Bank Lending and Strategic R&D Disclosure

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This paper examines the relationship between research and development expense classifications and loan spread in the syndicated loan market. Five percent of the firms used do not report any R&D expense information on Compustat, but still file for patents during a given year. I show that these firms on average pay up to 17 basis points less in loan spread compared to otherwise similar firms that disclose R&D. Banks with less lending experience in a given industry are more likely to lend at lower rates relative to banks with more experience, suggesting that experienced banks see through the hidden R&D expenses. These findings suggest that banks perceive R&D expenses as a risk factor and that some firms benefit from strategically classifying R&D expenses into other expense categories.

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1. Introduction

Businesses undertake research and development (R&D) projects in hopes of boosting future profitability and often disclose these high-risk projects in their financial statements and through other means to obtain external financing. In this paper, I investigate to what extent banks, a leading source of external financing, consider the disclosure choices of firms to provide information above and beyond what is disclosed. While Koh and Reeb (2015) find that managers can exercise discretion over what expenses to classify as R&D and hence, missing R&D reflects discretionary choices of the managers, rather than zero or immaterial corporate R&D, they do not provide any reasons for such discretionary R&D reporting. In this paper, I study whether garbling R&D expenses with other expenses prevent banks from pricing loan contracts properly.

R&D investments help companies innovate. Pharmaceutical companies develop new drugs and treatments, and technology companies create new systems and products that may revolutionize and improve how the world works, while still other firms use R&D to improve their processes in order to gain efficiency or create products they think will become future cash cows. However, these potential future benefits come with some degree of uncertainty. For example, in the pharmaceutical industry only one out of every 10,000 new compounds discovered in the laboratory ultimately become commercial drugs [see Pisano and Wheelwright (1995)]. Prior research documents a positive association between R&D and equity value. However, R&D investments may have different impacts on equity and debt valuation. R&D investments increase the mean of the firm's future cash flow distribution which impacts equity and debt in the same direction. However, such investments also increase the variance of the expected future cash flow distribution which impacts equity and debt in the opposite direction. Shi (2003) investigates this trade-off between the future benefit versus riskiness of R&D investments in order to determine which effect dominates within the bond market. He documents significant positive associations between R&D investments and bond default risks, concluding that R&D risk dominates the relative benefits for creditors. In contrast, Eberhart et al. (2008) point out that the association between bond loan spread and R&D investment changes signs from positive to negative when R&D intensity is measured using either sales or total assets as the deflator. However, more recently consistent with the findings of Shi (2003), Ciftci and Darrough (2016) find a positive association between loan spread and R&D suggesting that the riskiness of R&D outweighs its benefits for private lenders. Lenders therefore require a premium for bearing the higher risks of lending to firms reporting R&D expenses, which may motivate some firms to strategically classify R&D expenses into other expense categories.

Evidence for such managerial discretion is provided by Koh and Reeb (2015) who argue that managers can exercise discretion over which expenses to classify as R&D so that missing R&D reflects managers' discretionary choices, rather than either zero or immaterial corporate R&D. They find that 10.5 percent of firms listed as missing R&D receive patents (pseudo blank R&D firms) and that missing R&D firms file approximately 14 times more patents than zero R&D firms, suggesting that firms may not always disclose R&D expense separately. They more importantly find that these pseudo blank R&D firms are much more likely to report R&D expenses after forced auditor changes. This underscores the conclusion that, "missing R&D is not an accidental outcome but instead, a deliberate firm choice." (p. 92)

I investigate a rationale behind this discretionary reporting of R&D expenses within the context of bank loan contracts. Specifically, I examine whether the cost of debt is a potential reason for some firms' non-disclosure of R&D expenses. The intuition here is twofold. First, there must be some benefit that firms derive by not disclosing R&D expenses. Why would a firm bother not disclosing R&D expenses in financial statements if there is no benefit? Second, the cost of debt is primarily driven by the probability of default and estimated liquidation value of the loan. The disclosure of R&D expenses can potentially affect both a firm's perceived default risk and the estimated loan liquidation value. Disclosure may affect the former because as in Shi (2003) and Ciftci and Darrough (2016), I expect a positive association between R&D expenses and perceived firm riskiness. Disclosure may affect the latter because R&D investment is "intangible" and the benefits of R&D projects are usually very specialized to their current owners; such investments do not hold significant liquidation value, i.e., the liquidation costs are high. Alderson and Betker (1996) report a positive association between liquidation costs and R&D expenses. Taken together, I argue that the disclosure of R&D expenses is an important determinant of the loan spread at which the bank is willing to provide a loan since the disclosure of

R&D expenses may increase a firm's perceived default risk and decrease the estimated loan liquidation value.

Using loan pricing data from 1987 to 2009, I estimate the relationship between the non-disclosure of R&D expenses and the cost of debt. I find that pseudo blank R&D firms on average save up to 17 basis points in loan spread compared to control firms. This effect is economically large; in cash terms this 17 basis point difference corresponds to over US $833,680 in lower financing costs per year for pseudo blank R&D firms versus control firms. Next, I investigate whether or not lenders' industry-specific experience enables banks to "see through" these hidden R&D expenses. Banks are considered superior in accessing and processing information regarding their clients (Diamond, 1991; Bharath et al., 2008). In the syndicated loan setting explored in this study, banks typically have access to a borrower's private information. Moreover, patents are public information. How then do banks with better information accessing and processing capabilities not see through the hidden R&D expenses of pseudo blank R&D firms? A bank's experience within a given industry may be a crucial factor in determining whether or not it sees through this hidden R&D. Not all banks have same level of experience operating within all industries. Banks may differ in their abilities to access and process information regarding a potential borrower based on the bank's experience in a given industry. I expect that more experienced banks are better able to see through the hidden R&D of pseudo blank R&D firms and charge higher loan spreads considering the higher riskiness of pseudo blank R&D firms compared to less experienced banks. Consistent with this prediction, I find that pseudo blank R&D firms pay eight-to-ten percent more in loan spread when banks are experienced in lending to the pseudo blank R&D firm's industry, compared to a less experienced bank.

This paper contributes to the existing literature by exploring the effects of discretionary reporting choices on the cost of debt, with a focus on how the practice of strategic R&D expense obfuscation first documented by Koh and Reeb (2015) relate to the interest rate on syndicated loans. Specifically, while Koh and Reeb (2015) find that missing R&D is a deliberate firm choice, they do not provide any explanation as to why firms make such discretionary R&D reporting choices. The main contribution of this paper is that it provides an explanation for such discretionary choices by documenting that such firms get cheaper loans compared to control firms. The direct consequence of lower cost of debt to pseudo blank R&D firms is that banks are losing interest revenue from an average pseudo blank R&D firms to the tune of hundreds of thousands of US dollars. Banks can respond to this issue by carefully considering all public and private information about the borrower in pricing the loan.

