows:

$$\begin{aligned} Retained\ share_{i,j,l} =& \beta_0 + \beta_g \sum_{g=1}^{n} \left(Relationship_{i,j,l} \times Group_g \right) \\ & + X'\gamma + \eta_\kappa + \lambda_t + \varepsilon_{i,j,l} \end{aligned} \tag{10}$$

where $Group_g$ is a dummy variable that takes the value of one if a lead arranger belongs to group g, and zero otherwise. The remaining variables are defined similarly as in Regression Equation (4). The standard errors are clustered at the firm level and are also robust to heteroskedasticity. Table 6 reports the results.

Table 6. Analysis by lead arrangers' reputation.

	(1)	(2)	(3)
Prior relationship × Top 3 arranger	0.389		
	(0.66)		
Prior relationship × (1 − Top 3 arranger)	−3.680 ***		
	(0.60)		
Relationship intensity × Top 3 arranger		0.573	
		(0.76)	
Relationship intensity × (1 − Top 3 arranger)		−3.556 ***	
		(0.71)	
Relationship depth × Top 3 arranger			0.074
			(0.84)
Relationship depth × (1 − Top 3 arranger)			−2.613 ***
			(0.74)
Top 3 arranger	−6.550 ***	−5.829 ***	−5.109 ***
	(0.74)	(0.67)	(0.66)
Opacity	−0.086	−0.055	−0.080
	(0.83)	(0.83)	(0.84)
Ln(1 + #prev. borrow)	−0.142	−0.650	−0.581
	(0.58)	(0.59)	(0.59)
Firm size	−3.947 ***	−3.969 ***	−4.004 ***
	(0.37)	(0.37)	(0.37)
Profitability	−0.704	−0.686	−0.771
	(3.41)	(3.44)	(3.45)
Tangibility	−1.945	−2.053	−2.074
	(1.44)	(1.43)	(1.45)
Leverage	−2.435	−2.439	−2.478
	(1.51)	(1.52)	(1.52)
Financial distress	2.585 ***	2.653 ***	2.610 ***
	(0.71)	(0.71)	(0.71)
Ln(Amount)	−4.714 ***	−4.712 ***	−4.702 ***
	(0.38)	(0.37)	(0.38)
Ln(Maturity)	−4.519 ***	−4.503 ***	−4.508 ***
	(0.49)	(0.49)	(0.49)
Sponsor	−3.072 **	−3.055 **	−3.021 **
	(1.25)	(1.25)	(1.26)
Covenant	−0.417 **	−0.425 **	−0.412 **
	(0.17)	(0.17)	(0.17)
Loan type FE	Yes	Yes	Yes
Loan purpose FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
R^2	0.384	0.382	0.381
N	10,328	10,328	10,328
Δ interaction coefficient	21.48	16.32	5.89
	[0.000]	[0.000]	[0.015]

Note: The t-test of significance is: *** significant at the 1% level and ** significant at the 5% level. Heteroskedasticity robust standard errors are in parentheses. The p-values are in square brackets below the F-statistic.

Before estimating Regression Model (10), I use the dummy variable *Top 3 arranger*, which identifies lead arrangers in the top three percentiles in terms of market shares, and I construct two interaction terms: *Prior relationship* × *Top 3 arranger* and *Prior relationship* × *(1 − Top 3 arranger)*. In Column (1), I estimate Model (10) after replacing $Relationship_{i,j,l} \times Group_g$ with the two interaction terms. As the results show, the estimated coefficient of *Prior relationship* × *Top 3 arranger* is not statistically significant, but the coefficient of *Prior relationship* × *(1 − Top 3 arranger)* is negative and significant. These findings suggest that establishing a lending relationship is associated with a reduction in retained shares only for non-top-tier lead arrangers. Moreover, the Δ *interaction coefficient*, which tests the equality of the estimated coefficients and is reported at the bottom of Table 6, shows that the estimated coefficients of *Prior relationship* × *Top 3 arranger* and *Prior relationship* × *(1 − Top 3 arranger)* are significantly different from each other.

