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Finance Research Letters 38 (2021) 101485

Contents lists available at ScienceDirect

Finance Research Letters

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

How do banks finance R&D intensive firms? the role of patents in overcoming information asymmetry☆

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A R T I C L E I N F O

JEL Codes:
G21
G32
O32

Keywords:
Syndicated loan
Lead arranger
Innovation
Patent
Information asymmetry
Moral hazard

A B S T R A C T

We examine how banks finance R&D intensive firms, focusing on the role of patents in overcoming information asymmetry in bank lending. Consistent with moral hazard in due diligence and monitoring, we find that lead arrangers retain a larger share of syndicated loans when lending to R&D intensive firms. Patents can partly overcome moral hazard problems, as banks retain a smaller share of R&D intensive firms' loans if these firms have patents as a signal of the quality of their inventions. Our results are robust to alternative explanatory variable definitions and syndicate structure measures, different samples and subperiods, and difference-in-difference estimations.

1. Introduction

Innovation is critical to economic growth, but R&D intensive firms often struggle to obtain financing (Mann, 2018). Bank loans enable these firms to avoid costly dilution of ownership stakes, and are an important source of external capital (Kerr and Nanda, 2015). However, the market value of R&D intensive firms often rests on hard-to-value intangible assets that provide low collateral value, while their cash flows are volatile (Hochberg et al., 2018). Furthermore, the risk of innovation failure and the uncertain payoffs of R&D investments are important sources of information asymmetry, reducing R&D intensive borrowers' access to credit (Hu et al., 2017).

A complicating factor in bank lending is that many loans are "syndicated", meaning that multiple lenders jointly offer funds to a borrowing firm (Weidner, 2000). The loan's lead arranger is expected to perform due diligence on the borrower and monitor the loan. This is where moral hazard problems arise, as the monitoring efforts of the lead arranger as an informed lender are unobservable for the uninformed participant lenders. These moral hazard problems are compounded when there is more information asymmetry between the borrower and lender, and monitoring thus becomes more costly for the lead arranger. In these conditions, participating lenders require the lead arranger to retain a larger share of the loan, as only a bank with a sufficiently large stake in the borrower's performance will exert the necessary effort (see e.g., Dennis and Mullineaux, 2000; Kleimeier and Chaudhry, 2015; Simons, 1993; Sufi, 2007).

☆This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.
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https://doi.org/10.1016/j.frl.2020.101485
Received 7 August 2019; Received in revised form 13 January 2020; Accepted 5 March 2020
Available online 31 March 2020
1544-6123/

Extending the research by Sufi (2007), we investigate how banks finance R&D intensive firms, where moral hazard problems are prominent due to high information asymmetry. We test whether lead arrangers retain a larger share of the loan when firms are more R&D intensive, and whether patents can reduce the need to hold a larger stake by alleviating information asymmetry. Prior work shows that patents can help innovative firms signal the value of their inventions and reduce asymmetric information problems, thereby easing access to credit (Bhattacharya and Ritter, 1983; Francis et al., 2012; Hoffmann and Kleimeier, 2019; Hoffmann et al., 2019; Lin et al., 2017). In particular, prior research argues that patents provide tangible signals about the firm's ability to transform R&D investments into new and valuable knowledge (Talke et al., 2011).

Our research fills an important gap in the literature. On the one hand, prior research on bank lending and moral hazard problems approximated information asymmetry by considering whether a firms was private or unrated (Sufi, 2007), but did not investigate the unique challenges that banks face when information asymmetry is instead related to borrowers' innovativeness as defined by their R&D intensiveness. On the other hand, prior research on patents and debt financing (Hochberg et al., 2018; Hoffmann et al., 2019; Mann, 2018) examines how patents can affect innovative firms' access to and cost of debt finance, but left open the question of whether and how patents can reduce the need for lead arrangers to hold a larger share of syndicated loans that are made to R&D intensive firms in order to overcome moral hazard issues.

2. Data and methodology

We examine loans raised by public, non-financial U.S. borrowers between 1986 and 2016. We combine loan information from the Loan Pricing Corporation's DealScan database with company data from Compustat and patent data from the Worldwide Patent Statistical Database PATSTAT. We start with all U.S. loans in DealScan for which detailed lender information is available. To differentiate between loans to R&D intensive vs. non-R&D intensive firms, we restrict our sample to loans raised by public borrowers with information on R&D expenses in Compustat. Finally, we obtain the annual number of applied for and granted patents from PATSTAT. Following prior literature (e.g., Atanassov, 2013), we do not exclude borrowers without patents, but instead set the patent count to zero when no patent information is available. Patent and borrower variables are observed in the year before loan signing (see Francis et al., 2012). Our final sample includes 5739 loans raised by 1810 unique borrowers. Table 1 defines all variables and lists data sources.