This study is related to the literature examining the effects of innovation on loan pricing. Francis et al. (2012) and Chava et al. (2015) report a negative association between innovative firm activity and the cost of debt. My results suggest that lenders fail to evaluate the "true innovativeness" of some firms, charging a lower spread on loans made to otherwise similar firms that do not report R&D expenses. This study also relates to the literature analyzing the impact of lending expertise on loan pricing by showing that experienced banks see through the hidden R&D of pseudo blank R&D firms, accordingly charging higher loan spreads versus less experienced banks. This finding suggests that banks with significant experience operating within a given industry are well-versed in the reporting practices of firms within that industry; such banks are therefore able to identify pseudo blank R&D firms and price their loans accordingly. This finding is broadly similar to that of Bharath et al. (2011) showing that lending relationships play an important role in reducing the information asymmetry between lenders and borrowers. Finally, this study contributes to the literature on classification shifting by McVay (2006), Fan et al. (2010), Lee (2012), and Skaife et al. (2013) to the extent that pseudo blank R&D firm managers deliberately misclassify R&D expense into some other category within the income statement and thereby do not report R&D expenses.

The paper proceeds as follows. Section 2 reviews the relevant literature and develops the hypotheses. Sections 3 describes the sample and empirical methodology. Section 4 presents the results. Section 5 present robustness tests and additional results. Section 6 concludes.

2. Related Literature and Hypotheses Development

A public firm may use two major external financing channels, i.e., debt and equity, in order to finance its operations. However, corporate debt remains the most significant external financing channel.[1] Companies usually disclose R&D in one of the two ways. Some companies such as Apple and Tesla disclose R&D expenses as a separate line item in their income statements, while others such as Kellogg classify R&D expense as selling, general, and administrative expenses (SG&A) expenses; the relevant amounts are subsequently disclosed in either financial statement notes or the annual report's business section (Item 1 in Form 10k). However, which items should be included in R&D costs are not always clear[2]. Moreover, the

1 The Securities Industry and Financial Markets Association (SIFMA) reports that from 1996 to 2014 total corporate debt issuance amounted to US $16.4 trillion, while that from all IPOs during the same period totaled US $1.1 trillion (see ttp://www.sifma.org/research/statistics.aspx).

2 Paragraph 9 of SFAS 2 states that costs relevant to the "modification of the formulation or design of a product or process" should be included in R&D costs, whereas costs relevant to "routine, on-going efforts to refine, enrich, or otherwise improve upon the qualities of an existing product" should not be included. What if routine efforts lead to significant improvements in existing products or processes? Should these associated costs be included in R&D? Paragraph 8 of SFAS 2 states that even expenses related to product or process improvement should be recorded as R&D since, "research is planned search or critical investigation aimed at …… bringing about a significant improvement to an existing product or process . . . development is the translation of research findings ... for a significant improvement to an existing product or process whether intended for sale or use." The key determinant is then whether or not the improvements are significant. Routine on-going activities to improve on existing products therefore should not be included in R&D, but if the improvement is significant, then such costs should be included in R&D. This highlights the ambiguity in R&D disclosure guidelines. It is reasonable to assume that if the improvements are significant enough to warrant a patent filing, then the costs associated with such activity should be recorded as R&D.

implementation of SFAS 2 guidelines involves managerial discretion, suggesting room for biased R&D reporting. Since corporate debt represents the dominant external financing channel, it is important to know whether or not firms exercise discretion over their R&D expense reporting in order to present themselves as less risky borrowers and thereby reduce debt costs.

Managerial discretion over financial reporting has been the subject of considerable academic research. If financial reports are to convey timely and credible information regarding a firm's performance to various stakeholders, then standards must allow some room for managerial discretion over financial reporting. This will help managers use their firm-specific knowledge in determining appropriate estimates, methods, and disclosures that present a picture consistent with economic reality. However, because auditing is imperfect, this discretion also creates opportunities for earnings management (Healy and Wahlen, 1999) which may increase opacity creating a vulnerable environment for the banking industry (Lee et al., 2015). The bulk of the literature on earnings management focuses on either accrual management or the manipulation of real activities. However, McVay (2006) and Fan et al. (2010) investigate a third channel for earnings management, i.e., classification shifting, which is broadly related to this study. Classification shifting occurs when items are misclassified within the income statement. Although managers manipulate core earnings by misclassifying core expenses (such as the cost of goods sold and selling, general, and administrative expenses) as special items, the firm's GAAP earnings remain unchanged. Skaife et al. (2013) investigate a different type of classification shifting where managers classify routine operating expenses as R&D in order to justify missing earnings benchmarks without affecting operating income. It is therefore possible that pseudo blank R&D firm managers misclassify R&D expenses into some other category within the income statement and thereby avoid disclosing R&D expenses.

In order to understand the relationship between discretion over R&D expense reporting and the cost of debt, I follow the framework provided by Valta (2012) that links competition to the probability of default, and then to liquidation costs given default. A bank's decision to provide any loan and price such a loan accordingly depends on two criteria: the probability of default and the estimated liquidation value of the loan. I argue that the disclosure of R&D expenses may affect both criteria and could be a determinant for a firm's debt cost. R&D projects are inherently risky, which is most apparent in the pharmaceutical industry, where only one out of every 10,000 new compounds discovered in the laboratory ultimately become commercial drugs (Pisano and Wheelwright, 1995). Even managers may be unaware of the probability of success or probable future benefits for specific R&D projects (Cheng et al., 2016). Kothari et al. (2002) compare the future earnings variability associated with R&D and capital expenditures. They provide evidence consistent with R&D investments generating significantly more uncertain future earnings than investments in capital assets. Shi (2003) investigates the trade-off between the future benefit of R&D investments versus its riskiness in order to determine which of these effects dominates in the bond market. He documents a significant positive association between R&D investment and bond default risk to conclude that "for creditors, R&D expenditures reflect less asset-like characteristics but more risk attributes." (p. 230). In contrast, Eberhart et al. (2008) find that the association between loan spread and R&D investment changes signs from positive to negative when R&D intensity is measured using either sales or total assets as the deflator. However, using data on private debt from the United States, Ciftci and Darrough (2016) find a positive association between loan spread and R&D intensity. As in Shi (2003) and Ciftci and Darrough (2016), I argue that lenders are more worried about the downside risk than the upside potential of R&D. A firm reporting R&D is therefore viewed as riskier by creditors than a firm without such reporting. Overall, I posit that R&D increases a firm's riskiness in general and its default risk in particular.

R&D may also lower the firm's liquidation value given a default. Since most R&D spending is on the salaries and wages of highly educated employees, their efforts create an intangible asset in the firm's knowledge base (Hall, 2002). To the extent that this knowledge is tacit rather than codified, it is embedded within the firm's human capital and is therefore lost if these employees leave the firm. In the event of liquidation, creditors cannot sell human capital like other tangible assets in order to recoup their investments. Furthermore, R&D expenditures have low collateral value in part because there are typically few alternative uses for them. Alternative uses are limited because R&D investments are intangible and the benefits of R&D projects are usually tied to their current owners. Empirical evidence linking liquidation cost and R&D is provided by Alderson and Betker (1996); they investigate the relation between liquidation cost and a variety of liquidation cost proxies, finding a positive association between liquidation cost and R&D activity. The sunk costs associated with R&D investment are higher than those for ordinary investments, suggesting that the disclosure of R&D expenses may reduce the firm's estimated liquidation value and accordingly that of the loan.

It is possible that managers may be motivated to avoid disclosing R&D expenses in order to lower the cost of debt since the disclosure of R&D expenses can potentially increase a firm's perceived default risk and lower the estimated loan liquidation value. I thereby argue that discretion over R&D reporting is associated with a lower cost of debt. This is formalized in Hypothesis 1.

H1: Firms that report no information on R&D expenses but have patent activity (pseudo blank R&D firms), pay a lower cost of debt than control firms.