The above finding can be understood in the light of the lead arrangers' reputation argument. Gopalan et al. (2011) argue that a poor performance by borrowers damages the lead arrangers' subsequent syndication activities, a notion confirmed by Blickle et al. (2022). Furthermore, McCahery and Schwienbacher (2010) and Ross (2010) argue that top-tier lead arrangers already possess high reputational stakes. Consequently, these top-tier lead arrangers have incentives to avoid opportunistic behavior in order to prevent damage to their reputation. This, in turn, mitigates agency conflicts within lending syndicates. The finding that a reduction in retained shares due to lending relationships is limited to loan facilities administered by non-top-tier lead arrangers is, therefore, broadly consistent with the reputation argument.

In Column (2), I repeat the analysis in the first column by replacing the dummy measure of lending relationships with a measure that captures the intensity of lending interactions. As the estimates show, the coefficient of *Relationship intensity (#)* × *Top 3 arranger* is not statistically significant, while the coefficient of the interaction term *Relationship intensity (#)* × *(1 − Top 3 arranger)* is negative and significant. These results suggest that an increase in the intensity of lending interactions is associated with a significant reduction in retained shares only for non-top-tier lead arrangers. Moreover, the Δ *interaction coefficient* shows that the estimated coefficients of the two interaction terms differ significantly from each other.

In Column (3), I use *Relationship depth* ($) as a measure of relationship strength and obtain results similar to those reported in Column (2). Additionally, as the Δ *interaction coefficient* shows, the coefficients on *Relationship depth ($)* × *Top 3 arranger* and *Relationship depth ($)* × *(1 − Top 3 arranger)* significantly differ from each other. In sum, these findings strongly highlight the heterogeneous impact of lending relationships on retained shares depending on the degree of the lead arrangers' reputation.

4.3.2. Analysis by Opacity, Firm Size and Rating

Now I turn to investigate the impact of borrower characteristics on the association between lending relationships and retained shares. The results of this analysis are reported in Table 7. I begin the analysis by investigating whether the effect of lending relationships on retained shares differs between informationally opaque and transparent firms. To this end, I use the dummy variable *Opacity* and construct two interaction terms: *Prior relationship* × *Opacity* and *Prior relationship* × *(1 − Opacity)*. The estimation reported in Column (1) involves running Regression Model (10) after replacing $Relationship_{i,j,l} \times Group_g$ with the two interaction terms.

As can be seen from the results presented in this column, the estimated coefficients of the two interaction terms are negative and statistically significant. This result suggests that lending relationships are associated with a reduction in retained shares for loans held by both informationally opaque and transparent firms. To examine if there exists any differential effect of lending relationships, I test the equality of the estimated coefficients of the two interaction terms. As indicated by the Δ *interaction coefficient*, reported at the bottom of Table 7, the coefficients of the two interaction terms do not significantly differ from each other.

Table 7. Analysis by opacity, firm size, and rating.

	(1)	(2)	(3)
Prior relationship × Opacity	−3.188 ***		
	(0.64)		
Prior relationship × (1 − Opacity)	−1.672 **		
	(0.67)		
Prior relationship × Small firm		−2.017 ***	
		(0.67)	
Prior relationship × (1 − Small firm)		−3.190 ***	
		(0.55)	
Prior relationship × Speculative GR			−3.584 ***
			(0.99)
Prior relationship × (1 − Speculative GR)			−2.393 ***
			(0.49)
Top 3 arranger	−3.980 ***	−3.887 ***	−3.916 ***
	(0.47)	(0.47)	(0.47)
Opacity	0.728	−0.183	−0.485
	(1.00)	(0.84)	(0.88)
Ln(1 + #prev. borrow)	−0.142	−0.089	−0.080
	(0.59)	(0.58)	(0.58)
Firm size	−3.945 ***	−3.785 ***	−3.969 ***
	(0.37)	(0.38)	(0.37)
Profitability	−0.823	−0.989	−0.962
	(3.42)	(3.40)	(3.44)
Tangibility	−2.002	−1.958	−1.992
	(1.44)	(1.43)	(1.44)
Leverage	−2.395	−2.454	−2.348
	(1.51)	(1.51)	(1.52)
Financial distress	2.637 ***	2.633 ***	2.636 ***
	(0.71)	(0.71)	(0.71)
Ln(Amount)	−4.704 ***	−4.704 ***	−4.705 ***
	(0.37)	(0.37)	(0.37)
Ln(Maturity)	−4.497 ***	−4.497 ***	−4.489 ***
	(0.49)	(0.49)	(0.49)
Sponsor	−3.094 **	−3.111 **	−3.000 **
	(1.26)	(1.25)	(1.26)
Covenant	−0.413 **	−0.411 **	−0.397 **
	(0.17)	(0.17)	(0.17)
Loan type FE	Yes	Yes	Yes
Loan purpose FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
R^2	0.383	0.383	0.382
N	10,328	10,328	10,328
Δ interaction coefficient	2.72	2.20	1.46
	[0.099]	[0.138]	[0.227]

Note: The *t*-test of significance is: *** significant at the 1% level and ** significant at the 5% level. Heteroskedasticity robust standard errors are in parentheses. The *p*-values are in square brackets below the F-statistic.