For our dependent variable, we consider various syndicate structure proxies. First, we code a bilateral loan dummy for loans funded by a single lender and a dummy for loans for which the syndicate consists of lead arrangers only. In line with Sufi (2007), these two loan types are corner solutions to the asymmetric information problem and are thus included in our sample. Second, we count the number of lead arrangers, participants, and total lenders and use these as alternative measures. Third, we measure the lending share of the lead arrangers as the mean and maximum lending share across all lead arrangers and the Hirschman-Herfindahl-Index (HHI).

We identify R&D intensive firms based on the level of their R&D expenses. Specifically, a higher ratio of *R&D to assets* indicates a more R&D intensive firm. Alternatively, acknowledging that the distribution of R&D intensity is skewed to the right, we follow Coles et al. (2008) and consider firms to be R&D intensive if their R&D to assets ratio is above the 75th percentile for the universe of U.S. firms in Compustat during our sample period. Accordingly, our *High R&D to assets* dummy equals 1 if the borrower's R&D to assets ratio exceeds 11%, and 0 otherwise.[1] This choice of a common threshold for all firms – rather than, for example, an industry-specific threshold – is consistent with the empirical finance literature (see e.g., Coles et al., 2008; Custódio et al., 2013; Eberhart et al., 2008; Franzen and Radhakrishnan, 2009) and reflects our view that it is the absolute, and not the relative, level of information asymmetry that determines a bank's moral hazard problem and ultimately affects the syndicate structure.

We count the borrower's annual patent applications and define our main patent proxy Ln*(1+Patents)* as the natural logarithm of 1 plus the number of annual patent applications. According to Griliches (1990) and Hall et al. (2001), the year of the patent application reflects the actual timing of innovation. For robustness checks, we limit the number of patents to those that were eventually granted and define Ln*(1+Granted Patents)* accordingly.[2]

We assess several alternative mechanisms which Sufi (2007) shows to be effective in overcoming information asymmetry and moral hazard. First, we measure borrower reputation by differentiating between first-time and repeat borrowers. For repeat borrowers, monitoring is less costly, moral hazard is lower, and lead arrangers can thus hold smaller lending shares. Second, we determine lead arranger reputation based on its market share. With its reputation at stake, a lead arranger is less likely to shirk from monitoring and can hold a smaller lending share. Third, we consider the existence of a historic lending relationship. In relationship lending, lead arrangers are bettter informed about the borrower, face lower monitoring cost, and can consequently hold smaller lending shares.

We include borrower-specific and loan-specific control variables. We follow Sufi's (2007) specification for public borrowers including *Sales, Income to assets, Leverage ratio*, and industry fixed effects. Loan-specific control variables capture loan amount,

[1] For robustness, we also consider alternative cutoff levels ranging from 5% to 15% of *R&D to assets* (see Table A1 in the Online Appendix). Results indicate that our preferred model specification of Column (9) in Table 4 is robust in the range from 7% to 12% of *R&D to assets*. At levels below 7%, we misclassify non-R&D intensive borrowers as R&D intensive. At levels above 12%, our sample contains too few R&D intensive firms to deliver statistical significance.

[2] Our sample covers loans from June 1986 to April 2016, and we match loans raised in year *t* to patent applications in year *t-1*. Regarding granted patents, Hall et al. (2001) document an average granting time of 2 years. By using the autumn 2017 version of PATSTAT, we allow for a minimum granting period of 2.5 years and avoid the potential problem that later patent applications might still be under revision. Results are reported in Table A2 in the Online Appendix and indicate that our preferred specification of Column (9) in Table 4 is robust to the use of the Ln*(1+Granted Patents)* proxy.

Table 1
Variable definition and sources.

