INTER-CREDITOR CONFLICTS: EVIDENCE FROM THE BOND MARKETS

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Abstract

In the first chapter, I investigate the relationship between the number of outstanding public debt contracts of a firm, the firm's credit quality, and cost of debt. I find that firms with higher credit quality tend to use fewer public issues, as well as that firms with more issues tend to have a lower cost of debt, controlling for credit quality. My results are consistent with the idea that there are both costs and benefits to increasing the number of public debt contracts. Higher credit quality firms, starting out with a lower cost of debt, find the benefits insufficient to make up for the costs, and thus choose to have fewer debt issues than lower credit quality ones. I further find that information asymmetry is a significant moderating factor of the effect of number of debt issues on the cost of debt, with higher asymmetry decreasing the cost of debt benefit of a greater number of issues.

In the second chapter, I investigate the impact of firm-level competitive intelligence on the firm's cost of debt. I find that competitive intelligence is not fully incorporated into debt credit ratings, and further that the effect of increased competitive intelligence varies with firm credit quality. For high credit quality firms, I find that higher CI is associated with higher yield spreads, while the opposite is true for the lower credit quality firms. This suggests that the bondholders of a firm with generally low distress probability view CI expenditure as irrelevant or wasteful, whereas those of a firm for which financial distress is a more significant risk, view it as a valuable activity which reduces default probability.

In the third chapter, I examine the occurrence of informed trading in public debt issued by financial institutions. The sample is chosen from the set of firms subject to the FDIC call report regulations, and focuses on companies without publicly traded equity. I find that unexpected earnings are positively associated with price changes in debt instruments as a result of trading within the time period after report filing and before the release of report data to the public. Additionally, I find that the magnitude of the effect is greater for firms without public equity. Evidence further indicates an increase in the incidence of bond trading during this blackout window for firms with a greater magnitude of earnings surprise. These results suggest that there is information leakage taking place during the blackout window, leading to informed trading in public debt instruments of financial institutions.

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1.1 Introduction

While there is an extensive literature covering the interplay between debt and equity in the firm's capital structure, and a growing literature delving into the detailed characteristics of the firm's borrowings, the firm's choice of *how many* distinct debt offerings to issue has received relatively little attention. A given level of leverage, with a given target maturity, and various embedded features can be achieved with a greater or lesser number of debt issues, and the question of why a firm may choose to use more or fewer distinct issues to achieve its target capital structure does not lend itself to an immediately obvious answer.

Extant theoretical studies on the subject make distinct and conflicting predictions as to the determinants of and the optimal level of the number of creditors. Bolton and Scharfstein (1996) develop a model wherein having more creditors increases the costs of liquidation and reduces liquidation values, but also reduces incentives for strategic default, since the manager has to pay more to prevent creditors from liquidating. They predict that low default risk firms, for whom actual liquidation is not a likely scenario, don't worry about the lower liquidation value, and benefit from managerial discipline of having more creditors. Moreover, since more dispersed creditors make out better in case of distress, the ex-ante cost of debt for the firm is lower.[1] The basic

[1] A similar effect is predicted Cantillo and Wright (2000), who argue that cost of borrowing is

idea is that creditor dispersion has both costs and benefits, and that high-quality firms can take advantage of the benefits without incurring the costs, since costs are only incurred in case of default.

Bris and Welch (2005) on the other hand, relying on Gertner and Scharfstein (1991) and Bernardo and Talley (1996), argue that it is easier to expropriate from multiple creditors in distress through exit-exchange offers (i.e., cost of distress is *lower* with multiple creditors - opposite to the position taken by Bolton and Scharfstein (1996) and Cantillo and Wright (2000)). Since creditors know that, the borrower would ex-ante have to pay a higher rate to compensate. They argue that this implies an existence of an optimal concentration of creditors, balancing the two trade-offs. In a signaling model developed on this framework, they predict that high-quality borrowers would signal their quality by borrowing from a concentrated creditor base, and as a result benefiting from a lower rate. These conflicting hypotheses can be resolved empirically, since they offer opposing predictions both as to the quality of borrower that chooses to use more rather than fewer creditors, and, *ceteris paribus*, the required interest rates on a borrower with more rather than fewer creditors.

Prior empirical literature dealing with financial distress and the number of creditors suggests that having a smaller number of public debt contracts reduces the

lower in the public markets, since there are no intermediary costs, while the costs of reorganization are lower with a single creditor, such as with bank debt. They predict that low-risk firms borrow from public markets to borrow at a lower rate, avoiding intermediary costs, and high-risk firms borrow from intermediaries, to reduce distress costs and take advantage of banks' reorganization skills and/or screening abilities. This stance is also supported by the emipirical work of Denis and Mihov (2003), who show that highest-credit-quality firms prefer to borrow from public markets. The theoretical framework of Hackbarth, Hennessy, and Leland (2007) also suggests that strong firms would rely less on bank debt and more on public debt markets.

complexity of the debt renegotiation process. Gilson, John, and Lang (1990), analyzing a sample of restructuring events in distressed firms find that firms with a smaller number of public debt contracts are more likely to successfully restructure their debt outside of the Chapter 11 process. This is confirmed by Asquith et al. (1994), who in addition find that distressed firms with a greater number of public debt issues are more likely to resort to asset sales. Together with the findings of Franks and Torous (1994), that equityholders end up with a greater fraction of the reorganized firm with informal renegotiation, rather than in Chapter 11, these results suggest that a greater number of issues would thus reduce the equityholders' incentive for strategic default, lending support to the Bolton and Scharfstein (1996) framework. Investigating the issue from the market side, Davydenko and Strebulaev (2007) use the number of public issues as a proxy for renegotiation frictions, which reduce the incentive for strategic default, and find that it is associated with a lower cost of debt. Related theoretical models tend to have a similar stance on the effects of having multiple creditors. Berglöf and von Thadden (1994) develop a model showing that having multiple creditors with various claims can reduce inefficient liquidation in liquidity default, while maintaining disincentives for strategic default by equityholders. Berglöf, Roland, and von Thadden (2010), in modeling optimal contracting in the context of bankruptcy rules, show that multiple creditors can extract higher payments in renegotiation.

Other considerations may also enter into the firm's target issue mix. One benefit of having multiple debt issues outstanding is the ability to stagger their maturities, reducing the risks inherent in having to roll over a portion of debt. At the extreme, a firm that has all of its debt in one issue faces a lot of liquidity and refinancing risk when this debt issue comes due, since inability to reissue, or to reissue at a favorable rate has a relatively large impact. The firm is, in essense, at the mercy of the market conditions at time of rollover, since in the absence of a timely rollover issue, it must come up with the cash to repay all of the maturing debt. This refinancing risk would be expected by the debtholders, and thus would be expected to raise the ex-ante cost of debt. By comparison, a firm which splits its debt load into say, ten separate issues, each of which matures in a different year, has only a tenth of its total debt load subject to rollover at a given time. Further, it may have the opportunity to engage in some market timing, choosing to make a somewhat larger issue when rates are particularly low, and a smaller one when interest rates are high.

Additionally, a large established firm would usually have a multitude of projects, each with a different maturity. Thus a firm could go some ways toward reducing the underinvestment problem described by Myers (1977), by having multiple debt issues maturing at different times, which more closely matches with the maturities of its projects. By reducing this source of agency costs of debt, the firm should, all else equal, be able to secure financing at a lower rate. This particular issue, however, can be dealt with by other means, using a sinking fund for example, so all else equal this factor on its own would not necessarily drive a greater number of creditors.

Another issue that may be relevant is that of information asymmetry. Each bond issue requires a certain amount of disclosure on the part of the firm. A firm with a greater number of issues would overall provide greater disclosure to investors, at least from those parts of the disclosure that provide information in addition to that incorporated by reference from other reports. In addition to required direct disclosure, investors could glean information from the schedule of debt payments (Harris and Raviv, 1990), and would gather more of it from a firm with a richer debt repayment schedule due to its greater issue count. This reduction in information asymmetry would lower the required returns for a high-quality firm. Alternatively, the information asymmetry issue may be causally upstream of the number of creditors. A firm that has good disclosure practices and low information asymmetry, may enjoy lower required debt returns (See, e.g., Sengupta (1998), Lambert, Leuz, and Verrecchia (2007)), and as a result of that may choose to use more creditors, having easier access to the debt markets. All of the above may suggest that a high quality firm, and one with easy access to public debt markets, may stand to gain from reduced interest rates on its debt by making more bond issues, over and above a similar firm that chooses to make fewer of them.

The present paper undertakes an empirical investigation of the characteristics of firms that lead them to use more or fewer public issues, and how they fit into the extant theoretical frameworks. Using a sample of 1066 unique firms from the Russell 3000 that have outstanding public debt, I find evidence that firms with higher default risk tend to have a greater number of creditors. At the same time, my analysis indicates that having a greater number of creditors is associated with a lower cost of debt. After controlling for a number of firm characteristics, I find that a one standard deviation increase in default risk is associated with an increase of about 0.46 bond issues, and that a one standard deviation increase in the number of creditors is associated with a change of about -11.94 basis points in the cost of debt. These results are both statistically and economically significant, and are robust to alternative measures of key variables and alternative specifications.

These empirical findings do not fully support either the Bolton and Scharfstein (1996) or the Bris and Welch (2005) hypothesis. The combination of lower-distress-risk firms borrowing from fewer creditors (having fewer distinct issues); and of firms with greater number of issues having a lower weighted average cost of debt, controlling for credit risk, is not compatible with either of the hypotheses.

Additionally, I find that the relationship between the number of creditors and the cost of debt is nonuniform across firms of different credit quality, supporting the hypothesis that there are distinct tradeoffs in the choice of the number of creditors and that firms with different characteristics may have a different optimum number of creditors, as far as the cost of debt is concerned. Specifically, my results are consistent with the hypothesis that there are fixed issue costs involved in increasing the number of creditors, which act to countervail the positive effect of the number of creditors on reducing the cost of debt.

In further examining the relationship between firm characteristics and number of creditors, I find that firms which have more distinct issues have a higher weighted average debt duration, and a lower market information asymmetry. I also find that the effect of number of creditors on the cost of debt is moderated by information asymmetry, wherein firms with greatest information asymmetry evidence an increased cost of debt. The information asymmetry interaction effect suggests that the a greater number of issues is not in itself a source of reduction in information asymmetry.

My research contributes to the existing literature in a number of substantial aspects. First, I show that the number of issues utilized by a firm is positively associated with its default risk. Second, I find that in accordance with prior empirical work, controlling for distress risk, a greater number of creditors is associated with a lower cost of debt. Together, these two findings suggest a nonuniform relationship between the number of issues and the cost of debt, an idea which is supported by my empirical findings. Overall, the picture that emerges is that there are both benefits and costs to increasing the number of issues, and that higher-credit-quality firms find the benefits insufficient to make up for the costs.

The remainder of this paper is organized as follows. Section 1.2 details my research questions. Section 1.3 describes my data and sample selection procedures. Section 1.4 presents my research design and main empirical findings. In Section 1.5 I present some alternative model specifications. Section 1.6 concludes.

1.2 Research Focus

The relationship between the number of public debt issues and firm characteristics has not been emiprically addressed in the literature, and is my central research question. This study provides the first empirical research on the attributes of firms leading them to issue a greater or lesser number of public debt contracts, using firm-level data on publicly traded debt. Existing theories applicable to the matter make conflicting predictions on the relationships between number of creditors, firm credit quality, and the cost of debt.

In the broad conceptual sense, existing theories suggest that the number of creditors (creditor classes) affects the ease of restructuring/renegotiation in case of default, liquidation values, and how much value the equityholders end up with in the event of default. A firm looking to lower its cost of debt, then, would *ceteris paribus* want to adjust its number of creditors in such a way that the creditors would end up with the better deal in case of financial distress. Though theories differ as to whether more or fewer creditors is better for the creditors (and is one of the primary targets of this empirical investigation), the underlying idea of firms adjusting this number with a view to their cost of debt is the core argument. Of course, anything the creditors get in the event of default, the equityholders don't get, so by doing this the firm is "giving up" the expected value of the differential equityholder recovery in case of distress, multiplied by the probability of said distress occurring. Thus we have a classic case of signaling, with information asymmetry between the managers and debtholders regarding firm credit quality, and with differential costs of the signal depending thereon.

The total cost of credit, however, is made up of not only the market cost of debt, but also the associated issue costs. Empirical evidence, and the simple fact that there are fixed costs to making a debt issue, suggest that the costs of issuance are higher when the total debt load is split among a greater number of issues, all else equal. Thus, beyond the signaling setup described one would expect firms to take the transaction costs into account when structuring their debt.

To investigate this issue, I address several specific questions. First, I determine the relationship between the number of creditors and firm credit quality. Second, I look at other firm characteristics that existing literature suggests may have bearing on the firm's debt mix. Third, I investigate the relationship between the firm's cost of debt and the number of debt issues, and develop a framework to explain the results.

Considerations differentiating fewer from more debt issues, including maturity staggering, maturity matching, and quantity of disclosure, may be instrumental in impacting the required return on the firm's debt. While they all seem to point toward lower interest rates with multiple issues, this may be offset by increased debt issuance costs, since there could be certain economies of scale in making a debt issue. However, these costs, while present in the accounting financial statements, would not show up in the market measures of cost of debt, so in measuring the market 'cost of debt' I would only be seeing the benefits. I tackle these questions empirically by testing for relationships between debt maturity, information asymmetry, and their possible modifying effects on the relationship between the number of creditors and the cost of debt.

1.3 Data

The data for this study come from a number sources. The data on the firms' bond issues and their characteristics is taken from the Mergent FISD database. This database contains information on all bond issues and their characteristics, including issue date, maturity, coupon and coupon frequency, call schedule, conversion features, and ratings from S&P, Fitch, and Moody's. Historical bond prices are from the TRACE database, which contains all reported bond trades in the period from 2002 to 2008, including trade execution date, price, and yield. Additional bond trade information from earlier years is obtained from the FISD insurance bond transactions data file. Finally, I obtain various firm-year-specific financial information from the COMPUSTAT Annual Fundamentals data set, and the historical treasury yields from the US Treasury web site[2].

1.3.1 Measuring the Cost of Debt

The "cost of debt" for a firm is calculated as the weighted average yield spread over the duration-equivalent treasury, a commonly-used measure of debt risk premium (Silvers, 1973) Specifically, the following procedure is used to calculate the weighted average yield spreads for each firm-year.

For each firm-year, data on each of the bonds outstanding for a particular firm is collected from FISD. Bond pricing information is obtained from from TRACE, as well as from the FISD insurance bond transactions database, finding the earliest trade occurring within the 6 month time window from the report date. For non-callable bonds, I calculate the yield to maturity, and the Macaulay duration. For callable bonds, I use the lower of the yield to maturity or the yield to call (yield to worst), and use the duration measure corresponding to the yield to worst. If the lower yield is

[2] http://www.ustreas.gov/offices/domestic-finance/debt-management/interest-rate/yield_historical_main.shtml

the yield to call, I calculate duration on the assumption that the bond will be called; if the lower yield is the yield to maturity, duration is based on stated maturity. For each bond's trade execution date, the treasury yield curve is estimated using cubic spline interpolation, and the duration-equivalent treasury yield is found using the curve estimate. The yield spread for each bond is then the bond's yield to worst, minus its duration-equivalent treasury yield. The weighted average yield spread for the firm in a given year is the average of all the yield spreads, weighted by the market value of each bond issue.

The initial sample contained 9169 bond issues for 1072 unique firms. Due to the elimination of putable and convertible bonds, and the otherwise-sparse nature of the bond pricing data, the subsample used for the yield spread data analysis is based on 6393 bond issues for 993 unique firms.

Additionally, I use the "gross spread" data item from the FISD database to directly measure the issuance costs. Gross spread is the difference between the price that the issuer receives for its securities and the price that investors pay for them, which includes the selling concession plus the underwriting and management fees. I find the weighted average gross spread, *IssueCost*, for each firm-year as the average of all bonds' spreads, weighted by market value of each bond issue.

1.3.2 Number of Issues

The number of issues for each firm-year is the count of issues outstanding, as available from the FISD database. Prior literature suggests that the stronger determinant of success of informal debt renegotiation process is not the raw issue count, but the log of the count scaled by the log of total debt (Gilson et al., 1990),

$$NormNumIssues = \frac{\ln(Num.Issues)}{\ln(Total\ Liabilities)}. \tag{1}$$

Consequently, I use this normalized issue count in the analysis, though qualitatively the results are similar when using the plain count of public debt issues.

1.3.3 Control Variables

The number of creditors a firm uses in its public debt mix could potentially be affected by several factors. First, the larger the firm's leverage, the more likely it is that there are multiple debt issues that make up the outstanding debt. Second, firm profitability and operational liquidity can affect the ease with which the firm can access the public debt market, and at the same time, the necessity of such access. A larger firm, which for a given level of target leverage would have a larger absolute amount of debt, and at the same time have increased credibility in the public debt market, might also be expected to have more distinct bond issues.