The above hypothesis may seem inconsistent with the conventional wisdom on bank lending in the sense that banks are considered superior in accessing and processing information regarding their clients (Diamond, 1991; Bharath et al., 2008). Banks have access to both private information regarding the borrower and to patent information which is public. How then do banks not see through the hidden R&D of pseudo blank R&D firms? A bank's experience within a given industry may be an important factor that determines whether or not a bank sees through hidden R&D. If a bank relies on financial statements in order to tease out a firm's R&D involvement, ignoring patent information and other private information, then it may consider a pseudo blank R&D firm as one with no R&D expense, even though it potentially conducts R&D. However, an experienced bank is more likely to identify pseudo blank R&D firms because it is well versed in the reporting practices of firms within that industry. An experienced bank is therefore more likely to investigate further, if a pseudo blank R&D firm does not disclose R&D expenses, either by requesting more relevant private information from the management or searching patents filed by the borrowing firm, revealing the firm's actual R&D involvement. I accordingly predict that more experienced banks are better able to see through the hidden R&D of pseudo blank R&D firms and charge a higher loan spread relative to less experienced banks. This is formalized in Hypothesis 2.

H2: Pseudo blank R&D firms borrowing from more experienced banks pay a higher cost of debt, relative to those borrowing from less experienced banks.

3. Sample Selection and Methodology

3.1. Sample Selection and Descriptive Statistics

My initial sample consists of all corporate bank loans for the period from 1987 to 2009. The bank loan data is obtained from the DealScan database provided by the Loan Pricing Corporation (LPC). The DealScan database contains detailed pricing and non-pricing information on loans issued to firms since 1986. This database is compiled using information from SEC filings, public documents (10Ks, 10Qs, 8Ks etc.), and participating banks' self-reported loan activity, as well as other internal sources and independent research conducted by the LPC. According to Carey and Hrycray (1999), the DealScan database contains between 50 and 75 percent of all commercial loan values for the United States during the early 1990s. From 1995 onward the DealScan coverage increases to include an even greater share of commercial loans. The basic unit of observation in DealScan is a loan, also referred to as a facility or tranche. Loans are often grouped together into deals or packages, and data on firm-specific accounting variables is obtained from the Compustat database. I match the DealScan dataset to Compustat's using Robert's DealScan-Compustat linking database (see Chava and Robert, 2008 for details). This link is available in WRDS.

The primary patent data used for the study is Google Patents database as compiled for the NBER working paper: "Technological Innovation, Resource Allocation, and Growth" by Leonid Kogan, Dimitris Papanikolaou, Amit Seru, and Noah Stoffman (2012). This data was obtained from Noah Stoffman's website.[3]

3 https://iu.app.box.com/patents.

Table 1: Sample

Panel A: Loan Sample from LPC DealScan

	N
All loans initiated between 1987 and 2009.	55,651
Less: observations with missing loan information (Missing loan spread, facility amount, and loan maturity).	12,091
Less: observations with missing Compustat data*.	11,534
	32,026

Panel B: Frequency of Pseudo Blank R&D Firms

Year	Number of Pseudo Blank R&D Firms	Average Patents per Year
1987	30	4.9
1988	82	7.7
1989	33	5.1
1990	41	6.3
1991	31	5.4
1992	36	3.1
1993	62	6.2
1994	86	4.2
1995	92	5.2
1996	69	6.1
1997	113	4.4
1998	117	7.4
1999	127	6.7
2000	130	6.6
2001	113	5.2
2002	123	4.3
2003	93	5.7
2004	104	5.5
2005	77	4.6
2006	37	2.4
2007	43	3.6
2008	18	2.5
2009	1	1
Total Number of Pseudo Blank R&D Firms	**1,658**	

Notes: * Observations from firms with less than US $1 million in sales, total assets, or long-term debt are excluded from the sample. Observations from firms in the financial and utilities industries are also excluded from the sample.

The authors claim that this database is more comprehensive: "… even during the period covered by the NBER data, my database adds an average of 2,187 patents to the NBER data."[4] I combine this patent dataset with that from DealScan and Compustat.

4 I use NBER patent data for robustness tests.

Panel A of Table 1 presents derivations for my loan sample. I begin with 55,651 loans initiated between the period from 1987 and 2009. I exclude 12,091 observations for which I am unable to obtain information regarding the loan spread, amount, and maturity. I also exclude firm loan observations from financial and utilities industries, as well as firms with less than US $1 million in total assets, sales, or long-term debt. My final sample consists of 32,026 observations before matching.[5]

I further use propensity score matching (PSM) on these samples in order to test my hypotheses. A propensity score is the probability of a unit being treated with the intervention of interest, given a set of observed explanatory variables. Propensity scores are used to reduce selection bias by matching groups based on observed explanatory variables.[6] The idea is to match a treatment group to a control group with similar characteristics. I match samples based on the nearest neighbor matching approach without replacement. This approach attempts to match an individual control firm to an individual treatment firm that is closest in terms of propensity score. In this case, an individual pseudo blank R&D firm is matched to positive R&D firm with a similar level of patent applications and other variables that control for any cross-sectional influence on loan spread. All variables are defined in the appendix. I match samples on the following dimensions:

Treatment Group = f (Patent Application per Year, Leverage, ROA, Log (AT), Tangible Assets, CR, MB, Z_Score, Log (Amount), Log (Maturity), Secured, Industry- and Year-Fixed Effects).

Panel B of Table 1 reports the frequency of pseudo blank R&D firms by year. The final matched sample contain 3,316 loan year observations, i.e., 1,658 loan year observations from pseudo blank R&D firms and 1,658 from control firms. The number of pseudo blank R&D firms range per year from 1 in 2009 to 130 in 2000. The last column of Table B reports the average number of patents filed by pseudo blank R&D firms ranging from 1 in 2009 to 7.7 in 1988.

A more detailed examination of pseudo blank R&D firms reveals that these firms generally follow one of three trends in reporting R&D. Some firms do not report R&D at all during the sample period. Another group reports R&D during the early sample years and then stops reporting R&D for the remaining sample period. The final group of firms does not report R&D during the initial sample years; once they do start reporting R&D, they continue reporting it during the remaining sample period. Pseudo blank R&D firms therefore do not switch between reporting and non-reporting of R&D. This tendency of pseudo blank R&D firms to not change reporting

5 It is possible that some R&D figures are simply lost i.e., not captured by Compustat even when firms report those figures. I manually search 10 random Pseudo Blank R&D Firms and found that is not the case.

6 It is important to point out the limitations of using propensity scores. Although they can balance across observed covariates, they do not balance unobserved or unmeasured characteristics so that the results may still be influenced by such unobserved characteristics. Another limitation in the implementation of PSM is that it focuses on one variable only and requires a large samples size with significant overlap between matching variables for both groups.

practices may make it difficult for banks to evaluate the riskiness arising from R&D activity.