Category & variable	Definition	Units	Source
Syndicate structure			
Bilateral loan	Dummy equal to 1 if loan is bilateral, e.g. has a single lender, 0 otherwise	0/1	DealScan
Loan with lead arrangers only	Dummy equal to 1 if all lenders are lead arrangers, 0 otherwise	0/1	DealScan
Number of lead arrangers	Number of lead arrangers in syndicate	integer	DealScan
Number of participants	Number of participants in syndicate	integer	DealScan
Number of lenders	Total number of lenders in syndicate	integer	DealScan
% Held by Lead - mean	Lending share of lead arranger, average across all lead arrangers	percent (1.0 = 1%)	DealScan
% Held by Lead - max	Lending share of lead arranger, maximum across all lead arrangers	percent (1.0 = 1%)	DealScan
% Held by Lead - HHI	Lending share of lead arranger, HHI index across all lead arrangers	index (0 to 10,000)	DealScan
Management of information asymmetry			
# patents	Number of patent applications made by the borrower in year before loan signing	integer	PATSTAT
# granted patents	Number of patent applications made by the borrower in year before loan signing that are eventually granted	integer	PATSTAT
# previous loans by borrower	Number of loans raised by the borrower in the 36 months prior to loan signing	integer	DealScan (authors' calculations)
Lead is former lead for borrower	Dummy equal to 1 if at least one of the current lead arrangers has arranged a loan for the borrower in the 36 months prior to loan signing, 0 otherwise	0/1	DealScan (authors' calculations)
Market share of lead arranger	Market share of lead arranger in year before loan signing with market share based on loan volume, average across all lead arrangers	percent (1.0 = 100%)	DealScan (authors' calculations)
Borrower characteristics			
Sales	Sales in year before loan signing	$m	Compustat
Total assets	Total assets in year before loan signing	$m	Compustat
R&D to assets	R&D expenses divided by total assets in year before loan signing	ratio	Compustat
High R&D to assets	Dummy equal to 1 if R&D to assets ratio in year before loan signing is above the 75th percentile in the Compustat universe of U.S. non-financial borrowers during the sample period (this is equivalent to R&D to assets above 11%), 0 otherwise	0/1	Compustat
Income to assets	Income before extraordinary items divided by total assets in year before loan signing	ratio	Compustat
Leverage ratio	Sum of long-term debt and current portion of long-term debt divided by total assets in year before loan signing	ratio	Compustat
Loan characteristics			
Loan amount	Size of the loan tranche	$m	DealScan
Loan maturity	Maturity of the loan tranche	months	DealScan
Multi-loan deal	Dummy equal to 1 if loan tranche belongs to a multi-tranche deal, 0 otherwise	0/1	DealScan
Term loan	Dummy equal to 1 if loan tranche is a term loan, 0 otherwise	0/1	DealScan
Fixed effects			
Loan purpose	Loan purpose categories are working capital, acquisition, refinancing & general purposes, commercial paper backup, other	0/1	DealScan
Loan amount	Loan size categories are small, middle, and large and reflect the bottom, middle, and top annual in-sample loan size tercile	0/1	DealScan (authors' calculations)
Year	Year of loan signing	0/1	DealScan
Industry	2-digit SIC code	0/1	Compustat

maturity, purpose, type, and signing year.

For our bilateral loan and lead arranger-only dummy variables, we estimate probit regressions. For the number of lead arrangers, participants and total lenders, we estimate poisson regressions, as these dependent variables are count variables. For the lead arranger's mean, maximum or HHI lending share, we estimate tobit regressions, as these dependent variables are censored variables. We infer statistical significance based on robust standard errors clustered at the borrower level.[3]

Table 2 reports descriptive statistics. On average, loans to R&D intensive firms are more likely to be funded by a single lender or lead arrangers only. Regarding syndicate size, R&D intensive firms' loan syndicates contain fewer particpants. Consequently, lead arrangers hold larger, more concentrated lending shares when lending to R&D intensive firms. Compared to non-R&D intensive borrowers, loans made to R&D intensive borrowers are raised by firms that spend more on R&D, apply for more patents, and have a higher success rate in terms of granted patents.[4] Moreover, these loans are of smaller size and shorter-term, and are raised by smaller firms that have less experience as previous borrowers.

3. Results

Table 3 presents our baseline results. Columns (1) to (4) show that loans to R&D intensive firms are more likely to be bilateral or only involve lead arrangers. This result supports our decision to not exclude bilateral and lead arranger-only loans from our sample. Columns (5) to (10) indicate that loans to R&D intensive firms also involve fewer participants and consequently a smaller number of total lenders. Finally, Columns (11) to (16) demonstrate that for R&D intensive firms, lead arrangers need to retain a larger lending share. This result is robust for alternative lending share measures. Taken together, these results are consistent with moral hazard problems being higher when lending to R&D intensive firms. To indicate to participant lenders that they will exert satisfactory due diligence and monitoring efforts, lead arrangers have to demonstrate more "skin in the game".

Table 4 examines ways to overcome information asymmetry. From hereon, we focus on the mean level of lending share as dependent variable and the *High R&D to assets* dummy as our measure of a firm's R&D intensiveness. Consistent with Sufi (2007), Columns (1), (3), and (5) indicate that lead arranger reputation, borrower reputation, and lending relationships mitigate information assymmetry problems, and allow the lead arranger to retain a smaller share of the loan. Importantly, however, and extending Sufi's (2007) results, Columns (2), (4), and (6) show that these mechanisms are not effective in overcoming the higher information asymmetry banks face when lending to R&D intensive firms.