Hence, I introduce a number of control variables for the above, so that I can determine whether credit quality impacts the number of issues *in excess* of any any other effect. I include variables to control for firm leverage, size, and profitability. I measure firm leverage using the book ratio of total liabilities to total assets:

$$Leverage = \frac{Total\ Liabilities}{Total\ Liabilities + Total\ Equity}, \tag{2}$$

firm size as the natural log of firm book assets:

$$Size = \ln(Total\ Liabilities + Total\ Equity), \tag{3}$$

firm total debt as the natural log of firm book liabilities:

$$TotalDebt = \ln(Total\ Liabilities), \tag{4}$$

and firm performance as the ratio of cashflow to total assets, where cashflow is net income plus depreciation and amortization:

$$Profitability = \frac{Net\ Income + Depreciation\ and\ Amortization}{Total\ Liabilities + Total\ Equity}. \tag{5}$$

I use a couple of different measures of the firm's distress risk. The Altman Z-score (Altman, 1968), a purely accounting-based measure of credit risk, is built from the data in the annual COMPUSTAT database. The Z-score specifies the following five accounting ratios as components in the overall measure:

- $T_1 = \frac{Working\ Capital}{Total\ Assets}$
- $T_2 = \frac{Retained\ Earnings}{Total\ Assets}$

- $T_3 = \frac{Earnings\,Before\,Interest\,and\,Taxes}{Total\,Assets}$

- $T_4 = \frac{Market\,Value\,of\,Equity}{Total\,Liabilities}$

- $T_5 = \frac{Sales}{Total\,Assets}$

As per the latest specification of the Altman model[3], I use the following component weightings for my Z-score measure:

$$Zscore = 1.2 * T_1 + 1.4 * T_2 + 3.3 * T_3 + 0.6 * T_4 + 1.0 * T_5 \qquad (6)$$

The variable I use for measuring *DefaultRisk* is the inverted Z-score scale, so that higher values mean higher *DefaultRisk*.

Another measure, bond ratings, an obvious measure of credit quality when dealing with public debt, is based on the firm's bond ratings, measured as the weighted average rating by firm-year (*Rating*). The character ratings are numerically operationalized by assigning an integer to each rating, with AAA corresponding to a numerical rating of 1, and D corresponding to 22. Using this conversion, the bond rating is expected to be positively correlated with the cost of debt, as measured by the yield spread. The complete rating conversion chart is shown in Table 1. The rating used for each bond is the most recently issued rating prior to the issue-specific trade execution date used to determine the bond price. This procedure ensures that my rating measure incorporates the freshest possible information that bond ratings are supposed to reflect. The problem with ratings is that if the number of creditors

[3] Altman (1993), Altman (2005)

data carries any information about the creditworthiness of the firm, and if the credit ratings agencies know that, it would be incorporated into the rating. Thus though the very fact of a significant association between rating and number of creditors would prove informative, I could not draw conclusions as to the underlying causality.

Table 1: Numerical Credit Rating Scale

This table shows the numerical credit rating scale for Moody's, S&P, and Fitch ratings, used for the empirical analysis. Each letter rating code corresponds to a single numerical value.

Conversion number	S&P Rating	Moody's Rating	Fitch Rating
1	AAA	Aaa	AAA
2	AA+	Aa1	AA+
3	AA	Aa2	AA
4	AA-	Aa3	AA-
5	A+	A1	A+
6	A	A2	A
7	A-	A3	A-
8	BBB+	Baa1	BBB+
9	BBB	Baa2	BBB
10	BBB-	Baa3	BBB-
11	BB+	Ba1	BB+
12	BB	Ba2	BB
13	BB-	Ba3	BB-
14	B+	B1	B+
15	B	B2	B
16	B-	B3	B-
17	CCC+	Caa1	CCC+
18	CCC	Caa2	CCC
19	CCC-	Caa3	CCC-
20	CC	Ca	CC
21	C	C	C
22	D		D

Additional variables used for hypothesis testing are weighted average duration, and standard deviation of analyst estimates, which is my proxy for information asymmetry. I measure bond duration as standard Macaulay duration, and then compute a weighted average duration (*Duration*) for each firm-year. I use the standand deviation of analyst EPS estimates for each firm-year as a measure of information asymmetry (*InfoAsymmetry*), sourced from the I/B/E/S Summary database.

1.3.4 Descriptive and Univariate Statistics

Table 2 shows some descriptive statistics for the key variables in my sample. Included are the minimum, mean, median, maximum, and standard deviation for each variable. Firm size, as measured by log total assets (in millions), has a mean of \$7.92, standard deviation of \$1.43, with a minimum of \$3.06, and a maximum of \$13.59. Average firm profitability, as measured by the ratio of cash flows to total assets, is 6.54%; mean leverage ratio is 65.17%. As far as debt-specific measures go, the mean weighted average rating is 10.2, corresponding to a letter rating of approximately BBB-; mean weighted average duration is 6.32 years, and mean weighted average yield spread is 3.24 percent. The number of outstanding issues ranges from 1 to 96, with a mean of 5.75 and a standard deviation of 7.45.

Table 2: Summary Statistics, Chapter 1

This table shows summary statistics for the data used in the empirical analysis. The data set covers 10873 firm-years for 1066 unique firms, from 1994 to 2010. The variables include: *YieldSpread*, the weighted average yield spread; *NumIssues*, the number of outstanding bond issues; *NormNumIssues*, log of number of issues divided by log of total debt; *Leverage*, firm leverage (total debt / total assets); *Profitability*, firm profitability (cash flow / total assets); *Size*, firm size (ln(total assets)); *Duration*, weighted average debt duration; *Rating*, weighted average credit rating; and *InfoAsymmetry*, my proxy for information asymmetry; *DefaultRisk*, an Altman Z-score based measure of default risk; *TotalDebt*, log of total book debt.

	Min.	Mean	Median	Max.	St. dev.
YieldSpread	0.001	3.244	2.149	28.739	3.423
NumIssues	1.000	5.751	3.000	96.000	7.446
NormNumIssues	0.000	0.159	0.156	0.473	0.106
Leverage	0.084	0.652	0.631	2.851	0.223
Profitability	−4.996	0.065	0.078	2.270	0.144
Size	3.060	7.915	7.827	13.590	1.431
Duration	0.126	6.316	5.653	29.696	3.410
Rating	1.000	10.204	9.905	22.000	4.010
InfoAsymmetry	0.000	0.064	0.020	21.290	0.320
DefaultRisk	117.821	158.990	159.294	236.111	3.212
TotalDebt	2.730	7.428	7.326	13.436	1.470
GrossSpread	0.100	1.397	0.875	9.000	1.004

Univariate analysis results are shown in Table 2. *Size* and *TotalDebt* are positively associated with *NumIssues*, as are *Leverage*, *Profitability*, and *Duration*. While the *YieldSpread* is lower for firms with more issues, *DefaultRisk* is positively associated with *NumIssues*, which suggests that *NumIssues* has an effect on the *YieldSpread* that is not subsumed by any correlation with default risk. Interestingly, *Rating*, another measure of default risk, is negatively associated with *NumIssues*, wherein firms with more risk tend to have fewer creditors. This is in contrast to the story being told by *DefaultRisk*. Further investigation reveals that *Rating* is relatively highly correlated with *Size*, and once *Size* is controlled for in a multivariate setting (See Section 1.4) the *Rating* effect points in the same direction as that of *DefaultRisk*.

Table 3: Univariate Analysis, Chapter 1

This table shows the univariate test results, breaking up the sample into two groups around the median of *NumIssues*. The variables included are *YieldSpread*, the weighted average yield spread; *Leverage*, firm leverage (total debt / total assets); *Profitability*, firm profitability (cash flow / total assets); *Size*, firm size (ln(total assets)); *Duration*, weighted average debt duration; *Rating*, weighted average credit rating; *DefaultRisk*, a measure of default risk; *InfoAsymmetry*, my proxy for information asymmetry; and *TotalDebt*, log of total book debt.

	Low NumIssues	High NumIssues	Difference	t-Stat.	p-value
YieldSpread	3.9520	2.9542	0.9978	9.9311	0.0000***
Leverage	0.6192	0.6765	−0.0574	−12.9381	0.0000***
Profitability	0.0561	0.0725	−0.0163	−5.4366	0.0000***
Size	7.1132	8.5252	−1.4120	−58.9001	0.0000***
Duration	6.1679	6.3839	−0.2161	−2.3126	0.0208*
Rating	11.4505	9.7183	1.7322	17.1092	0.0000***
InfoAsymmetry	0.0665	0.0621	0.0044	0.5150	0.6066
DefaultRisk	158.7110	159.1915	−0.4805	−6.2726	0.0000***
TotalDebt	6.5554	8.0916	−1.5362	−63.6957	0.0000***

1.4 Multivariate Empirical Results

First, I examine the relationship between the normalized number of creditors (*NormNumIssues*) and the firm's distress risk, using a cross-sectional multivariate model, with a number of control variables. My base specification is

$$NormNumIssues = \alpha_0 + \alpha_1 DefaultRisk + \alpha_2 Size + \alpha_3 Leverage + \varepsilon, \tag{7}$$

where *DefaultRisk* is the inverted Altman Z-score, and *Size* is the natural logarithm of total assets. The main coefficient of interest is α_1, the effect of *DefaultRisk* on the number of issues. If positive, it would indicate that firms with higher credit risk make more issues.

The coefficient on *DefaultRisk* (and *Rating*, which I use as a secondary specification), if significant, will tell us which of the competing theories is more likely.

Column 1 of Table 4 presents the regression results following the specification shown in Eq. (7). The main finding is that firms with less credit risk as measured by either *DefaultRisk* or *Rating* issue significantly fewer distinct bond issues. The coefficient on *DefaultRisk* of 0.00350 is significant, and translates into a change of 0.011 normalized issues for a change of one standard deviation in *DefaultRisk*. At the median, this translates to an increase of 0.26 issues for a one standard deviation change in *DefaultRisk*. In the *Rating* regression, the coefficient on rating is close to zero and not significant. The *Rating* measure is relatively highly correlated with *Leverage*, and it seems that the presence of the latter in the regression subsumes the *Rating* effect.

Columns 3 and 4 of Table 4 include additional variables of *Duration* and *InfoAsymmetry*, in the regressions using *DefaultRisk* and *Rating*. The coefficients are

Table 4: Multivariate Analysis: Normalized Number of Issues vs. Credit Risk

This table shows the estimated coefficients of regressing the number of creditors on proxies for credit risk (*DefaultRisk* and *Rating*), and various controls. The variables included are: *Size*, the natural logarithm of total assets; *DefaultRisk*, the inverted firm-year Altman Z-score; *Rating*, the firm-year weighted average rating.
The primary specification is:

$$NormNumIssues = \alpha_0 + \alpha_1 DefaultRisk + \alpha_2 Size + \alpha_3 Leverage + \varepsilon$$

These results are reported in column 1. Column 2 replaces *DefaultRisk* with *Rating*. Columns 3 and 4 add *Duration* and *InfoAsymmetry*; Columns 5 and 6 add *Callable*, a dummy variable for the presence of callable bond issues.

Significance levels: '***' 0.001 '**' 0.01 '*' 0.05 '†' 0.1 . Robust t-statistics using the Huber-White sandwich estimator of variance are listed in parentheses below each coefficient estimate.

	Dependent variable: NormNumIssues					
	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	−0.681***	−0.088**	−0.924***	−0.125***	−0.943***	−0.176***
	(−3.31)	(−2.74)	(−3.59)	(−3.86)	(−3.74)	(−5.80)
DefaultRisk	0.004**		0.005**		0.005**	
	(2.66)		(3.10)		(3.02)	
Rating		−0.001		0.000		−0.001
		(−1.05)		(0.39)		(−0.59)
Size	0.031***	0.027***	0.029***	0.027***	0.027***	0.024***
	(16.52)	(9.09)	(14.77)	(9.20)	(14.04)	(8.45)
Leverage	0.062***	0.098***	0.095***	0.117***	0.088***	0.113***
	(5.17)	(6.20)	(6.06)	(7.01)	(5.67)	(6.92)
Duration			0.001	0.001*	0.000	0.001
			(1.06)	(2.03)	(0.15)	(1.47)
InfoAsymmetry			−0.024**	−0.010	−0.024**	−0.011
			(−3.04)	(−1.36)	(−3.00)	(−1.43)
Callable					0.083***	0.096***
					(11.34)	(11.15)
N	8633	7456	5579	5726	5579	5726
R-squared	0.211	0.165	0.217	0.174	0.258	0.224
Adj. R-squared	0.21	0.164	0.216	0.174	0.257	0.223

of varying significance between the two regressions, but with consistent sign. The coefficient on *Duration* is positive, indicating that firms with greater weighted average duration tend to have more issues, while that on *InfoAsymmetry* is negative and significant, indicating that firms with greater information asymmetry (as measured by standard deviation of analyst estimates) tend to use fewer creditors. This result is in accordance with the discussion above, where I proposed two possible mechanisms for lower information asymmetry to be associated with a greater number of creditors. The presence of these variables does not qualitatively affect the coefficients of *DefaultRisk* and *Rating*.

Further, I test the hypothesis that firms that issue callable bonds, and thus can more easily control the number of outstanding debt issues, are more likely to make more distinct issues. Using a dummy variable *Callable*, which is 1 for observations which have at least one callable issue outstanding, I find that the presence of callable issues is indeed strongly positively associated with number of issues outstanding. This result is seen in Columns 5 and 6 of Table 4.

As a quick robustness check, I repeat the same regressions using the raw number of issues (*NumIssues*). The results can be seen in Table 5, and are qualitatively similar to those produced in the primary specification. In yet another robustness test, I construct a combined metric of default risk, based on the combined deciles of *Rating* and *DefaultRisk*, each ranging from 1 to 10, for a combined variable *DRCombined* ranging from 2 to 20. These results are shown in Table 6, with both *NormNumIssues* and *NumIssues* as dependent variables, and are qualitatively similar to the base spec-

Table 5: Multivariate Analysis: Number of Issues vs. Credit Risk

This table shows the estimated coefficients of regressing the raw number of issues on proxies for credit risk (*DefaultRisk* and *Rating*), and various controls. The variables included are: *Size*, the natural logarithm of total assets; *DefaultRisk*, the inverted firm-year Altman Z-score; *Rating*, the firm-year weighted average rating.
The primary specification is:

$$NumIssues = \alpha_0 + \alpha_1 DefaultRisk + \alpha_2 Size + \alpha_3 Leverage + \varepsilon$$

These results are reported in column 1. Column 2 replaces *DefaultRisk* with *Rating*. Columns 3 and 4 add *Duration* and *InfoAsymmetry*; Columns 5 and 6 add *Callable*, a dummy variable for the presence of callable bond issues.

Significance levels: '***' 0.001 '**' 0.01 '*' 0.05 '†' 0.1 . Robust t-statistics using the Huber-White sandwich estimator of variance are listed in parentheses below each coefficient estimate.

	Dependent variable: NumIssues					
	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	−59.474***	−24.029***	−95.763***	−27.454***	−96.231***	−29.111***
	(−4.96)	(−8.22)	(−4.24)	(−8.48)	(−4.27)	(−9.10)
DefaultRisk	0.252***		0.444**		0.439**	
	(3.43)		(3.18)		(3.15)	
Rating		−0.063		0.029		−0.002
		(−0.87)		(0.38)		(−0.02)
Size	2.788***	3.176***	3.320***	3.375***	3.269***	3.283***
	(13.39)	(10.87)	(12.77)	(10.92)	(12.56)	(10.63)
Leverage	4.478***	8.371***	6.757***	9.098***	6.582***	8.966***
	(5.50)	(7.06)	(5.13)	(6.92)	(4.99)	(6.86)
Duration			0.045	0.040	0.032	0.024
			(1.27)	(0.87)	(0.90)	(0.54)
InfoAsymmetry			−1.590*	−0.687*	−1.594*	−0.701*
			(−2.41)	(−2.16)	(−2.41)	(−2.23)
Callable					2.067***	3.098***
					(5.46)	(6.92)
N	8633	7456	5579	5726	5579	5726
R-squared	0.322	0.285	0.344	0.307	0.348	0.314
Adj. R-squared	0.321	0.284	0.343	0.307	0.347	0.313

ification. An additional test, including the year fixed effects to control for changes in the general financial environment over time (results not shown), also shows no qualitative changes in the relationship between variables of interest. All results point to greater default risk being associated with greater number of issues.

Table 6: Multivariate Analysis: Normalized Number of Issues vs. Credit Risk, Combined Measure

This table shows the estimated coefficients of the normalized and raw number of issues on a combined proxy for credit risk, *DRCombined*, and various controls. The variables included are: *Size*, the natural logarithm of total assets; *DRCombined*, the combined measure of default risk; *Leverage* the book leverage.
The primary specification is:

$$NormNumIssues = \alpha_0 + \alpha_1 DRCombined + \alpha_2 Size + \alpha_3 Leverage + \varepsilon$$

These results are reported in column 1. Column 2 adds *Duration* and *InfoAsymmetry*; Columns 3 adds *Callable*, a dummy variable for the presence of callable bond issues. Columns 4-6 repeat the same for raw number of issues, *NumIssues*, as a dependent variable.