Table 2: Descriptive Statistics
Panel A: Full sample

Variables	Mean	Std. Dev.	25th P	50th P	75th P
All-in-Drawn Spread	180.24	121.27	75.00	175.00	250.00
Log All-in-Drawn	4.91	0.85	4.32	5.16	5.52
Pseudo Blank R&D Firms	0.05	0.22	0.00	0.00	0.00
Leverage	0.35	0.24	0.18	0.30	0.47
ROA	0.02	0.15	-0.00	0.03	0.06
AT	5,642	23,487	283	869	3,026
Log AT	6.89	1.75	5.65	6.77	8.02
Tangible Assets	0.34	0.24	0.15	0.29	0.49
Current Ratio	1.67	0.99	1.03	1.49	2.08
MB	1.54	0.86	1.02	1.31	1.78
Z Score	1.83	2.70	0.57	1.94	3.22
Loan Amount	335.24	826.81	40.00	125.00	300.00
Log Loan Amount	4.73	1.51	3.69	4.83	5.70
Maturity (in months)	49.50	25.78	34.00	58.00	60.00
Log Maturity	3.63	0.78	3.22	3.97	4.09
Secured	0.51	0.50	0.00	1.00	1.00
Patents per Year	15.26	111.93	0.00	0.00	0.00
RD Dummy	0.52	0.50	0.00	1.00	1.00
No of Obs.	32,026				

Panel A of Table 2 presents summary statistics for the full sample of 32,026 loan year observations before matching. The average all-in-drawn spread for the sample is 180.24 basis points, and approximately five percent of the sample firms are pseudo blank R&D firms. The average loan maturity is over four years and the average loan size is approximately US $335 million. The average leverage is 0.35 and the average asset size is US $5.6 billion. Sample firms typically apply for 15 patents per year and more than half of the sample firms have missing R&D expenses. Collateral reduces the loan risk by providing the bank with a legal claim against a well-defined set of assets. Approximately 50 percent of the 32,026 loans for which this information is available are secured. Note that the missing collateral fields are treated as unsecured in order to prevent losing observations from the matched sample. However, approximately 72 percent are secured and the remainder are unsecured for the sample with non-missing data on collateral.

Panel B of Table 2 presents summary statistics for the matched sample from pseudo blank R&D dummy groups. The mean all-in-drawn spread for pseudo blank R&D firms (control firms) is 135 (141) basis points. Note that in Panel B (as in the full sample) the average all-in-drawn spread for pseudo blank R&D firms is significantly lower than that of positive R&D firms. The last two columns in Panel B present the difference in means and associated p-values testing the null hypothesis that pseudo blank R&D firms and control firms are the same across matching dimensions. I find no significant differences between the pseudo blank R&D firms and control firms across all matching dimensions.

Table 2: Panel B: Matched sample

Variables	**Mean**		**Std. Dev.**		**Median**		**Differences in Mean**
Pseudo Blank R&D Firms	0	1	0	1	0	1	
All-in-Drawn Spread	141	135	106	112	100	100	6.79*
Log All-in-Drawn	4.66	4.54	0.78	0.91	4.61	4.61	0.13***
Leverage	0.31	0.30	0.22	0.18	0.27	0.27	0.00
ROA	0.03	0.04	0.10	0.08	0.04	0.04	0.00
AT	9,526	9,332	26,945	19,212	2,086	2,024	193.80
Log AT	7.68	7.71	1.73	1.79	7.64	7.61	-0.03
Tangible Assets	0.35	0.36	0.23	0.22	0.30	0.31	-0.01
Current Ratio	1.67	1.67	1.03	0.91	1.46	1.54	0.00
MB	1.60	1.62	0.93	0.72	1.34	1.43	-0.02
Z Score	2.27	2.36	2.79	2.22	2.14	2.41	-0.09
Loan Amount	492	489	1,169	952	200	175	3.67
Log Loan Amount	5.18	5.17	1.43	1.45	5.30	5.16	0.01
Maturity	48	48	28	27	55	58	0.06
Log Maturity	3.55	3.56	0.83	0.83	3.87	3.96	0.00
Secured	0.32	0.33	0.47	0.47	0.00	0.00	-0.01
Patents per Year	4.71	5.46	16.75	10.56	0.00	2.00	-0.75
No of Obs.	1,658	1,658	1,658	1,658	1,658	1,658	

Notes: Panel A presents summary statistics for the variables used in estimating Equation 1 for the full sample. Panel B presents summary statistics for the variables used in estimating Equation 1 for the matched sample. The last column in panel B present the difference in means between pseudo blank R&D firms and control firms. I winsorize all continuous variables at the 1st and 99th quintiles. All variables are defined in the Appendix.

3.2. Model

I examine the association between pseudo blank R&D firms and cost of debt using the following model:

$$Ln\ \{Cost\ of\ Debt\ (AIS)\} = \beta_0 + \beta_1\ Pseudo\_Blank\_RD\_Firms + \beta_2\ Leverage + \beta_3\ ROA + \beta_4\ Log\ (AT) + \beta_5\ Tangible\ assets + \beta_6\ CR + \beta_7\ MB + \beta_8\ Z\_Score + \beta_9\ Log\ (Amount) + \beta_{10}\ Log\ (Maturity) + \beta_{11}\ Secured + \varepsilon. \quad (1)$$

The cost of debt in Equation 1 is given as the natural logarithm of the DealScan data item all-in-spread (AIS) drawn, which is calculated as the amount the borrower pays in basis points over the London Interbank Offered Rate (LIBOR) or equivalent for each dollar drawn. Pseudo Blank R&D Firms is a dummy variable that takes a value of 1 for firms that report no R&D expense information, but file for patents during a given year, and 0 otherwise. According to H1 these pseudo blank R&D firms present themselves as less risky firms by not disclosing R&D expenses and therefore pay less cost of debt relative to a control sample. The expected sign on β_1 is therefore negative. The list of control variables and their definitions are described in Appendix I.

The rationale behind and the expected sign on the control variable coefficients used in Equation 1 are explained next. Firm leverage is expected to be positively related to loan spreads since firms with high debt usage are associated with higher bankruptcy costs, causing an increased loan spread (Anderson et al. 2004). In order control for profitability and size I include return on assets (ROA) and log of total assets respectively. I expect loan spread to vary inversely with firm size because large firms are viewed as less risky and tend to have better reputations within the debt market (Diamond, 1989; Petersen and Rajan, 1994). I expect a negative relationship between tangible assets and loan spread because a firm with greater tangible assets will have lower liquidation costs. I further control for financial risk by using the current ratio (CR) which measures a firm's ability to meet its short-term obligations. I use market-to-book (MB) in order to proxy for a firm's growth opportunities. All else being equal, a firm recognized as having better growth opportunities is expected to have a lower borrowing cost (Graham, Li, and Qiu, 2008). Growth firms may be either vulnerable to financial distress or subject to information asymmetry. Given that I control for other characteristics such as the tangible assets and current ratios, I expect that the market-to-book may affect the loan spread negatively, if it represents the additional value over book assets that debt holders can access in the event of a default. A higher Z-score indicates better financial health and therefore lower default risk. The amount of the loan, i.e., log (amount) is expected to be inversely related to the loan spread. Lenders require a liquidity premium for longer-term debt and this liquidity premium translates into a higher loan spread (Graham, Li, and Qiu, 2008). The parameter on loan maturity is accordingly expected to have a positive sign. Consistent with prior studies including Berger and Udell (1990), Bharath et al. (2008), and others, I find that secured loans bear a higher loan spread that is consistent with riskier loans facing both higher loan spread and collateral requirement.

Table 3 presents the pairwise correlations between the regression variables. These correlation coefficients are consistent with my expectations. I find a significant negative correlation between loan spread and pseudo blank R&D firms. However, the log total assets and log loan amount are highly correlated with one another (correlation coefficients greater than 0.50). This correlation coefficient is comparable to that documented by Files and Gurun (2015). I also find that the Z-score and MB are highly correlated; this is expected because the Z-score calculation includes the market-to-book ratio. The main results are also computed using a modified Z-score which excludes the market-to-book ratio.

