Journal of Financial Economics 92 (2009) 300–319

Contents lists available at ScienceDirect

Journal of Financial Economics

journal homepage: www.elsevier.com/locate/jfec

Asymmetric information effects on loan spreads ☆

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ARTICLE INFO

Article history:
Received 22 August 2007
Received in revised form
2 June 2008
Accepted 23 June 2008
Available online 12 February 2009

JEL classifications:
G21
G24

Keywords:
Information asymmetry
Syndicated loans
Cost of capital

ABSTRACT

This paper estimates the cost arising from information asymmetry between the lead bank and members of the lending syndicate. In a lending syndicate, the lead bank retains only a fraction of the loan but acts as the intermediary between the borrower and the syndicate participants. Theory predicts that asymmetric information will cause participants to demand a higher interest rate and that a large loan ownership by the lead bank should reduce this effect. In equilibrium, however, the asymmetric information premium demanded by participants is offset by the diversification premium demanded by the lead. Using shifts in the idiosyncratic credit risk of the lead bank's loan portfolio as an instrument, I measure the asymmetric information effect of the lead's share on the loan spread and find that it accounts for approximately 4% of the total cost of credit.

1. Introduction

Theory suggests that ownership should be an important mechanism for mitigating the effects of asymmetric information. According to the Leland and Pyle (1977) model, an increase in the informed party's share of ownership would signal a higher quality of the underlying project, thereby reducing the cost of asymmetric information. However, there is little, if any, direct evidence supporting this prediction. The effect of ownership on asymmetric information is difficult to show because ownership is endogenous. The syndicated loan market offers a special case of asymmetric information between the lead bank and participants in the lending syndicate. Consistent with theoretical predictions, the lead bank's ownership of the loan should reduce asymmetric information between the lead and participants, which should lower the overall loan spread. The advantage of looking at the syndicated loan market is that the lead bank's loan portfolio is observable. This enables me to identify shifts in the lead's ownership that are driven by the lead bank's loan portfolio diversification and that are exogenous to the asymmetric information in the lending syndicate. Using the diversification shifts as an instrument, I can isolate the asymmetric information effect of the lead's loan ownership on the spread.

Over the past two decades, the syndicated loan market has become the largest source of worldwide corporate financing. In the United States, syndicated loan issuance grew from approximately \$150 billion in 1987 to \$1.7 trillion in 2006, surpassing corporate bond issuance, which in 2006 reached a record \$1.04 trillion. The US market accounts for half of the worldwide activity. In contrast to a traditional bank loan, which involves a single lender, a syndicated loan involves a group of lenders. The loan is originated by a lead bank which sells pieces of the

☆ I am grateful for helpful discussions with members of my thesis committee: Kose John, Anthony Saunders, Alexander Ljungqvist, Holger Muller, and Daniel Wolfenzon. I also thank the anonymous referee, Ed Altman, Mark Carey, Bill Greene, Daniel Paravisini, Mitchell Petersen, David Scharfstein and Greg Udell for especially insightful comments. This paper benefited significantly from suggestions by seminar participants at NYU (Stern), University of Michigan (Ross), Harvard Business School, Boston College, Stanford University, London Business School, Northwestern University (Kellogg), Dartmouth University (Tuck), Cornell University, the Financial Management Association Conference, and the Federal Reserve Bank of New York, New York City Area, Financial Intermediation Conference. I gratefully acknowledge financial support from the Nasdaq Derivatives Research Project at the Salomon Center.

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doi:10.1016/j.jfineco.2008.06.003

loan to other (participant) banks. Although the lead bank retains only part of the loan, it acts as the manager for the loan with primary responsibility for exante due diligence and for expost monitoring of the borrower. Participant banks depend on the information collected by the lead bank. However, there is an adverse selection problem because the lead bank has incentives to syndicate bad or risky loans. In addition, there is a moral hazard problem because, after the lead bank sells parts of the loan to syndicate participants, its incentive to continue monitoring is reduced. Thus, whereas spread in a traditional bank loan is determined by borrower characteristics, in a syndicated loan the private content of the information collected by the lead bank induces an additional premium, driven by the degree of information asymmetry between the lead and participant banks.

An increase in the lead bank's share of the loan would reduce asymmetric information between the lead and participants, thus *decreasing* the premium demanded by the participant banks. This prediction is the same for the adverse selection and moral hazard effects. On the other hand, an increase in the lead bank's share of the loan would also increase the lead's credit-risk exposure, thus *increasing* the premium demanded by the lead bank. Indeed, Pavel and Phillis (1987), Pennacchi (1988), Gorton and Pennacchi (1995), and Demsetz (1999) showed that credit-risk diversification is among the main reasons for loan sales by the lead bank. Thus, two opposing effects—asymmetric information and diversification—*simultaneously* influence the loan spread. The loan spreads and syndicate structures observed in the data represent a set of equilibrium points; therefore, the adverse selection/moral hazard effect cannot be identified without an exogenous instrument.

The instrument proposed here builds on the intuition of Leland and Pyle (1977). The lead bank typically retains a very large share of the loan and is therefore uniquely exposed to idiosyncratic credit risk. Thus, controlling for overall credit risk, a *unique* contribution to the lead bank's portfolio credit risk would shift the diversification premium demanded by the lead bank without affecting the premium required by the participant banks. To construct the instrument, I build the lead bank's loan portfolio for each loan and use annual information on industry-level default correlations to construct the standard deviation of the probability of default of the lead's loan portfolio, a measure that positively correlates with the credit-risk premium demanded by the lead bank.

After instrumenting the lead bank's share, I find the asymmetry of information amongst the syndicate participants to have a large economic cost reflected in the spread charged to the borrower: A 9 percentage points change in lead share (from 10% to 19%) translates to a change in loan spread of approximately 29 basis points (bps). This estimate implies that information asymmetry within the lending syndicate accounts for approximately 4% of the total credit cost. This result is robust to controls for credit ratings and lead bank reputation.

Several previous papers have looked at the determinants of the lending syndicate, including Simons (1993), Preece and Mullineaux (1996), Dennis and Mullineaux (2000), Jones, Lang, and Nigro (2000), Lee and Mullineaux (2004), Panyagometh and Roberts (2002), Esty and Megginson (2003), and Sufi (2007). Their common finding is that syndicate structure is determined by the availability of public information about the borrower as much as by loan-contract characteristics and borrower credit risk. As there is more public information available about a borrower, a larger fraction of a loan is likely to be syndicated. This relation was previously interpreted as evidence of an information asymmetry problem between the lead bank and the participants in a lending syndicate. However, as discussed earlier, the lead share observed in the data is a set of equilibriums resulting from interactions between the lead and participant banks. In the absence of instruments, interpretation of the observed data is problematic.

To the best of my knowledge, Gorton and Pennacchi (1995) is the only other paper that focuses on the effect of the lead bank's share on the loan spread. In the context of secondary-market loan sales, the authors find a negative relation between the selling bank's share and the premium demanded by purchasing banks. However, the economic effect is insignificant. More recently, Carey and Nini (2007) found, in a cross-country study of the interest rate spreads, that, for a given loan size, larger lending syndicates tend to be associated with higher loan spread. This result is consistent with my findings.[1] Overall, the novelty of my paper is that I instrument the asymmetric information and diversification effects.

The remainder of the paper is structured in four sections: empirical framework and data, results, robustness checks, and conclusions.

2. Empirical framework and data

2.1. Empirical framework

Loan syndication is a process whereby a lead bank initiates a loan and then sells shares of that loan to other financial institutions. Before and after the syndication, the lead bank acts as an agent for the lending syndicate by collecting and processing information about the borrower. Prior to syndication, the lead bank conducts due diligence on the borrower and presents a confidential memorandum to potential buyers, summarizing its assessment of the borrower's quality. After syndication, the lead bank is in charge of monitoring the borrower. Before the loan is syndicated, then, there is an adverse selection problem because the lead bank has an incentive to syndicate loans of lower quality.[2] After the loan is syndicated, there is a

[1] For the US sample, the correlation between the loan share retained by the lead bank and the number of lenders in the syndicate is −0.70.

[2] Lead banks may have an incentive to originate high-risk loans due to the private benefits of building a relationship with the borrower and/or to the underwriting fees charged to the borrower at the origination of the loan. Examples of wrongdoing by lead banks include the collapse of Penn Square Bank, which was servicing in excess of $2 billion in participations when it defaulted, and Chase Manhattan's $245 million loan to AroChem (Bank Brussels Lambert and Skopbank v. Chase Manhattan Bank, 1996 US Dist. LEXIS 15631). In general, litigation between syndicate members is rare because: (a) syndicate loans are not

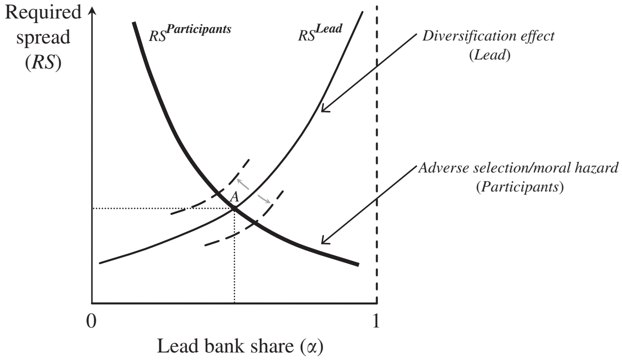


Fig. 1. The lead bank share and loan spread are simultaneously determined as the result of interaction between the syndicate participants' demand (adverse selection/moral hazard effect) and the lead bank's demand (diversification effect). Only the equilibrium outcome (point A) is observable in the data. The asymmetric information effect implied in the slope of the participant's demand must be identified using exogenous shifts in the lead bank's pricing behavior.

moral hazard problem because the lead bank only retains part of the loan so its incentives to monitor the borrower are reduced. Both adverse selection and moral hazard imply that syndicate participants are exposed to the risk of wrongdoing by the lead bank; as a result, they will demand a higher loan spread.

The adverse selection problem can be reduced if the lead bank retains a larger fraction of the loan. Because the lead bank knows the true underlying quality of the loan, a larger share would signal a higher-quality loan and would reduce the spread demanded by the syndicate participants. If the lead's share is indeed an effective mechanism for reducing the adverse selection problem in the lending syndicate, we would expect the data to show a negative relation between the loan spread and the lead bank's share. The moral hazard problem presents a similar case: The larger the lead bank's share, the better the incentives alignment between the lead and the syndicate participants and the lower the loan spread.[3]

Both adverse selection and moral hazard effects suggest a negative relation between loan spread and the lead bank's share. However, there is an additional and opposing effect that *simultaneously* affects the observed relation between the two variables. A larger lead bank's share increases the lead's credit-risk exposure. Hence, the spread demanded by the lead bank is a function of diversification and should be positively related to the share that it retains.

In the absence of instruments, the *observed* relation between loan spreads and a lead bank's shares corresponds to a set of equilibrium points resulting from the interaction of the two opposing effects: adverse selection/moral hazard (participants) and diversification (lead bank). Appendix A presents a moral hazard version of the theoretical framework that captures identification of the adverse selection/moral hazard effect. Fig. 1 summarizes the basic elements of the identification. The horizontal axis is the lead share and the vertical axis is the loan spread. The curve with the negative slope corresponds to the participants' demand and captures the adverse selection/moral hazard effect. The curve with the positive slope corresponds to the lead bank's demand and captures the diversification effect. These demands are not observable directly. For each loan we observe only the equilibrium lead share and loan spread, corresponding to the intersection of the two pricing schedules. Thus, regressing the loan spread against the lead bank's share is similar to regressing price against quantity in the context of a supply-and-demand analysis, which is meaningless.