In Column (2), I examine whether the effect of lending relationships on retained shares varies between loans made to small and large firms. To this end, I create a binary variable *Small firm*. This dummy variable takes the value of one for borrowers with total assets below the sample median, and zero otherwise. Using this dummy variable, I construct the interaction terms *Prior relationship* × *Small firm* and *Prior relationship* × *(1 − Small firm)*. These interaction terms are used to replace $Relationship_{i,j,l} \times Group_g$ before estimating Model (10). The results show that both interaction terms are negative and significant. This finding suggests that lending relationships lead to smaller retained shares whether the borrowers are small or large firms. Moreover, the Δ *interaction coefficient* shows that these effects are not significantly different from each other.

In Column (3), I replace $Relationship_{i,j,l} \times Group_g$ in Model (10) with the interaction terms *Prior relationship* × *Speculative GR* and *Prior relationship* × *(1 − Speculative GR)*. The dummy variable *Speculative GR* takes the value of one for borrowers with speculative-grade ratings, and zero otherwise. The estimated coefficients on both interaction terms are negative and statistically significant, indicating that lending relationships are associated with smaller retained shares for loans made to both speculative- and non-speculative-grade-rating firms. Again, as indicated by the Δ *interaction coefficient*, these effects do not significantly differ from each other. Taken together, these findings support the hypothesis that postcontractual moral hazards are more important than precontractual adverse selection problems in the syndicated loan market.

4.4. Additional Robustness Checks

In this section, I address concerns related to the presence of multiple lead arrangers in a loan facility. The concern is that multiple lead arrangers may increase the likelihood that a loan is arranged by a relationship lead arranger. This is because when there are multiple lead arrangers, the likelihood of at least one of them having an existing lending relationship with the firm is higher. Thus, the presence of multiple lead arrangers could potentially influence the empirical association between lending relationships and retained loan shares.

To address this concern, I re-estimate the baseline Regression Model (4), this time excluding loans facilities with multiple lead arrangers from the sample. The results of this analysis are reported in Table 8. As can be seen from the results, the estimated coefficients of lending relationships remain negative and statistically significant at the 1% level. These negative coefficients suggest that the establishment of lending relationships with firms enables lead arrangers to retain smaller loan shares. Thus, despite the potential influence of multiple lead arrangers on retained shares, the results presented in this section provide clear evidence of the impact of lending relationships.

Table 8. Evidence from facilities with a single lead arranger.