In Columns (7) and (8) of Table 4, we investigate the role of patents. Column (7) indicates that in general, patents require lead arrangers to retain a marginally larger lending share. When adding the interaction of patents with being an R&D intensive firm in Column (8), we find that the direct and positive effect of patents on lending share is limited to non-R&D intensive firms. For R&D intensive firms, in contrast, a higher number of patents allows lead arrangers to retain a smaller share of the loan. These results can be explained as follows. Interpreting the information content of patents requires considerable effort from the lead arranger. For non-R&D intensive borrowers, the presence of patents might be considered inconsistent with the firm's strategic innovation orientation (Talke et al., 2011). Accordingly, patents increase moral hazard problems associated with information asymmetry and require lead arrangers to hold a larger lending share. In contrast, for R&D intensive borrowers, patents represent tangible outputs of the firm's strategic innovation orientation (Griliches, 1990) which help value its intangible assets and enhance cash flow predictability, easing the lead arranger's due diligence and monitoring burden. In sum, the results suggests that for banks arranging loans for R&D intensive firms, patents represent the only effective signal to reduce information asymmetry and ease moral hazard problems.

[3] Our model estimation might suffer from endogeneity problems related to, for example, reverse causality, simultaneity, omitted variables, or selection bias. First, we do not consider reverse causality or simultaneity to be a major concern in our estimation, as it is unlikely that a borrower's decisions to invest in R&D or file patents are a direct function of the loan's syndicate structure. Nevertheless, we measure all proxies for borrower characteristics and for management of information asymmetry *prior* to loan signing in order to alleviate any potential reverse causality concerns. Second, to reduce potential omitted variables concerns, we include a large number of control variables and fixed effects. Nevertheless, we conduct two robustness checks by adding additional fixed effects to our preferred specification of Column (9) in Table 4: (1) Given our focus on information asymmetry, our empirical model follows Sufi (2007). However, other empirical syndicate structure models include credit risk proxies as independent variables to capture time-varying differences in borrower risk (see e.g., Gatev & Strahan, 2009; Lin et al., 2012). Our results are robust to adding credit risk fixed effects and are reported in Table A3 in the Online Appendix. (2) We add borrower fixed effects which capture any potentially relevant, yet omitted time-invariant borrower characteristics and transform our estimation into a difference-in-difference (DID) setting. This DID model is estimated as an OLS. We must restrict our sample to borrowers who raise loans in at least two years. We furthermore restrict the DID sample to loans made to a control and treatment group. The control group includes only non-R&D intensive borrowers for whom the *High R&D to assets* dummy is always 0. The treatment group includes borrowers who switch from non-R&D intensive to R&D intensive or vice versa. Results are robust and reported in Table A4 of the Online Appendix. Third, when constructing our sample, we note that a substantial fraction of borrowers does not report R&D expenses in the year before loan signing. Excluding loans raised by these borrowers might lead to a selection bias. To reduce such a potential bias, we first include loans to borrowers with missing *R&D to assets* in our sample, and categorize these borrowers as non-R&D intensive. Second, we replace missing values for *R&D to assets* in the year before loan signing with the average *R&D to assets* across all fiscal years which are available in Compustat and code our *High R&D to assets* dummy based on this average. In both cases, we add a *Missing R&D to assets* dummy to our independent variables. Results are robust and reported in Table A5 of the Online Appendix. Taken together, we do not believe that endogeneity problems represent a concern.

[4] As R&D intensive borrowers apply for more patents, the R&D intensive firm and patent measures are positively correlated. However, multicollinearity is not a concern in our regression sample as correlations are low, ranging from 0.08 to 0.13.

Table 2
Descriptive statistics.