Table 3: Pearson Correlation Coefficients, N = 3316

	Variables	1	2	3	4	5	6	7	8	9	10	11
1	**Log All-in-Drawn**											
2	**Pseudo Blank R&D Firms**	-0.07***										
3	**Leverage**	0.37***	-0.01									
4	**ROA**	-0.28***	0.03	-0.23***								
5	**Log Total Assets**	-0.38***	0.01	-0.08*	0.02							
6	**Tangible Assets**	-0.08***	0.02	0.15***	-0.03*	0.16***						
7	**Current Ratio**	0.12***	0.00	-0.09***	0.08***	-0.47***	-0.22***					
8	**MB**	-0.19***	0.01	-0.11***	0.27***	0.00	-0.08***	0.04**				
9	**Z Score**	-0.20***	0.02	-0.41***	0.38***	-0.21***	-0.12***	0.43***	0.55***			
10	**Log Loan Amount**	-0.36***	0.00	-0.02	0.05***	0.69***	0.11***	-0.35***	0.04**	-0.11***		
11	**Log Maturity**	0.19***	0.00	0.17***	-0.01	-0.14***	0.04**	0.06***	-0.05***	-0.02	-0.05***	
12	**Secured**	0.52***	0.01	0.24***	-0.17***	-0.33***	-0.07***	0.12***	-0.08***	-0.09***	-0.20***	0.25***

Notes: $***$, $**$, and $*$ denote significance at the 1%, 5%, and 10% levels respectively. All variables are defined in the Appendix.

4. Results

Table 4 presents the main results. The dependent variable is the natural logarithm of the all-in-spread. Columns 1 to 3 report results for the overall sample, while Columns 4 to 6 report results for the matched sample. According to Hypothesis 1, I expect to find lower loan spreads for pseudo blank R&D firms. Consistent with the hypothesis and univariate results, I find that pseudo blank R&D firms have significantly lower loan spreads compared to control firms in tests using both the full and matched samples. In Column 1 (4) of the test using the full (matched) sample, I find that the coefficient on pseudo blank R&D firms is -0.10 (-0.12) and is significant at the 1 percent confidence level. This implies that pseudo blank R&D firms enjoy a 10 percent (12 percent) lower loan spread compared to reporting firms (control firms). In my sample, with an average loan spread of 180.24 (138.02), the difference is close to 18 (17) basis points. This effect is economically large; in cash terms this 18 (17) basis point difference corresponds to over US $603,000 (833,680)[7] in lower financing costs per year for pseudo blank R&D firms versus other firms (control firms). These loan spreads are increasing as expected in firm leverage while decreasing in size (*log_at*), tangible assets, and market-to-book ratio. Loan spreads are decreasing in Z-score consistent with the notion that a higher Z-score indicates better financial health and therefore a lower default risk.[8] The sign on loan size (*Log_Amount*) is negative; this may suggest either economies of scale in bank lending or that risker borrowers are granted smaller loans with higher loan spreads. Finally, as expected, secured loans bear a higher loan spread.

In Column 2 (5), I include dummies for year in order to capture pricing differences due to unobserved time effects and dummies for two-digit SIC code in order to control for time-invariant differences in risk and debt pricing across industries unrelated to pseudo blank R&D firms. While the coefficients on pseudo blank R&D firms' in the full (matched) sample drops to -0.03 (-0.10), they remain statistically significant at the 5 percent (1 percent) confidence level.

Finally, in Column 3 (6) I include dummies for loan purpose, loan type, year and two-digit SIC code. Loan purpose dummies capture different risks associated with the purposes for which the loan is used. Loans may be used for different purposes such as debt repayment, equipment purchase, securities purchase, stock buyback, working capital, takeovers etc. Loans are of different types such as 364-day loans, term loans, and revolving loans. Since loans with different types are associated with different risks, they may be priced differently. The results hold for both samples. There is consistent and statistically significant evidence of a negative

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7 (18/10,000)*335.24 (mean loan amount) *1,000,000 = approx. US $603,432. (17/10,000)* 490.40 (mean loan amount for matched sample, not reported)*1,000,000= approx. US $833,680.

8 Results are robust to the use of a modified Z-score by excluding the market-to-book ratio and to addition of credit rating as an additional control variable.

association between the pseudo blank R&D firms and loan spread. This suggests that pseudo blank R&D firms pay lower loan spreads compared to control firms which may potentially motivate non-disclosure of R&D expense by such firms.

Table 4: Do Pseudo Blank R&D Firms Receive Cheaper Loans?

	Full Sample (n=32,026)			**Matched Sample (n= 3,316)**		
Dependent Variable =Loan Spread (Log (All-in-Drawn Spread) - DealScan)						
Variable	**1**	**2**	**3**	**4**	**5**	**6**
Intercept	5.57***	5.64***	5.69***	5.30***	5.22***	5.24***
Pseudo Blank R&D Firms	-0.10***	-0.03**	-0.03**	-0.12***	-0.10***	-0.07***
Leverage	0.65***	0.69***	0.58***	0.95***	0.97***	0.74***
ROA	-0.37***	-0.32***	-0.49***	-1.13***	-1.04***	-0.87***
Log Total Assets	-0.08***	-0.12***	-0.13***	-0.04***	-0.09***	-0.09***
Tangible Assets	-0.15***	-0.21***	-0.16***	-0.26***	-0.36***	-0.35***
Current Ratio	0.00	0.00	-0.01*	-0.01	-0.01	0.01
MB	-0.10***	-0.11***	-0.09***	-0.08***	-0.11***	-0.09***
Z Score	-0.03***	-0.02***	-0.01***	-0.01	0.00	0.00
Log Loan Amount	-0.10***	-0.10***	-0.09***	-0.13***	-0.12***	-0.11***
Log Maturity	0.03***	0.05***	-0.06***	0.04***	0.06***	-0.05**
Secured	0.57***	0.49***	0.43***	0.65***	0.59***	0.46***
R^2	0.46	0.55	0.72	0.45	0.54	0.64
Year Dummy		Yes	Yes		Yes	Yes
Purpose of Loan Dummy			Yes			Yes
Type of Loan Dummy			Yes			Yes
Two-Digit SIC Dummy		Yes	Yes		Yes	Yes

Notes: The table presents regression results where the dependent variable is *Log(All-in-Drawn Spread*) and the independent variable of interest is pseudo blank R&D firms. The dummy variable pseudo blank R&D firms takes on the value 1 if a firm has no research and development data on Compustat but filed for patents during a given year, and 0 otherwise. Columns 1 to 3 present results for the full sample and Columns 4 to 6 present results for the matched sample. Matched sample firms are drawn from both pseudo blank R&D firms and positive R&D firms and are matched using the nearest propensity score based on the following logit model: *Treatment Group= f(Patent Applications per Year, Leverage, ROA, Log (AT), tangible assets, CR, MB, Z_Score, Log (Amount), Log (Maturity), Secured, Industry, and Year-Fixed Effects)*. *Treatment Group* takes a value of 1 for pseudo blank R&D firms, and 0 otherwise. All variables are defined in the appendix. All continuous variables are winsorized at the 1% and 99% levels. ∗∗∗, ∗∗, and ∗ denote significance at the 1%, 5%, and 10% levels respectively.