To identify the premium demanded by the participant banks, we need to identify a variable (instrument) that would affect the lead's diversification without directly affecting the degree of adverse selection or moral hazard in the lending syndicate. In Fig. 1, this corresponds to shifting the lead's demand while keeping the participants' demand fixed. The instrument I use to isolate the adverse selection/moral hazard effect measures each loan's contribution to the credit risk of the lead bank's loan portfolio. The rationale behind this method is that the lead bank's portfolio is not perfectly diversified and is uniquely exposed to idiosyncratic risk. In other words, there is a risk component that will be priced by the lead bank but not by the participant banks.

The central financial risk faced by any bank is the credit risk of its loan portfolio.[4] For each loan, I calculate the change in credit risk resulting from the addition of that loan to the lead bank's loan portfolio. To measure credit risk, I use the *standard deviation* of the loan portfolio default probability. This measure is an essential element

(*footnote continued*)
regulated by the Security Act of 1933 and (b) loan agreements typically limit the lead bank's liability.

[3] Several recent papers on creditor concentration, including Bannier (2007) and Ongena, Tümer-Alkan, and Westernhagen (2007), focus on the tradeoff between the asymmetric information cost and the hold-up problem, as modeled by Rajan (1992). Similarly, in my analysis, an increasing lead share while reducing an asymmetric cost could be introducing a hold-up problem. The presence of this effect should bias the estimates of an asymmetric information cost downwards (i.e., flatter participants' demand).

[4] Using data for over 300 US bank holding companies, Kuritzkes and Schuermann (2008) estimate that credit risk accounts for approximately half of total earnings volatility.

of credit-risk management and directly affects the loan spread demanded by the lead bank.[5] It also has the advantage of being computationally similar to the standard deviation of returns of an equity portfolio. Accordingly, for a given bank:

$$\textit{Default probability standard deviation} = (w'\Omega w)^{1/2}, \qquad (1)$$

where w is the loan portfolio weights (bank-specific), Ω the probability of default covariance matrix (economy-specific).

Loan portfolio weights and the covariance matrix are computed at the two-digit Standard Industrial Classification (SIC) level. Typically, banks would use their historical default data to estimate expected default probability and its standard deviation. I use probability of default covariance matrices (Ω) calculated for the US market by Standard & Poor's CreditPro database at the two-digit SIC level (83×83 matrix).[6] The matrices are computed annually (there are 12 matrices corresponding to 1993–2004), using default data over the previous three years. A diagonal element of the matrix is the variance of the probability of default of a given industry; each off-diagonal element is the probability of default covariance between the two corresponding industries.

Portfolio weights (w) are calculated using all completed loans (including non-syndicated loans) issued to US borrowers and reported in the Reuters DealScan database. For a given loan, weights are computed using all outstanding loans originated during the previous three years, which is the maturity of a median loan. For example, if a given loan was issued on July 1, 2004, the relevant loan portfolio includes all loans issued after July 1, 2001 and outstanding as of July 1, 2004.[7]

The instrument—the loan's contribution to the credit risk of the lead bank's loan portfolio—is the difference between the default probability standard deviation measured *after* and *before* the loan was added to the portfolio. Only the fraction of the loan retained by the lead is relevant for its portfolio. However, the actual lead's share is determined in equilibrium and, for this reason, it cannot be used in the construction of the instrument. In place of the actual share, therefore, I use the median lead bank's share for each loan-size quartile as the new ("after") loan weight. This is a simple and non-parametric rule that allows me to generate magnitudes comparable to those of the other holdings in the lead's loan portfolio. I match loan-size quartile to the lead share because loan size is the central variable in explaining variation in the lead share.[8]

There are alternative ways to generate lead share proxies. Specifically, I could use multivariate analysis to generate a predicted value for the lead share based on general loan and borrower's characteristics. However, given that as part of the analysis I will estimate the fitted value of lead share using the instrument and a comprehensive set of control variables, there is little, if any, additional value in using a detailed model to generate a proxy for lead share to be used in construction of the instrument.

The final sample includes 120 lead banks with an average portfolio size of 3,049 different loans. For example, the loan portfolio for Bank of America, constructed using DealScan, is approximately 75% of the bank's total domestic commercial loan volume (50% of its total loan portfolio) as stated in its annual reports. These numbers suggest that a significant fraction of the loan portfolio is incorporated into the analysis.[9] The implied expected default probability for the lead bank's domestic commercial loan portfolio is approximately 0.3%.[10] This is consistent with Carey and Treacy (1998), who found that the probability of default of the banking industry aggregate commercial loan portfolio in 1997 was 0.2%.

Using the change in the lead's portfolio default probability standard deviation as the instrument, the adverse selection/moral hazard effect is estimated recursively in two stages. Eqs. (2) and (3) correspond to the first and second stages, respectively. A fitted value of the lead share, computed using the first-stage estimates, is used to

[5] The following quote from a JPMorgan Chase 2000 10-K report highlights the assumptions used in the construction of the default probability standard deviation: "Credit risk management begins with an assessment of the risk of loss resulting from the default by a borrower or counterparty. $\langle \ldots \rangle$ Using statistical techniques, estimates are made of both expected losses (on average, over a cycle) and unexpected losses for each segment of the portfolio. Unexpected losses represent the potential volatility of actual losses relative to the expected level of loss. These estimates drive the credit cost and capital allocations to each business unit".

[6] The Standard & Poor's CreditPro database uses economy-wide default data. For example, if at the beginning of 2004 there are 10 companies identified with SIC code 21 and two of them default within a year, then the probability of default for SIC code 21 in 2004 is 0.2. The variance matrix (Ω) is estimated using binomial distribution and can also be calculated using the option-pricing approach first proposed by Merton (1974). For a comparative analysis of the two methods of assessing probability of default correlations, see De Servigny and Renault (2002).

[7] Loan portfolios are constructed at the parent level and account for bank mergers. Because loan participants often sell their shares in the secondary market, I exclude those deals in which the loan share is smaller than 4%. I use loans originated during the previous three years to account for the fact that loans are often refinanced before the maturity date. The exposure on revolver lines is calculated to be 50% of the total commitment; this is consistent with a study conducted by JPMorgan Chase (see Araten and Jacobs, 2001). The results do not depend on these assumptions and are verified in the robustness section.

[8] The logarithm of the loan amount explains approximately 39% of the variation in the lead share. The quartile of the logarithm of the loan amount has similar explanatory power.

[9] It is very hard to accurately reconcile the industry composition of the loan portfolio with annual reports, because banks use non-standard industry definitions. Broadly, however, industry composition of the loan portfolios constructed using DealScan is consistent with the numbers reported by the banks. For example, according to the 2004 Bank of America 10-K report, 7.8% of its commercial loan portfolio was concentrated in "retailing", the largest exposure to a non-financial industry. Defining "retailing" as industries with two-digit SIC codes 52–59, the exposure in my sample is also 7.8%. Similarly, "food, beverages, and tobacco", which should correspond to two-digit SIC codes 20 and 21, is reported to be 3.9% of the loan portfolio in the 10-K report and is 3.1% in my sample.

[10] The average default probability variance of a loan portfolio is estimated to be 0.0037. Using the naïve binomial approach, this corresponds to the expected default probability of 0.3% ($0.0037 = 0.003^*(1-0.003)$).

replace the observable lead share in the second stage.

$$\textit{Lead share} = \alpha_1 \textit{ Controls} + \alpha_2 \textit{ Instruments} + \varepsilon, \tag{2}$$

$$\textit{Required loan spread} = \beta_1 \textit{ Lead bank share}_F + \beta_2 \textit{ Controls} + \upsilon. \tag{3}$$

I control for factors that might affect: (a) the level of adverse selection or moral hazard within the lending syndicate and (b) the borrower's credit risk. I specifically control for the lead bank's reputation, presence of collateral, and covenants because these mechanisms could moderate adverse selection and moral hazard in the lending syndicate. The general set of controls includes non-price loan characteristics, lender and borrower characteristics, and market conditions.

The loan amount and other non-pricing features of the loan—such as maturity, collateral, and covenants—are fixed before the syndication process. This justifies my use of loan characteristics as control variables.[11] Before the syndication, the lead bank usually agrees with the borrower on the target spread range over London Interbank Offered Rate (LIBOR); say, between 150 and 200 bps. The lead then commits to a share-spread investment schedule; for example, \$30 million at 150 bps, \$40 million at 175 bps, or \$50 million at 200 bps. When the syndication begins, potential investors announce commitments that are tied to the spread. The lead bank collects the commitment schedules from the potential participants and sets the final spread to match the loan amount to the investors' demand at the lowest price. Thus, if the loan is oversubscribed at 200 bps, the spread will be lowered.[12] The final loan spread and the syndicate structure are determined simultaneously as a result of interaction between the participants' and the lead bank's pricing schedules.

The full structural model is a system consisting of three equations: a participant's demand, a lead bank demand, and an equilibrium condition. Because I use two-stage least squares (2SLS) method, estimating the adverse selection/moral hazard effect independently from the diversification effect is equivalent to estimating the two effects simultaneously in a system of equations. I will address the credit-risk premium (the lead bank's demand) in the robustness section.

2.2. Data and overview of the main variables

Each observation in the analysis corresponds to a separate loan agreement, for which data were collected from the Reuters DealScan database.[13] The starting sample includes information on 23,087 completed dollar-denominated loans issued between 1993 and 2004, involving 9,931 US borrowers and excluding regulated and financial industries identified as SIC 40–45 and 60–64. There is only partial availability of the data for several of the variables in the analysis. To better understand the potential bias in the data reporting, Table 1 looks at the annual data availability of the variables included in the regressions, as compared to the unconstrained sample.

The central explanatory variable in the analysis, loan share retained by the lead bank, is available in only 30% of the cases (38% of the cases conditional on availability of all other variables). According to DealScan, the lead bank share and other data (such as pricing grid and covenants) are collected from Securities and Exchange Commission (SEC) filings. Because lenders' commitments, including the lead bank's share, are settled at the end of loan syndication, they are typically reported as an attachment to the credit agreement. To better understand the reporting bias, I reviewed SEC reports for 10 random companies that had loans reported in DealScan, but for which the lead share was missing. In six cases, the SEC filings did not have attachments disclosing bank holdings. However, there did not appear to be any systematic bias in the characteristics of the companies that enclose commitment schedules. In fact, of all the companies with more than one loan, 48% have deals in DealScan both with and without lead share.

The percentage of loans where the lead share is reported drops over time. This is not the case for the reporting of other variables. At the same time, the relative size of the deal for which the lead share is reported increases. In other words, where the lead share is available, there is a progressive bias over time toward the largest loans in the sample. One potential explanation for this is that the recording of the lead share did not keep up with the rapid expansion of the syndicated loan market; instead, the data collection effort was focused on the largest loans. The construction of the league tables is based on the titles rather than actual commitments of the syndicate members. In that sense, there is no direct incentive for the banks to report the loan holdings or for DealScan to collect them. Given that these loans are typically issued to larger and more transparent companies, it is likely that the bias introduced by the availability of the lead share data weakens the asymmetric information in the later part of the sample. To assure that the time effect in the reporting of the lead share does not affect the results, I control for year fixed effects throughout the analysis.[14]

There could be an additional bias in the type of bank for which detailed information is available. Although

[11] Although formally, only the spread changes during the syndication process, the non-pricing contract terms could be affected by the expected outcome of the syndication. To account for potential endogeneity of loan characteristics, I also estimate Heckman (1978) treatment effects. The results are qualitatively similar to the results reported below and available upon request.