	(1)	(2)	(3)	(4)	(5)	(6)
Prior relationship	−2.281 ***			−2.106 ***		
	(0.57)			(0.58)		
Relationship intensity		−2.334 ***			−2.082 ***	
		(0.69)			(0.69)	
Relationship depth			−2.451 ***			−2.186 ***
			(0.68)			(0.69)
Top 3 arranger	−4.295 ***	−4.351 ***	−4.313 ***			
	(0.61)	(0.61)	(0.61)			
Top 10 arranger				−4.949 ***	−4.987 ***	−4.952 ***
				(0.62)	(0.62)	(0.62)
Opacity	−0.540	−0.504	−0.478	−0.552	−0.518	−0.495
	(0.93)	(0.93)	(0.93)	(0.93)	(0.93)	(0.93)
Ln(1 + #prev. borrow)	−0.305	−0.759	−0.715	−0.299	−0.715	−0.676
	(0.64)	(0.64)	(0.64)	(0.64)	(0.64)	(0.64)
Firm size	−3.911 ***	−3.931 ***	−3.951 ***	−3.848 ***	−3.867 ***	−3.885 ***
	(0.37)	(0.37)	(0.37)	(0.37)	(0.37)	(0.37)
Profitability	0.525	0.646	0.617	0.928	1.033	1.004
	(3.65)	(3.66)	(3.66)	(3.59)	(3.60)	(3.60)
Tangibility	0.025	−0.035	−0.039	−0.231	−0.287	−0.289
	(1.61)	(1.60)	(1.60)	(1.61)	(1.61)	(1.61)
Leverage	−2.726	−2.690	−2.728	−2.522	−2.489	−2.524
	(1.68)	(1.69)	(1.69)	(1.67)	(1.68)	(1.68)
Financial distress	2.492 ***	2.546 ***	2.503 ***	2.502 ***	2.551 ***	2.512 ***
	(0.87)	(0.88)	(0.88)	(0.87)	(0.87)	(0.87)
Ln(Amount)	−5.809 ***	−5.806 ***	−5.784 ***	−5.621 ***	−5.619 ***	−5.600 ***
	(0.38)	(0.39)	(0.39)	(0.38)	(0.39)	(0.39)
Ln(Maturity)	−3.837 ***	−3.811 ***	−3.808 ***	−3.788 ***	−3.763 ***	−3.761 ***
	(0.56)	(0.56)	(0.56)	(0.56)	(0.56)	(0.56)
Sponsor	−5.558 ***	−5.531 ***	−5.589 ***	−5.321 ***	−5.291 ***	−5.345 ***
	(1.45)	(1.45)	(1.45)	(1.46)	(1.46)	(1.46)
Covenant	−0.463 **	−0.470 **	−0.469 **	−0.456 **	−0.463 **	−0.461 **
	(0.19)	(0.19)	(0.19)	(0.19)	(0.19)	(0.19)

Table 8. *Cont.*

	(1)	(2)	(3)	(4)	(5)	(6)
Loan type FE	Yes	Yes	Yes	Yes	Yes	Yes
Loan purpose FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.377	0.377	0.377	0.381	0.380	0.380
N	7445	7445	7445	7445	7445	7445

Note: The *t*-test of significance is: *** significant at the 1% level and ** significant at the 5% level. Heteroskedasticity robust standard errors are in parentheses.

5. Conclusions

While studies suggest that lending relationships between lead arrangers of syndicated loans and borrowers should influence the loan shares retained by lead arrangers, the literature lacks a clear consensus on the precise direction. Furthermore, empirical research providing direct evidence on the association between lending relationships and retained loan shares is scarce. Therefore, the purpose of this paper is to investigate how the loan shares retained by lead arrangers are affected when they establish lending relationships with borrowers.

The hypothesis is that when lending relationships facilitate the production of firm-specific information, moral hazard problems are mitigated and that should be reflected in decreased retained loan shares. In contrast, when relationship lead arrangers exploit their information advantage, syndicate participants may require these lead arrangers to hold a higher share of the loans. As these two effects may not be mutually exclusive, the net impact depends on the relative strength of these opposing effects. Using a random sample of 10,328 syndicated loans made to 7316 nonfinancial U.S. firms over the period from 1987 to 2013, this paper investigates which of these opposing effects dominates in the syndicated loan market.

The findings demonstrate that when lead arrangers establish lending relationships with borrowers, they retain smaller shares of the loans, thus supporting the monitoring cost advantage perspective of lending relationships. This finding is robust to alternative estimation techniques applied to address the potential endogenous choice of forming lending relationships. The analysis further indicates that the effect of establishing lending relationships with borrowers is particularly significant for reputationally less prestigious lead arrangers. The evidence shows that lending relationships result in a decrease in retained loan shares for non-top-tier lead arrangers, but not for those with already well-established reputations.

Additionally, this paper provides evidence that lead arrangers with lending relationships retain smaller shares even when dealing with syndicated loans provided to informationally opaque firms, small firms, or firms with speculative-grade ratings. This evidence suggests that postcontractual conflicts are more important than precontractual conflicts in the syndicated loan market. Therefore, relationship lead arrangers are not required to have considerable "skin in the game". This finding has important implications for lenders seeking to reduce their risk exposure in syndicated loans. Investigating whether lending relationships reduce the retained shares of lead arrangers by increasing the number of syndicate participants, increasing the amount of capital allocated by each participant, or both, will be the focus of future research.

Funding: This research received no external funding.

Informed Consent Statement: Not applicable.

Data Availability Statement: Data are available upon request.

Acknowledgments: Thanks are due to the conference participants at the National PhD Workshop in Finance at the Swedish House of Finance (SHoF) at the Stockholm School of Economics and seminar participants at the Knut Wicksell Centre for Financial Studies, Lund University. The author also thanks the academic editor and three anonymous referees for offering valuable comments and suggestions.