Significance levels: '***' 0.001 '**' 0.01 '*' 0.05 '†' 0.1 . Robust t-statistics using the Huber-White sandwich estimator of variance are listed in parentheses below each coefficient estimate.

	NormNumIssues			NumIssues		
	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	−0.147***	−0.172***	−0.233***	−30.257***	−32.174***	−33.923***
	(−6.08)	(−6.85)	(−9.47)	(−10.20)	(−10.04)	(−10.62)
DRCombined	0.002***	0.003***	0.002***	0.225***	0.255***	0.241***
	(3.49)	(3.98)	(3.29)	(4.02)	(4.20)	(3.91)
Size	0.030***	0.030***	0.029***	3.614***	3.754***	3.708***
	(12.71)	(12.46)	(12.10)	(12.16)	(11.83)	(11.69)
Leverage	0.086***	0.102***	0.098***	7.036***	7.490***	7.373***
	(5.63)	(6.09)	(5.93)	(5.90)	(5.87)	(5.80)
Duration		0.002*	0.001†		0.053	0.040
		(2.40)	(1.90)		(1.14)	(0.88)
InfoAsymmetry		−0.025***	−0.025***		−1.670**	−1.673**
		(−3.96)	(−3.79)		(−2.73)	(−2.70)
Callable			0.090***			2.571***
			(9.93)			(4.98)
N	5973	5117	5117	5973	5117	5117
R-squared	0.185	0.201	0.24	0.331	0.337	0.341
Adj. R-squared	0.184	0.201	0.239	0.331	0.336	0.34

The next aspect of the number of issues problem that I investigate is that of the cost of debt. Since cost of debt is in large part determined by the credit risk (Longstaff, Mithal, and Neis, 2005), and since the number of issues is both theorized and empirically shown to influence the distress renegotiation process, I expect to see some association between the number of issues and the cost of debt. To this end, I examine the data for the relationship between *YieldSpread*, the weighted average spread between corporate bond yields and duration-equivalent treasuries, and *NormNumIssues*, the normalized number of outstanding bond issues.

I use a cross-sectional multivariate model, with a number of control variables. The base specification is:

$$\begin{aligned} YieldSpread = \alpha_0 + \alpha_1 NormNumIssues + \alpha_2 Rating + \alpha_3 Profitability + \\ + \alpha_4 Size + \alpha_5 Leverage + \varepsilon \end{aligned} \tag{8}$$

The dependent variable, *YieldSpread*, is the firm-year weighted average spread between corporate bond yields and duration-equivalent treasuries; *NormNumIssues* is the normalized number of distinct bond issues outstanding in each firm-year; *Leverage* is the book debt scaled by total assets; *Profitability* is cash flow scaled by total assets; *Size* is the natural logarithm of total assets; *Rating* is the firm-year weigted average rating. The main coefficient of interest is α_1, the effect of the number of issues on the yield spread.

I expect the coefficients on *Profitability* and *Size* to be negative, with more profitable and larger firms having lower cost of debt; *Leverage* and *Rating* to be positive, with more highly levered and poorer-rated firms having higher cost of debt. The coefficient on *NormNumIssues* will tell us whether firms with more issues tend to have a higher or lower cost of credit.

Table 7: Multivariate Analysis: Yield Spread vs. Normalized Number of Issues

This table shows the estimated coefficients of regressing the weighted average yield spread on the number of creditors, and various controls. The variables included are: *NormNumIssues*, the normalized number of distinct bond issues outstanding in each firm-year; *Leverage*, the book debt scaled by total assets; *Profitability*, cash flow scaled by total assets; *Size*, the natural logarithm of total assets; *Rating*, the firm-year weighted average rating.

$$YieldSpread = \alpha_0 + \alpha_1 NormNumIssues + \alpha_2 Rating + \alpha_3 Profitability + \\ + \alpha_4 Size + \alpha_5 Leverage + \varepsilon$$

These results are reported in Column 1. Column 2 uses *DefaultRisk* instead of *Rating*. Columns 3 and 4 additionally include *Duration* and *InfoAsymmetry*. Columns 5 and 6 include indicator variables for the presence of various bond features: *Convertible*, *Callable*, *Puttable*, *Exchangeable*.

Significance levels: '***' 0.001 '**' 0.01 '*' 0.05 '†' 0.1 . Robust t-statistics using the Huber-White sandwich estimator of variance are listed in parentheses below each coefficient estimate.

	Dependent variable: YieldSpread					
	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	−1.299***	−16.209***	−0.333	−14.313***	−0.601	−14.866***
	(−3.94)	(−4.52)	(−0.89)	(−4.17)	(−1.51)	(−4.34)
NormNumIssues	−1.308***	−2.732***	−0.926*	−1.242*	−1.122**	−1.976***
	(−3.62)	(−5.43)	(−2.28)	(−2.52)	(−2.58)	(−3.79)
Rating	0.413***		0.372***		0.379***	
	(38.89)		(31.11)		(30.25)	
DefaultRisk		0.149***		0.140***		0.139***
		(6.59)		(6.46)		(6.43)
Leverage	0.863***	2.619***	0.936***	1.836***	0.871***	1.886***
	(4.45)	(10.37)	(4.20)	(7.07)	(3.89)	(7.28)
Profitability	−5.546***	−5.968***	−5.065***	−5.498***	−5.144***	−5.299***
	(−18.09)	(−16.29)	(−16.24)	(−15.68)	(−16.48)	(−14.97)
Size	0.051	−0.585***	0.038	−0.508***	0.035	−0.495***
	(1.60)	(−16.10)	(1.06)	(−14.17)	(0.97)	(−13.49)
Duration			−0.110***	−0.185***	−0.112***	−0.194***
			(−7.76)	(−11.84)	(−7.62)	(−11.89)
InfoAsymmetry			1.374***	1.551***	1.373***	1.493***
			(7.95)	(6.58)	(7.96)	(6.34)
Callable					0.393*	0.686***
					(2.38)	(3.72)
Putable					0.155	0.004
					(1.60)	(0.03)
Convertible					−0.285**	0.397***
					(−3.28)	(4.09)
Exchangeable					−0.610	−0.101
					(−1.63)	(−0.23)
N	6569	5464	5409	5085	5409	5085
R-squared	0.35	0.204	0.341	0.219	0.343	0.224
Adj. R-squared	0.349	0.203	0.34	0.218	0.341	0.222

Column 1 of Table 7 presents the regression results following the specification shown in Eq. (8). The main finding is that firms with more bond issues have significantly lower yield spreads, even controlling for rating. The coefficient on *NormNumIssues* of -1.30753 is significant, and translates into -13.18 basis points for a change of one standard deviation in *NormNumIssues*. Qualitatively this finding is similar to that of Davydenko and Strebulaev (2007), who also find a negative association between number of issues and the cost of debt.

The coefficients on the control variables are in accordance with my expectations, with better-rated, more profitable, less leveraged firms having a lower cost of debt. Interestingly, size is positively associated with higher cost of credit, all else equal. Since size is generally highly correlated with rating, size here represents the component of size that is not incorporated into *Rating*. So I am seeing here the effect of some component of *Size* that is seen negatively by the market.

Column 2 is the same specification substituting *DefaultRisk* for *Rating*, showing the same results qualitatively, with the exception of that on *Size*. Since the *DefaultRisk* variable is actually not very correlated with *Size*, I am here seeing a more 'complete' size effect, which is, expectedly, in the direction of lower cost of debt.

I show in Columns 3 and 4 model specifications which add *Duration* and *InfoAsymmetry*, variables which were explored earlier and found to be significantly associated with *NormNumIssues*. The inclusion of these variables does not qualitatively change the results.

In Columns 5 and 6 I show the effects of the presence of various bond features in the issue mix of a firm. The variables *Callable*, *Putable*, *Convertible*, and *Exchangeable* are dummy variables which have a value of one if at least one issue outstanding in a firm-year contains that feature, and zero otherwise. None have significance with the exception of *Convertible* and *Callable*. However, it is difficult to draw any strong conclusions here, since the dummy variables carry no information about the *proportion* of outstanding debt that carries the feature.

Several robustness tests confirm the basic finding that a greater number of issues is associated with lower yield spread. Columns 1-3 of Table 8 show the regression results using the combined default risk variable, *DRCombined*, defined, as above, as the sum of deciles of *DefaultRisk* and *Rating*. Further, to address possible endogeneity concerns in the number of issues variable, I try a two-stage least squares specification, where in the first stage I regress *NormNumIssues* on a number of predictor variables, and then use the predicted values from that specification as the independent variable in a regression on *YieldSpread*. The first-stage specification is

$$NormNumIssues = \alpha_0 + \alpha_1 Size + \alpha_2 DefaultRisk + \alpha_3 Leverage + \\ + \alpha_4 Duration + \alpha_5 InfoAsymmetry + \alpha_6 Callable + \varepsilon, \qquad (9)$$

the regression results of which are shown in Column 5 of Table 4. Columns 4-6 of Table 8, then, show the results using the predicted values from the second stage model. The coefficients for number of issues are consistently negative and significant, suggesting that *ceteris paribus*, an increase in number of issues in the cross-section is associated with a reduction in the cost of debt as measured by *YieldSpread*.

The overall picture that emerges from my results thus far is not unequivocally unidirectional. On the one hand, as per the results shown in Table 4, I find that firms with less credit risk, as measured by *DefaultRisk* or *Rating*, tend to have fewer creditors in their debt mix. Of the two competing theories, this lends support to that of Bris and Welch (2005), since it shows that higher-quality borrowers tend to borrow from a more concentrated creditor base. However, this theory also necessitates that borrowers with fewer creditors have a lower cost of debt. In contrast, my results, shown in Table 7, point toward a greater number of creditors being associated with a lower cost of debt, which in isolation would support the Bolton and Scharfstein (1996) framework.

This suggests that having more creditors, while by itself beneficial in terms of lower cost of debt, possibly through the managerial discipline hypothesis proposed by Bolton and Scharfstein (1996), also has associated costs, possibly due to the fixed costs associated with floating a public debt issue. As a result, a lower-quality firm may find it beneficial to use more creditors in order to lower its cost of debt, with the reduction in yields more than offsetting the costs of multiple issues, while the very high-quality firm may have see little to no benefit to incurring the costs of multiple issues.

Empirical evidence on the structure of issue costs is consistent with this framework. Lee, Lochhead, Ritter, and Zhao (1996), in their overview of debt and equity flotation costs, find that while total debt issue costs are correlated with credit qual-

Table 8: Multivariate Analysis: Yield Spread vs. Normalized Number of Issues, Other Models

This table shows the estimated coefficients of regressing the weighted average yield spread on the number of issues, and various controls. The variables included are: *NormNumIssues*, the normalized number of distinct bond issues outstanding in each firm-year; *Leverage*, the book debt scaled by total assets; *Profitability*, cash flow scaled by total assets; *Size*, the natural logarithm of total assets; *DRCombined*, the combined measure of default risk.

$$YieldSpread = \alpha_0 + \alpha_1 NormNumIssues + \alpha_2 DRCombined + \alpha_3 Profitability + \\ + \alpha_4 Size + \alpha_5 Leverage + \varepsilon$$

These results are reported in Column 1. Column 2 additionally includes *Duration* and *InfoAsymmetry*. Column 3 includes indicator variables for the presence of various bond features: *Convertible*, *Callable*, *Puttable*, *Exchangeable*. Columns 4-6 repeat the results from Columns 1-3, using the fitted values for *NormNumIssues* from a first-stage regression.

Significance levels: '***' 0.001 '**' 0.01 '*' 0.05 '†' 0.1 . Robust t-statistics using the Huber-White sandwich estimator of variance are listed in parentheses below each coefficient estimate.

	Dependent variable: YieldSpread					
	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	2.784***	3.445***	3.218***	2.048***	3.145***	−5.789***
	(7.74)	(9.64)	(8.21)	(4.47)	(6.72)	(−4.99)
NormNumIssues	−3.939***	−2.631***	−3.077***			
	(−8.46)	(−5.72)	(−6.32)			
NumIssuesFitted				−8.991***	−5.313*	−47.032***
				(−4.39)	(−2.55)	(−8.76)
DRCombined	0.301***	0.275***	0.272***	0.296***	0.277***	0.330***
	(27.32)	(25.60)	(24.91)	(26.15)	(24.24)	(25.08)
Leverage	0.972***	0.455†	0.498†	1.169***	0.732*	4.853***
	(3.92)	(1.79)	(1.95)	(3.59)	(2.23)	(8.28)
Profitability	−4.514***	−4.210***	−4.178***	−4.413***	−4.318***	−4.953***
	(−12.75)	(−12.36)	(−12.24)	(−12.77)	(−12.62)	(−14.17)
Size	−0.272***	−0.229***	−0.240***	−0.088	−0.150*	1.019***
	(−7.37)	(−6.25)	(−6.44)	(−1.25)	(−2.11)	(6.53)
Duration		−0.135***	−0.142***		−0.143***	−0.138***
		(−8.74)	(−8.93)		(−9.29)	(−8.69)
InfoAsymmetry		1.004***	0.996***		0.971***	0.069
		(4.64)	(4.60)		(4.39)	(0.28)
Callable			0.408*			4.048***
			(2.14)			(8.41)
Putable			0.118			0.019
			(1.11)			(0.18)
Convertible			0.129			0.031
			(1.38)			(0.33)
Exchangeable			−0.604			−0.664
			(−1.46)			(−1.61)
N	5171	4820	4820	4820	4820	4820
R-squared	0.31	0.31	0.312	0.292	0.307	0.317
Adj. R-squared	0.309	0.309	0.311	0.291	0.306	0.316

ity, the cost of issuing debt securities also exhibits significant economies of scale. The variable components of the total issue costs include items like the management fee, underwriting fee, and selling concession, which are set as percentage of issue size. The fixed components of the issue cost include items like the registration fee, legal, accounting, and auditing costs, and document preparation costs. Some representative statistics show that the fixed cost component is far from insignificant. For the median convertible bond issue of $75 million, the variable spread component makes up 2.64 percent of issue size, while the fixed cost component, 0.59 percent of issue size. For the median straight bond issue of $100 million, the variable spread component is 1.55 percent of issue, while the fixed cost component is 0.61 percent of issue.

Refactoring the data from Lee, Lochhead, Ritter, and Zhao (1996) for my framework, holding the total debt size constant, and increasing number of issues the debt is split into, assuming equal apportionment, shows an approximately linear, somewhat concave relationship between number of issues and total per-dollar issue costs. Figure 1 shows the graphs of the issue costs for investment- and non-investment-grade issuers (the relationship looks like a step function due to the discrete nature of the source data). While the graphs show a significantly higher issue costs for non-investment-grade firms, the data in the study cover years 1990 through 1994, before significant efficiencies and liquidity were introduced into the high-yield bond market. With my data covering a period from 2002 to 2008, and with current high yield total issue costs being about a quarter of what they were then (Cresci, 2006), the two cost functions for investment- and non-investment-grade issuers have come a lot closer together.

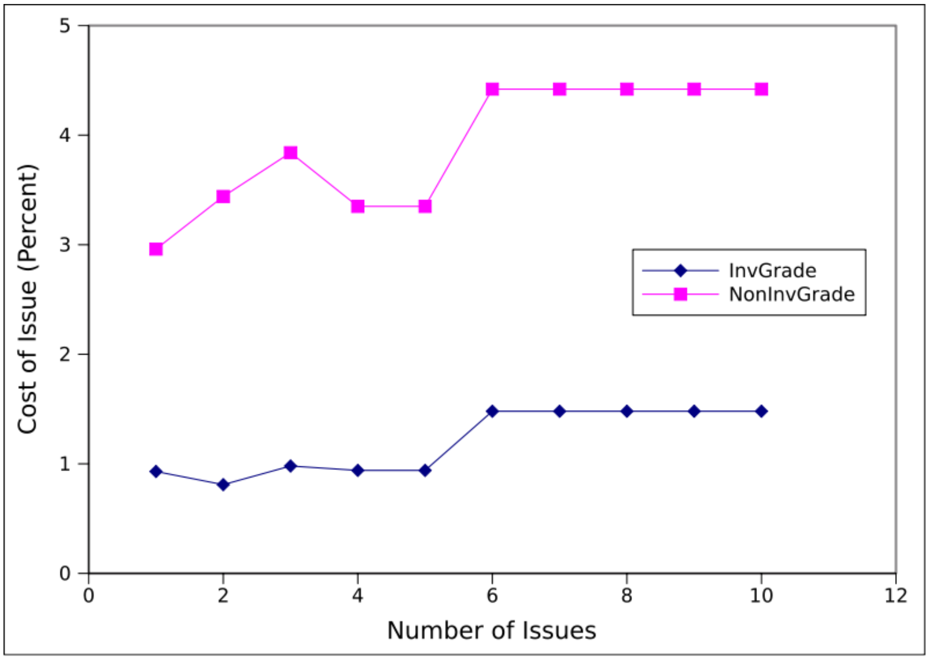

Figure 1: Cost of Issue vs Number of Issues

To test this empirically more directly, I use the issue cost data (*IssueCost*) from the FISD database to measure the actual weighted average issue costs. As described in the data section, *IssueCost* is derived from the "gross spread" data item, which is the difference between actual issue offering price, and the cash received by the issuer. To determine the association between issue costs and number of issues, I regress *IssueCost* on *NumIssues*, along with a number of controls. The primary specification is

$$IssueCost = \alpha_0 + \alpha_1 NumIssues + \alpha_2 Size + \alpha_3 DRCombined + \\ + \alpha_4 Leverage + \varepsilon, \quad (10)$$

the results of which are shown in Column 1 of Table 9. Column 2 tries the same with *NormNumIssues*; Columns 3 and 4 add the second-order term for the issue count measure, to observe any nonlinearity of effect, as seen in the descriptive statistics of Lee, Lochhead, Ritter, and Zhao (1996). The results show that the number of issues measure is positively associated with the cost of issuance, and further, as the coefficient on the second order term is negative, that the effect is nonlinear and concave. Columns 5 and 6 add the investment grade indicator *IG*, and its interaction with the first- and second-order terms for number of issues. As expected, the coefficient on the indicator variable is negative, suggesting that investment-grade firms tend to have a lower baseline cost of issuance. The interactions suggest that for investment-grade firms, the increase in issue costs with number of issues is less steep, but the concavity is also less pronounced (closer to linearity).