[12] The process of changing the loan spread based on the investors' demand is known as market-flex language. More details on how setting the loan price works in practice can be found in Standard & Poor's (2006) or Loan Syndications and Trading Association (LSTA) (2006).

[13] For information on DealScan data, see Carey, Post, and Sharpe (1998).

[14] The data collection for DealScan began in August 1996; loan information for the previous years was recorded retroactively. In that sense, the coverage in the earlier part of the sample could be less accurate. A potential bias due to the data gathering should also be accounted for by year fixed effects.

Table 1
Analysis of DealScan coverage, 1993–2004.

This table looks at the distribution of the sample conditional on availability of the variables used in the analysis. The four samples presented are: (1) DealScan sample that includes completed dollar-denominated loans, originated between 1993 and 2004, to US companies excluding regulated and financial industries identified with two-digit SIC codes 40–45 and 60–64 but without any additional restriction; (2) sample (1) conditional on availability of all the control variables used in the analysis; (3) sample (2) conditional on availability of *All-in spread drawn*; (4) sample (3) conditional on the availability of the *Lead share*. *All-in spread drawn* is a total interest margin paid over LIBOR. *Lead share* is the percentage of the loan retained by the lead arranger at the loan origination. ***, **, and * indicate *p*-values of 1%, 5%, and 10%, respectively.

Year	Unconstrained sample			Sample with all control variables				Sample with all control variables and *All-in spread drawn*				Sample with all control variables, *All-in spread drawn*, and *Lead share*			
	Obs.	Median	Mean (A)	Obs.	Median	Mean (B)	Diff. (A−B)	Obs.	Median	Mean (C)	Diff. (A−C)	Obs.	Median	Mean (D)	Diff. A−D)
1993	954	109.00	261.42	597	105.00	245.72	15.70	543	110.00	250.31	11.11	328	102.00	249.94	11.48
1994	1,289	120.00	304.93	788	125.00	324.86	−19.93	703	132.88	341.62	−36.69	429	120.00	265.91	39.02*
1995	1,278	135.00	326.98	779	140.00	304.50	22.48	708	150.00	318.61	8.37	415	125.00	267.04	59.94*
1996	1,609	150.00	326.36	924	150.00	329.71	−3.35	869	150.00	328.86	−2.50	490	150.00	265.10	61.26***
1997	1,923	170.00	371.52	1,232	180.00	389.56	−18.04	1,191	180.00	382.43	−10.91	602	155.00	322.38	49.15**
1998	1,476	180.00	389.29	846	200.00	408.50	−19.22	819	200.00	412.09	−22.81	347	180.00	385.28	4.00
1999	2,023	160.00	360.99	1,013	200.00	400.69	−39.70**	977	200.00	405.39	−44.40**	406	197.50	354.45	6.54
2000	2,328	150.00	371.88	1,386	200.00	409.12	−37.24**	1,318	200.00	416.20	−44.31**	395	200.00	469.73	−97.85***
2001	2,181	150.00	378.45	1,472	175.00	393.99	−15.54	1,360	189.48	409.42	−30.97*	393	200.00	475.09	−96.64***
2002	2,335	125.00	306.22	1,615	150.00	340.68	−34.46**	1,468	150.00	357.72	−51.50***	470	200.00	393.84	−87.62***
2003	2,586	120.00	272.76	1,447	140.76	309.45	−36.69***	1,310	150.00	322.08	−49.32***	377	200.00	381.58	−108.82***
2004	3,105	135.00	323.51	1,945	175.00	405.72	−82.20***	1,768	185.00	411.04	−87.53***	365	250.00	547.63	−224.12***
1993–2004	23,087	145.50	334.42	14,044	160.00	363.86	−29.44***	13,034	172.00	372.54	−38.11***	5,017	165.00	360.68	−26.26***

DealScan collects most of its data from the SEC filings, it also incorporates information directly from the banks as a secondary source. Because league tables published by DealScan are a powerful marketing tool in the syndicated loan market, lenders have incentives to report this data. Smaller banks are likely to be more sensitive to the rankings and therefore would have greater incentive to directly report the detailed information. To account for this bias, the results in the paper control for the lead bank's ranking and include bank fixed effects; in that sense, this selection bias should not affect the identification strategy.

Syndicated loans can be structured in several tranches, also called facilities. For US companies, a syndicated loan, on average, consists of 1.4 facilities per loan with a median of one. Identity of participants, syndicate structure, and general contract terms are typically determined at the deal level. Consequently, for deals with multiple facilities, I look at the loan characteristics of the largest tranche that starts at the loan initiation. This classification does not significantly affect the distribution of loan type in the final sample.

Multiple titles can be assigned to the members of the lending syndicate. However, different titles typically do not correspond to different roles. In fact, according to Standard & Poor's (2006), most of the loans have only one lead bank and the majority of the important-sounding titles simply indicate participants with large commitments. The league tables (the main marketing tool for the banks) require that within the same syndicate there can be no more than two banks with the same prestigious title. Hence, use of multiple titles allows more lenders to receive a league table credit.

To single out the lead bank, I follow the Standard & Poor's (2006) and LSTA (2006) definitions. If identified, the administrative agent is defined to be the lead bank, given that this is the bank that conducts due diligence, handles all the payments, and monitors the loan. If the syndicate does not have an administrative agent, then lenders that act as agent, arranger, bookrunner, lead arranger, lead bank, or lead manager are defined to be lead banks.[15] Consequently, in the regression sample the lead is called *administrative agent* in 74% of the cases and is called *agent* in 25% of the cases. The remaining 1% includes any other titles or combinations of titles. To ensure that different titles are not associated with different expectations about the lead's monitoring, in unreported analysis I included controls for the lead's title. These additional variables are jointly insignificant and the results remain qualitatively similar.

Following the above methodology to identify the lead bank, approximately 2% of the deals in the regression sample have multiple lead banks (including loans with more than one administrative agent). In these cases, I calculate the share retained by the lead bank to be the sum of the shares retained by the multiple leads. As one would expect, the loans with multiple arrangers are typically much larger. The average amount for loans with one lead is $348.88 million; it is $882.36 million for loans with multiple leads and those loans tend to go to much

[15] Standard & Poor's (2006) identifies these titles as "prestigious" but does not indicate which of them would carry due diligence and/or monitoring responsibilities in the absence of an administrative agent. Therefore, I do not subordinate these roles to each other.

larger companies. Excluding loans with multiple leads from the sample does not affect the results.

The dependent variable in the analysis is spread, which I measure using all-in spread drawn *net* of upfront fees. All-in spread drawn is measured in basis points and is defined by DealScan as the total annual cost, including a set of fees and fixed spread, paid over LIBOR for each dollar used under the loan commitment. The largest fraction of an upfront fee typically goes to the lead arranger as compensation for structuring the loan. Because my focus is on the participant banks' demand, I consider spread net of upfront fees.

Other data sources used in the analysis include Standard & Poor's CreditPro and Compustat. Table 2 presents summary statistics for the variables in the analysis. Their construction and data sources are explained in Appendix B.

3. Results

3.1. Instrumental variables

The premise underlying my instrument is that the lead bank is not fully diversified and has unique exposure to idiosyncratic credit risk. Indeed, in the process of syndication, the lead bank retains by far the largest fraction of the loan. The lead bank's average share is 27%

Table 2
Summary statistics.

This table presents descriptive statistics for completed dollar-denominated loans, originated between 1993 and 2004, to US companies excluding regulated and financial industries identified with two-digit SIC 40–45 and 60–64. *All-in spread drawn* is the interest margin paid over LIBOR net of upfront fees. *Lead share* is the percentage of the loan retained by the lead arranger at the loan origination. *Fitted lead share* is the fitted value of the lead share from the first-stage regression in Table 4, Model (1). *Industry default probability* is the expected loss probability computed at the two-digit SIC level, measured in percent. *Not rated* is a dummy equal to one if the borrower is not rated and zero otherwise. *Commercial paper rating* is a dummy equal to one if the firm has commercial paper rating and zero otherwise. *Public* is a dummy equal to one if the company is publicly traded and zero otherwise. *Previous lending relationship* is a dummy equal to one if over the past three years the borrower had loans arranged by the same lead bank. *Sales at close* is the borrower's sales in millions of US dollars measured at the loan origination. *Assets* is the total assets of the company in millions of US dollars. *Leverage* is the industry-median-adjusted ratio of book value of debt to total assets. *ROA* is the industry-median-adjusted ratio of operating income to total assets. *Facility amount* is the size of the largest tranche in the loan package, measured in millions of US dollars. *Maturity* is the maturity of the facility measured in months. *Number of facilities* is the number of different tranches that form part of the same loan. *Collateral* is a dummy equal to one if the loan is securitized and zero otherwise. *Financial covenants* is a dummy equal to one if the loan has financial covenants and zero otherwise. *Prime base rate* is a dummy equal to one if the base rate for the loan is Prime and zero otherwise. *Performance pricing* is a dummy equal to one if the loan has a performance pricing provision and zero otherwise. *Ranking* is the lead arranger's ranking. *Syndicate reputation*: *lead to participant* is the maximum number of links between the lead bank and the members of the syndicate, scaled by the total number of deals arranged by the lead bank, measured over the preceding three years. *Syndicate reputation*: *reciprocal* is a dummy equal to one if, over the past three years, the lead bank was a participant in a syndicate led by one of the current participant banks. *Δ Default probability std. dev.* is the change in default probability standard deviation of the lead bank's loan portfolio. *Lending limit* corresponds to the 75th size percentile of the loans issued by the bank over the preceding three years. Borrowers' and lenders' characteristics are computed as of the earliest date prior to the origination of the loan. For more information on the definition of the variables, see Appendix B. ***, **, and * indicate *p*-values of 1%, 5%, and 10%, respectively.