Conflicts of Interest: The author declares no conflict of interest.

Appendix A

Table A1. Variable definitions.

Variable	Definition	Source
Syndicated loans	Loans that are jointly provided by a group of lenders to a firm.	DealScan
Lead arrangers	Lenders responsible for syndicated loan screening and monitoring.	DealScan
Retained share	The percentage of a syndicated loan retained by the lead arranger.	DealScan
Prior relationship	A dummy variable equal to 1 if the lead arranger and the borrower have a prior lending interaction in the last five years, and 0 otherwise.	DealScan
Relationship intensity	The ratio of the number of times the lead arranger and the borrower have interacted in the last five years to the total number of loans the borrower has taken during the same period.	DealScan
Relationship depth	The ratio of the total amount of loans the lead arranger has made to the borrower in the last five years to the total amount of loans taken by the firm during the same period.	DealScan
Top 3 arranger	A dummy variable equal to 1 if at least one of the lead arrangers of the syndicated loan is among the top 3 percentile in terms of market share in the syndicated loan market, and 0 otherwise.	DealScan
Top 10 arranger	A dummy variable equal to 1 if at least one of the lead arrangers of the syndicated loan is among the top 10 percentile in terms of market share in the syndicated loan market, and 0 otherwise.	DealScan
Ln(Amount)	The natural logarithm of the loan facility amounts in millions of U.S. dollars.	DealScan
Ln(Maturity)	The natural logarithm of the number of months from the facility start date to the facility end date.	DealScan
Sponsor	A dummy variable equal to 1 if the loan facility has sponsor, and 0 otherwise.	DealScan
Covenant	The total number of covenants in the loan facility.	DealScan
Term Loan	A dummy variable equal to 1 if the loan type is a term loan, and 0 otherwise.	DealScan
Revolver	A dummy variable equal to 1 if the loan type is a revolver, and 0 otherwise.	DealScan
364-day facility	A dummy variable equal to 1 if the loan type is a 360-day facility, and 0 otherwise.	DealScan
Corporate purpose	A dummy variable equal to 1 if the loan purpose is for a corporate purpose, and 0 otherwise.	DealScan
Working capital	A dummy variable equal to 1 if the loan purpose is for working capital, and 0 otherwise.	DealScan
Takeover	A dummy variable equal to 1 if the loan purpose is for a takeover, and 0 otherwise.	DealScan
Debt repayment	A dummy variable equal to 1 if the loan purpose is for debt repayment, and 0 otherwise.	DealScan
Ln(1 + #prev. borrow)	The natural logarithm of one plus the number of times that the firm has previously borrowed in the syndicated loan market during the last five years.	DealScan
Opacity	A dummy variable equal to 1 if a firm has no Standard and Poor long-term issuer ratings, and 0 otherwise.	Compustat
Firm size	The natural logarithm of the firm's total assets.	Compustat
Small firm	A dummy variable equal to 1 if a firm has below the sample median values of total assets, and 0 otherwise.	Compustat

Table A1. *Cont.*

Variable	Definition	Source
Profitability	The ratio of earnings before interest, taxes, depreciation, and amortization (EBITDA) to total assets.	Compustat
Tangibility	The ratio of plant, property, and equipment to total assets.	Compustat
Leverage	The ratio of total debt (i.e., the sum of debt in current liability and long-term debt) to total assets.	Compustat
Financial distress	A dummy variable equal to 1 if a firm has an Altman (1968) Z-Score less than or equal to 1.81, and 0 otherwise.	Compustat
Distance	The spherical distance measured in kilometers between the borrowing firm's headquarters and the headquarters of the lead arranger of a syndicated loan.	Compustat, SEC DealScan, NIC

This table presents the definitions of the variables used in this study.

Notes

1. I use a five-year history window to search for previous lending interactions because the sample has a median loan maturity of 48 months.
2. Other studies have also found a larger increase in coefficient estimates. For example, Bharath et al. (2011) observe that the coefficient for relationships increases approximately 5.1 times compared to OLS estimates.
3. According to McFadden (1973), values for pseudo R^2 ranging from 0.2 to 0.4 represent a very good model fit.