In light of these findings, a cost-benefit tradeoff framework emerges, shown graphically in Figure 2. The black dashed line shows the total issue costs growing with number of issues, scaled in terms of extra effective bond yield. These costs, which include items like registration fee, legal, and other human capital costs required to attend to the issue process, do not show up in a market measure of the cost of debt such as the yield spread. Instead, they get expensed or amortized, following IRS regulation T.D. 9107, Sections 263 and 446[4], and are effectively hidden in other deductible expenses. The dotted lines in red and in blue in the figure, represent the market cost of debt for a high and a low credit quality firm, respectively. As per my

[4] http://www.irs.gov/irb/2004-07_IRB/ar07.html

Table 9: Multivariate Analysis: Issue Cost vs. Normalized Number of Issues

This table shows the estimated coefficients of regressing the weighted average issue cost on the number of issues, and various controls. The variables included are: *NumIssues*, the normalized number of distinct bond issues outstanding in each firm-year; *Leverage*, the book debt scaled by total assets; *Size*, the natural logarithm of total assets; *DRCombined*, the combined measure of default risk.

$$IssueCost = \alpha_0 + \alpha_1 NumIssues + \alpha_2 Size + \alpha_3 DRCombined + \\ + \alpha_4 Leverage + \varepsilon$$

These results are reported in Column 1. Column 2 uses *NormNumIssues*; Columns 3 and 4 include the second-order terms.

Significance levels: '***' 0.001 '**' 0.01 '*' 0.05 '†' 0.1 . Robust t-statistics using the Huber-White sandwich estimator of variance are listed in parentheses below each coefficient estimate.

	Dependent variable: IssueCost					
	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	2.180∗∗∗	2.134∗∗∗	1.952∗∗∗	1.937∗∗∗	2.213∗∗∗	2.146∗∗∗
	(22.18)	(24.02)	(18.94)	(21.28)	(20.58)	(21.83)
NumIssues	0.032∗		0.250∗∗∗		0.323∗∗∗	
	(2.29)		(7.33)		(6.37)	
NormNumIssues		0.352∗∗		2.964∗∗∗		3.287∗∗∗
		(3.07)		(9.15)		(6.69)
Size	−0.168∗∗∗	−0.164∗∗∗	−0.158∗∗∗	−0.163∗∗∗	−0.127∗∗∗	−0.128∗∗∗
	(−15.57)	(−17.61)	(−14.59)	(−17.59)	(−11.84)	(−13.64)
DRCombined	0.083∗∗∗	0.083∗∗∗	0.084∗∗∗	0.084∗∗∗	0.049∗∗∗	0.050∗∗∗
	(31.58)	(31.56)	(32.07)	(32.14)	(14.20)	(14.43)
Leverage	−0.730∗∗∗	−0.730∗∗∗	−0.719∗∗∗	−0.718∗∗∗	−0.574∗∗∗	−0.592∗∗∗
	(−10.80)	(−10.92)	(−10.69)	(−10.83)	(−8.67)	(−9.02)
NumIssuesSq			−0.066∗∗∗		−0.102∗∗∗	
			(−7.00)		(−6.81)	
NormNumIssuesSq				−7.167∗∗∗		−8.163∗∗∗
				(−8.61)		(−6.00)
IG					−0.478∗∗∗	−0.405∗∗∗
					(−7.88)	(−6.36)
NumIssues:IG					−0.117†	
					(−1.74)	
NumIssuesSq:IG					0.066∗∗∗	
					(3.50)	
NormNumIssues:IG						−1.029
						(−1.58)
NormNumIssuesSq:IG						3.758∗
						(2.18)
N	4474	4474	4474	4474	4474	4474
R-squared	0.284	0.285	0.292	0.297	0.329	0.328
Adj. R-squared	0.284	0.284	0.291	0.296	0.328	0.326

empirical results, I show that a greater number of issues is associated with a lower market yield spread, and that higher credit quality, all else equal, is associated with lower yield spreads. Finally, the solid red and blue lines represent the total cost of debt, including both the market yield spread and the issue costs that do not show up in the spread. The "optimum" number of debt issues for a high credit quality firm ends up being lower than the optimum number of issues for a low credit quality firm.

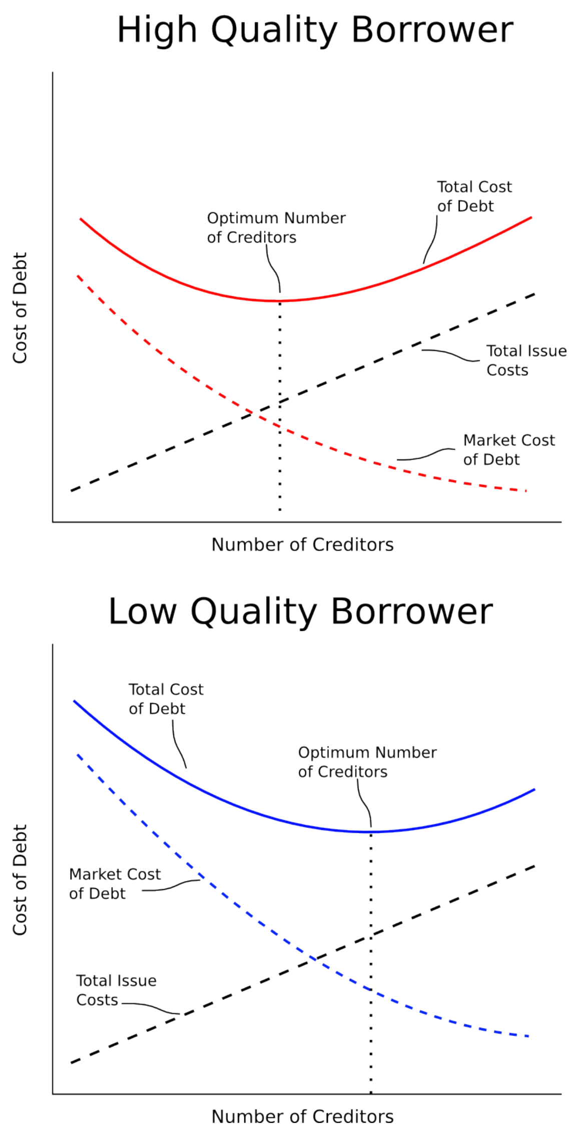

Figure 2: Optimum Number of Creditors

To test the validity of this model, I investigate the relationship of the *NormNumIssues* coefficient with the credit quality of the issuing firm. To this end, I create an indicator variable, *IG* ("Investment Grade"), which is 1 if the firm is below the median of the sample combined default risk (*DRCombined*), and 0 otherwise. If the model holds up, it should be the case that the negative effect of *NormNumIssues* on the *YieldSpread* is lower for firms of lower default risk. The main model specification for this test is

$$\begin{aligned} YieldSpread &= \alpha_0 + \alpha_1 NormNumIssues + \alpha_2 DRCombined + \alpha_3 Profitability + \\ &+ \alpha_4 Size + \alpha_5 Leverage + \alpha_6 Duration + \alpha_7 InfoAsymmetry + \\ &+ \alpha_8 Callable + \alpha_9 IG + \alpha_{10} IG : NormNumIssues + \varepsilon, \end{aligned} \tag{11}$$

where all other variables are as previously defined. The results appear in Table 10, Column 1.

The pattern of coefficients that emerges from Table 10 lends support to my hypothesis that there's a tradeoff between costs and benefits of increasing the number of debt issues, and that lower-quality firms get more of a benefit. Comparing the associations across firm credit quality, the speculative-grade firms get a greater benefit (base *NormNumIssues* coefficient) from increased number of issues than do the investment-grade firms (sum of *NormNumIssues* and *NormNumIssues:IG* coefficients). Columns 2 and 3 repeat the full sample regression using *Rating* and *DefaultRisk* measures of credit quality, respectively, producing qualitatively similar results. The result is also

Table 10: Multivariate Analysis: Norm Number of Issues vs. Yield Spread, Subsamples

This table shows the estimated coefficients of regressing the weighted average yield spread on the number of issues, and various controls. The variables included are: *NormNumIssues*, the normalized number of distinct bond issues outstanding in each firm-year; *Leverage*, the book debt scaled by total assets; *Profitability*, cash flow scaled by total assets; *Size*, the natural logarithm of total assets; *Duration*, the weighted average debt duration; and *InfoAsymmetry*, my proxy for information asymmetry; *DRCombined*, the combined measure of default risk; *IG* the investment grade indicator.

$$
\begin{aligned}
YieldSpread = \alpha_0 + \alpha_1 NormNumIssues + \alpha_2 DRCombined + \alpha_3 Profitability + \\
+ \alpha_4 Size + \alpha_5 Leverage + \alpha_6 Duration + \alpha_7 InfoAsymmetry + \\
+ \alpha_8 Callable + \alpha_9 IG + \alpha_{10} IG : NormNumIssues + \varepsilon
\end{aligned}
$$

Columns 1-3 show the result for the full sample regression with the *NormNumIssues:IG* interaction term, using *DRCombined*, *Rating*, and *DefaultRisk* measures of credit quality, respectively. Columns 4 and 5 show subsample regressions on high- and low-credit quality firms.

Significance levels: '***' 0.001 '**' 0.01 '*' 0.05 '†' 0.1 . Robust t-statistics using the Huber-White sandwich estimator of variance are listed in parentheses below each coefficient estimate.

	Full Sample			IG	SP
	(1)	(2)	(3)	(4)	(5)
Intercept	3.134***	0.638	9.328*	1.445***	2.984**
	(4.70)	(0.91)	(2.16)	(4.10)	(3.09)
NormNumIssues	−4.629***	−3.384***	−4.498***	−0.700†	−3.464***
	(−5.14)	(−4.34)	(−4.42)	(−1.81)	(−3.64)
Rating		0.345***			
		(14.24)			
DefaultRisk			−0.010		
			(−0.37)		
DRCombined	0.300***			0.184***	0.409***
	(11.20)			(10.79)	(10.16)
Leverage	0.433	1.113***	1.772***	−0.310	0.442
	(1.29)	(3.52)	(4.61)	(−1.51)	(0.83)
Profitability	−4.125***	−4.684***	−5.556***	0.962	−4.503**
	(−3.88)	(−3.84)	(−3.74)	(1.40)	(−3.21)
Size	−0.222***	0.009	−0.370***	−0.114***	−0.269***
	(−4.52)	(0.19)	(−8.13)	(−3.82)	(−3.60)
Duration	−0.141***	−0.117***	−0.158***	0.005	−0.304***
	(−6.92)	(−6.15)	(−7.72)	(0.52)	(−9.12)
InfoAsymmetry	0.968	0.898	1.343†	1.834†	0.761
	(1.46)	(1.38)	(1.65)	(1.89)	(1.27)
Callable	0.313†	0.107	0.425*	0.264*	−0.039
	(1.72)	(0.60)	(2.26)	(2.18)	(−0.09)
IG	−0.514†	−1.026***	−2.671***		
	(−1.75)	(−4.21)	(−9.76)		
NormNumIssues:IG	4.174***	4.216***	5.340***		
	(4.21)	(4.91)	(4.93)		
N	4820	4820	4820	2186	2634
R-squared	0.316	0.334	0.272	0.138	0.242
Adj. R-squared	0.314	0.333	0.271	0.135	0.24

consistent with the regressions in Columns 4 and 5, which are regressions on subsamples of firms based on their credit quality. The association of *NormNumIssues* with *YieldSpread* is smaller for investment grade (Column 4) than non-investment grade (Column 5) firms.

The coefficients on the control variables, while they lose significance in some specifications, remain largely qualitatively similar across the board. *Profitability* appears to be much more important for speculative-grade firms. *Duration* is negatively associated with yields for non-investment-grade debt, possibly because having more time to repay the principal gives a low-quality borrower a better chance of getting it together by the time it comes due.

Additionally, there remain unaddressed questions in the subsidiary hypotheses, relating to the effects of *Duration* and *InfoAsymmetry*. I investigate these relationships further by looking at the interaction terms between the number of issues and those variables. The regression results of variations on the following model specification,

$$\begin{aligned} YieldSpread = \alpha_0 + \alpha_1 NormNumIssues + \alpha_2 DRCombined + \alpha_3 Profitability + \\ + \alpha_4 Size + \alpha_5 Leverage + \alpha_6 Duration + \\ + \alpha_7 InfoAsymmetry + \sum_i \alpha_i Interaction_i + \varepsilon, \end{aligned} \tag{12}$$

are available in Table 11.

Looking at Columns 1 and 2, we see that the interaction term of *NormNumIssues* and *InfoAsymmetry* is large, positive, and significant. This suggests that firms with

Table 11: Multivariate Analysis: Norm Number of Issues vs. Yield Spread, Interactions

This table shows the estimated coefficients of regressing the weighted average yield spread on the number of creditors, and various controls. The variables included are: *NormNumIssues*, the normalized number of distinct bond issues outstanding in each firm-year; *Leverage*, the book debt scaled by total assets; *Profitability*, cash flow scaled by total assets; *Size*, the natural logarithm of total assets; *DRCombined*, combined measure of default risk; *Duration*, the weighted average debt duration; and *InfoAsymmetry*, my proxy for information asymmetry.

$$
\begin{aligned}
YieldSpread = \alpha_0 + \alpha_1 NormNumIssues + \alpha_2 DRCombined + \alpha_3 Profitability + \\
+ \alpha_4 Size + \alpha_5 Leverage + \alpha_6 Duration + \\
+ \alpha_7 InfoAsymmetry + \sum_i \alpha_i Interaction_i + \varepsilon
\end{aligned}
$$

Column 1 includes the interaction of *InfoAsymm* with *NormNumIssues*, Column 2 adds the investment-grade indicator interaction to account for effect differentials by firm credit quality. Columns 3 and 4 repeat this for *Duration*.

Significance levels: '***' 0.001 '**' 0.01 '*' 0.05 '†' 0.1 . Robust t-statistics using the Huber-White sandwich estimator of variance are listed in parentheses below each coefficient estimate.

	Dependent variable: YieldSpread			
	(1)	(2)	(3)	(4)
Intercept	3.727***	3.769***	3.447***	3.298***
	(7.01)	(5.70)	(5.72)	(4.52)
NormNumIssues	−3.601***	−5.674***	−2.645†	−3.977*
	(−5.79)	(−6.33)	(−1.80)	(−2.42)
DRCombined	0.269***	0.290***	0.275***	0.300***
	(15.33)	(10.84)	(15.81)	(11.30)
Leverage	0.484	0.465	0.455	0.425
	(1.43)	(1.38)	(1.36)	(1.27)
Profitability	−4.257***	−4.163***	−4.209***	−4.117***
	(−3.93)	(−3.90)	(−3.93)	(−3.90)
Size	−0.243***	−0.236***	−0.229***	−0.219***
	(−5.03)	(−4.85)	(−4.67)	(−4.46)
Duration	−0.132***	−0.137***	−0.135***	−0.122**
	(−6.69)	(−6.84)	(−3.45)	(−3.14)
InfoAsymmetry	−1.382*	−1.512*	1.004	0.971
	(−2.06)	(−2.29)	(1.51)	(1.46)
IG		−0.646*		−0.565*
		(−2.22)		(−2.00)
NumIss:IG		4.632***		4.401***
		(4.75)		(4.73)
NumIss:InfoAsymm	18.553***	19.344***		
	(3.82)	(3.95)		
NumIss:Duration			0.002	−0.102
			(0.01)	(−0.55)
N	4820	4820	4820	4820
R-squared	0.315	0.32	0.31	0.315
Adj. R-squared	0.314	0.319	0.309	0.314

greater information asymmetry experience a smaller (if any) reduction in yield spreads associated with increasing number of issues. This is inconsistent with the idea that having more issues is itself a mechanism providing greater disclosure to investors. If that were the case, the more opaque firm would benefit more from greater disclosure, in whatever guise. Thus, the alternative hypothesis, that firms with good disclosure practices and lower information asymmetry have easier access to debt markets, and thus may choose to make more issues, is more likely. Columns 3 and 4 show that the interaction term with *Duration* are small and insignificant, suggesting that *Duration* does not have a modifying effect on the number of issues.