	Full sample observations = 5,017			Compustat sample observations = 3,617			Differences in	
	Median (A)	Mean (B)	Std. dev.	Median (C)	Mean (D)	Std. dev.	Medians (A−C)	Means (B−D)
All-in spread drawn	120.00	140.30	102.01	110.00	132.96	100.39	10.00	7.34 ***
Lead share	22.45	27.17	17.17	21.50	26.55	17.14	0.95	0.62 *
Fitted lead share	27.45	27.17	12.35	26.62	26.55	12.87	0.83	0.62 **
Industry default probability	1.24	2.16	2.41	1.51	2.33	2.44	−0.27	−0.16 ***
Not rated	0	0.49	0.50	0	0.46	0.50	0	0.03 ***
Commercial paper rating	0	0.18	0.38	0	0.21	0.41	0	−0.03 ***
Public	1	0.75	0.44	1	0.92	0.27	0	−0.17 ***
Previous lending relationship	1	0.60	0.49	1	0.63	0.48	0	−0.03 ***
Sales at close	520.00	2,383.68	7,473.69	696.66	2,854.79	8,338.42	−176.66	−471.11 ***
Log (*Sales at close*)	6.25	6.35	1.67	6.55	6.60	1.64	−0.30	−0.25 ***
Assets	–	–	–	649.47	3,294.25	8,657.48	–	–
Log (*Assets*)	–	–	–	6.48	6.67	1.66	–	–
Leverage	–	–	–	0.02	0.06	0.29	–	–
ROA	–	–	–	0.03	0.05	0.11	–	–
Facility amount	125.00	270.69	527.33	135.00	299.73	595.12	−10.00	−29.04 **
Log (*Facility amount*)	4.83	4.81	1.28	4.91	4.88	1.29	−0.08	−0.07 ***
Maturity	36	39.44	21.97	36	38.41	21.62	0	1.03
Number of facilities	1	1.35	0.68	1	1.34	0.63	0	0.01
Collateral	0	0.43	0.50	0	0.43	0.48	0	0.00
Financial covenants	0	0.12	0.32	0	0.13	0.33	0	−0.01
Prime base rate	0	0.03	0.16	0	0.02	0.15	0	0.01
Performance pricing	1	0.66	0.47	1	0.69	0.46	0	−0.03 ***
Ranking	6	12.49	16.98	6	11.83	16.55	0	0.66 *
Syndicate reputation: *lead to participant*	11.02	12.51	8.02	11.32	12.93	8.15	−0.30	−0.42 **
Syndicate reputation: *reciprocal*	1	0.97	0.18	1	0.97	0.17	0	0.00
Credit risk: *Δ default probability std. dev.*	0.00	0.00	0.22	0.00	0.00	0.20	0	0.00
Credit risk: *lending limit*	55.00	63.07	58.03	55.00	64.11	54.55	0	−1.04

Table 3
Distribution of the change in default probability standard deviation.
This table presents descriptive statistics for the change in the standard deviation of the default probability, used as an instrument to identify the spread required by the participant banks. Change in default probability standard deviation is calculated at the loan level and measures the contribution of the particular loan to the standard deviation of the probability of default of the lead bank loan portfolio. Default probability standard deviation is constructed using two-digit SIC default covariance matrices from the Standard & Poor's CreditPro database and bank-specific two-digit SIC portfolio weights are computed using DealScan. The first row corresponds to the measure used in this paper. Other rows are presented for comparison. *Largest participant* is the participant bank that retains the largest fraction of the loan. *Comparable participant* is the participant bank that is closest to the lead bank in terms of size. *Random competitor* is a non-participant bank randomly selected among banks reported in DealScan that are comparable to the lead bank in terms of loan and client size. The last column reports the correlation between the changes in default probability standard deviation of the lead bank and the comparison group. ***, **, and * indicate p-values of 1%, 5%, and 10%, respectively.

	Default probability standard deviation (%)		Change in default probability standard deviation (%)						
	Mean		5th %	Median	95th %	Mean		Corr.	
1 *Lead bank*	6.1	***	−0.025	0.0018	0.047	0.001		–	
2 *Largest participant* (*loan share*)	12.9	***	−0.151	0.0053	0.144	−0.010		0.012	
3 *Random participant*	7.5	***	−0.041	0.0037	0.126	0.025	**	0.013	
4 *Comparable participant* (*size*: *market share*)	6.9	***	−0.022	0.0030	0.034	0.002		0.002	
5 *Comparable participant* (*size*: *loan portfolio*)	c	***	−0.019	0.0031	0.037	0.013	**	0.022	
6 *Random competitor* (*loan size*)	6.6	***	−0.006	0.0034	0.037	0.008	***	0.035	**
7 *Random competitor* (*loan and client size*)	7.9	***	−0.009	0.0064	0.109	0.019	***	0.082	***

or \$44 million, whereas the largest non-syndicated loans typically do not exceed \$5 million. Average participant share is 4%. Participants are likely to sell or securitize their risk.[16]

The change in standard deviation of the loan portfolio default probability is calculated using portfolio weights specific to the lead bank. In Table 3, I verify that the instrument is unique to the portfolio of the lead bank. Specifically, I compute the change in standard deviation of default probability, using the portfolio weights of several other banks, and look at the correlation between the instrument and these alternative measures. The first row in Table 3 corresponds to the instrument. The other rows correspond to alternative benchmarks: the participant with the largest loan share (row 2), a random participant with a commitment in excess of 4% (row 3), comparable participants based on market share and portfolio size (rows 4 and 5, respectively), and random competitors outside the lending syndicate, based on average loan size and client size (rows 6 and 7, respectively).[17] The correlation between the measure calculated for the lead bank and the measures calculated for the participant banks is very small and statistically insignificant, confirming that the instrument measures a unique feature of the lead bank's loan portfolio.

Measurement error in the calculation of the default probability standard deviation would make my instrument weak and would bias the instrumental variables (IV) estimate of the adverse selection/moral hazard effect in the same direction as that of ordinary least squares (OLS) estimates. Furthermore, to account for potential measurement problems, I include another instrument: the lead bank's lending limit. With one endogenous variable and two instruments, the identification is not affected by the weak instruments problem typically raised in the literature (e.g., Bound, Jaeger, and Baker, 1995; or Ibens and Wooldridge, 2007).

The lending limit is a simple additional proxy for the lead's loan portfolio diversification. Since banking is a regulated industry, there are regulatory lending restrictions aimed at reducing banks' portfolio credit risk. In particular, loans to a single lender cannot exceed 15% of a bank's capital for uncollateralized loans or 25% for its collateralized loans. Regulatory lending limits are rarely binding. But in addition to regulatory lending limits, banks have internal lending limits that reflect their internal structures and are often binding. Industry studies indicate that many banks with assets in excess of \$1 billion have loan-size limits in the \$2-\$10 million range.[18] Because I do not directly observe the lending limit, I use the DealScan sample and measure the lending limit as a 75th percentile of the dollar size of the lead bank's share, calculated over the three years prior to the date of analysis. The results are robust to alternative cutting points. As expected, the distribution of the lead share reveals the average lending limit to be only \$35 million, much smaller than the regulatory limit.

Table 4 presents results for the first-stage regression. The table focuses on the two instruments, change in default probability standard deviation and lending limit, both of which are jointly statistically significant in explaining the share retained by the lead bank. In addition, the signs on these coefficients are consistent with the instruments' economic interpretations.

[16] Ivashina and Sun (2007) show that, in the two years following loan origination, approximately half of the participants in lending syndicates sell their shares on the secondary loan market, while the lead banks tend to remain as part of the syndicate.

[17] Participant banks are likely to have smaller in-sample portfolios because it appears that banks that enter syndicated loans as participants are unlikely to be syndicated loan underwriters (lead banks). This fact partially explains the increase in standard deviation of the default probability (rows 2–5). If we pick a random comparable competitor from the pool of lead underwriters (rows 6 and 7), the default probability standard deviation is comparable to that of the lead bank.

[18] See, for example, Bromiley and Stansifer (1994).

Table 4
First-stage regression: syndicate structure.

This table presents results of the first-stage regression. The dependent variable is the share of the loan retained by the lead arranger. The sample contains completed dollar-denominated loans, originated between 1993 and 2004, to US companies excluding regulated and financial industries identified with two-digit SIC 40–45 and 60–64. Model (1) corresponds to the sample for which loan level data were available. Models (2) and (3) reexamine the result for the subsample of loans matched to Compustat. Borrowers' and lenders' characteristics are computed as of the earliest date prior to the origination of the loan. Coefficients on the senior debt ratings should be interpreted as incremental effects with respect to the BBB−, which is used as an intercept. For definitions of the explanatory variables, see Appendix B. Syndicate reputation variables are used as identifying instruments for diversification effect (Table 5). ***, **, and * indicate *p*-values of 1%, 5%, and 10%, respectively.

		(1)			(2)			(3)		
		Coeff.	*t*-stat		Coeff.	*t*-stat		Coeff.	*t*-stat	
Borrower characteristics										
Industry default probability		0.24	3.0	***	0.06	0.7		0.03	0.3	
Not rated		5.29	7.3	***	6.49	7.5	***	5.66	6.5	***
Senior debt rating										
AAA		7.41	1.2		12.93	1.6		12.91	1.6	
AA+		4.06	0.9		8.51	1.3		8.67	1.3	
AA		6.92	2.3	**	4.33	1.3		4.68	1.4	
AA−		5.01	2.4	**	3.58	1.5		3.86	1.6	*
A+		5.54	3.5	***	5.73	3.3	***	5.59	3.2	***
A		4.16	3.5	***	4.47	3.5	***	4.37	3.4	***
A−		2.71	2.4	**	3.27	2.5	**	3.19	2.5	***
BBB+		1.99	2.0	**	1.84	1.6	*	1.95	1.7	*
BBB		1.10	1.2		1.20	1.2		1.20	1.2	
BB+		1.04	0.9		2.73	2.0	**	2.69	2.0	**
BB		−0.49	−0.4		−0.32	−0.3		−0.32	−0.3	
BB−		1.13	1.1		1.59	1.3		1.60	1.4	
B+		4.49	4.5	***	4.82	4.1	***	4.62	3.9	***
B		4.48	3.6	***	5.03	3.4	***	4.83	3.3	***
B−		2.69	1.7	*	0.77	0.4		0.84	0.4	
CCC+		5.61	2.6	***	6.76	2.9	***	6.31	2.8	***
CCC		4.51	1.1		4.24	1.0		4.46	1.0	
CCC−		7.71	1.7	*	7.52	1.5		7.00	1.4	
Commercial paper rating		0.73	1.1		0.94	1.2		1.26	1.6	*
Public		0.21	0.5		0.63	0.8		0.54	0.7	
Previous lending relationship		−1.11	−3.0	***	−1.13	−2.6	***	−1.03	−2.4	**
Log (Sales at close)		−0.52	−3.4	***	−0.44	−2.2	**			
Log (Assets)		–			–			−1.35	−5.5	***
Leverage		–			–			−1.19	−1.6	***
ROA		–			–			−4.01	−2.1	**
Contract characteristics										
Log (Facility amount)		−6.69	−30.7	***	−6.49	−24.8	***	−5.88	−20.7	***
Maturity		−0.03	−3.7	***	−0.03	−3.0	***	−0.03	−3.3	***
Number of facilities		−5.80	−19.2	***	−5.31	−14.3	***	−4.95	−13.3	***
Collateral		0.49	1.2		0.81	1.6	*	0.50	1.0	
Financial covenants		−0.20	−0.4		−0.21	−0.3		−0.33	−0.5	
Prime base rate		1.14	1.0		0.85	0.6		0.95	0.7	
Performance pricing		−1.80	−4.3	***	−1.85	−3.8	***	−2.06	−4.2	***
Lead bank characteristics										
Ranking		0.10	3.8	***	0.11	3.8	***	0.11	3.8	***
Credit risk: Δ default probability std. dev.	z_1	−2.58	−3.2	***	−1.09	−2.2	**	−1.01	−2.2	**
Credit risk: lending limit	z_2	0.01	2.5	***	0.01	2.2	**	0.01	2.3	**
Syndicate characteristics										
Syndicate reputation: lead to participant	z_3	−0.48	−14.3	***	−0.48	−12.1	***	−0.47	−11.8	***
Syndicate reputation: reciprocal	zz_4	−5.00	−5.1	***	−3.67	−3.1	***	−3.68	−3.1	***
Instruments										
F-test: $(z_1 = z_2 = z_3 = z_4 = 0)$			6.9	***		6.8	***		6.2	***
F-test: $(z_1 = z_2 = 0)$			3.0	**		2.8	**		2.8	**
F-test: $(z_3 = z_4 = 0)$			10.3	***		12.0	***		9.8	***
Fixed effects										
Bank		Yes			Yes			Yes		

Table 4 (*continued*)

	(1)		(2)		(3)	
	Coeff.	*t*-stat	Coeff.	*t*-stat	Coeff.	*t*-stat
Year	Yes		Yes		Yes	
Loan purpose	Yes		Yes		Yes	
Observations	5,017		3,617		3,617	
Adjusted R^2	0.53		0.55		0.55	

Specifically, an increase in default probability standard deviation reflects a higher credit risk; if the loan share is held constant, the lead bank will demand a larger spread. This predicts a negative partial correlation between the lead bank's share and change in default probability standard deviation. Similarly, a lower lending limit is associated with a higher credit risk. This predicts a positive partial correlation between the lead bank's share and the lending limit.