References

Abadie, Alberto, and Guido W. Imbens. 2006. Large Sample Properties of Matching Estimators for Average Treatment Effects. *Econometrica* 74: 235–67. [CrossRef]

Adamuz, María de las Mercedes, and Janko Hernández Cortés. 2015. Endogenous screening and the formation of loan syndicates. *International Review of Economics & Finance* 37: 290–307. [CrossRef]

Aktas, Nihat, Eric de Bodt, Frédéric Lobez, and Jean-Christophe Statnik. 2012. The information content of trade credit. *Journal of Banking & Finance* 36: 1402–13. [CrossRef]

Alexandre, Hervé, Karima Bouaiss, and Catherine Refait-Alexandre. 2014. Banking Relationships and Syndicated Loans during the 2008 Financial Crisis. *Journal of Financial Services Research* 46: 99–113. [CrossRef]

Altman, Edward I. 1968. Financial Ratios, Discriminant Analysis and the Prediction of Corporate Bankruptcy. *Journal of Finance* 23: 589–609. [CrossRef]

Aramonte, Sirio, Seung Jung Lee, and Viktors Stebunovs. 2022. Risk Taking and Low Longer-Term Interest Rates: Evidence from the U.S. Syndicated Term Loan Market. *Journal of Banking & Finance* 138: 105511. [CrossRef]

Balasubramanyan, Lakshmi, Allen N. Berger, and Matthew M. Koepke. 2019. How Do Lead Banks Use Their Private Information about Loan Quality in the Syndicated Loan Market? *Journal of Financial Stability* 43: 53–78. [CrossRef]

Baliga, Sandeep. 1999. Monitoring and Collusion with 'Soft' Information. *Journal of Law, Economics, and Organization* 15: 434–40. [CrossRef]

Beatty, Anne, Scott Liao, and Haiwen (Helen) Zhang. 2019. The Effect of Banks' Financial Reporting on Syndicated-Loan Structures. *Journal of Accounting and Economics* 67: 496–520. [CrossRef]

Bharath, Sreedhar T., Sandeep Dahiya, Anthony Saunders, and Anand Srinivasan. 2011. Lending Relationships and Loan Contract Terms. *Review of Financial Studies* 24: 1141–203. [CrossRef]

Bharath, Sreedhar, Sandeep Dahiya, Anthony Saunders, and Anand Srinivasan. 2007. So What Do I Get? The Bank's View of Lending Relationships. *Journal of Financial Economics* 85: 368–419. [CrossRef]

Blickle, Kristian S., Quirin Fleckenstein, Sebastian Hillenbrand, and Anthony Saunders. 2022. The Myth of the Lead Arranger's Share. *FRB of New York Staff Report No. 922*. Available at SSRN3594525. Available online: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3594525 (accessed on 21 September 2023).

Bolton, Patrick, and David S Scharfstein. 1990. A Theory of Predation Based on Agency Problems in Financial Contracting. *American Economic Review* 80: 93–106.

Boot, Arnoud W. A. 2000. Relationship Banking: What Do We Know? *Journal of Financial Intermediation* 9: 7–25. [CrossRef]

Bruche, Max, Frederic Malherbe, and Ralf R Meisenzahl. 2020. Pipeline Risk in Leveraged Loan Syndication. *Review of Financial Studies* 33: 5660–705. [CrossRef]

Carrasco, Vinicius, and João Manoel Pinho De Mello. 2010. Repeated lending under contractual incompleteness. *Annals of Finance* 6: 51–82. [CrossRef]

Cerulli, Giovanni. 2014. Ivtreatreg: A Command for Fitting Binary Treatment Models with Heterogeneous Response to Treatment and Unobservable Selection. *Stata Journal* 14: 453–80. [CrossRef]