5. Robustness and Additional Analyses

5.1. Robustness Check

In this section, I investigate whether or not my primary results (that pseudo blank R&D firms acquire cheaper loans) are robust to the use of alternate and more comprehensive cost of debt measures, as well as using an alternate patent data set. While DealScan is the widely used database for cost of debt related studies, it suffers from one major drawback: It does not cover several firms with bank loans. For robustness, I replace all-in-drawn from DealScan with interest expenses from Compustat. The advantage of using interest expenses from Compustat as a dependent variable is that I do not exclude firms that are not covered by the DealScan database. Prior studies including Pittman and Fortin (2004) use this measure as a proxy for the cost of debt. I also replace Google patent dataset with the NBER patent dataset. The NBER patent dataset is widely used for patent-related studies. The NBER database comprises detailed information on over three million US utility patents from the United States Patent and Trademark Office (USPTO) Technology Assessment and Forecast (TAF) database that were either filed or granted during the period from 1976 to 2006. I combine this NBER patent dataset with Compustat dataset in order to evaluate the robustness of the main results. Following Pittman and Fortin (2004) I exclude firms with interest rates outside 5th and 95th percentiles of the pooled distribution in order to address extreme observations. I also exclude firms with long-term debt of less than US $1 million and those with missing interest expenses from the sample. I match samples on the following dimensions:

Treatment Group = f (Patent Applications per Year, Leverage, Log (AT), Tangible assets, Prime_Rate, Default Rate, Firm_Age, CFO, Neg_Equity, Industry- and Year-Fixed Effects).

Table 5 presents descriptive statistics for the variables used in these robustness tests. As expected the number of observations increases substantially from 32,026 to 84,211 for the full sample and from 3,316 to 6,766 for the matched sample. The average interest rate in the sample is 13.24 percent and approximately four percent of the sample firms are pseudo blank R&D firms. The average leverage is 0.39 and the average assets size is US $2.3 billion. The average number of patents applied by a firm is approximately seven per year, and approximately half of the sample firms have missing R&D expenses. Panel B of Table 5 presents the descriptive statistics by pseudo blank R&D dummy groups for the matched sample. The average interest rate for pseudo blank R&D firms (12.77 percent) is significantly lower than that of control firms (13.20 percent).

I estimate whether or not pseudo blank R&D firms receive cheaper bank loans using the following model:

$$\textit{Cost of debt (Interest rate)} = \beta_0 + \beta_1\, Pseudo\_Blank\_RD\_Firms + \beta_2\, Leverage + \beta_3\, Log\ (AT) + \beta_4\, Tangible\ assets + \beta_5\, Prime\_Rate + \beta_6\, Default\_Rate + \beta_7\, Firm\_Age + \beta_8\, CFO + \beta_9\, Neg\_Equity + \varepsilon. \quad (2)$$

Table 5: Descriptive Statistics

Panel A: Full Sample

Variables	**Mean**	**Std. Dev.**	**25th P**	**50th P**	**75th P**
Interest Expense	13.24	6.64	8.78	11.46	15.68
Pseudo Blank R&D Firms	0.04	0.20	0.00	0.00	0.00
Leverage	0.39	0.33	0.15	0.31	0.55
Total Assets	2,303	12,123	53	205	931
Log Total Assets	5.49	2.02	3.99	5.33	6.84
Tangible Assets	0.37	0.23	0.18	0.32	0.53
Prime Rate	8.72	3.06	6.91	8.35	9.93
Default Rate	2.12	0.47	1.73	2.06	2.34
Firm Age	14.39	12.66	5.00	10.00	21.00
CFO	0.06	0.18	0.02	0.08	0.13
Neg. Equity	0.05	0.22	0.00	0.00	0.00
Patent per Year	6.53	63.55	0.00	0.00	0.00
RD Dummy	0.50	0.50	0.00	1.00	1.00
No. of Obs.	84,211				

Panel B: Matched sample

Variables	**Mean**		**Std. Dev.**		**Median**		**Differences in Mean**
Pseudo Blank R&D Firms	**0**	**1**	**0**	**1**	**0**	**1**	
Interest Expense (%)	13.20	12.77	6.30	6.21	11.43	11.11	0.43***
Leverage	0.37	0.37	0.29	0.30	0.31	0.31	0.00
Total Assets	3,829	3,591	16,908	9,377	616	522	237.73
Log Total Assets	6.43	6.42	1.93	1.92	6.42	6.26	0.01
Tangible Assets	0.38	0.38	0.22	0.21	0.34	0.33	0.00
Prime Rate	9.35	9.35	3.20	3.20	8.44	8.44	0.00
Default Rate	2.13	2.13	0.46	0.46	2.06	2.06	0.00
Firm Age	21.70	21.78	14.61	13.87	20.00	21.00	-0.07
CFO	0.09	0.09	0.13	0.15	0.09	0.09	0.00
Neg. Equity	0.03	0.03	0.17	0.16	0.00	0.00	0.00
Patents per Year	3.30	3.40	13.36	7.15	0.00	1.00	-0.11
No. of Obs.	3,383	3,383	3,383	3,383	3,383	3,383	

Note: Panel A presents summary statistics for the variables used in estimating Equation 2 for the full sample. Panel B presents summary statistics for the variables used in estimating Equation 2 for the matched sample. The last column in panel B present the difference in means between pseudo blank R&D firms and control firms I winsorize all continuous variables at the 1st and 99th quintiles. All variables are defined in the Appendix.

where the debt cost in Equation 2 is given as the interest expense (Compustat data item XINT) divided by the average of the long-term debt during the year (Compustat data item DLTT).

The rationale behind and expected sign on the coefficients for the distinct control variables used in Equation 2 are explained next. The prime rate controls for the underlying cost of capital. The prime rate includes the risk-free rate and a default premium for the bank's best customers; firms that are not among the bank's best customers incur an additional default premium. The annual difference between the yield on BAA-rated corporate bonds and the yield on 10-year government bonds controls for aggregate variations in this default premium (Petersen and Rajan, 1994).[9] Firm age is inversely related to interest rates since firms build their reputations and good credit histories over time (Diamond, 1989). Cash flow from operations controls for profitability (Petersen and Rajan, 1994), which is predicted to have a negative sign since profitable firms are more likely to service their debt. Finally, negative equity is a dummy variable identifying when the book value of common equity is negative in order to reflect firms experiencing financial distress since such firms incur higher interest rates (Graham et al., 1998).

Table 6 presents the result for this robustness test. Consistent with Hypothesis 1, I find that pseudo blank R&D firms have significantly lower cost of debt compared to non-pseudo blank R&D firms. In Column 1 (3), the coefficient on pseudo blank R&D firms in the full (matched) sample is -0.016 (-0.004) and is significant at the 1 percent confidence level. This implies that on average pseudo blank R&D firms pay 1.6 percent (0.4 percent) less interest expense than control firms. The interest rate is increasing with leverage, prime rate, default rate, and negative equity. Similarly, the interest rate is decreasing with firm size (log at), tangible assets, and cash flow from operations. All control variables are statistically significant in the predicted directions.