1.5 Alternative Specifications

In the analyses above, I do account for the potential of data clustering through the use of the Huber-White estimator of variance. Since number of issues outstanding is a fairly persistent metric from year to year, as are a lot of the other variables, I would be underestimating the standard errors of the coefficients with standard pooled regression. As a further robustness check addressing this issue, here I aggregate the data by firm, taking the median values of variables over the sample period. The results of selected model specifications with firm-aggregated data are shown in Table 12. The sign and significance of the relationship between the number of issues and measures of default risk remains unaffected by this change in specification, indicating that firms with greater credit risk tend to have a greater number of issues. The results also hold for the relationship between yield spreads and number of issues, with all major coefficients retaining sign and significance.

Table 12: Multivariate Analysis: Data Aggregated by Firm

This table shows the results of an alternative specification, using firm-aggregated data. Each firm data point is the median of the available firm-years. Columns 1 and 2 show the coefficients of regressing the normalized number of issues, and raw number of issues, respectively, on a proxy for credit risk, and various controls. Columns 3 and 4 show the regressions of yield spread on normalized number of creditors, controlling for credit risk, with Column 2 adding an interaction for firm credit quality.

Significance levels: '***' 0.001 '**' 0.01 '*' 0.05 '†' 0.1 . Robust t-statistics using the Huber-White sandwich estimator of variance are listed in parentheses below each coefficient estimate.

	NormNumIssues	NumIssues	YieldSpread	
	(1)	(2)	(3)	(4)
Intercept	−0.146∗∗∗	−25.781∗∗∗	3.744∗∗∗	3.575∗∗∗
	(−5.35)	(−13.16)	(5.22)	(4.51)
DRCombined	0.002†	0.197∗∗∗	0.272∗∗∗	0.305∗∗∗
	(1.94)	(3.40)	(12.07)	(9.10)
NormNumIssues			−3.810∗∗∗	−5.730∗∗∗
			(−4.34)	(−5.51)
Leverage	0.097∗∗∗	6.390∗∗∗	0.083	0.006
	(4.78)	(4.41)	(0.17)	(0.01)
Profitability			−1.334	−1.290
			(−0.78)	(−0.76)
Size	0.028∗∗∗	3.084∗∗∗	−0.321∗∗∗	−0.313∗∗∗
	(10.45)	(16.01)	(−4.71)	(−4.62)
Duration	0.001	0.020	−0.099∗∗∗	−0.108∗∗∗
	(0.83)	(0.29)	(−3.63)	(−3.97)
InfoAsymmetry	−0.020†	−0.933	0.311	0.296
	(−1.85)	(−1.18)	(1.18)	(1.14)
IG				−0.632
				(−1.56)
NormNumIssues:IG				6.025∗∗∗
				(3.51)
N	761	761	739	739
R-squared	0.171	0.292	0.411	0.422
Adj. R-squared	0.166	0.287	0.405	0.415

Another potential area of concern with the results thus far is the fact that the data sets only look at the public debt of the firm, with no information on the sources of private debt. It may thus be argued that the number of public issues is not an accurate measure of the number of creditor classes (which is the effectively important issue for the debt renegotiation angle), for firms with relatively low proportion of public debt in the total debt mix. To address this issue, I test the main model specifications against a subsample of firms in the top quartile by fraction of total debt that is made up of public debt. This subsample consists of firms with the fraction of public debt of 0.73 or greater. The results appear in Table 13. The signs of the major coefficients remain unaffected in these regressions, suggesting that in the cross section, the dispersion of sources of private debt is not systematically associated with that of public debt.

Table 13: Multivariate Analysis: High Proportion of Public Debt Sample

This table shows the results of an alternative specification, using only observations from the top quartile by fraction of public debt in the total debt mix. Columns 1 and 2 show the coefficients of regressing the normalized number of issues, and raw number of issues, respectively, on a proxy for credit risk, and various controls. Columns 3 and 4 show the regressions of yield spread on normalized number of creditors, controlling for credit risk, with Column 2 adding an interaction for firm credit quality.

Significance levels: '***' 0.001 '**' 0.01 '*' 0.05 '†' 0.1 . Robust t-statistics using the Huber-White sandwich estimator of variance are listed in parentheses below each coefficient estimate.

	NormNumIssues	NumIssues	YieldSpread	
	(1)	(2)	(3)	(4)
Intercept	−0.129***	−27.969***	2.297*	2.519*
	(−8.20)	(−29.01)	(2.24)	(2.29)
DRCombined	0.002***	0.235***	0.263***	0.249***
	(5.30)	(8.52)	(8.84)	(5.59)
NormNumIssues			−2.691	−3.204
			(−1.44)	(−1.58)
Leverage	0.085***	4.860***	1.453**	1.498**
	(10.78)	(10.04)	(2.78)	(2.84)
Profitability			−3.453***	−3.449***
			(−6.82)	(−6.79)
Size	0.036***	3.800***	−0.107	−0.094
	(22.54)	(38.34)	(−0.86)	(−0.75)
Duration	−0.002***	−0.098***	−0.179***	−0.180***
	(−3.80)	(−3.83)	(−4.81)	(−4.82)
InfoAsymmetry	−0.044**	−2.278**	3.612***	3.606***
	(−3.13)	(−2.61)	(4.17)	(4.15)
IG				−0.799
				(−0.79)
NormNumIssues:IG				2.688
				(0.66)
N	1199	1199	1079	1079
R-squared	0.355	0.573	0.266	0.266
Adj. R-squared	0.352	0.571	0.261	0.26

1.6 Conclusions

This article has analyzed the relationship between the number of public debt issues a firm chooses to borrow through and various firm characteristics. The main findings are that, all else equal, more creditworthy firms tend to have fewer distinct public debt issues outstanding, and that, all else equal, a greater number of outstanding issues is associated with a lower cost of debt. These results do not support any of the existing hypotheses, being in accordance with neither the Bolton and Scharfstein (1996) nor the Bris and Welch (2005) theoretical framework.

Instead, I find that there's a nonlinear relationship between number of issues, cost of debt, and credit quality, which supports the hypothesis that there are both costs and benefits to having a greater number of creditors. The presence of benefits lends partial support to the Bolton and Scharfstein (1996) framework, which hypothesizes that greater number of creditors is associated with better creditor recovery and better managerial discipline, leading to lower cost of debt. Bris and Welch (2005) propose a higher cost of debt for less concentrated creditors, which is incompatible with my results. The possibility of costs, offsetting the yield gains from multiple creditors, has not been considered by either theory.

Further, my results shed light on other characteristics of firms that have a bearing on the number of creditors the firm chooses to use. I found that firms with lower manager-market information asymmetry, and those with greater weighted average debt duration, tend to have a greater number of outstanding issues. These factors, while having their own effects on a firm's cost of debt, do not explain the lower cost of debt experienced by firms with a greater number of creditors.

While these results bear further investigation, insofar as I have only hypothesized on the mechanisms underlying the observed statistical results, I have, at the very least, shown that the number of creditors a firm chooses to use in its public debt structure is not random, but rather is a function of firm characteristics, and has significant implications for the firm's overall cost of debt.

2 Chapter 2. Competitive Intensity, Competitive Intelligence, and the Cost of Debt

2.1 Introduction

The recent bankruptcies of GM and Chrysler, as a culmination of a gradual decades-long bleeding of market share to competitors, underscore the magnitude of the impact that a firm's competitive environment can have on its medium- and long-term prospects. The intensity of competition confronting a firm in its target markets is a factor that influences many aspects of a firm's operations. A firm that does not keep track of its competition and does not respond by hastening the cycle of product innovation and continuously reassessing and streamlining its internal processes stands to suffer reduced profitability, loss of market share, and, eventually, failure.[5]

One of the components in a firm's strategy of keeping up with the competition is the process of competitive intelligence, which involves gathering, analyzing, and internally disseminating information about the individual competitors of the firm and the overall competitive landscape. A competent competitive intelligence function can provide the firm with valuable information on all aspects of its competitive environment and enable it to respond nimbly to any changes therein.[6]

Given the influence of competitive pressure in decreasing the survival likelihood

[5]For example, Cool, Roller, and Leleux (1999), using a sample of pharmaceutical firms, show that competition has an adverse effect on profitability.

[6]Daft, Sormunen, and Parks (1988) find that higher frequency and breadth of environmental scanning is associated with better firm performance.

of the firm, and the importance of the firm's responses to said pressure in mitigating the effects thereof, I expect that the corporate bondholders will take these issues into account, and thus, assuming efficiency of the corporate bond markets, I should see that reflected in the firm's cost of debt. While it is not immediately clear how much information the bond markets have about the intensity of competition facing a firm, and about the degree of effort being invested into competitive intelligence and subsequent responses, theory suggests that this information should be priced to the extent of its availability.[7] The implication is that the cost of debt capital would be positively associated with a higher competitive intensity, and negatively associated with competitive intelligence effort, *ceteris paribus*. The basic framework is shown graphically in Figure 3. More competitive intelligence may also be an indicator of generally greater managerial effort in response to competition, further enhancing the effect.[8]

This hypothesized association of competitive intelligence with cost of debt may not be in evidence for a number of reasons, however. First, the effect of CI effort may be minor enough as to be below the threshold of detectability. Second, competitive intelligence effort may be ineffective at counteracting the negative effect of competition on profitability. Third, bond investors could be diversified and not care which particular subset of firms in an industry wins the game. Fourth, my measure of CI effort may be inadequate, and/or the bond market does not have access to sufficient

[7]Using credit default swap data, Longstaff, Mithal, and Neis (2005) show that default risk is the largest component of the corporate yield spread.

[8]Schmidt (1997) finds that greater competition may increase managerial effort and reduce slack.

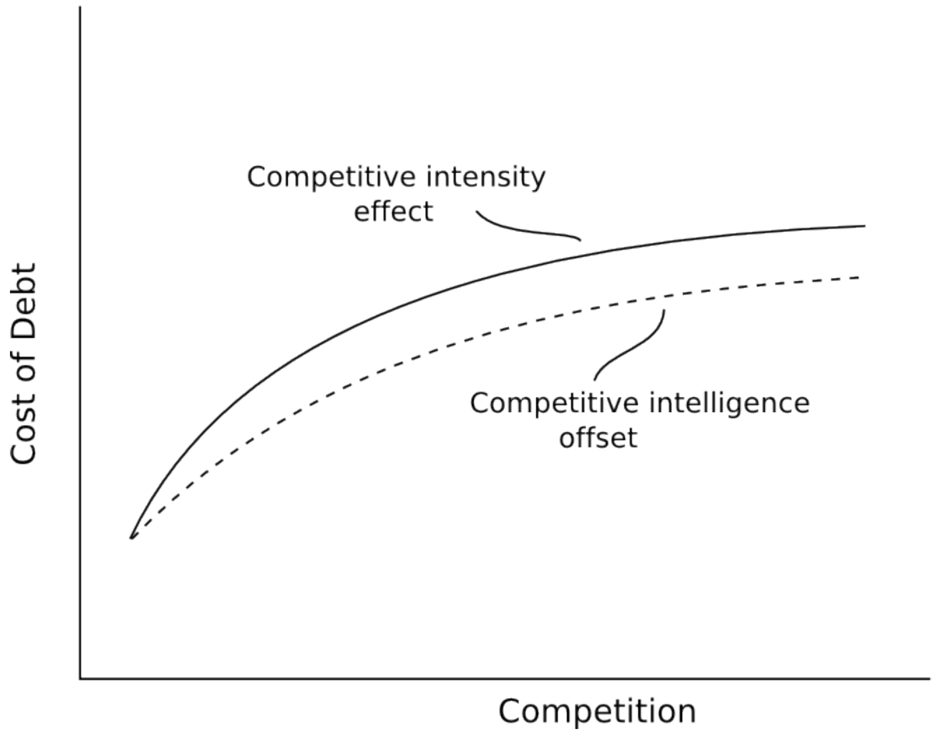

Figure 3: Cost of Debt vs Competition

information on this issue. Any one or a combination of these scenarios may result in a null or positive effect.

I analyze these issues by studying a sample of Russell 3000 firms with outstanding debt between 1997 and 2008, examining the relationship between the bond yield spreads, competition and competitive intelligence. In my analysis I attempt to answer the following questions. First, to what extent are the levels of competition and competitive intelligence priced into the corporate debt? Second, what characteristics of firms make their debt more or less sensitive to the competitive factors? Third, to what extent is the information on competition and competitive intelligence incorporated into credit ratings assigned to the corporate debt by the credit rating agencies?

One major contribution of the present research is the introduction of a measure of firm-level competitive intelligence effort. My measure is based on the extent of discussion of competition in the firm's annual report. It is certainly not a clean or direct measure by any means. The quantity of discussion about competition in an annual report is directly attributable to three factors: (1) the intensity of competition facing the firm in the markets it participates in, (2) how much the firm knows about its competitive landscape, and (3), how much the firm feels would be appropriate to disclose, given its competitive environment and given the SEC regulatory guidelines. Thus, I get three entangled pieces of information - the underlying competitive characteristics of the firm environment, the amount the firm invests in competitive intelligence (CI), and how forthcoming the firm is in the 10-K report with the information it acquires through its CI effort.

While it is difficult to disentangle these effects, I suggest that, intuitively, (1) the amount of CI effort is proportional to competitive intensity, and (2) the amount of disclosure is, in turn, proportional to the amount of information produced by the CI function. At the end of the day, regardless of the underlying mechanisms of 10-K production, the more competitive pressure the firm feels as a result of its CI effort, the more discussion of competition would be appropriate for the annual report, according to the SEC guidelines. The relevant SEC regulations concerning the disclosure of this information lend support this idea.[9] SEC regulation S-K[10] item 101 (101.c.1.x), states that Item 1: "Description of Business" should, among other things, contain disclosure on "competitive conditions in the business involved". Item

[9] http://www.sec.gov/about/forms/form10.pdf
[10] http://www.law.uc.edu/CCL/regS-K/

1A: "Risk Factors", described in SEC regulation S-K, 503.c, in practice often involves discussion of risks due to competitive pressures.

Due to the two-step mechanism underlying my new measure, its relationship to a firm's cost of debt is not unequivocally unidirectional. On the one hand, the market may have enough detailed information on the firm's operations from other sources to be able to measure competitive intensity, separately from the investment in competitive intelligence. In this case, the incremental value provided by the discussion of competition in the annual report would be that of a metric of CI effort. All else equal, a firm that does more CI than another, gives itself an informational leg up in the game of competition for the market, thereby increasing its probability of survival, and reducing the default risk on its debt. Therefore, in this case, my measure would be correlated with a lower cost of debt, *ceteris paribus*, assuming I can adequately control for competitive intensity using other measures thereof.

However, it is also possible that a good knowledge of a particular firm's competitive pressures requires too much private information which the market at large may have no access to. For example, in empirical literature thus far, common proxies for competition, from number of firms in the same SIC or SIC industry group, to various measures of concentration, have been industry-specific, rather than firm specific.[11] This approach is quite coarse, since two firms in "the same industry", however measured, could be in very different market or geographic niches, and thus be subject to drastically divergent intensity of competition. By comparison, the firm-specific

[11] See, e.g., Aggarwal and Samwick (1999) for an example using industry Herfindahl-Hirschman Indices, Haushalter, Klasa, and Maxwell (2007) for using HHI and top-four market share.

measure I develop here may give the market enough new information on competitive intensity in the firm's environment that its 'competitive intensity content' completely masks its 'competitive intelligence content'. In this case, the discussion of competition in the 10-K is likely to be taken more as a measure of competitive intensity - not as a measure of CI effort, given a known competitive intensity. Since greater competition, all else equal, reduces the firm's likelihood of survival, and increases default risk, my measure would be positively correlated with the cost of debt.

Other concerns may affect the core relationship between competitive intelligence and the cost of debt. The value of any information revealed in a firm's annual report is strongly dependent on overall report quality and information asymmetry. In the issue at hand, if a firm with low information asymmetry reports little concern about competition, for example, one expects that the markets will be more likely to take that at face value than if the same were gleaned from a report of a firm with high information asymmetry. Thus, I expect that any effect would be more pronounced in the subset of firms with good disclosure quality than in that of those with poor disclosure quality.

That said, low information asymmetry would point not only to the quality of the annual report, but also to the overall quantity and quality of information about the firm available to the market. With more and better information available, the rather indirect measure of competitive intelligence in the form of the extent of discussion in the annual report may lose its relative importance. Thus, if the pool of other available information allows the market to come up with better or more detailed metrics, I could see a decrease in the significance of my metric of choice.