Chaudhry, Sajid M., and Stefanie Kleimeier. 2015. Lead Arranger Reputation and the Structure of Loan Syndicates. *Journal of International Financial Markets, Institutions and Money* 38: 116–26. [CrossRef]
Chava, Sudheer, and Michael R. Roberts. 2008. How Does Financing Impact Investment? The Role of Debt Covenants. *Journal of Finance* 63: 2085–121. [CrossRef]
Cochran, William G., and Donald B. Rubin. 1973. Controlling Bias in Observational Studies: A Review Author. *Sankhyā: The Indian Journal of Statistics* 35: 417–46.
Dass, Nishant, and Massimo Massa. 2011. The Impact of a Strong Bank-Firm Relationship on the Borrowing Firm. *Review of Financial Studies* 24: 1204–60. [CrossRef]
Dennis, Steven A., and Donald J. Mullineaux. 2000. Syndicated Loans. *Journal of Financial Intermediation* 9: 404–26. [CrossRef]
Diamond, Douglas W. 1984. The Review of Economic Studies Ltd. Financial Intermediation and Delegated Monitoring. *Review of Economic Studies* 51: 393–414. [CrossRef]
Donker, Han, Alex Ng, and Pei Shao. 2020. Borrower Distress and the Efficiency of Relationship Banking. *Journal of Banking & Finance* 112: 105275. [CrossRef]
Down, Andrea K., Christopher D. Williams, and Regina Wittenberg-Moerman. 2022. Strategic Syndication: Is Bad News Shared in Loan Syndicates? *Review of Accounting Studies*. [CrossRef]
Even-Tov, Omri, Xinlei Li, Hui Wang, and Christopher Williams. 2023. The Importance of Individual-Pair Lending Relationships. *Review of Accounting Studies*. [CrossRef]
Gadanecz, Blaise, Alper Kara, and Philip Molyneux. 2012. Asymmetric Information among Lending Syndicate Members and the Value of Repeat Lending. *Journal of International Financial Markets, Institutions and Money* 22: 913–35. [CrossRef]
Gârleanu, Nicolae, and Jeffrey Zwiebel. 2009. Design and Renegotiation of Debt Covenants. *Review of Financial Studies* 22: 749–81. [CrossRef]
Gatev, Evan, and Philip E. Strahan. 2009. Liquidity risk and syndicate structure. *Journal of Financial Economics* 93: 490–504. [CrossRef]
Gatti, Stefano, Stefanie Kleimeier, William Megginson, and Alessandro Steffanoni. 2013. Arranger Certification in Project Finance. *Financial Management* 42: 1–40. [CrossRef]
Godlewski, Christophe J., Bulat Sanditov, and Thierry Burger-Helmchen. 2012. Bank Lending Networks, Experience, Reputation, and Borrowing Costs: Empirical Evidence from the French Syndicated Lending Market. *Journal of Business Finance & Accounting* 39: 113–40. [CrossRef]
Gopalan, Radhakrishnan, Vikram Nanda, and Vijay Yerramilli. 2011. Does Poor Performance Damage the Reputation of Financial Intermediaries? Evidence from the Loan Syndication Market. *Journal of Finance* 66: 2083–120. [CrossRef]
Gryglewicz, Sebastian, Simon Mayer, and Erwan Morellec. 2021. Screening and Monitoring Corporate Loans. Swiss Finance Institute Research Paper No. 21-82. Available at SSRN3938511. Available online: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3938511 (accessed on 21 September 2023).
Gu, Xing Sam, and Paul R. Rosenbaum. 1993. Comparison of Multivariate Matching Methods: Structures, Distances, and Algorithms. *Journal of Computational and Graphical Statistics* 2: 405–20. [CrossRef]
Gustafson, Matthew T., Ivan T. Ivanov, and Ralf R. Meisenzahl. 2021. Bank Monitoring: Evidence from Syndicated Loans. *Journal of Financial Economics* 139: 452–77. [CrossRef]
Heckman, James J. 1978. Dummy Endogenous Variables in a Simultaneous Equation System. *Econometrica* 46: 931–59. [CrossRef]
Heckman, James J. 1979. Sample Specification Bias as a Selection Error. *Econometrica* 47: 153–61. [CrossRef]
Heckman, James J., Hidehiko Ichimura, and Petra E. Todd. 1997. Matching as an Econometric Evaluation Estimator: Evidence from Evaluating a Job Training Programme. *Review of Economic Studies* 64: 605–54. [CrossRef]
Heckman, James J., Hidehiko Ichimura, and Petra E. Todd. 1998. Matching As An Econometric Evaluation Estimator. *Review of Economic Studies* 65: 261–94. [CrossRef]
Holmstrom, B., and J. Tirole. 1997. Financial Intermediation, Loanable Funds, and the Real Sector. *Quarterly Journal of Economics* 112: 663–91. [CrossRef]
Hu, Yunzhi, and Felipe Varas. 2021. A Theory of Zombie Lending. *Journal of Finance* 76: 1813–67. [CrossRef]
Imbens, Guido W., and Jeffrey M. Wooldridge. 2009. Recent Developments in the Econometrics of Program Evaluation. *Journal of Economic Literature* 47: 5–86. [CrossRef]
Jensen, Michael C., and William H. Meckling. 1976. Theory of the Firm: Managerial Behavior, Agency Costs and Ownership Structure. *Journal of Financial Economics* 3: 305–60. [CrossRef]
Jones, Jonathan D., William W. Lang, and Peter J. Nigro. 2005. Agent Bank Behavior in Bank LOAN Syndications. *Journal of Financial Research* 28: 385–402. [CrossRef]
Lee, Seung Jung, Lucy Qian Liu, and Viktors Stebunovs. 2022. Risk-taking spillovers of U.S. monetary policy in the global market for U.S. dollar corporate loans. *Journal of Banking & Finance* 138: 105550. [CrossRef]
Leland, Hayne E., and David H. Pyle. 1977. Informational Asymmetries, Financial Structure, and Financial Intermediation. *Journal of Finance* 32: 371–87. [CrossRef]
Lim, Jongha, Bernadette A. Minton, and Michael S. Weisbach. 2014. Syndicated Loan Spreads and the Composition of the Syndicate. *Journal of Financial Economics* 111: 45–69. [CrossRef]
McCahery, Joseph, and Armin Schwienbacher. 2010. Bank Reputation in the Private Debt Market. *Journal of Corporate Finance* 16: 498–515. [CrossRef]