	Panel A: All loans (N = 5739)					Panel B: Loans to R&D intensive borrowers (N = 768)					Panel C: Loans to non-R&D intensive borrowers (N = 4971)				
			Distribution					Distribution					Distribution		
	Mean	SD	10th	50th	90th	Mean	SD	10th	50th	90th	Mean	SD	10th	50th	90th
Syndicate structure															
$D = 1$ if loan is bilateral	0.36	0.48	0	0	1	0.73	0.45	0	1	1	0.31	0.46	0	0	1
$D = 1$ if loan with lead arrangers only	0.38	0.48	0	0	1	0.74	0.44	0	1	1	0.32	0.47	0	0	1
Number of lead arrangers	1.39	1.15	1	1	2	1.09	0.43	1	1	1	1.44	1.22	1	1	2
Number of participants	5.96	8.57	0	2	17	1.49	4.14	0	0	5	6.65	8.87	0	4	18
Number of lenders	7.35	8.98	1	4	19	2.58	4.31	1	1	7	8.09	9.28	1	5	20
% Held by Lead - Mean	52.24	39.02	9	40	100	82.44	31.06	23	100	100	47.58	38.03	8	31	100
% Held by Lead - Max	52.67	38.94	9	40	100	82.58	30.90	23	100	100	48.05	37.99	9	32	100
% Held by Lead - HHI	4383.62	4434.54	128	1736	10,000	7823.83	3744.43	625	10,000	10,000	3852.12	4292.87	111	1225	10,000
Management of information asymmetry															
# patents	13.38	62.60	0	0	23	16.64	71.55	0	1	30	12.87	61.09	0	0	22
# granted patents	11.92	55.89	0	0	20	15.58	68.27	0	1	27	11.35	53.71	0	0	19
# previous loans by borrower	1.58	1.92	0	1	4	0.97	1.78	0	0	3	1.68	1.92	0	1	4
Lead is former lead for borrower	0.39	0.49	0	0	1	0.24	0.43	0	0	1	0.41	0.49	0	0	1
Market share of lead arranger	0.05	0.06	0.00	0.02	0.15	0.02	0.05	0.00	0.00	0.08	0.05	0.06	0.00	0.02	0.15
Borrower characteristics															
Sales ($m)	4020.36	16,160.65	30.08	483.25	7132.65	536.60	1842.66	5.79	65.52	1146.95	4558.59	17,286.84	44.29	624.48	8344.20
Total assets ($m)	3902.05	17,005.79	25.73	385.27	7006.00	569.97	2115.83	10.22	67.51	1086.00	4416.85	18,199.29	35.01	505.70	8289.00
R&D to assets	0.05	0.10	0.00	0.02	0.13	0.23	0.17	0.12	0.17	0.40	0.02	0.03	0.00	0.01	0.06
Income to assets	0.00	0.47	−0.11	0.04	0.12	−0.18	0.45	−0.71	−0.02	0.15	0.03	0.47	−0.05	0.05	0.12
Leverage ratio	0.26	0.28	0.01	0.23	0.52	0.15	0.22	0.00	0.08	0.38	0.28	0.28	0.02	0.25	0.53
Loan characteristics															
Loan amount ($m)	339.51	1018.37	4.00	70.00	800.00	72.69	240.61	1.50	10.00	175.00	380.73	1084.29	5.00	100.00	910.00
Loan maturity (months)	41.87	24.77	12.00	37.00	61.00	30.74	21.79	11.00	24.00	60.00	43.59	24.76	12.00	46.00	63.00
Multi-loan deal	0.43	0.50	0	0	1	0.39	0.49	0	0	1	0.44	0.50	0	0	1
Term loan	0.24	0.43	0	0	1	0.27	0.44	0	0	1	0.23	0.42	0	0	1

This table provides descriptive statistics for our sample of 5739 loans raised from 1986 to 2016 by 1810 public U.S. non-financial borrowers. R&D intensive borrowers are firms with an R&D to assets ratio above the 75th percentile in the Compustat universe of U.S. non-financial borrowers during the sample period (this is equivalent to R&D to assets above 11%).

Table 3
Syndicate structure and borrower R&D intensiveness.