Further, a diversified firm, with a number of related or unrelated segments, may in the aggregate end up with a lot of discussion of competition, even if each individual segment does not face much competitive pressure. Thus, I might expect that the quantity of competitive discussion in the annual report would not have such a pronounced impact in the subset of highly diversified firms. Moreover, a diversified firm is less likely to fail if one of its divisions does poorly, which would further reduce the importance of the competitive factor.

Additionally, in the event of firm failure, a number of factors could mitigate the expected losses that bond holders might sustain. Accordingly, a firm with very low leverage might not see as strong a relationship between discussion of competition and the cost of debt, because even in the event of liquidation, there are plenty of assets to pay off the debt holders. This effect, in addition to having the direct and obvious relationship to the cost of debt, is also anticipated to modify the effect of the discussion of competition in the annual report thereon.

Finally, competitive intelligence is likely a relatively minor determinant of cost of debt, compared with other indicators of default risk, such as credit rating. As a result, I would expect that a highly rated firm would see little to no appreciable effect of competitive intelligence on its cost of debt, simply because it's overall default probability is so low. A poorly-rated firm, on the other hand, may be a lot more sensitive to all kinds of factors affecting default probability, including CI.

The question of the effect of competitive intelligence on the cost of debt is ultimately an empirical one, and one that I address in the present paper. My research makes several important contributions to the existing literature. First, using a sample of 5468 firm-years on 1046 unique firms, I find a non-uniform relationship between more detailed discussion of competition in the annual report and cost of debt. Specifically, controlling for a number of variables traditionally considered to affect the cost of debt, I find that high credit quality firms, as measured by credit rating, exhibit a positive relationship between CI and yield spread, while the lower quality firms a negative one. Second, since the aforementioned result is evident in the presence of a control for bond ratings, it further indicates that competitive intelligence is only partially incorporated into the bond ratings from the major credit rating agencies. Third, I find that lower credit ratings are given to firms with more discussion of competition - an increase of one standard deviation in the discussion of competition is associated with an average decrease in the rating by 0.76 points (see my credit ratings conversion scale in Section 2.2, Table 1).

The remainder of this paper is organized as follows. Section 2.2 details my data and sample selection procedures. Section 2.3 presents my research design and main empirical findings. Section 2.4 concludes.

2.2 Data

The data for this study come from a number sources. The data on the firms' bond issues and their characteristics is taken from the Mergent FISD database. This database contains information on all bond issues and their characteristics, including issue date, maturity, coupon and coupon frequency, call schedule, conversion features, and ratings from S&P, Fitch, and Moody's. Historical bond prices are from the TRACE database, which contains all reported bond trades starting from 2002, including trade execution date, price, and yield. Additional trade data is sourced from the FISD insurance bond transactions database. The competitive intensity measure is derived from the length of discussion about competition in the firms' annual reports (10-K filings), collected from the SEC's EDGAR system[12]. Finally, I obtain various firm-year-specific financial information from the COMPUSTAT Annual Fundamentals data set, and the historical treasury yields from the US Treasury web site[13].

2.2.1 Measuring the Cost of Debt and Competitive Intelligence

The "cost of debt" for a firm is calculated as the weighted average yield spread over the duration-equivalent treasury, a commonly-used measure of debt risk premium (Silvers, 1973)[14]. Specifically, the following procedure is used to calculate the weighted average yield spreads for each firm-year.

For each firm-year, data on each of the bonds outstanding for a particular firm is collected from FISD. Bond pricing information is matched from TRACE and FISD insurance transactions data set, finding the earliest trade occurring within the 6 month time window starting from the report filing date. For non-callable bonds, I calculate the yield to maturity, and the Macaulay duration. For callable bonds, I use the lower

[12] http://www.sec.gov/idea/searchidea/companysearch_idea.html

[13] http://www.ustreas.gov/offices/domestic-finance/debt-management/interest-rate/yield_historical_main.shtml

[14] A similar procedure was used by Anderson, Mansi, and Reeb (2003).

of the yield to maturity or the yield to call (yield to worst), and use the duration measure corresponding to the yield to worst. If the lower yield is the yield to call, I calculate duration on the assumption that the bond will be called; if the lower yield is the yield to maturity, duration is based on stated maturity. For each bond's trade execution date, the treasury yield curve is estimated using cubic spline interpolation, and the duration-equivalent treasury yield is found using the curve estimate. The yield spread for each bond is then the bond's yield to worst, minus its duration-equivalent treasury yield. The weighted average yield spread for the firm in a given year is the average of all the yield spreads, weighted by the market value of each bond issue. My final measure is the log of this spread.

The initial sample of all bonds contained 8412 bond issues for 1053 unique firms. Due to the sparse nature of the bond pricing data, the subsample used for the main yield spread data analysis is based on 6331 bond issues for 1004 unique firms.

The competitive intelligence measure is collected from the firms' annual reports. The numerical measure is the log of the word count of all the sections and paragraphs of the report that talk about any aspect of competition the firm is facing and the firm's competitive position in any of the markets it participates.

Though it may seem that a discussion-based measure of CI is rather arbitrary, may not vary much due to the related disclosure regulations, or may be otherwise uninformative, a closer inspection of the data reveals that the extent of discussion of competitive factors in firms' annual reports is highly variable in length and content, and is generally quite detailed and informative when the firm chooses to make it so. As can be seen from summary statistics in Table 14, the length of competitive discussion ranges from none to over ten thousand words. I include a handful of representative extracts from firm annual reports in the appendix, which demonstrate just how much variability there is in the discussion of competitive factors in 10-K filings. Appendix A includes some samples from firms on the higher end of the CI spectrum, and appendix B on the lower end. There clearly are large differences in the amount of effort firms put into discussing (and by inference, learning about) the competitive factors affecting their business.

2.2.2 Control Variables

Fierce competition facing a firm can potentially affect its cost of debt in a number of ways. First, the firm may be looking at reduced profitability. Second, it may be forced to take on more risky investments in its bid to outmaneuver the competition. Third, the firm may take on more debt as a result of its reduced internal cash generation. All of the above factors would point to a higher cost of debt. Fourth, larger firms, which are usually more horizontally and/or geographically diversified, are likely, in the aggregate, to be facing more distinct competitive pressures. Due to their diversification, however, idiosyncratic risk to the bondholders would be reduced, and so would the yield spreads. Hence, I introduce a number of control variables for the above, so that I can determine whether my measure of competition impacts the cost of debt *in excess* of any previously documented effect. I include variables to control for firm leverage, size, profitability, credit ratings, and duration.

I measure firm leverage using the book ratio of total liabilities to total assets:

$$Leverage = \frac{Total\ Liabilities}{Total\ Liabilities + Total\ Equity}, \tag{13}$$

firm size as the natural log of firm book assets:

$$Size = \ln(Total\ Liabilities + Total\ Equity), \tag{14}$$

and firm profitability as the ratio of cashflow to total assets, where cashflow is net income plus depreciation and amortization:

$$Profitability = \frac{Net\ Income + Depreciation\ and\ Amortization}{Total\ Liabilities + Total\ Equity}. \tag{15}$$

I measure bond duration as standard Macaulay duration, and then compute a weighted average duration (*Duration*) for each firm-year.

I control for other sources of firm and issue-specific default risk using the firm's bond rating, measured as the weighted average rating by firm-year (*Rating*). The character ratings are numerically operationalized by assigning an integer to each rating, with AAA corresponding to a numerical rating of 1, and D corresponding to 22.[15] Using this conversion, the bond rating is expected to be positively correlated with the cost of debt, as measured by the yield spread. The complete rating conversion chart is shown in Table 1. The rating used for each bond is the most recently

[15] Same procedure as used in Reeb, Mansi, and Allee (2001) and Anderson, Mansi, and Reeb (2003)

issued rating prior to the issue-specific trade execution date used to determine the bond price. This procedure ensures that my rating measure incorporates the freshest possible information that bond ratings are supposed to reflect.

I also include several traditional industry-specific measures of competition as controls. First, I use a metric of yearly counts of firms in the same 2, 3, and 4 digit SIC codes. The counts are based on the universe of firms that is included in the COMPUSTAT Annual Fundamentals database. The reason I don't use only the full 4-digit code counts is that SIC code groupings are not clear-cut as far as competitive interactions between firms are concerned. For example, looking at the SIC code descriptions in SIC industry group 251 (Household Furniture), I would certainly expect some competition between the component 4-digit SIC codes - metal (2514) vs wood (2511, 2512) furniture, upholstered (2512) vs unupholstered (2511) furniture, etc. Looking further up the classification tree, some measure of competition between office (252) and household (251) furniture would also not be unexpected. To better account for both the narrower and the broader competitive pressure, I try a number of alternate specifications: including the counts individually; as an equally-weighted scaled factor for the three count measures; and using the log of the first varimax-rotated factor ($Industry.competition$). There is no qualitative difference between the various specifications; the latter is used in the results presented herein.

Second, I use a measure of the Herfindahl Hirschman Index (HHI), based on the universe of COMPUSTAT firms. I try several alternative specifications for HHI, aggregating by NAICS, SIC code, SIC indistry group, and SIC major group. Additionally, I try an HHI measure taken directly from the 2002 US Census data, which is more accurate for that one year, inasmuch as it includes all firms, not just those in COMPUSTAT. However, it only includes the manufacturing sector, rather than all industries, and further, is only for a single point in time, year 2002. All produce qualitatively similar results, so only the COMPUSTAT SIC code based measure is shown below. The final *HHI* variable is inverted, so that higher values mean more competition, in line with the counts-based measure described above, and transformed with the log.

To test my subsidiary hypotheses, I define the following additional variables. My diversification measure (*Diversification*) is the yearly count of firm segments with distinct primary NAICS codes for each firm, sourced from the COMPUSTAT Segments database. I construct my metric for information asymmetry, *InfoAsymm*, as the sum of the quantiles (deciles) of the observations along two variables - the inverted number of analyst EPS estimates for each firm-year, and the standard deviation of analyst EPS estimates for each firm-year, sourced from the I/B/E/S Summary database. Higher values point to higher manager-market information asymmetry.

2.2.3 Descriptive and Univariate Statistics

Table 14 shows the summary statistics of the key variables in my sample. Included are the minimum, mean, median, maximum, and standard deviation.

Firm size, as measured by log total assets (in millions), has a mean of \$7.93, standard deviation of \$1.4, with a minimum of \$3.06, and a maximum of \$13.59.

Table 14: Summary Statistics, Chapter 2

This table shows summary statistics for the data used in the empirical analysis. The data set covers 8079 firm-years for 1046 unique firms, from 1997 to 2008. The variables include: *YieldSpread*, the weighted average yield spread; *CI*, competitive intensity measure (length of competition discussion in annual report); *Industry.competition*, an industry-specific measure of competitive intensity, based on the count of competitors in the same SIC at the 2, 3, and 4 digit level; *Leverage*, firm leverage (total debt / total assets); *Profitability*, firm profitability (cash flow / total assets); *Size*, firm size (ln(total assets)); *Duration*, weighted average debt duration; *Rating*, weighted average credit rating; *Diversification*, number of firm segments with distinct primary NAICS; *InfoAsymm*, the measure of information asymmetry.

	Min.	Mean	Median	Max.	St. dev.
RawYieldSpread	0.005	3.487	2.385	28.739	3.444
YieldSpread	−5.316	0.892	0.869	3.358	0.852
RawCI	0.000	933.613	642.000	10403.000	960.864
CI	−0.693	6.358	6.465	9.250	1.139
Leverage	0.084	0.650	0.627	2.851	0.224
Industry.competition	0.987	5.746	5.992	8.090	1.085
HHI	−0.693	8.862	9.031	9.194	0.878
Profitability	−4.996	0.066	0.078	2.270	0.145
Size	3.060	7.931	7.836	13.590	1.404
Duration	0.164	6.556	5.657	29.696	3.731
Rating	1.000	10.472	10.000	22.000	3.959
Diversification	1.000	1.963	2.000	10.000	1.210
InfoAsymm	2.000	11.730	12.000	20.000	3.821

Average firm profitability, as measured by the ratio of cash flows to total assets, is 6.59%; mean leverage ratio is 65%; and mean diversification (number of corporate segments with distinct NAICS) is 1.96. As far as debt-specific measures go, the mean weighted average rating is 10.47, corresponding to a letter rating of approximately BBB-; mean weighted average duration is 6.56 years, and mean weighted average yield spread is 3.49 percent. The competitive intelligence measure ranges from 0 to 10403, with a mean of 933.61 and a standard deviation of 960.86.

Table 15 presents a basic univariate analysis of the data, broken up into high-CI and low-CI firms across the median of the competitive intelligence measure. I show the results for *YieldSpread*, *Duration*, *Rating*, *Industry.competition*, *HHI*, *Profitability*, *Diversification*, *InfoAsymm*, *Size*, and *Leverage*, for high and low CI firms.

The univariate results show that high-CI firms have a higher cost of debt. They

Table 15: Univariate Analysis, Chapter 2

This table shows univariate test results, breaking the firm into two groups around the median of the *CI* measure. The variables included are: *YieldSpread*, the weighted average yield spread; *Industry.competition*, an industry-specific measure of competitive intensity, based on the count of competitors in the same SIC at the 2, 3, and 4 digit level; *Leverage*, firm leverage (total debt / total assets); *Profitability*, firm profitability (cash flow / total assets); *Size*, firm size (ln(total assets)); *Duration*, weighted average debt duration; *Rating*, weighted average credit rating; *Diversification*, number of firm segments with distinct primary NAICS; *InfoAsymm*, the measure of information asymmetry.

	Low CI	High CI	Difference	t-Stat.	p-value
YieldSpread	2.9820	4.0573	−1.0752	−11.8041	0.0000∗∗∗
Leverage	0.6404	0.6595	−0.0191	−3.8215	0.0001∗∗∗
Industry.competition	5.6095	5.8831	−0.2736	−11.4222	0.0000∗∗∗
HHI	8.8835	8.8403	0.0432	2.2124	0.0270∗
Profitability	0.0831	0.0488	0.0343	10.7177	0.0000∗∗∗
Size	7.9635	7.8975	0.0660	2.1127	0.0347∗
Duration	6.3613	6.7577	−0.3964	−4.2203	0.0000∗∗∗
Rating	9.6779	11.3947	−1.7168	−16.7952	0.0000∗∗∗
Diversification	2.0005	1.9234	0.0771	2.7455	0.0061∗∗
InfoAsymm	11.4421	12.0157	−0.5736	−6.4563	0.0000∗∗∗

also have lower duration, higher (poorer) credit rating, lower profitability, and higher leverage. The latter three would also lead us to expect a higher cost of debt - so only in the multivariate analysis will I be able to determine whether the CI measure has any incremental explanatory power. The associations between CI and the two industry-level measures of competition point in different directions. The HHI measure is slightly lower for high-CI firms, while the firm-count based measure is higher. This, along with the low correlation between the two, suggests that they measure different aspects of industry-level competition. The univariate analysis also shows that high-CI firms have significantly higher information asymmetry and duration.

2.3 Multivariate Empirical Results

2.3.1 Yield Spread Basics

The base-case multivariate model specification is a cross-sectional test of the relationship between my competitive intensity measure and the firm-level cost of debt, with a number of control variables:

$$\begin{aligned} YieldSpread \sim\ & \alpha_0 + \alpha_1 CI + \alpha_2 Leverage + \alpha_3 HHI \\ & + \alpha_4 Profitability + \alpha_5 Size + \alpha_6 Duration \\ & + \alpha_7 Rating + \varepsilon \end{aligned} \tag{16}$$

YieldSpread is the firm-year weighted average bond yield in excess of duration equivalent treasury, *CI* is my competitive intelligence measure, *Leverage* is the book debt scaled by total assets, *Profitability* is cash flow scaled by total assets, *Size* is the natural logarithm of total assets, *Duration* is the firm-year weighted average Macaulay duration, *Rating* is the firm-year weighted average rating, and *HHI* an industry-specific HHI measure of competitive intensity, based on the universe of firms in the COMPUSTAT database. The main coefficient of interest is α_1, the effect of my competitive intelligence measure on the cost of debt. If positive, it would indicate that discussion of competition in the annual report is perceived by the market to be a metric of competitive intensity; if negative, the same is seen as a measure of a firm's competitive intelligence effort, given a known competitive intensity.

I expect the coefficient on *Leverage* and *Duration* to be positive (implying higher cost of debt), and *Profitability* and *Size* to be negative (implying lower cost of debt), at least inasmuch as the rating variable may not include all of the information present therein. The coefficient on *Rating* is expected to be positive, as higher (poorer) rating is anticipated to be correlated with higher cost of debt. The coefficient on the *HHI* variable, if it is indeed representative in some way of the competitive intensity facing the firm, is expected to be positively correlated with the cost of debt.