3.2. Identification

The general rule for identification of a structural model is that both rank and order conditions must be satisfied. Consistent with the rank condition, equations in my system are linearly independent. The order condition requires the number of instruments to be no smaller than the number of endogenous variables in any equation; this is satisfied in my model in that the premiums demanded by both participants and lead are overidentified (i.e., there are more instruments than endogenous variables). Having two instruments enables me to test the overidentifying restrictions. Accordingly, the overidentifying restriction is not rejected with p-value equal to 0.30. This confirms the joint validity of my instruments and is further evidence of the efficacy of my economic model.

To ensure that identifying instruments are jointly significant, I estimate the reduced form for lead bank loan share reported in Table 4 before estimating the equation by 2SLS. The critical value for the F-test of joint significance is large; thus, I proceed with the second stage of the 2SLS estimation of the loan spread equation.[19]

3.3. Spread required by the participant banks: asymmetric information effect

The main result of this paper is presented in Table 5. In each regression, the dependent variable is the loan spread and the focus is on the coefficient on the lead share. There is a dramatic difference between the OLS (using unconditional lead share) and 2SLS (using fitted lead share) estimates. This illustrates the bias present in the estimates if the joint determinants of the loan spread and the lead share are not properly accounted for. The negative coefficient on the fitted lead bank share measures the relation between the lead share and the loan spread demanded by the syndicate participants due to adverse selection/moral hazard problem.

The economic significance of this coefficient is large: A 1 percentage point increase (from 10% to 11%) in lead bank share corresponds to a reduction in the average participant's premium of 3.26 basis points. Thus, a decrease of one standard deviation in the fitted value of the lead bank's share implies an increase in the loan spread of 41 basis points. However, one standard deviation is a very large change in the lead share. As a reference point, the first-stage regression indicates that the log of the facility amount is one of the central determinants of the lead bank's share and a one standard deviation change in the log of the facility amount implies a 9% change in the lead share. Therefore, conditional on economically sound variation in loan size, a 9% change in the lead share translates into a change in loan spread of approximately 29 basis points. At an average LIBOR of 559 basis points and upfront fees of 40 basis points, information asymmetry within the lending syndicate accounts for 4% of the total credit cost.[20] That said, a 9% change in lead share is equivalent to a $24 million increase in the lead bank's exposure and could still be economically large.[21]

The economic magnitude of my findings is in line with several studies on relationship lending that focus on providing estimates of information asymmetry cost, although my paper focuses on a direct measure of information asymmetry within a lending syndicate and has a different methodology. In particular, Kim, Kliger, and Vale (2003) and Yasuda (2005) study rents derived by banks from customer-switching costs, which are interpreted as a cost of information asymmetry. Kim, Kliger, and Vale (2003) estimate a total cost of switching banks to be 21 basis points; Yasuda (2005) indicates that the upper

[19] Under these conditions, the conventional two-stage least squares method provides the best estimators. For a discussion, see Ibens and Wooldridge (2007).

[20] According to Datastream, LIBOR of 559 corresponds to the 1993–2004 average of a three-month interbank rate.

[21] Standard errors used to compute the significance of the second-stage estimates account for the use of fitted value from the first stage as an instrument. Given that the first and second stages are linear and that all exogenous variables are included in the first stage, this adjustment is a special case of the Murphy-Topel two-step adjustment. In general, using clustered errors in two-step estimation is questionable. Following the analysis by Petersen (2007), clustering of standard errors should be evaluated as a reference rather than as the ultimate result. I considered clustering of errors at the bank, firm, and industry levels. The changes in standard errors are relatively small, suggesting that auto-correlation in the residuals is not significant. The results are available upon request.

Table 5
Determinants of loan spreads: asymmetric information effect.

This table reports results of the second-stage regression corresponding to the spread required by the participant banks (asymmetric information effects). Participants' pricing behavior is identified using *Δ Default probability std. dev.* and *Lending limit*, which exogenously shift the spread demanded by the lead bank. The dependent variable, *All-in spread drawn*, includes fees (except the upfront fee) and the spread that the borrower pays for each dollar drawn down under loan commitment. Each observation in the regression corresponds to a different deal. The first set of results reports coefficients estimated by OLS. Models (1), (2), and (3) report point estimates for the second-stage regression using predicted values for share retained by the lead arranger from Table 4. Model (1) corresponds to the sample for which loan data were available. Models (2) and (3) reexamine the result for the subsample of loans matched to Compustat. The sample contains completed dollar-denominated loans, originated between 1993 and 2004, to US companies excluding regulated and financial industries identified with two-digit SIC 40–45 and 60–64. Borrowers' and lenders' characteristics are computed as of the earliest date prior to the origination of the loan. Coefficients on the senior debt ratings should be interpreted as incremental effects with respect to the BBB−, which is used as an intercept. For definitions of the explanatory variables, see Appendix B. ***, **, and * indicate *p*-values of 1%, 5%, and 10%, respectively.

	OLS			2SLS (1)			2SLS (2)			2SLS (3)		
	Coeff.	*t*-stat		Coeff.	*t*-stat		Coeff.	*t*-stat		Coeff.	*t*-stat	
Syndicate structure												
Lead share	0.26	3.3	***	−3.26	−2.0	**	−2.18	−1.6	*	−2.13	−1.6	*
Borrower characteristics												
Industry default probability	0.79	1.7	*	1.68	2.4	**	0.25	0.4		0.16	0.3	
Not rated	6.49	1.6		25.24	2.5	**	21.63	1.3		23.25	1.6	
Senior debt rating												
AAA	−23.89	−0.7		2.02	0.1		30.93	0.5		21.28	0.4	
AA+	−77.97	−3.1	***	−63.37	−2.1	**	−43.04	−0.9		−35.98	−0.8	
AA	−27.48	−1.6		−3.53	−0.2		−20.30	−0.9		−5.89	−0.3	
AA−	−52.85	−4.6	***	−33.62	−2.0	**	−38.20	−2.1	**	−27.99	−1.6	
A+	−53.41	−6.0	***	−33.57	−2.4	**	−36.61	−2.0	**	−31.43	−1.8	*
A	−51.40	−7.7	***	−36.60	−3.4	***	−39.90	−2.9	***	−34.53	−2.7	***
A−	−39.19	−6.1	***	−29.57	−3.3	***	−26.61	−2.3	**	−23.25	−2.2	**
BBB+	−28.97	−5.1	***	−21.82	−2.9	***	−24.12	−2.9	***	−19.25	−2.3	**
BBB	−23.12	−4.7	***	−19.12	−3.1	***	−20.14	−2.9	***	−17.25	−2.6	***
BB+	11.43	1.7	*	15.20	1.9	**	22.80	2.1	**	23.10	2.2	**
BB	20.87	3.4	***	19.45	2.7	***	21.65	2.9	***	23.32	3.2	***
BB−	27.39	4.9	***	31.48	4.5	***	31.27	3.8	***	32.84	4.1	***
B+	44.58	8.0	***	60.85	5.9	***	54.64	3.8	***	52.93	4.0	***
B	59.01	8.5	***	75.36	6.6	***	64.82	4.2	***	60.08	4.1	***
B−	60.71	6.8	***	70.23	6.1	***	69.16	5.6	***	62.39	5.1	***
CCC+	107.53	9.0	***	127.23	7.5	***	127.25	5.8	***	119.35	5.9	***
CCC	193.74	8.4	***	209.99	7.4	***	205.83	7.2	***	198.12	7.1	***
CCC−	164.41	6.5	***	191.96	5.8	***	158.11	4.5	***	126.61	3.8	***
Commercial paper rating	−10.51	−2.8	***	−7.90	−1.7	*	−7.40	−1.4		−5.97	−1.1	
Public	−11.44	−5.0	***	−10.66	−3.9	***	−7.52	−1.6		−1.97	−0.4	
Previous lending relationship	0.77	0.4		−3.02	−1.0		0.03	0.0		0.21	0.1	
Log (Sales at close)	−5.06	−5.9	***	−6.91	−5.1	***	−5.36	−3.3	***			
Log (Assets)	–			–			–			−9.70	−2.7	***
Leverage	–			–			–			33.51	6.5	***
ROA	–			–			–			−103.60	−7.1	***
Contract characteristics												
Log (Facility amount)	−12.13	−9.2	***	−35.68	−3.1	***	−26.80	−1.6	*	−23.68	−1.7	*
Maturity	−0.05	−1.1		−0.17	−2.1	**	−0.21	−2.1	**	−0.19	−1.9	*
Number of facilities	6.79	3.9	***	−13.61	−1.4		−9.77	−0.7		−8.48	−0.7	
Collateral	47.04	20.2	***	48.82	16.9	***	54.97	15.0	***	49.06	15.2	***
Financial covenants	13.30	4.3	***	12.54	3.4	***	15.08	3.9	***	15.55	4.1	***
Prime base rate	161.82	25.3	***	165.95	21.2	***	169.76	19.9	***	160.94	19.1	***
Performance pricing	−19.76	−8.5	***	−26.16	−6.3	***	−19.58	−3.5	***	−19.25	−3.3	***
Lead bank characteristics												
Ranking	0.40	2.7	***	0.74	3.1	***	0.58	1.7	*	0.55	1.8	*
Syndicate characteristics												
Syndicate reputation: lead to participant	−0.73	−3.8	***	−2.40	−2.9	***	−2.13	−1.7	*	−1.95	−1.7	*
Syndicate reputation: reciprocal	7.24	1.3		−10.13	−1.0		−4.29	−0.4		−4.54	−0.4	

Table 5 (*continued*)

	OLS		2SLS (1)		2SLS (2)		2SLS (3)	
	Coeff.	*t*-stat	Coeff.	*t*-stat	Coeff.	*t*-stat	Coeff.	*t*-stat
Fixed effects								
Bank		Yes		Yes		Yes		Yes
Year		Yes		Yes		Yes		Yes
Loan purpose		Yes		Yes		Yes		Yes
Observations		5,017		5,017		3,617		3,617
Adjusted R^2		0.59		0.50		0.55		0.61

limit on this cost is 123 basis points.[22] The firms in my sample, given their average loan size, are likely to be larger than the firms in these other studies. In the sense that larger firms are associated with higher information transparency, the estimate of asymmetric information cost found in my sample is lower.

3.4. Asymmetric information controls

In addition to controlling for year, loan purpose, and bank fixed effects, throughout the paper I control for the lead bank's reputation and for several loan characteristics (including performance pricing, covenants, and collateral) that affect the level of information asymmetry within a syndicate.[23] Asquith, Beatty, and Weber (2005) find that performance pricing is more likely to be included in bank debt contracts when the borrower is less transparent. Consistent with my finding, the presence of performance pricing should reduce the costs of asymmetric information within the lending syndicate, reducing the premium demanded by the participant banks. The same intuition applies to the inclusion of collateral and financial covenants, although I find a positive sign for these two features.[24]

The availability of public information about borrowers directly affects the information asymmetry between the lead bank and the syndicate participants. The less transparent the borrower is, the more the syndicate members will have to rely on information collected and reported by the lead bank. Throughout the paper, I measure information transparency by introducing explicit controls for credit ratings and borrower size. The estimates on the credit ratings are comparable to those estimated by Carey and Nini (2007). In addition, for the sample matched to Compustat, I control for asset size, leverage, and profitability. The results continue to hold and their diminished statistical and economic significance is consistent with the reduced importance of bank information collection in a sample of publicly transparent companies. To assure that the reduction in statistical significance is not attributed to omitted variables, regressions (2) and (3) in Table 5 present results before and after the inclusion of accounting measures. If measurement of credit risk were a problem, the coefficient on the lead share without proper controls would be downward-biased (there would be a steeper negative slope in the participants' demand). Thus, the introduction of controls for size, leverage, and profitability should bring the coefficient on the lead share up. However, the change is insignificant, suggesting that imprecision in the controls for credit risk is an unlikely source of bias.