McFadden, Daniel. 1973. Conditional Logit Analysis of Qualitative Choice Behavior. In *Frontiers in Econometrics*. Edited by Paul Zarembka. New York: Academic Press, pp. 105–42.
Mora, Nada. 2015. Lender Exposure and Effort in the Syndicated Loan Market. *Journal of Risk and Insurance* 82: 205–51. [CrossRef]
Myers, Stewart C. 1977. Determinants of Corporate Borrowing. *Journal of Financial Economics* 5: 147–75. [CrossRef]
Panyagometh, Kamphol, and Gordon S. Roberts. 2010. Do Lead Banks Exploit Syndicate Participants? Evidence from Ex Post Risk. *Financial Management* 39: 273–99. [CrossRef]
Petersen, Mitchell A., and Raghuram G. Rajan. 2002. Does Distance Still Matter? The Information Revolution in Small Business Lending. *Journal of Finance* 57: 2533–70. [CrossRef]
Plosser, Matthew C., and João A. C. Santos. 2016. Bank Monitoring. Available at SSRN2697146. Available online: https://ssrn.com/abstract=2697146 (accessed on 21 September 2023).
Rosenbaum, Paul R., and Donald B. Rubin. 1983. The Central Role of the Propensity Score in Observational Studies for Causal Effects. *Biometrika* 70: 41–55. [CrossRef]
Ross, David Gaddis. 2010. The 'Dominant Bank Effect': How High Lender Reputation Affects the Information Content and Terms of Bank Loans. *Review of Financial Studies* 23: 2730–56. [CrossRef]
Rubin, Donald B. 1973. Matching to Remove Bias in Observational Studies. *Biometrics* 29: 159–83. [CrossRef]
Rubin, Donald B. 1980. Bias Reduction Using Mahalanobis-Metric Matching. *Biometrics* 36: 293–98. [CrossRef]
Shen, Yang-pin, Chou-Yen Wu, and Chiuling Lu. 2023. U.S. REIT banking relationships and syndicated loan pricing. *Review of Quantitative Finance and Accounting* 61: 447–79. [CrossRef]
Stiglitz, Joseph, and A Weiss. 1983. Incentive Effects of Terminations: Applications to the Credit and Labor Markets. *American Economic Review* 73: 912–27.
Sufi, Amir. 2007. Information Asymmetry and Financing Arrangements: Evidence from Syndicated Loans. *Journal of Finance* 62: 629–68. [CrossRef]
Von Thadden, Ernst Ludwig. 1995. Long-Term Contracts, Short-Term Investment and Monitoring. *Review of Economic Studies* 62: 557–75. [CrossRef]
Winton, Andrew, and Vijay Yerramilli. 2021. Monitoring in Originate-to-Distribute Lending: Reputation versus Skin in the Game. *Review of Financial Studies* 34: 5886–932. [CrossRef]
Zhang, Donghang, Yafei Zhang, and Yijia (Eddie) Zhao. 2023. Lending Relationships and the Pricing of Syndicated Loans. *Management Science*. [CrossRef]