Column 1 of Table 16 presents the regression results following the specification shown in Eq. (16). The main finding is that firms with higher *CI* experience a significantly higher cost of debt. The coefficient on *CI* of 0.0287 is significant, and translates into 7.9 basis points for a change of one standard deviation in *CI*. The fact that higher *CI* is associated with higher yield spread may be due to several issues. It may be that competitive intelligence is not priced in the bond market, or is not seen as valuable. Alternatively, it could be that competitive intensity is not adequately controlled for by the industry-based measures of competition, leaving the intensity component of *CI* to overwhelm the intelligence component of the measure. The coefficients on the control variables are in accordance with my expectations. Higher leverage, poorer credit rating, and higher information asymmetry are all positively associated with the cost of debt, while better profitability is negatively associated with yield spread. The coefficient on duration has no significance, suggesting that it may be adequately incorporated into the rating measure. The addition of diversification into the regression reduces the coefficient on *CI* to insignificance, though it retains

Table 16: Multivariate Analysis: Yield Spread and Competitive Intelligence

This table shows the estimated coefficients of regressing the corporate yield spreads on my firm-level measure of competitive intelligence, and various controls. The variables included are: *YieldSpread*, the weighted average yield spread; *CI*, competitive intelligence measure (log of length of competition discussion in annual report); *HHI*, the COMPUSTAT-based measure of HHI; *Leverage*, firm leverage (total debt / total assets); *Profitability*, firm profitability (cash flow / total assets); *Size*, firm size (ln(total assets)); *Duration*, weighted average debt duration; *Rating*, the weighted average credit rating; *Diversification*, number of firm segments with distinct primary NAICS; *InfoAsymm*, the measure of information asymmetry.
The primary specification is:

$$\begin{aligned} YieldSpread \sim\ & \alpha_0 + \alpha_1 CI + \alpha_2 Leverage + \alpha_3 HHI \\ & + \alpha_4 Profitability + \alpha_5 Size + \alpha_6 Duration \\ & + \alpha_7 Rating + \varepsilon \end{aligned}$$

These results are reported in Column 1. In Column 2 I add *InfoAsymm*, the measure of information asymmetry, and in Column 3, I add the *Diversification* measure. In Columns 4-6 I repeat these tests using the *Industry.competition*, an industry-specific measure of competitive intensity, based on the count of competitors in the same SIC at the 2, 3, and 4 digit level.

Significance levels: '***' 0.001 '**' 0.01 '*' 0.05 '†' 0.1 . Robust t-statistics using the Huber-White sandwich estimator of variance are listed in parentheses below each coefficient estimate.

	Dependent variable: YieldSpread					
	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	−0.483∗∗	−0.941∗∗∗	−0.568∗∗	−0.200	−0.731∗∗∗	−0.385∗
	(−2.96)	(−5.73)	(−3.24)	(−1.25)	(−4.45)	(−2.32)
CI	0.029∗∗∗	0.029∗∗∗	0.008	0.031∗∗∗	0.031∗∗∗	0.009
	(3.38)	(3.34)	(0.92)	(3.56)	(3.50)	(1.05)
Leverage	0.314∗∗∗	0.203∗∗	0.196∗∗	0.315∗∗∗	0.204∗∗	0.198∗∗
	(4.56)	(2.84)	(2.76)	(4.61)	(2.86)	(2.79)
Industry.competition				−0.031∗∗	−0.024∗	−0.014
				(−3.01)	(−2.44)	(−1.43)
HHI	0.012†	0.007	0.011			
	(1.83)	(1.16)	(1.32)			
Profitability	−0.884∗∗	−0.784∗∗	−0.687∗∗	−0.886∗∗	−0.788∗∗	−0.691∗∗
	(−3.09)	(−3.15)	(−3.05)	(−3.15)	(−3.20)	(−3.07)
Size	−0.024∗	0.002	−0.029∗∗	−0.025∗	0.001	−0.030∗∗
	(−2.19)	(0.17)	(−2.58)	(−2.28)	(0.05)	(−2.64)
Duration	−0.009	−0.004	0.004	−0.008	−0.003	0.004
	(−1.44)	(−0.69)	(0.67)	(−1.33)	(−0.60)	(0.68)
Rating	0.114∗∗∗	0.109∗∗∗	0.108∗∗∗	0.114∗∗∗	0.108∗∗∗	0.108∗∗∗
	(23.77)	(23.39)	(22.64)	(23.44)	(23.08)	(22.42)
InfoAsymm		0.031∗∗∗	0.020∗∗∗		0.031∗∗∗	0.020∗∗∗
		(10.45)	(7.19)		(10.23)	(7.09)
Diversification			0.001			0.000
			(0.13)			(0.04)
N	5468	5068	4661	5468	5068	4661
R-squared	0.427	0.422	0.455	0.428	0.423	0.455
Adj. R-squared	0.426	0.421	0.454	0.428	0.422	0.454

its sign. This indicates that there may be a more complex relationship that may need further investigation. The coefficient on the industry-based *HHI* measure of competitive intensity is positive, but largely insignificant, suggesting that either it has already been incorporated into *Rating*, or is a poor measure of firm-level competitive intensity. The *Industry.competition* measure based on firm counts is significant, but negatively associated with *YieldSpread*, contrary to my expectations. One possibility is that a higher number of firms is more of an indicator of the vibrancy of the industry, rather than competitive intensity.

2.3.2 Response Ratings

One criticism that can be leveled at the above analysis is the method used to arrive at the *YieldSpread* measure as a measure of the cost of debt. The method contains a number of intermediate estimates and assumptions, as described in Section 2.2, each of which is subject to its own errors. To allay these concerns, I use an alternative specification, where the dependent variable is the debt rating, rather than the cost of debt. Even if the credit rating agencies are not perfect in assimilating the competitive landscape information into the bond ratings, if at least some portion of it does make it into the ratings, then I should see a relationship between my measure of competitive intelligence, *CI*, and the bond rating.

In the prior specification, the response variable was the yield spread, while rating was one of the inputs, so I used the latest available rating prior to the bond trade date. Now, rating is the response, so I am going to use the earliest available rating subsequent to the issuance of the firm's annual report (*ResponseRating*). Besides that, the basic empirical specification is similar to that in the previous section,

$$
\begin{aligned}
ResponseRating \sim \alpha_0 + \alpha_1 CI + \alpha_2 Leverage + \alpha_3 Profitability \\
+ \alpha_4 Size + \alpha_5 Duration + \alpha_6 HHI + \varepsilon,
\end{aligned}
\tag{17}
$$

with all the other variables specified as before.

The empirical regression results are presented in Table 17. Column 1 of Table 17 presents the results of the regression as specified in Eq. (17). Columns 2 and 3 add *InfoAsymm* and *Diversification*, and Column 4 includes industry dummies for major industry groups (2-digit SIC codes, coefficients not shown). All results show coefficients that are the same qualitatively as in the cost of debt specifications; most notably the coefficients on *CI* are everywhere positive and significant. The result from Column 1 indicates that an increase of one standard deviation in *CI* results in a change of 0.76 points on the ratings scale (where higher numbers mean poorer credit rating). Similar magnitudes are obtained in the other specifications. An alternative specification using the *Industry.competition* measure is examined in Table 17 as a quick robustness check. The results are qualitatively similar to ones using *HHI*.

2.3.3 Yield Spread Interactions

I next turn to the analysis of interactions between these variables. In particular, I have hypothesized that ratings, leverage, diversification, and information asymmetry

Table 17: Multivariate Analysis: Ratings and Competitive Intelligence, HHI Control

This table shows the estimated coefficients of regressing the response bond ratings on my firm-level measure of competition, and various controls. The variables included are: *ResponseRating*, the earliest available rating after report issuance; *CI*, competitive intelligence measure (length of competition discussion in annual report); *HHI*, a COMPUSTAT-based HHI measure; *Leverage*, firm leverage (total debt / total assets); *Profitability*, firm profitability (cash flow / total assets); *Size*, firm size (ln(total assets)); *Duration*, weighted average debt duration; *Diversification*, number of firm segments with distinct primary NAICS; *InfoAsymm*, the measure of information asymmetry..
The primary specification is:

$$\begin{aligned} ResponseRating \sim \alpha_0 + \alpha_1 CI + \alpha_2 Leverage + \alpha_3 Profitability \\ + \alpha_4 Size + \alpha_5 Duration + \alpha_6 HHI + \varepsilon \end{aligned}$$

These results are reported in Column 1. In Column 2, I add *InfoAsymm*, in Column 3 I add also *Diversification*. In column 4, I add industry dummies for major industry groups (2-digit SIC codes, coefficients not shown).

Significance levels: '***' 0.001 '**' 0.01 '*' 0.05 '†' 0.1 . Robust t-statistics using the Huber-White sandwich estimator of variance are listed in parentheses below each coefficient estimate.

	Dependent variable: ResponseRating			
	(1)	(2)	(3)	(4)
Intercept	16.375∗∗∗	13.352∗∗∗	13.754∗∗∗	10.385∗∗∗
	(12.80)	(9.28)	(9.76)	(5.55)
CI	0.649∗∗∗	0.628∗∗∗	0.600∗∗∗	0.539∗∗∗
	(6.75)	(6.45)	(6.72)	(5.56)
Leverage	4.342∗∗∗	3.770∗∗∗	3.659∗∗∗	4.209∗∗∗
	(7.36)	(6.05)	(5.98)	(6.86)
HHI	0.097	0.098	−0.020	−0.028
	(1.20)	(1.15)	(−0.23)	(−0.31)
Profitability	−7.073∗∗	−6.271∗∗	−6.046∗	−5.908∗
	(−2.74)	(−2.66)	(−2.44)	(−2.34)
Size	−1.539∗∗∗	−1.384∗∗∗	−1.155∗∗∗	−1.050∗∗∗
	(−21.31)	(−18.09)	(−14.57)	(−12.51)
Duration	−0.061∗	−0.032	−0.047∗	−0.046∗
	(−2.50)	(−1.32)	(−1.99)	(−2.09)
InfoAsymm		0.167∗∗∗	0.191∗∗∗	0.234∗∗∗
		(6.25)	(7.41)	(10.02)
Diversification			−0.588∗∗∗	−0.357∗∗∗
			(−7.69)	(−4.69)
N	5098	4755	4427	4427
R-squared	0.447	0.448	0.474	0.567
Adj. R-squared	0.446	0.447	0.473	0.56

Table 18: Multivariate Analysis: Ratings and Competitive Intelligence, Count Control

This table shows the estimated coefficients of regressing the response bond ratings on my firm-level measure of competition, and various controls. The variables included are: *ResponseRating*, the earliest available rating after report issuance; *CI*, competitive intelligence measure (length of competition discussion in annual report); *Industry.competition*, a measure of competition based on firm counts by industry; *Leverage*, firm leverage (total debt / total assets); *Profitability*, firm profitability (cash flow / total assets); *Size*, firm size (ln(total assets)); *Duration*, weighted average debt duration; *Diversification*, number of firm segments with distinct primary NAICS; *InfoAsymm*, the measure of information asymmetry..
The primary specification is:

$$\begin{aligned} ResponseRating \sim\ & \alpha_0 + \alpha_1 CI + \alpha_2 Leverage + \alpha_3 Profitability \\ & + \alpha_4 Size + \alpha_5 Duration + \alpha_6 Industry.competition + \varepsilon \end{aligned}$$

These results are reported in Column 1. In Column 2, I add *InfoAsymm*, in Column 3 I add also *Diversification*. In column 4, I add industry dummies for major industry groups (2-digit SIC codes, coefficients not shown).

Significance levels: '***' 0.001 '**' 0.01 '*' 0.05 '†' 0.1 . Robust t-statistics using the Huber-White sandwich estimator of variance are listed in parentheses below each coefficient estimate.

	Dependent variable: ResponseRating			
	(1)	(2)	(3)	(4)
Intercept	18.455∗∗∗	15.187∗∗∗	14.351∗∗∗	10.650∗∗∗
	(16.85)	(11.97)	(11.64)	(4.91)
CI	0.663∗∗∗	0.639∗∗∗	0.611∗∗∗	0.539∗∗∗
	(6.75)	(6.44)	(6.77)	(5.56)
Leverage	4.323∗∗∗	3.761∗∗∗	3.649∗∗∗	4.193∗∗∗
	(7.41)	(6.07)	(6.00)	(6.91)
Industry.competition	−0.233∗	−0.167†	−0.138	−0.124
	(−2.52)	(−1.80)	(−1.51)	(−0.39)
Profitability	−7.063∗∗	−6.296∗∗	−6.076∗	−5.917∗
	(−2.79)	(−2.69)	(−2.46)	(−2.34)
Size	−1.540∗∗∗	−1.391∗∗∗	−1.161∗∗∗	−1.050∗∗∗
	(−21.40)	(−18.24)	(−14.67)	(−12.52)
Duration	−0.056∗	−0.028	−0.043†	−0.046∗
	(−2.29)	(−1.17)	(−1.86)	(−2.08)
InfoAsymm		0.163∗∗∗	0.187∗∗∗	0.233∗∗∗
		(6.07)	(7.20)	(9.75)
Diversification			−0.581∗∗∗	−0.358∗∗∗
			(−7.86)	(−4.71)
N	5098	4755	4427	4427
R-squared	0.45	0.449	0.475	0.567
Adj. R-squared	0.45	0.448	0.475	0.56

will moderate the effect of *CI*. I have proposed that *Rating* affects the base probability of default, and thus the relative importance of *CI*; that *Diversification* may have a mechanical effect on my measure due to the structure of the firm's annual report; that *Leverage* affects bondholder recovery in case of distress; and that *InfoAsymm* may affect both the credibility and relative importance of the *CI* measure. To explore these effects, I turn to the following regression specification:

$$\begin{aligned} YieldSpread \sim\ & \alpha_0 + \alpha_1 CI + \alpha_2 Leverage + \alpha_3 HHI \\ & + \alpha_4 Profitability + \alpha_5 Size + \alpha_6 Duration \\ & + \alpha_7 Rating + \alpha_8 InfoAsymm + \alpha_9 Diversification \\ & + \sum_i \alpha_i Interaction_i + \varepsilon \end{aligned} \tag{18}$$

I test the hypothesis that a poorer rating would exacerbate the effect of *CI* in Column 1 of Table 19. What I find is that the interaction term coefficient is negative, and instead points to firms with poorer (numerically higher) ratings having a lower association between CI and yield spread. While the base coefficient on CI almost triples in magnitude relative to the no-interaction regression, the interaction term coefficient is large enough to pull lower-rated firms into negative territory for the CI-yield spread relationship. This suggests that competitive intelligence plays a significant role in reducing default risk for firms which are relatively likely to default, while firms which are very far from default are seen as merely wasting their resources

Table 19: Multivariate Analysis: Yield Spread and Competitive Intelligence, Interactions

This table shows the estimated coefficients of regressing the corporate yield spreads on my firm-level measure of competitive intelligence, and various controls. The variables included are: *YieldSpread*, the weighted average yield spread; *CI*, competitive intelligence measure (log of length of competition discussion in annual report); *HHI*, the COMPUSTAT-based measure of HHI; *Leverage*, firm leverage (total debt / total assets); *Profitability*, firm profitability (cash flow / total assets); *Size*, firm size (ln(total assets)); *Duration*, weighted average debt duration; *Rating*, the weighted average credit rating; *Diversification*, number of firm segments with distinct primary NAICS; *InfoAsymm*, a measure of information asymmetry.
The primary specification is:

$$\begin{aligned} YieldSpread \sim\ & \alpha_0 + \alpha_1 CI + \alpha_2 Leverage + \alpha_3 HHI \\ & + \alpha_4 Profitability + \alpha_5 Size + \alpha_6 Duration \\ & + \alpha_7 Rating + \alpha_8 InfoAsymm + \alpha_9 Diversification \\ & + \sum_i \alpha_i Interaction_i + \varepsilon \end{aligned}$$

In Column 1 I try the interaction of *CI* with *Rating*, in Column 2, that with *Diversification*, in Column 3, that with *Leverage*, and in Column 4, that with *InfoAsymm*. Column 5 includes all of the above interaction terms. Finally, Column 6 adds industry dummies for SIC major groups (coefficients not shown).

Significance levels: '***' 0.001 '**' 0.01 '*' 0.05 '†' 0.1 . Robust t-statistics using the Huber-White sandwich estimator of variance are listed in parentheses below each coefficient estimate.