Dependent variable	$D = 1$ if bilateral loan		$D = 1$ if loan with lead arrangers only		Number of lead arrangers		Number of participants		Number of Lenders		% Held by Lead					
											Mean		Max		HHI	
Methodology	Probit (1)	Probit (2)	Probit (3)	Probit (4)	Poisson (5)	Poisson (6)	Poisson (7)	Poisson (8)	Poisson (9)	Poisson (10)	Tobit (11)	Tobit (12)	Tobit (13)	Tobit (14)	Tobit (15)	Tobit (16)
R&D to assets	0.62		0.87		0.12		−1.65		−0.61**		42.02***		42.02***		5161.28***	
	(1.18)		(1.54)		(0.99)		(−3.17)		(−2.42)		(2.81)		(2.78)		(2.75)	
High R&D to assets		0.27**		0.26**		−0.00		−0.21**		−0.14**		10.33***		10.48***		1249.42***
		(2.57)		(2.50)		(−0.03)		(−2.41)		(−2.53)		(3.81)		(3.85)		(3.68)
Income to assets	−0.03	−0.04	−0.05	−0.09	0.00	−0.00	0.18	0.22	0.03	0.03	−0.95	−2.64	−0.91	−2.61	−251.26	−533.73
	(−0.21)	(−0.27)	(−0.31)	(−0.53)	(0.21)	(−0.12)	(0.84)	(1.02)	(0.79)	(0.95)	(−0.32)	(−0.45)	(−0.29)	(−0.44)	(−0.35)	(−0.79)
Leverage ratio	−0.15	−0.13	−0.20	−0.19	0.03	0.02	0.35***	0.36***	0.26***	0.26***	−7.85**	−7.80**	−7.63**	−7.56**	−779.73**	−779.46**
	(−1.18)	(−1.01)	(−1.59)	(−1.52)	(0.59)	(0.40)	(3.21)	(3.38)	(2.91)	(2.93)	(−2.40)	(−2.40)	(−2.32)	(−2.31)	(−2.04)	(−2.06)
Ln[firm sales]	−0.03	−0.03	−0.01	−0.02	0.06**	0.06**	0.12***	0.12***	0.10***	0.10***	−2.45***	−2.55***	−2.54***	−2.62***	−203.75**	−214.35**
	(−0.92)	(−0.91)	(−0.45)	(−0.50)	(2.10)	(2.11)	(5.71)	(5.75)	(5.98)	(6.01)	(−3.19)	(−3.32)	(−3.26)	(−3.38)	(−2.21)	(−2.32)
Ln[loan amount]	−0.78***	−0.78***	−0.77***	−0.77***	−0.08***	−0.08***	0.94***	0.94***	0.34***	0.34***	−25.66***	−25.47***	−25.75***	−25.55***	−3240.15***	−3217.19***
	(−11.79)	(−11.78)	(−11.77)	(−11.77)	(−4.01)	(−4.00)	(16.77)	(16.91)	(13.48)	(13.39)	(−16.18)	(−16.14)	(−16.10)	(−16.05)	(−16.87)	(−16.82)
Ln[loan amount] x middle	0.04	0.04	0.02	0.02	0.09***	0.10***	−0.26***	−0.26***	0.18***	0.17***	3.62**	3.61**	3.86**	3.85**	744.19***	744.11***
	(0.59)	(0.56)	(0.26)	(0.26)	(4.90)	(5.06)	(−5.19)	(−5.34)	(7.00)	(6.92)	(2.41)	(2.41)	(2.55)	(2.55)	(4.07)	(4.09)
Ln[loan amount] x large	0.52***	0.52***	0.52***	0.52***	0.17***	0.18***	−0.63***	−0.64***	−0.06**	−0.06**	20.59***	20.61***	20.68***	20.69***	2835.43***	2838.34***
	(6.04)	(6.01)	(6.67)	(6.66)	(8.65)	(8.90)	(−11.94)	(−12.21)	(−2.16)	(−2.25)	(13.82)	(13.92)	(13.78)	(13.88)	(16.05)	(16.19)
Ln[loan maturity]	−0.26***	−0.26***	−0.30***	−0.30***	0.03**	0.03**	0.17***	0.17***	0.14***	0.14***	−7.67***	−7.63***	−7.63***	−7.59***	−866.22***	−860.83***
	(−5.97)	(−5.89)	(−6.71)	(−6.66)	(2.13)	(2.08)	(6.88)	(6.92)	(7.28)	(7.32)	(−7.75)	(−7.77)	(−7.69)	(−7.71)	(−7.45)	(−7.41)
Multi-loan deal	−0.64***	−0.64***	−0.63***	−0.63***	0.11***	0.11***	0.42***	0.42***	0.37***	0.37***	−13.99***	−13.98***	−13.75***	−13.74***	−1511.07***	−1509.77***
	(−8.94)	(−8.89)	(−9.08)	(−9.05)	(3.59)	(3.59)	(13.47)	(13.50)	(14.64)	(14.62)	(−10.77)	(−10.74)	(−10.47)	(−10.44)	(−9.49)	(−9.46)
Term loan	0.28***	0.28***	0.30***	0.31***	−0.04	−0.04	−0.02	−0.02	−0.03	−0.03	6.50***	6.60***	7.44***	7.54***	801.13***	811.94***
	(3.73)	(3.76)	(4.19)	(4.23)	(−1.29)	(−1.28)	(−0.49)	(−0.53)	(−0.89)	(−0.91)	(3.82)	(3.90)	(4.28)	(4.35)	(3.92)	(3.97)
N	5739	5739	5739	5739	5739	5739	5739	5739	5739	5739	5739	5739	5739	5739	5739	5739
of which left censored											69	69	69	69	69	69
of which right censored											2104	2104	2111	2111	2111	2111
Pseudo R^2	0.548	0.549	0.539	0.539	0.108	0.108	0.606	0.606	0.558	0.558	0.147	0.148	0.145	0.145	0.076	0.076

The table reports the regressions with different syndicate structure measures as dependent variables. For each independent variable, the top row reports the estimated coefficient, the bottom row reports t-statistics. All regressions include fixed effects for loan purpose, loan size, borrower industry, and year. Standard errors are robust and clustered at the borrower level.