According to Petersen and Rajan (1994) and Berger and Udell (1995), repeated lending also makes it possible to reduce the information asymmetry about the borrower, leading to a lower loan spread. Thus, I also control for a history of previous loans with the same lead bank. The results in Table 5 indicate that repeat borrowers receive cheaper financing. The economic magnitudes of my estimates are smaller than—but consistent with—the findings of Petersen and Rajan (1994) and Berger and Udell (1995). This is not surprising, as both studies look at data from the National Survey of Small Business, where even the largest companies in the sample are below $5 million, while the firms in my sample have assets over $3 billion and are likely to be more transparent and to face lower asymmetric information costs.[25]

It is also important to control for the degree of asymmetric information within the lending syndicate; in other words, it matters who is part of the syndicate. For example, if participant banks have expertise in the borrower's industry, it could reduce the asymmetric information between the lead bank and the rest of the lending syndicate. To address this specific concern, in unreported results I use a direct measure of the participant banks' industry specialization and find the asymmetric information effect to be unaffected by this

[22] In a related study, Degryse and Ongena (2005) use banks' geographical price discrimination to estimate that the upper limit on the information cost is approximately 200 basis points.

[23] Performance pricing ties loan spread to the firm's financial indicators, allowing the spread to change automatically with changes in the leverage and/or interest coverage ratio.

[24] I consider alternative definitions of the financial covenants, including that of Bradley and Roberts (2004). These changes do not affect the results.

[25] Also, the estimated effect of the repeat-lending relationship is not directly comparable across the two samples. Because I look at the sample of syndicated loans, even if the information gap between the lead bank and the borrower is reduced in a process of repeated lending, it does not fully resolve the information asymmetry between the lead bank and the syndicate participants. Thus, the reduction in the loan spread due to repeat-lending relationships should be smaller for syndicated loans.

additional control. Moreover, measures of industry specialization are not important in explaining the loan spread.

Asymmetric information within a lending syndicate could also be reduced through optimization by the lead bank across lending syndicates. The syndicated loan market is a private market and the choice of participants is determined primarily by the lead bank. Thus, the information asymmetry between the lead bank and participants is alleviated if the lead bank repeatedly deals with the same lenders. Allocation of reciprocal deals could also help to reduce asymmetric information between the banks. If bank A participates in deals arranged by bank B and vice versa, then the threat of losing each other's business could serve as a pre-commitment mechanism. If bank A misbehaves, it will lose business from bank B. I directly control for these two possibilities—reputation building and reciprocal relationships—throughout the paper.[26] However, while it is important to control for asymmetric information to correctly assess the sensitivity of the asymmetric information premium to the lead share (i.e., the slope of the participants' pricing schedule), it is unlikely that these factors would affect the identification strategy because they are unlikely to be correlated with the idiosyncratic component of the lead bank's credit-risk exposure.

4. Robustness of the results

4.1. Spread required by the lead bank: diversification effect

The identification of the adverse selection/moral hazard effect depends on the fact that the lead bank is not fully diversified. In Table 6, I directly test the relation between the lead's share and the spread that the lead demands. The diversification effect presumes that as the lead bank's share increases, the bank becomes more exposed to credit risk and will demand a higher spread. Like the adverse selection/moral hazard effect, the diversification effect is not directly observable. To identify it, I need an instrument that exogenously shifts the level of asymmetric information within the lending syndicate without directly affecting the lead bank's credit-risk exposure. The lead bank's reputation directly affects the level of asymmetric information within the syndicate, but it is an unlikely element of a credit-risk model. Instead, I use syndicate-specific reputation, measured in terms of the previous connections between syndicate members, to instrument the diversification effect.

My main reputation measure is the maximum number of deals arranged by the same lead bank with the same participants, measured over a three-year horizon and expressed as a percent of the total deals underwritten during this period. To illustrate, assume that for a given syndicate loan, A is the lead bank and banks B and C are the participants. If bank B and bank C participated in 10% and 20%, respectively, of the deals underwritten by bank A over the past three years, the reputation measure for this loan would be 20%. In my sample, the median and mean of this reputation measure are 11% and 12.5%, respectively. To account for reciprocal relationships, I use a dummy variable that indicates a past relationship in which the participant and lead banks switched roles. Correlation between the reputation variables is low, confirming that they measure different aspects of reputation.[27]

Higher reputation measures reflect lower levels of information asymmetry within the syndicate. Alternatively, for a given spread, when reputation is high, the lead bank would syndicate a larger fraction of the loan. Consequently, I expect a negative relation between the lead bank share and reputation measures. These predictions are consistent with the first-stage results in Table 4.

Table 6 reports results of the second-stage regression, corresponding to the lead bank's required spread. Measures of syndicate-specific reputation are the identifying instruments and are therefore not included in the second-stage regression. As in Table 5, the key coefficient corresponds to the lead bank's loan share. The point estimate is, again, significantly different from the OLS analysis. The positive relation between the share retained by the lead bank and the required spread is consistent with the diversification effect. As expected, the risk factors' impact on the spread demanded by the lead bank is similar to their impact on the spread demanded by the participant banks. It is important to notice that the asymmetric information effect and the diversification effect are tested *independently* of each other, reinforcing the overall validity of the findings.

4.2. Alternative credit-risk management techniques

Standard deviation of the default probability of the lead's loan portfolio is, most likely, measured with an error. However, because it is used as an instrument, precision in the measurement is of secondary importance. The central point is that my instrument correlates with the portfolio-specific credit risk. Additionally, for the adverse selection/moral hazard identification to be conceptually wrong, the lead bank needs to be able to eliminate its idiosyncratic exposure at zero or fixed costs. Using active risk management is costly and would thus directly affect the cost of credit. Nevertheless, a bank's actual credit-risk exposure might be difficult to measure because banks use unobservable risk-management techniques, including credit derivatives swaps (CDS), securitization through collateralized loan obligations (CLO), and loan sales on the secondary market.

While these mechanisms are becoming more popular now, they were not very important between 1993 and 2004. In fact, loan CDSs started trading in 2004 and standard documentation for the US market was published by the International Swaps and Derivatives Association in June 2006. The first CLO completed by a US bank occurred in late 1997. Total CLO volume for 1997–2001 (US market)

[26] Construction of these proxies is discussed in Section 4.1.

[27] The results are robust to using alternative time windows and mean number of past syndicated links with the lead bank to measure reputation.

Table 6
Determinants of loan spreads: diversification effect.

This table reports results of the second-stage regression corresponding to the spread required by the lead bank (diversification effects). The spread demanded by the lead bank is identified using syndicate-specific *Reputation* measurements that exogenously shift the spread required by the participant banks. The dependent variable, *All-in spread drawn*, includes fees (except the upfront fee) and the spread that the borrower pays for each dollar drawn down under the loan commitment. Each observation in the regression corresponds to a different deal. Models (1), (2), and (3) report point estimates for the second-stage regression using predicted values for share retained by the lead arranger from Table 4. As in Table 5, Model (1) corresponds to the sample for which loan data were available and Models (2) and (3) reexamine the result for the subsample of loans matched to Compustat. Coefficients on the senior debt ratings should be interpreted as incremental effects with respect to the BBB−, which is used as an intercept. Borrowers' and lenders' characteristics are computed as of the earliest date prior to the origination of the loan. For definitions of the explanatory variables, see Appendix B. ***, **, and * indicate p-values of 1%, 5%, and 10%, respectively.

	(1)			(2)			(3)		
	Coeff.	*t*-stat		Coeff.	*t*-stat		Coeff.	*t*-stat	
Syndicate structure									
Lead share	1.36	3.7	***	1.98	4.4	***	1.80	4.1	***
Borrower characteristics									
Industry default probability	0.52	1.1		−0.01	0.0		0.04	0.1	
Not rated	0.71	0.2		−5.33	−0.9		0.27	0.1	
Senior debt rating									
AAA	−32.41	−1.0		−23.13	−0.5		−29.35	−0.6	
AA+	−80.60	−3.1	***	−77.63	−2.0	**	−69.16	−1.8	*
AA	−34.64	−2.0	**	−37.57	−2.0	*	−23.46	−1.3	
AA−	−55.17	−4.6	***	−53.77	−3.9	***	−44.11	−3.3	***
A+	−59.17	−6.4	***	−60.32	−5.9	***	−53.13	−5.3	***
A	−55.74	−8.0	***	−58.45	−7.7	***	−51.55	−6.9	***
A−	−42.22	−6.4	***	−40.43	−5.4	***	−35.87	−4.9	***
BBB+	−31.14	−5.4	***	−31.85	−4.9	***	−26.88	−4.2	***
BBB	−24.41	−4.8	***	−25.20	−4.3	***	−21.99	−3.9	***
BB+	10.42	1.5		11.29	1.4		12.45	1.6	
BB	21.69	3.5	***	23.17	3.4	***	24.89	3.7	***
BB−	25.77	4.5	***	24.25	3.6	***	26.26	4.0	***
B+	40.08	6.7	***	34.70	4.9	***	35.08	5.1	***
B	54.35	7.4	***	43.66	5.0	***	41.01	4.9	***
B−	57.95	6.4	***	66.11	5.8	***	59.20	5.3	***
CCC+	101.99	8.2	***	99.53	7.4	***	94.90	7.3	***
CCC	186.15	7.9	***	185.68	7.5	***	178.56	7.4	***
CCC−	156.57	6.0	***	127.12	4.6	***	99.13	3.6	***
Commercial paper rating	−11.38	−2.9	***	−11.70	−2.7	***	−11.08	−2.6	***
Public	−11.65	−5.0	***	−10.45	−2.4	**	−4.03	−1.0	
Previous lending relationship	2.13	1.0		5.00	2.0	**	3.91	1.6	*
Log (Sales at close)	−4.61	−5.1	***	−3.64	−3.2	***			
Log (Assets)	–			–			−5.28	−3.6	***
Leverage	–			–			37.45	9.3	***
ROA	–			–			−92.34	−8.9	***
Contract characteristics									
Log (Facility amount)	c	−1.7	*	0.12	0.0		0.06	0.0	
Maturity	−0.02	−0.3		−0.08	−1.3		−0.04	−0.6	
Number of facilities	12.89	4.4	***	12.35	3.6	***	12.20	3.8	***
Collateral	46.68	19.6	***	51.57	18.0	***	47.63	17.3	***
Financial covenants	13.49	4.3	***	15.88	4.4	***	16.86	4.9	***
Prime base rate	160.31	24.6	***	165.89	21.5	***	160.04	21.7	***
Performance pricing	−17.65	−7.1	***	−11.72	−4.0	***	−10.97	−3.9	***
Lead bank characteristics									
Ranking	0.26	1.7	*	0.07	0.4		0.04	0.2	
Credit risk: Δ default probability std. dev.	9.91	2.2	**	11.33	2.0	**	14.19	2.5	**
Credit risk: lending limit	−0.07	−2.5	**	−0.02	−1.0		−0.02	−0.8	
Fixed effects									
Bank	Yes			Yes			Yes		
Year	Yes			Yes			Yes		
Loan purpose	Yes			Yes			Yes		
Observations	5,017			3,617			3,617		
Adjusted R^2	0.58			0.58			0.61		

Table 7
Robustness check: upfront fee.