In Column 2 (4), I use dummies for the initial public offering (IPO) year in order to capture any lingering variation in credit risk. According to Loughran and Ritter (1995), companies issuing stock during the period from 1970 to 1990, whether an initial public offering or a seasoned equity offering, have been poor long-run investments for investors. Since there is considerable debate regarding the average quality of firms going public during various time periods, I include an IPO year dummy in order to control for effect of IPO year on interest rates. I also include dummies for one-digit SIC code in order to control for industry influence on interest rates.[10] The coefficient on pseudo blank R&D firms in the full sample is -0.018, while that in the matched sample remains at -0.004. Both remain statistically significant,

9 I obtain the prime rate, yields on government bonds and yield on BAA corporate bonds from the Federal Reserve website at: http://www.federalreserve.gov/releases/h15/data.htm.

10 Results are robust to the use of two-digit SIC codes.

implying that pseudo blank R&D firms pay an interest rate that is 1.8 percent (0.4 percent) lower than control firms. The results in this section are consistent with the view that firms failing to report R&D, but still filing patents, benefit from a lower cost of debt.

Table 6: Robustness with Alternate Dataset and Dependent Variable

	Full Sample (N= 84,575)		Matched Sample (N= 6,766)	
Dependent Variable =Interest Rate (Interest Expense/Long-Term Debt)				
Variable	**1**	**2**	**3**	**4**
Intercept	0.107***	0.194***	0.101***	0.194***
Pseudo Blank R&D Firms	-0.016***	-0.018***	-0.004***	-0.004***
Leverage	0.030***	0.032***	0.024***	0.026***
Log Total Assets	-0.004***	-0.004***	-0.002***	-0.002***
Tangible Assets	-0.039***	-0.039***	-0.052***	-0.055***
Prime Rate	0.006***	0.004***	0.006***	0.003***
Default Rate	0.003***	0.001*	0.004**	0.003*
Firm Age	-0.000***	-0.001***	-0.000***	-0.001***
CFO	-0.013***	-0.012***	-0.004	-0.005
Neg. Equity	0.005***	0.006***	0.014***	0.017***
Adj. Rsq.	0.170	0.190	0.160	0.200
IPO Year Dummy		Yes		Yes
One-Digit SIC Dummy		Yes		Yes

Notes: This table presents regression results where the dependent variable is interest expense (XINT/Average DLTT) and the independent variable of interest is pseudo blank R&D firms. The dummy variable pseudo blank R&D firms takes on the value 1, if a firm has no research and development data on Compustat, but has filed for patents during a given year, and 0 otherwise. Columns 1 to 2 present results for the full sample and Columns 3 to 4 present results for the matched sample. Matched sample firms are drawn from both pseudo blank R&D firms and positive R&D firms matched using the nearest propensity score based on the following logit model: Treatment Group = f (Patent Applications per Year, Leverage, Log (AT), Tangible assets, Prime Rate, Default Rate, Firm Age, CFO, Neg. Equity, Industry- and Year-Fixed Effects). Treatment Group takes the value 1 for pseudo blank R&D firms, and 0 otherwise. All variables are defined in the Appendix. All continuous variables are winsorized at the 1% and 99% levels. $***$, $**$, and $*$ denote significance at the 1%, 5%, and 10% levels respectively.

5.2. Propriety Cost Argument

An alternate explanation for hiding R&D, but filing for patents, may be that firms want to hide their R&D from competitors early on, but once successful, they do not mind patenting a successful product. This implies that the real reason for not disclosing R&D, but filing for patents, is to protect important information regarding a successful product from competitors, rather than lowering the cost of debt. However, Arundel and Kabla (1998) document that less than 40 percent of firms file patents for their technological breakthroughs. They note that firms that find secrecy to be an important way to protect product innovations are less likely to patent. In order to investigate whether or not there is any difference in patent quality between these two set of firms, I examine two widely used measures of patent quality, i.e., generality and originality. Generality measures the impact of a patent on future innovations. If a patent is cited by subsequent patents that belong to a narrow (wide) range of fields, then the measure will be low (high). Similarly, originality measures the breadth of the underlying technology used to develop the patent. The originality score is low (high) if a patent cites previous patents that belong to a narrow (wide) set of fields. The results (untabulated) show that the patents of pseudo blank R&D firms are not significantly different than those of control firms in terms of generality. In fact, the patents of pseudo firms are less original than those of control firms. I accordingly do not find any evidence supporting the assumption that patents filed by pseudo blank R&D firms are more successful than those of control firms.

5.3. Effect of Bank Experience on Loan Spread of Pseudo Blank R&D Firms

In order to determine whether or not a bank's industry-specific experience enables it to see through these hidden R&D expenses, I include interactions between pseudo blank R&D firms and a bank experience dummy. The intuition here is that the banks with significant experience operating within an industry are well-versed in the reporting practices of firms from that industry; they are able to identify pseudo blank R&D firms and charge higher loan spreads considering the higher riskiness of such firms:

$$Ln\ \{Cost\ of\ Debt\ (AIS)\} = \beta_0 + \beta_1\ Pseudo\_Blank\_RD\_Firms + \beta_2\ Bank\ Experience\ Dummy + \beta_3\ Pseudo\_Blank\_RD\_Firms * Bank\ Experience\ Dummy + \beta_4\ Leverage + \beta_5\ ROA + \beta_6\ Log\ (AT) + \beta_7\ Tangible\ Assets + \beta_8\ CR + \beta_9\ MB + \beta_{10}\ Z\_Score + \beta_{11}\ Log\ (Amount) + \beta_{12}\ Log\ (Maturity) + \beta_{13}\ Secured + \varepsilon. \quad (3)$$

I measure bank experience as follows. First, I sum the bank loan in US dollars for each lead bank across two-digit SIC codes for the last five years. I then rank industries based on that sum into five groups for each lead bank. For example, Wells Fargo (lead bank) issued loans to several firms across five industries (two-digit SIC code). The industry in which Wells Fargo lent the most money during the last five years would be ranked as 5, the industry in which Wells Fargo lent the second greatest sum of money during the last five years would be ranked as 4, etc. Finally, I create a dummy variable *Bank Experience Dummy* that takes on the value 1 if Wells Fargo's rank for a given industry and year is above the sample median rank for that industry year combination, and 0 otherwise. If Wells Fargo is a lead bank for a given loan (facility), then I compare the rank of Wells Fargo for that industry year combination to the sample median rank for that industry year combination of all lead banks. The *Bank Experience Dummy* for Wells Fargo would take on the value 1, if its rank is higher than the median, and 0 otherwise.