*** 1% significance,

** 5% significance, * 10% significance.

Table 4
Overcoming information asymmetry.

Dependent variable	% Held by Lead - Mean								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
High R&D to assets	10.24***	11.06***	10.07***	11.69***	10.18***	11.96***	9.79***	14.40***	14.25***
	(3.78)	(3.18)	(3.72)	(3.45)	(3.79)	(3.97)	(3.57)	(3.81)	(3.82)
Market share of lead arranger	−36.52***	−35.26***							−33.25***
	(−3.71)	(−3.49)							(−3.39)
Market share of lead arranger * High R&D to assets		−20.25							
		(−0.58)							
Ln[1+# previous loans by borrower]			−4.19***	−3.96***					−1.48
			(−3.91)	(−3.60)					(−1.19)
Ln[1+# previous loans by borrower] * High R&D to assets				−2.72					
				(−0.65)					
Lead is former lead for borrower					−7.55***	−7.10***			−6.24***
					(−6.15)	(−5.69)			(−4.40)
Lead is former lead for borrower * High R&D to assets						−5.44			
						(−1.17)			
Ln[1+# patents]							0.77*	1.14**	1.10**
							(1.75)	(2.51)	(2.43)
Ln[1+# patents] * High R&D to assets								−2.80**	−2.88**
								(−2.18)	(−2.24)
Income to assets	−2.28	−2.09	−2.44	−2.16	−2.38	−2.15	−2.45	−2.07	−1.45
	(−0.40)	(−0.37)	(−0.41)	(−0.37)	(−0.41)	(−0.37)	(−0.42)	(−0.37)	(−0.27)
Leverage ratio	−7.48**	−7.40**	−6.04*	−6.02*	−7.03**	−7.00**	−7.63**	−7.49**	−5.95*
	(−2.27)	(−2.25)	(−1.83)	(−1.82)	(−2.15)	(−2.13)	(−2.35)	(−2.30)	(−1.77)
Ln[borrower sales]	−2.37***	−2.37***	−2.11***	−2.09***	−2.22***	−2.20***	−2.75***	−2.68***	−2.09***
	(−3.09)	(−3.09)	(−2.73)	(−2.71)	(−2.88)	(−2.85)	(−3.46)	(−3.37)	(−2.59)
Ln[loan amount]	−25.21***	−25.19***	−25.26***	−25.24***	−25.36***	−25.38***	−25.50***	−25.45***	−25.05***
	(−16.08)	(−16.06)	(−16.14)	(−16.13)	(−16.15)	(−16.18)	(−16.14)	(−16.06)	(−16.02)
Ln[loan amount] x middle	3.71**	3.70**	3.39**	3.37**	3.63**	3.63**	3.62**	3.56**	3.59**
	(2.50)	(2.50)	(2.28)	(2.27)	(2.45)	(2.45)	(2.42)	(2.38)	(2.44)
Ln[loan amount] x large	20.66***	20.62***	20.52***	20.47***	20.76***	20.74***	20.50***	20.15***	20.28***
	(14.11)	(14.06)	(13.85)	(13.81)	(14.14)	(14.12)	(13.82)	(13.50)	(13.81)
Ln[loan maturity]	−7.53***	−7.52***	−7.82***	−7.82***	−7.82***	−7.82***	−7.63***	−7.60***	−7.72***
	(−7.67)	(−7.66)	(−7.96)	(−7.97)	(−7.99)	(−8.00)	(−7.77)	(−7.73)	(−7.88)
Multi-loan deal	−13.73***	−13.76***	−13.56***	−13.60***	−13.71***	−13.73***	−14.02***	−14.15***	−13.56***
	(−10.53)	(−10.56)	(−10.28)	(−10.29)	(−10.56)	(−10.57)	(−10.77)	(−10.87)	(−10.30)
Term loan	6.32***	6.32***	7.07***	7.03***	6.71***	6.66***	6.62***	6.78***	6.80***
	(3.77)	(3.76)	(4.22)	(4.20)	(4.00)	(3.97)	(3.91)	(4.01)	(4.13)
N	5739	5739	5739	5739	5739	5739	5739	5739	5739
of which left censored	69	69	69	69	69	69	69	69	69
of which right censored	2104	2104	2104	2104	2104	2104	2104	2104	2104
Pseudo R^2	0.148	0.148	0.148	0.148	0.149	0.149	0.148	0.148	0.150

The table reports the results of tobit regressions. For each independent variable, the top row reports the estimated coefficient, the bottom row reports t-statistics. All regressions include fixed effects for loan purpose, loan size, year of loan signing and borrower industry. Standard errors are robust and clustered at the borrower level.