This table verifies that the diversification premium demanded by the lead bank is part of the *All-in spread drawn* and not the *Upfront Fee*. Results of the Table 5 are reexamined for the subsample for which upfront fee is available. *All-in spread drawn* includes fees and the spread that the borrower pays for each dollar drawn down under the loan commitment, net of upfront fee. Panel A highlights results from the first-stage regression where the dependent variable is *All-in spread drawn*. Full specification of the first stage is the same as in Table 4, Model (1). Panel B reports results of the second-stage regression corresponding to the spread required by the participant banks (asymmetric information effects). To save space, credit ratings are not reported. For definitions of the explanatory variables, see Appendix B. ***, **, and * indicate p-values of 1%, 5%, and 10%, respectively.

Dependent variable	All-in spread drawn			Upfront Fee		
	Coeff.	*t*-stat		Coeff.	*t*-stat	
Panel A: First-stage regression (spread)						
Credit risk: Δ default probability std. dev.	31.19	2.9	***	8.62	1.4	
Credit risk: lending limit	−0.02	−0.4		−0.01	−0.3	
Adjusted R^2	0.54			0.25		
Panel B: Second-stage regression (Participants' pricing)						
Syndicate structure						
Lead share	−3.86	−1.7	*	−1.41	−1.2	
Borrower characteristics						
Industry default probability	0.34	0.3		0.83	1.4	
Not rated	33.23	1.9	*	−4.63	−0.6	***
Commercial paper rating	11.30	0.7		−1.81	−0.2	***
Public	−5.54	−0.8		−5.57	−1.7	***
Previous lending relationship	−0.67	−0.1		−6.02	−2.3	
Log (Sales at close)	−4.72	−1.8	*	−2.80	−2.2	***
Contract characteristics						
Log (Facility amount)	−37.81	−2.3	**	−8.71	−1.1	***
Maturity	−0.40	−2.5	**	0.00	0.0	
Number of facilities	−17.47	−1.3		−3.36	−0.5	*
Collateral	51.66	7.6	***	17.85	5.6	***
Financial covenants	−3.31	−0.4		−0.21	−0.1	**
Prime base rate	133.28	9.5	***	26.51	4.0	***
Performance pricing	−18.75	−2.9	***	−13.68	−4.5	***
Lead bank characteristics						
Ranking	0.81	2.0	**	0.12	0.6	
Syndicate characteristics						
Syndicate reputation: lead to participant	−2.18	−1.8	*	−0.57	−1.0	**
Syndicate reputation: reciprocal	−12.65	−0.5		−17.58	−1.6	***
Fixed effects						
Senior debt credit rating		Yes			Yes	
Bank		Yes			Yes	
Year		Yes			Yes	
Loan purpose		Yes			Yes	
Observations		1,067			1,067	
Adjusted R^2		0.39			0.21	

is estimated to be around $100 billion, less than 2% of the total amount of syndicated loans.

Fractions of syndicated loans can also be resold on the secondary loan market. However, less than 5% of the loans originated between 2000 and 2004 are quoted in the secondary loan market. The numbers are even smaller for previous years. Since most of the quoted loans are packaged specifically for institutional investors and are therefore unlikely to have an important information asymmetry problem within the syndicate, I excluded all quoted loans from my sample. More broadly, while loan contracts do not explicitly prohibit the lead bank from selling its share, they do require the borrower's approval for the sale. In that sense, it is unlikely that selling loans on the secondary market is an important way for the lead bank to reduce its credit risk due to "sensitive client relationship issues arising from loan transfer notification requirements, loan assignment provision, and loan participation restrictions" (OCC, Capital Interpretations, 1999). Analysis of the secondary-market data indicates that trading of syndicated loans typically occurs at the participant level and that most traded loans are syndicated to institutional investors. Additional supporting evidence can be found in work on loan sales by Dahiya, Puri, and Saunders (2003), Drucker and Puri (2009), and Ivashina and Sun (2007).

4.3. Upfront fees

The lead bank's compensation consists of an upfront fee that is not shared with the rest of the syndicate and is not part of the all-in spread drawn. One might wonder if the upfront fee, rather than the spread, could be used to compensate the lead bank for its credit-risk exposure, in which case the diversification premium would not affect

Table 8
Robustness check: information collection expertise.

This table reexamines the results for the subsample of loans extended to companies in industries where the lead bank does not have monitoring (or information collection) expertise. A bank is said not to have monitoring expertise if its loan portfolio in a given two-digit SIC industry is below the median level of 3%. Results are comparable to Model (1) in Tables 4–6. The dependent variable for the second stage is *All-in spread drawn*; it includes fixed fees (excluding upfront fee) and the variable spread that the borrower pays for each dollar drawn down under the loan commitment. Each observation in the regression corresponds to a different deal. For definitions of the explanatory variables, see Appendix B. ***, **, and * indicate p-values of 1%, 5%, and 10%, respectively.

	First-stage			Second-stage					
	Lead share			Participants' pricing			Lead's pricing		
	Coeff.	*t*-stat		Coeff.	*t*-stat		Coeff.	*t*-stat	
Syndicate structure									
Lead share				−2.82	−1.6	*	0.71	1.4	
Borrower characteristics									
Industry default probability	0.14	1.3		0.60	0.8		0.05	0.1	
Not rated	4.24	3.8	***	13.43	1.2		−1.76	−0.3	
Commercial paper rating	0.40	0.4		−9.43	−1.3		−10.99	−1.7	*
Public	0.59	1.0		−11.88	−2.8	***	−13.63	−3.7	***
Previous lending relationship	−1.67	−3.0	***	−1.85	−0.4		3.86	1.1	
Log (Sales at close)	−0.55	−2.2	**	−6.50	−3.3	***	−4.61	−3.0	***
Contract characteristics									
Log (Facility amount)	−6.70	−19.4	***	−35.46	−2.6	***	−11.65	−2.6	***
Maturity	−0.03	−2.5	**	−0.15	−1.4		−0.03	−0.4	
Number of facilities	−6.08	−13.1	***	−12.79	−1.0		8.68	1.9	**
Collateral	0.39	0.6		52.93	12.6	***	51.80	14.3	***
Financial covenants	0.01	0.0		13.97	2.5	***	13.96	2.9	***
Prime base rate	−0.14	−0.1		176.52	15.8	***	177.03	18.0	***
Performance pricing	−1.77	−2.8	***	−36.60	−6.8	***	−30.09	−7.9	***
Lead bank characteristics									
Ranking	0.11	3.2	***	0.50	1.7	*	0.08	0.4	
Credit risk: Δ default probability std. dev.	−4.41	−3.2	***	–			11.39	1.5	
Credit risk: lending limit	0.01	1.0		–			−0.09	−2.5	***
Syndicate characteristics									
Syndicate reputation: lead to participant	−0.51	−10.5	***	−1.84	−1.9	*	–		
Syndicate reputation: reciprocal	−4.09	−3.0	***	−4.50	−0.4		–		
Fixed effects:									
Senior debt credit rating		Yes			Yes			Yes	
Bank		Yes			Yes			Yes	
Year		Yes			Yes			Yes	
Loan purpose		Yes			Yes			Yes	
Observations		2,397			2,397			2,397	
Adjusted R^2		0.51			0.53			0.60	

the all-in spread drawn. Anecdotal evidence suggests that there is not much cross-sectional variability in the upfront fee, making it an unlikely channel for settling a diversification premium. I provide additional evidence in Table 7, where I analyze the key result of the paper for the sample in which upfront fees are available—approximately 20% of my entire sample. Thus, Table 7 uses the same specification for two different dependent variables: (1) all-in spread drawn net of upfront fee and (2) upfront fee.[28] If upfront fee were to be used to compensate the lead bank for credit-risk exposure, then the standard deviation of the default probability of the loan portfolio, constructed to measure the lead's idiosyncratic risk exposure, should explain upfront fee and not net spread. But the estimation of a reduced form for spread (as a function of all the exogenous variables) confirms that default probability standard deviation is important in explaining spread and not upfront fee. When upfront fee is used as the dependent variable, there is a significant drop not only in the statistical but also in the economic explanatory power of the standard deviation of default probability.

Conceptually, it is not clear if asymmetric information cost is due to the moral hazard problem or to the adverse selection problem between lead banks and syndicate participants. If it is an adverse selection problem, consistent with Leland and Pyle (1977), it cannot be resolved through a fixed payment (upfront fee).

4.4. Monitoring synergies

Consistent with the diversification effects, loan portfolio concentration in a particular industry should be associated with higher credit risk and the lead bank should therefore demand a higher spread. However, if industry concentration of the loan portfolio is associated

[28] DealScan reports upfront fee as an annuity measured in basis points.

Table 9
Robustness check: alternative definitions of default probability standard deviation.

This table evaluates the robustness of the relationship between spread and lead bank share reported in Tables 5 and 6 to alternative definitions of *Default probability standard deviation*. The first line repeats the central result of the paper reported in Tables 5 and 6, using the original measure of *Default probability standard deviation* calculated using lagged cross-industry matrices of default correlations. Loan effective maturity was assumed to be less than three years, and revolver lines were scaled by 50%. The rest of the lines report point estimates of the *Lead share* for alternative definitions of *Default probability standard deviation*. The first column reports correlation with the original measure; the last column reports the F-stat of the joint significance of the four instruments used in the reduced form of the *Lead share*. Lines 2–5 consider alternative specifications for the default correlations matrices. Lines 6 and 7 consider alternative assumptions for the outstanding loan portfolio. Lines 8–11 consider several methods of incorporating recovery rates in the analysis. ***, **, and * indicate p-values of 1%, 5%, and 10%, respectively.

		Corr.	Participant banks (Table 5)			Lead bank (Table 6)			Instruments
			Coeff.	t-stat		Coeff.	t-stat		F-stat
1	***Original measure* (Tables 5 and 6)**	–	−3.26	−2.0	**	1.36	3.7	***	6.9
2	*Loan share: median share by loan size*	0.98	−2.86	−1.8	*	1.36	3.8	***	6.8
3	*Default matrix*: 1-*year default horizon*	0.79	−4.06	−2.0	**	1.44	3.9	***	7.2
4	*Default matrix*: *not lagged*, 1-*year horizon*	0.71	−2.30	−1.7	*	1.20	3.2	***	5.1
5	*Default matrix*: *not lagged*, 3-*year horizon*	0.73	−2.01	−1.7	*	1.20	3.2	***	4.9
6	*Loan portfolio*: *no restrictions on loan maturity*	0.97	−3.43	−1.9	**	1.36	3.7	***	6.9
7	*Loan portfolio*: 100% *of revolver lines*	0.95	−2.46	−1.7	*	1.35	3.7	***	6.6
8	*Recovery rates*: *credit rating*	0.96	−3.00	−1.9	*	1.34	3.7	***	6.8
9	*Recovery rates*: *asset tangibility*	0.96	−3.92	−2.2	**	1.34	3.7	***	7.3
10	*Recovery rates*: *collateral*	0.96	−2.35	−1.7	*	1.34	3.7	***	6.6
11	*Recovery rates*: *loan size/sales*	0.95	−3.90	−2.1	**	1.31	3.6	***	7.3

with synergies in information collection and monitoring, the spread demanded by the lead bank should be lower. In terms of Fig. 1, higher credit risk would shift the lead bank's demand to the right and the lead bank's industry-monitoring expertise would shift its demand to the left. Thus, we have opposite predictions for the coefficient on the standard deviation of the probability of default in the first-stage regression. Table 4 indicates that an increase in standard deviation of the default probability is associated with the lower lead bank share. This result is consistent with the diversification effect.