Table 7: Effect of Bank Experience on Interest Spread of Pseudo Blank R&D Firms Dependent Variable =Loan Spread (Log All-in-Drawn- DealScan)

Variable	Full Sample	Matched Sample
Intercept	5.92***	5.90***
Pseudo Blank R&D Firms	-0.05**	-0.06**
Bank Experience Dummy	-0.02*	-0.06*
Pseudo Blank R&D firms * Bank Experience Dummy	0.08***	0.10**
Leverage	0.49***	0.72***
ROA	-0.42***	-1.28***
Log Total Assets	-0.09***	-0.12***
Tangible Assets	-0.22***	-0.35***
Current Ratio	0.00	-0.05***
MB	-0.11***	-0.09***
Z Score	-0.02***	0.00
Log Loan Amount	-0.09***	-0.08***
Log Maturity	-0.08***	-0.03
Secured	0.45***	0.40***
No. of Obs.	26,656	2,530
Adj. Rsq.	0.58	0.58
Purpose of Loan Dummy	Yes	Yes
Type of Loan Dummy	Yes	Yes
Two-Digit SIC Dummy	Yes	Yes

Notes: The table presents the regression results where the dependent variable is Log (All-in-Drawn Spread) and the independent variable of interest is the interaction term Pseudo Blank R&D Firms * Bank Experience Dummy. The dummy variable for pseudo blank R&D firms takes on the value 1, if a firm has no research and development data on Compustat, but filed for patents during a given year, and 0 otherwise. The dummy variable bank experience takes on the value 1, if a lead bank's industry experience rank for a given industry and year is above the median rank of industry experience for that industry and year for all lead banks, and 0 otherwise. Column 1 presents results for the full sample and Column 2 presents results for the matched sample. Matched sample firms are drawn from both pseudo blank R&D firms and positive R&D firms matched using the nearest propensity score based on the following logit model: Treatment Group= f (Patent Applications per Year, Leverage, ROA, Log (AT), Tangible assets, CR, MB, Z_Score, Log (Amount), Log (Maturity), Secured, Industry- and Year-Fixed Effects). Treatment Group takes the value 1 for pseudo blank firms, and 0 otherwise. All variables are defined in the Appendix. All continuous variables are winsorized at the 1% and 99% levels. ∗∗∗, ∗∗, and ∗ denote significance at the 1%, 5%, and 10% levels respectively.

The results presented in Table 7 indicate that more experienced banks are in fact able to see through the hidden R&D expenses of pseudo blank R&D firms and accordingly charge higher loan spreads versus less experienced banks. Specifically, the coefficient estimates associated with the interaction term *Pseudo Blank R&D Firms * Bank Experience Dummy* are 0.08 for the full sample and 0.10 for the matched sample; they are significant at the one and five percent confidence levels, respectively. This implies that pseudo blank R&D firms pay 8-to-10 percent more in loan spread when banks are experienced in lending to the pseudo blank R&D firm's industry. This evidence is consistent with experienced lenders using inside knowledge regarding firms operating within the same industry in order to increase the cost of debt for pseudo blank R&D firms.

6. Conclusion

While corporate R&D is vital to keeping up with ever-changing consumer demands by improving processes and producing goods efficiently, it may also be perceived as a risk factor by lenders. It is a well-known fact that the cost of debt increases with the risks that lenders bear. Although the US GAAP provides guidelines regarding what line items may or may not be classified as R&D expenses, there is ample room for biased R&D disclosures. Managers may therefore be motivated to obfuscate R&D disclosures in order to present the firm as less risky and lower the cost of debt.

In this paper I examine one potential reason for firm discretionary R&D reporting decisions by investigating why some firms may not disclose R&D expenses separately. Specifically, I examine whether or not the cost of bank debt is systematically lower for firms that do not disclose R&D expenses, but file patents, compared to firms with similar patent levels that disclose R&D expenses. The main finding is that pseudo blank R&D firms have significantly lower costs of debt financing. This finding is robust to both the use of an alternate measure of cost of debt and an alternate patent dataset across a variety of specifications. Moreover, experienced banks seem to see through these hidden R&D expenses and charge higher loan spreads relative to less experienced banks; this highlights the conditional nature of debt cost savings in strategic R&D expense disclosure.

This study impacts banks because it highlights that banks do not price loan correctly for a subset of firms because they (banks) fail to evaluate riskiness of firms and charge different interest rate based on disclosure of R&D. One implication for banks is that they are losing on interest revenue from pseudo blank R&D firms and those banks should price protect themselves by charging a higher interest rate on loans made to such firms. Banks should evaluate the reported R&D expenses in conjunction with the patent application filings. Combining these two pieces of information would give banks a full picture about the research and development activities of a firm and therefore help banks identify pseudo blank R&D firms. By doing so, banks can more accurately price corporate loan rates.

My study is subject to several limitations. First, while efforts were made to control for all observed characteristics between treatment and control group, the results may still be influenced by some unobserved characteristics. Second, I focus on a small group of firms operating within a special setting from which broad generalizations may be difficult. Third, it is important to note that while R&D non-disclosure may save interest expenses for some firms, there are costs associated with such non-disclosure. Many studies including Lev and Sougiannis (1996) document a positive association between R&D investments and equity value. For pseudo blank R&D firms, any savings in interest expenses may come with the potential cost of lower equity value. Bena and Li (2014) also document a positive association between R&D and the likelihood of a firm becoming a target for merger and acquisition (M&A). By not disclosing R&D, these pseudo blank R&D firms are potentially hurting their equity value and/or their probability of becoming a target firm, if the pseudo firm wants to be acquired. Finally, it is equally important to note that a result in the predicted direction does not suggest an overall negative association between innovation and loan spread; it only suggests that for this sub-set of firms deliberate accounting choices seem to have some beneficial consequences. There may be other costs or benefits from this deliberate choice which I may have not covered in this study.

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Appendix I: Variable Definitions

AIS Drawn over LIBOR	All-in-drawn spread charged by the bank over LIBOR for the drawn portion of the loan facility obtained from the LPC database.
Pseudo Blank R&D Firms	Dummy variable that takes the value 1 if a firm has no research and development data on Compustat but has filed for patents during a given year, and 0 otherwise.
Leverage	Long-term debt (Compustat data item 9) divided by total assets (Compustat data item 6).
ROA	Income before extraordinary items (Compustat data item 18) divided by total assets (Compustat data item 6).
Log Total Assets	Log of total assets (Compustat data item 6).
Tangible Assets	Net PP&E (Compustat data item 8) divided by total assets (Compustat data item 6)
Current Ratio (CR)	Current assets (Compustat data item 4) divided by current liabilities (Compustat data item 5).
Market-to-Book (MB)	Market value of equity plus the book value of debt (Compustat data item 6 – Compustat data item 60 + Compustat data item 24 * Compustat data item 25) divided by total assets (Compustat data item 6).
Z Score	Altman's (1968) Z-score computed as Z = 1.2 (working capital/total assets) + 1.4 (retained earnings/total assets) + 3.3 (EBIT/total assets) + 0.6 (market value of equity/book value of total liabilities) + (sales/total assets).
Log Loan Amount	Log of the loan amount obtained from the LPC database.
Log Maturity	Log of the maturity period for the bank loan obtained from the LPC database.
Secured	Dummy variable that takes the value 1 if the loan facility is secured with collateral, and 0 otherwise.
Prime Rate	Prime is the average prime rate for the year.
Default Rate	The default spread is the difference between the yield on BAA-rated corporate bonds and the yield on 10-year government bonds for a given year.
Firm Age	Age is the number of years that have elapsed since the firm appeared in the Compustat database.
CFO	Cash flow is cash flow from operations (Compustat data item 308) scaled by total assets (Compustat data item 6).
Neg. Equity	The negative book equity dummy indicates whether or not the book value of equity is negative (Compustat data item 144+ Compustat data item 35 - Compustat data item 10).
Bank Experience Dummy	Dummy variable that takes the value 1 if a lead bank's industry experience rank for a given industry and year is above the median rank of industry experience for that industry and year for all lead banks, and 0 otherwise.

Patent Application per Year	Total number of patents applications in a year. This data was obtained from Noah Stoffman's website. https://iu.app.box.com/patents.
RD Dummy	Dummy variable that takes the value 1 if a firm has no research and development data on Compustat, and 0 otherwise.