*** 1% significance,.
** 5% significance,.
* 10% significance.

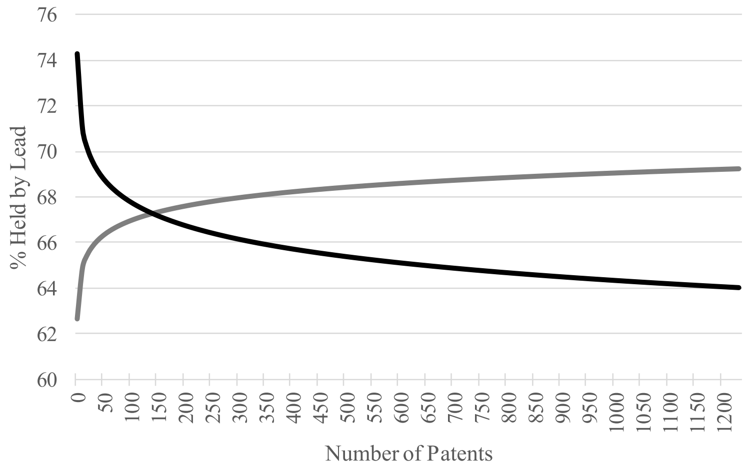

Fig. 1. Lead arranger's lending share as a function of patents.

Column (9) of Table 4 indicates that the previous result is robust to simultanously including the other lead arranger and borrower reputation as well as relationship banking measures.[5] Fig. 1. graphically depicts the predicted lending share of the lead arranger for R&D intensive and non-R&D intensive firms, respectively. This figure indicates that for loans to R&D intensive firms, a sufficiently high number of patents allows lead arrangers to substantially reduce their lending share. Indeed, when reaching the right-hand tail of the patent distribution in our sample, the lending share for loans made to R&D intensive firms almost approximates that of non-R&D intensive firms without any patents.[6]

4. Conclusion

Bank loans are an important source of finance for innovative firms, but involve moral hazard problems driven by a heightened level of information asymmetry between the borrower and lender. We find that in syndicated loan arrangements, lead arrangers need to retain a larger share of the loan when an innovative borrower (i.e., R&D intensive firm) is involved, but show that patents can overcome this necessity. By retaining a larger lending share, lead arrangers signal to participant lenders their incentive to exert the necessary effort in due diligence and monitoring of borrowers with high information asymmetry. However, patents are a signal of succesful outcomes of the otherwise intangible innovation process, reducing a borrower's cash flow volatility and R&D payoff uncertainty, suggesting that less due diligence and monitoring efforts are required and moral hazard is lower.

CRediT authorship contribution statement

Arvid O.I. Hoffmann: Conceptualization, Methodology, Writing - original draft, Writing - review & editing. **Stefanie Kleimeier:** Conceptualization, Methodology, Writing - original draft, Writing - review & editing, Investigation, Formal analysis.

Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.frl.2020.101485.

[5] This figure shows the in-sample, predicted lending share of the lead arranger based on Column (9) of Table 4. The black line indicates the predicted lending share for loans to R&D intensive borrowers, the grey line indicates the prediced lending share for loans to non-R&D intensive borrowers. The x-axis is scaled to range from the in-sample minimum to maximum number of patents (e.g. 0 to 1,233 patents).

[6] We provide additional robustness checks of our preferred specification of Column (9) of Table 4. First, we verify that the results are robust for the maximum lending share and HHI across all lead arrangers. Second, we acknowledge that the coverage of the DealScan database is limited in the early years of our sample period. To avoid potential biases in borrower selection, we exclude loans signed before 1990. Again, results are robust. Third, during the sample period, the American Inventors Protection Act (AIPA) was implemented. AIPA requires U.S. patent applications filed on and after November 29, 2000 to be published 18 months after the application date. Hoffmann et al. (2019) argue that post-AIPA, patents are a better proxy for successful innovation activity than pre-AIPA, as the mandatory disclosure gives firms an incentive to only apply for patents if commercial success is likely. Thus, our results might be driven by the post-AIPA period only. We split our sample period in a pre- and post-AIPA period and demonstrate that the results are robust across these two subperiods. All of these robustness checks are reported in Tables A6 and A7 of the Online Appendix.

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