Table 8 provides additional evidence by reexamining the central result of Table 5 for the sample in which loans are issued to industries in which the lead bank's share of the loan portfolio is less than the sample median (3%). This subsample corresponds to the cases in which the lead bank does not have industry-monitoring expertise. If concentration of the loan portfolio is affected by the monitoring expertise of the lead bank, then the results for this subsample should not hold. However, the results remain qualitatively the same.

4.5. Adjustment for recovery rates

In the second section, I discussed the construction of change in default probability standard deviation, my main instrument for identifying adverse selection/moral hazard effect. Table 9 examines the robustness of the relation between the spread and the lead share (presented in Tables 5 and 6) to alternative specifications of the change in standard deviation of default probability.

Overall, the results in Table 9 confirm the economic and statistical significance of the adverse selection/moral hazard and diversification effect. Perhaps most interesting is the part that corresponds to adjustments for recovery rates (lines 8–11). Loss in the event of default is an important component of expected loss but was not considered in the calculation of the original instrument. I use four alternative proxies for the recovery rates: credit ratings, industry asset tangibility, presence of collateral, and leverage. I scale down the default probabilities for companies likely to have high recovery rates. The results are not sensitive to the scaling factor. Overall, the adjusted measures are highly correlated with the original measure and the central results remain economically strong and robust.

5. Conclusions

In this paper, I examine how the lead bank's ownership share of a syndicated loan affects the information asymmetry in the lending syndicate and measure the lead share's impact on the loan spread charged to the borrower. The observable relation between the lead share and the loan spread is endogenous. I instrument the true effect of ownership on the information asymmetry premium, using shifts in the lead bank's idiosyncratic credit-risk exposure. I find that the information asymmetry problem within a syndicate has an important economic impact on loan spread. In particular, I find that a 9% increase in the share retained by the lead bank reduces the spread required by participants by approximately 29 basis points (4% of the total cost). I conclude that information asymmetry within a lending syndicate—and thus, the cost of borrowing—can be effectively reduced by increasing the share of the loan retained by the lead arranger.

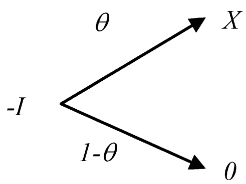
Because an increase in the lead share is associated with larger credit-risk exposure, the equilibrium syndicate structure and the loan spread are determined through the interaction between the two opposing effects: the information asymmetry effect (affecting the participants' pricing) and the diversification effect (affecting the lead's pricing). My analysis is based on the within-bank variation; however, the findings imply that banks with larger and more diversified portfolios have a competitive advantage because they can offer lower financing costs to the borrower. Thus, the framework of a tradeoff between asymmetric information cost and diversification cost provided in this paper could be useful in understanding the structure of the syndicated loan market (specifically, the fact that syndicated lending is dominated by large banks) and in understanding banking industry consolidation in general.

More broadly, this paper provides direct evidence that ownership is an important mechanism for mitigating the effects of information asymmetry. The motivation behind the instrument used to identify the information asymmetry effect could be used in any context characterized by information asymmetry in which diversification is important.

Appendix A. Theoretical framework

A lead bank's credit-risk exposure is an increasing function of its loan share. However, the credit-risk exposure of the syndicate participants (per dollar of the loan held) is unaffected by the lead's share. Thus, I argue that, for each loan, the credit-risk component *specific* to the portfolio of the lead bank exogenously affects the lead's share of the loan; i.e., it only affects interest rate through the lead share. This is the nature of the instrument used to identify the asymmetric information effect. The following simple setup formalizes this idea in a moral hazard framework:

The borrower's investment opportunity is a risky project which, at the initial date 0, requires an investment of I dollars and, at date 1, pays X in the high state and zero in the low state. The probability of the high outcome is $\theta\in[0,1]$; it is a function of monitoring effort by the lead bank. I assume that $X>I>0$ and that the risk-free rate is zero. Only the lead bank knows its effort and the contracts cannot be written contingent on the monitoring effort or the state.



The project is fully financed using a syndicated loan. The borrower pays the lead bank a fixed fee $F\in[0,X]$. In addition, conditional on the high outcome, the borrower pays back the principal plus the interest rate, R, both of which are shared pro rata by the lending syndicate. The lead bank retains $\alpha\in[0,1]$ of the loan and $(1-\alpha)$ is held by the rest of the syndicate participants. Therefore, the lead bank receives $(F+\alpha\theta R)$. Assuming perfect competition between the banks, the interest rate at equilibrium is determined by the zero-profit condition:

$$I=\theta R \Rightarrow R=\frac{I}{\theta}. \tag{A.1}$$

For a given lead bank share, α, the lead decides what monitoring effort level θ to exert by maximizing:

$$\max_{\theta}\ \alpha\theta R-\frac{1}{2}\beta\theta^2. \tag{A.2}$$

The second term, $\frac{1}{2}\beta\theta^2$, represents the cost of monitoring. This term is increasing and convex in effort. $\beta>0$ is introduced to parameterize the firm's systematic characteristics priced by all lenders. For example, a publicly traded company, as compared to a privately held company, would be more transparent—requiring a lower monitoring effort—and therefore would be associated with a lower β. Similarly, better credit rating, the presence of collateral, and previous lending relationship, among other characteristics, would be reflected in a lower β.

The optimal monitoring $\hat{\theta}$ solves the first-order condition to (A.2):

$$\alpha R-\hat{\theta}\beta=0.$$

Using (A.1):

$$\alpha\frac{I}{\theta}-\hat{\theta}\beta=0,$$

so that

$$\hat{\theta}=\sqrt{\frac{\alpha I}{\beta}}, \tag{A.3}$$

$$R=\sqrt{\frac{\beta I}{\alpha}}. \tag{A.4}$$

Eq. (A.4) shows the moral hazard effect of the lead share on the interest rate: The lower the lead share, the higher the required return on the loan due to the reduced monitoring effort by the lead bank.

The lead bank incurs an additional cost due to lack of diversification, αC. As the lead's share of the loan increases, its loan portfolio becomes more concentrated and it faces a higher *idiosyncratic* credit-risk cost. Monitoring cost is independent of the lead's credit-risk exposure. Thus, optimal loan share maximizes the lead bank's expected payoff, subject to the borrower's participation constraint:

$$\max_{\alpha}\left(F+\alpha\theta R-\frac{1}{2}\beta\theta^2-\alpha C\right)-\alpha I.$$

$$\text{s.t.}\quad \theta(X-R)-F\geqslant 0$$

The optimal lead share $\hat{\alpha}$ solves:

$$\frac{d}{d\alpha}\left(\theta(X-R)+\alpha(\theta R-I)-\frac{1}{2}\beta\theta^2-\alpha C\right)=0.$$

Substituting (A.1),

$$\frac{d}{d\alpha}\left(\theta X-\frac{1}{2}\beta\theta^2-\alpha C\right)=\frac{d\theta}{d\alpha}X-\frac{d\theta}{d\alpha}\beta\theta-C=0.$$

Using (A.3):

$$\frac{d\hat{\theta}}{d\alpha}=\frac{1}{2}\sqrt{\frac{I}{\alpha\beta}},$$

$$\frac{1}{2}\sqrt{\frac{I}{\hat{\alpha}\beta}}X-\frac{1}{2}I-C=0,$$

$$\widehat{\alpha}=\frac{X^2}{\beta(2C+I)^2}.$$

As a consequence:

$\downarrow C \Rightarrow \uparrow \hat{\alpha} \Rightarrow \downarrow R.$

That is, idiosyncratic credit risk specific to the lead's portfolio, C, affects the interest rate *only* through the lead's loan share. The firm's general characteristics, parameterized by β and I, affect the interest rate both directly and through the lead's loan share. Thus, changes in the lead's idiosyncratic risk exposure represent exogenous shifts in the participants' pricing schedule. This allows me to use an IV approach to measure the asymmetric information effect on the interest rate. Finally, it is important to note that the identification strategy is unaffected by the fee structure.

Appendix B. Definitions of variables

Variable	Units	*Definition*	Source
Endogenous variables			
All-in spread drawn	Basis points	*Total (fees and interest) annual spread paid over LIBOR for each dollar drawn down from the loan net of upfront fees*	DealScan
Lead share	%	*Share of the loan that is retained by lead arranger at loan origination*	DealScan
Borrower characteristics			
Industry default probability	%	Two-digit SIC industry expected loss probability	S&P
Not rated	Dummy	One if the borrower is not rated, zero otherwise	DealScan/S&P
Senior debt ratings	Dummy	*A set of 20 dummies for Standard & Poor's senior debt ratings (AAA thought CCC−) equal to 1 for borrowers with the corresponding senior debt rating, zero otherwise*	*DealScan/S&P*
Commercial paper rating	Dummy	One if the borrower has a commercial paper rating, zero otherwise	DealScan/S&P
Public	Dummy	*One if the borrower is a publicly traded company, zero otherwise*	Compustat
Previous lending relationship	Dummy	*One if over the previous three years the same lead bank arranged other loans for the same borrower, zero otherwise*	DealScan
Sales at close	Millions USD	Borrower's sales at the loan origination	DealScan
Log (Sales at close)		Natural logarithm of *Sales at close*	DealScan
Assets	Millions USD	Total assets (Data6)	Compustat
Log (Assets)		Natural logarithm of *Assets*	Compustat
Leverage		Industry-median-adjusted ratio of book value of debt [total liabilities (Data181)+preferred stock (Data10)−convertible debt (Data35)] to total assets (Data6); for preferred stock, if Data10 was not available, I used Data56 or Data130	Compustat
ROA		Industry-median-adjusted ratio of operating income before depreciation (Data13) to total assets (Data6)	Compustat
Contract characteristics			
Facility amount	Millions USD	Size of the largest facility within loan package that starts at the loan origination date	DealScan
Log (Facility amount)		Natural logarithm of *Facility amount*	DealScan
Maturity	Months	*Maturity of the largest facility within loan package that starts at the loan origination date*	DealScan
Number of facilities		Number of facilities in the loan package	DealScan
Collateral	Dummy	*One if the loan is secured, zero otherwise*	DealScan
Financial covenants	Dummy	*One if the loan has financial covenants, zero otherwise*	DealScan
Prime base rate	Dummy	*One if the base rate is prime rate, zero otherwise*	DealScan
Performance pricing	Dummy	*One if the loan has performance pricing, zero otherwise*	DealScan
Lead bank characteristics			
Ranking		Lead arranger's ranking calculated using lead's market share based on the number of deals	DealScan
Δ Default probability standard deviation	%	Change in default probability standard deviation of the lead bank's loan portfolio calculated at the loan level using portfolio weights constructed from DealScan and Standard & Poor's CreditPro default correlation matrices	DealScan/S&P
Lending limit	Millions USD	Bank-specific variable defined as 75th size percentile of the loans issued over the past three years	DealScan
Syndicate characteristics			
Syndicate reputation: lead to participant		Maximum number of links between the lead bank and a member of the syndicate, scaled by the total number of deals arranged by the lead bank; this is a syndicate-specific measure calculated over a three-year horizon	DealScan
Syndicate reputation: Reciprocal	Dummy	One if over the past three years lead bank was a participant in a syndicate led by one of the current participants (i.e., lead banks and participant bank switched their roles), zero otherwise; this is a syndicate-specific measure	DealScan

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