	Dependent variable: YieldSpread					
	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	−0.884∗∗∗	−0.621∗∗	−0.896∗∗	−0.718∗∗	−1.207∗∗∗	−0.828∗∗∗
	(−3.94)	(−3.14)	(−3.14)	(−3.04)	(−3.43)	(−3.45)
CI	0.058∗	0.016	0.060	0.032	0.109∗	0.054∗
	(2.35)	(1.02)	(1.62)	(1.29)	(2.22)	(2.19)
Leverage	0.208∗∗	0.196∗∗	0.697∗	0.198∗∗	0.509	0.274∗∗∗
	(2.90)	(2.76)	(2.05)	(2.78)	(1.48)	(3.55)
HHI	0.011	0.011	0.011	0.011	0.010	0.005
	(1.36)	(1.30)	(1.32)	(1.34)	(1.30)	(0.57)
Profitability	−0.690∗∗	−0.687∗∗	−0.681∗∗	−0.683∗∗	−0.686∗∗	−0.714∗∗
	(−3.05)	(−3.05)	(−3.04)	(−3.04)	(−3.04)	(−2.96)
Size	−0.030∗∗	−0.029∗	−0.030∗∗	−0.029∗∗	−0.030∗	−0.029∗
	(−2.59)	(−2.55)	(−2.61)	(−2.58)	(−2.55)	(−2.44)
Duration	0.004	0.004	0.004	0.004	0.004	0.004
	(0.70)	(0.67)	(0.65)	(0.69)	(0.70)	(0.70)
Rating	0.141∗∗∗	0.108∗∗∗	0.108∗∗∗	0.108∗∗∗	0.142∗∗∗	0.131∗∗∗
	(8.92)	(22.61)	(22.63)	(22.66)	(8.34)	(8.06)
Diversification	0.001	0.026	0.001	0.001	0.054	0.003
	(0.09)	(0.59)	(0.14)	(0.09)	(1.13)	(0.31)
InfoAsymm	0.020∗∗∗	0.020∗∗∗	0.020∗∗∗	0.033∗	0.020	0.021∗∗∗
	(7.24)	(7.14)	(7.12)	(2.51)	(1.53)	(6.69)
CI:Rating	−0.005∗				−0.005∗	−0.005†
	(−2.08)				(−1.98)	(−1.84)
CI:Diversification		−0.004			−0.009	
		(−0.57)			(−1.12)	
CI:Leverage			−0.077		−0.046	
			(−1.47)		(−0.86)	
CI:InfoAsymm				−0.002	0.000	
				(−0.98)	(0.02)	
N	4661	4661	4661	4661	4661	4661
R-squared	0.456	0.455	0.455	0.455	0.456	0.472
Adj. R-squared	0.455	0.454	0.454	0.454	0.455	0.465

on CI, from the bondholders' point of view.

The interaction terms for *Diversification*, *Leverage*, and *InfoAsymm* are all insignificant, either separately (columns 2-4) or together (column 5). However, since the *Rating* seems to have such a significant moderating effect on *CI*, these other effects may simply be pointing in different directions for high and low credit quality firms. In Column 6 I show the result of a regression with industry dummies (coefficients are of varying signs and significance, and are not shown for the sake of brevity), industry being measured by 2-digit SIC codes (SIC major group), in an attempt to control for industry effects. The results remain qualitatively similar.

As a control for any possible endogeneity issues with the *CI* variable, in part possibly resulting from measurement error on *CI* since it is such an indirect metric, I try an alternative specification, using a two-stage least squares regression. In the first stage, I regress *CI* on variables that are likely to affect the competitive intelligence metric: size, and industry-specific measures of competitive intensity,

$$CI \sim \alpha_0 + \alpha_1 Size + \alpha_2 Industry.competition + \alpha_3 HHI + \varepsilon. \tag{19}$$

These results are shown in Table 20, Column 1. In Column 2 I introduce the *Diversification* measure, and in Column 3 the *InfoAsymmetry* variable, since both are likely have explanatory power on *CI*, as described earlier. Then I use the predicted value from the first stage regression in a number of specifications examined previously, to see if the results are markedly different (results using Column 3 from Table 20 shown

Table 20: Multivariate Analysis: CI vs Industry-specific measures

This table shows the estimated coefficients of regressing the firm-specific *CI* measure on industry-specific measures of competition of *HHI* and *Industry.competition*. The variables included are: *HHI*, the COMPUSTAT-based measure of HHI; *Industry.competition*, firm-count based measure of competition; *Size*, firm size (ln(total assets)); *Diversification*, number of firm segments with distinct primary NAICS; *InfoAsymm*, a measure of information asymmetry.
The primary specification is:

$$CI \sim \alpha_0 + \alpha_1 Size + \alpha_2 Industry.competition + \alpha_3 HHI + \varepsilon.$$

Column 1 shows the base specification, as above, Column 2, includes *Diversification*, and Column 3 adds *InfoAsymm*.

Significance levels: '***' 0.001 '**' 0.01 '*' 0.05 '†' 0.1 . Robust t-statistics using the Huber-White sandwich estimator of variance are listed in parentheses below each coefficient estimate.

	Dependent variable: CI		
	(1)	(2)	(3)
Intercept	6.192***	6.151***	5.753***
	(19.66)	(19.45)	(13.66)
HHI	−0.063**	−0.068**	−0.073**
	(−2.96)	(−3.15)	(−2.89)
Industry.competition	0.162***	0.171***	0.179***
	(6.38)	(6.56)	(6.41)
Size	−0.026	−0.020	0.001
	(−1.08)	(−0.73)	(0.03)
Diversification		−0.025	−0.041
		(−0.92)	(−1.38)
InfoAsymm			0.022**
			(2.65)
N	8079	7445	6757
R-squared	0.024	0.028	0.033
Adj. R-squared	0.024	0.027	0.032

- other specifications produce qualitatively similar output). The second-stage results on the *YieldSpread* regressions are shown in Table 21. While in the no-interaction regressions (in Columns 1-3) the coefficient on *CI.fitted* loses significance, the results in Columns 4 and 5 retain significance and show the same pattern of coefficients, wherein the relationship between *CI* and *YieldSpread* is of different sign for firms on opposite sides of the rating spectrum.

Overall, the results are consistent with the full-sample regression with interactions, showing that firms with good ratings experience a higher yield spread with more *CI*, while once I drop into the lower end of the ratings scale, more *CI* is actually associated with a decrease in yield spreads. This result may have a couple of alternative interpretations. It could be the case that *CI* is indeed a measure of competitive intelligence, and the investment in such is seen as wasteful by the bondholders of low risk firms, and as useful for higher-risk firms. Alternatively, it could be more of a measure of competition and industry vibrancy and vitality, or be an indicator of takeover likelihood, which would also benefit higher-risk firms more than the lower-risk firms from the bondholder point of view.

2.4 Conclusions

The intensity of competition facing a firm has the potential to significantly affect firm profitability, and in the extreme, lead to firm failure. At the same time, good competitive intelligence can mitigate these effects by allowing a firm to keep abreast of the competition. Rational bondholders should recognize these effects and require

Table 21: Multivariate Analysis: Yield Spread and Competitive Intelligence, 2SLS

This table shows the estimated coefficients of regressing the corporate yield spreads on fitted values of the firm-level measure of competitive intelligence from the stage one regression, and various controls. The variables included are: *YieldSpread*, the weighted average yield spread; *CI.fitted*, the fitted values of competitive intelligence measure (log of length of competition discussion in annual report); *HHI*, the COMPUSTAT-based measure of HHI; *Leverage*, firm leverage (total debt / total assets); *Profitability*, firm profitability (cash flow / total assets); *Size*, firm size (ln(total assets)); *Duration*, weighted average debt duration; *Rating*, the weighted average credit rating; *Diversification*, number of firm segments with distinct primary NAICS; *InfoAsymm*, a measure of information asymmetry.
The primary specification is:

$$\begin{aligned} YieldSpread \sim \alpha_0 &+ \alpha_1 CI.fitted + \alpha_2 Leverage + \alpha_3 HHI \\ &+ \alpha_4 Profitability + \alpha_5 Size + \alpha_6 Duration \\ &+ \alpha_7 Rating + \varepsilon \end{aligned}$$

Column 1 shows the base specification as above. In Column 2 I add *InfoAsymmetry* and in Column 3 *Diversification*. Column 4 includes the interaction term between *CI.fitted* and *Rating*. Finally, Column 5 repeats the latter result using *Industry.competition* instead of *HHI* as a measure of industry-level competition.

Significance levels: '***' 0.001 '**' 0.01 '*' 0.05 '†' 0.1 . Robust t-statistics using the Huber-White sandwich estimator of variance are listed in parentheses below each coefficient estimate.

	Dependent variable: YieldSpread				
	(1)	(2)	(3)	(4)	(5)
Intercept	−0.332	0.020	0.035	−2.655**	−1.866†
	(−0.84)	(0.05)	(0.08)	(−2.58)	(−1.79)
CI.fitted	0.012	−0.086	−0.088	0.336*	0.199
	(0.23)	(−1.56)	(−1.54)	(2.13)	(1.15)
Leverage	0.260***	0.194**	0.194**	0.188**	0.188**
	(3.49)	(2.76)	(2.77)	(2.69)	(2.69)
HHI	0.011	0.008	0.008	0.010	
	(1.27)	(0.95)	(0.88)	(1.23)	
Industry.competition					0.025
					(1.23)
Profitability	−0.711**	−0.690**	−0.691**	−0.697**	−0.697**
	(−2.92)	(−3.10)	(−3.08)	(−3.23)	(−3.23)
Size	−0.042***	−0.029**	−0.029*	−0.027*	−0.027*
	(−3.76)	(−2.64)	(−2.55)	(−2.42)	(−2.41)
Duration	0.003	0.004	0.004	0.003	0.003
	(0.54)	(0.71)	(0.70)	(0.53)	(0.53)
Rating	0.113***	0.109***	0.109***	0.372***	0.372***
	(23.95)	(23.86)	(22.87)	(4.05)	(4.05)
InfoAsymm		0.022***	0.022***	0.021***	0.024***
		(7.27)	(7.21)	(7.05)	(6.58)
Diversification			−0.001	−0.001	−0.006
			(−0.16)	(−0.09)	(−0.69)
CI.fitted:Rating				−0.042**	−0.042**
				(−2.85)	(−2.85)
N	4661	4661	4661	4661	4661
R-squared	0.447	0.455	0.455	0.457	0.457
Adj. R-squared	0.446	0.454	0.454	0.456	0.456

higher yields to compensate for the extra risk stemming from competition, while also recognizing the default-probability-reducing impact of competitive intelligence effort. While in theory the credit rating agencies should incorporate this information into the bond ratings they issue, in which case bondholders do not have any extra work to do, that may not be the case.

Using a sample of firms from the Russell 3000, the Mergent FISD database, and the TRACE bond pricing database, I find that competitive intelligence measured on a firm-year level does have an incremental effect on the yields required by the bond market over and above that of the credit ratings. I further find that the effect is not uniform across the firm credit quality scale. Firms with low distress probability exhibit a positive association between CI and yield spreads, while those of lower credit quality show the opposite effect. One possible explanation for this empirical result is that for a high quality firm, any incremental effect of competitive intelligence on distress risk is so small as to be negligible. For a low quality firm, on the other hand, starting with a baseline of high distress probability, competitive intelligence may have a more significant impact, giving the firm that extra bit of edge in the game and more significantly reducing probability of distress.

Alternatively, it may be proposed that the competitive intensity component in my measure of *CI* overwhelms any intelligence component, while the industry-based measures I use as controls are inadequate. In this case, for high credit quality firms, higher competitive intensity would spell lower profitability, as hypothesized above. For a low quality firm, on the other hand, high competitive intensity may mean a higher chance of being taken over by a competitor, which is more likely to happen, *ceteris paribus*, to a poorly performing firm, and to one which has more acquirer candidates around it.

While there is no substitute for performing in-depth fundamental research on specific firms, in the cross-section, I find that competitive intelligence/intensity have significant impact on firm ratings and cost of debt. I intend to explore other areas likely to be impacted by competition in future work.

3 Chapter 3. Informed Trading in Financial Institutions: Evidence from Debt Markets

3.1 Introduction

The prevention of insider trading is an important regulatory issue, with a lot of resources being devoted to maintaining a level playing field on the securities markets. Due to the complexities of information flows, however, it is difficult for anyone to make sure trading on private information does not occur. The unending flow of SEC enforcement actions in this regard[16] serves as ample evidence of continuing occurrence of insider trading.[17] Most empirical studies in this area focus on the equity side of the market, and tend to deal with equities of large, publicly held and widely traded firms. Studies such as Bhattacharya and Daouk (2002), looking at the impact of insider trading across the world, or Bettis, Coles, and Lemmon (2000), examining internal corporate policies against insider trading, look exclusively at the equities side of the picture. The analysis of equity insider trading is generally greatly facilitated by the SEC-mandated reporting of equity trades by insiders, which provides researchers with a large data set to look for abnormal returns to insider trading, such as in Meulbroek (1992).

Though most think of equities in connection with insider trading, and until the

[16] http://www.sec.gov/litigation/litreleases.shtml

[17] Smith (2011) cites 37 insider trading enforcement actions in 2009, 53 in 2010, and 30 in 2011 as of July.

1990s, the very legal foundation of "insider trading" in debt securities was uncertain[18], the Securities Exchange Act of 1934 casts a broad net as to what constitutes a "security"[19], and makes no distinction between security types when defining insider trading. The SEC website today succinctly summarizes the definition of illegal insider trading as "Insider trading is illegal when a person trades a security while in possession of material nonpublic information in violation of a duty to withhold the information or refrain from trading."[20] It is difficult to say whether the relative scarcity of SEC enforcement actions outside the equity markets is due to the relative lack of regulatory attention to other markets, or simply to the low frequency of occurrence of illegal insider trading therein. Given the *appearance* of sparse enforcement and publicity in non-equity markets, however, one might hypothesize that insider trading may move to less scrutinized markets in an attempt to avoid detection[21].

Recent SEC anti-insider trading actions have targeted various non-equity markets, such as credit default swaps (*SEC v Rorech, et. al., 2009*), public debt issues (*SEC v. Barclays Bank PLC and Steven J. Landzberg, 2007*), and even treasury bonds (*SEC v. Nothern, 2009*). Concomitant with the apparent uptick in SEC enforcement actions on non-equity insider trading, there has been an increase in academic attention

[18] Harvard Law Review (1992)

[19] Section 3.10 of the Securities Exchange Act of 1934 begins: "The term 'security' means any note, stock, treasury stock, security future, security-based swap, bond, debenture, certificate of interest or participation in any profit-sharing agreement or in any oil, gas, or other mineral royalty or lease, any collateral-trust certificate, preorganization certificate or subscription, transferable share, investment contract, voting-trust certificate, certificate of deposit for a security, any put, call, straddle, option, or privilege on any security, certificate of deposit, or group or index of securities..."

[20] `http://www.sec.gov/about/laws.shtml`

[21] McInish, Frino, and Sensenbrenner (2011) find that insider trading tends to take place on high-volume days, and take that as evidence of insiders attempting to hide their trades. Ascioglu, Comerton-Forde, and McInish (2011), examining the Tokyo Stock Exchange, find support for the hypothesis that informed traders break up their orders to hide among the liquidity traders.

given to the debt side of the market. Datta and Iskandar-Datta (1996) have found that information revealed by insider trading in equities carries over into public debt markets. Acharya and Johnson (2007) have examined the credit default swap market for public firms, and found significant incremental information revelation for negative credit news, consistent with informed trading. Ivashina and Sun (2011) have looked at the link between private information leakage in the corporate loan market and insider equity trading.

Illegal insider trading is only a subset of all informed trading activity - current statutory and case law requires the trading to be done on information in violation of fiduciary duty, which may be either direct, or derivative (*SEC v. Maio, 1995*). Direct fiduciary duty is usually extant for a corporate officer or other insider. Derivative duty arises when the outsider recipient of non-public information is aware that it is being disclosed to him in breach of an insider's fiduciary duty (*Dirks v. Securities and Exchange Commission, 1983*). Without having direct information on the identity of the traders, as exists in the case of equities due to the SEC reporting requirements, empirical research on other markets is unable to determine whether trading is being done by an insider, and certainly not whether it is being done in violation of any fiduciary duties. Thus, in stepping away from the highly-scrutinized public equity area of research, I may only attempt to detect informed trading, but cannot make any determination of whether said trading constitutes a violation of the relevant insider trading laws and constitutes "illegal insider trading" via direct or derivative breach of fiduciary duty. However, if trading activity is found to be predicted by future earnings surprises, one may surmise that *some* private information is leaking out at some point, which may warrant further regulatory examination.

Keeping these issues in mind, I attempt to investigate the occurrence of informed trading in privately held firms. Examining the trading activity in privately held companies is problematic, since there is rarely any publicly available pricing or earnings information to analyze. In this study I look at this issue using a specific set of firms - my primary target is privately held firms with outstanding public debt issues.

To get a clear look on the availability of private information, I further limit my sample to financial institutions that have to file Reports of Condition and Income (popularly known as call reports) with the FDIC every quarter, including detailed financial data on firm performance. These reports must be filed within 30 days of the end of the calendar quarter, and are made publicly available starting approximately 40 days of the report date[22]. This provides a clearly defined period of time when there exists explicitly private information that is supposed to be unknown to the public.

I conduct my analysis by studying a sample of financial firms subject to call report requirements from 2001 to 2010, examining the relationship between unexpected quarterly earnings, and bond market activity for the firms' publicly issued debt. In my research, I attempt to answer the following questions. First, is there evidence of informed trading in these firms' public debt? Second, are the results different between private and public firms? Third, what other firm characteristics make it more or less likely that informed trading will occur?

[22] http://www2.fdic.gov/call_tfr_rpts/inform.html

Ex-ante, the presence of informed trading is not a given. The public debt markets may not be liquid enough to provide a good enough opportunity for profiting from inside information, or there may simply not be enough/any leakage of this information to be detectable to the empirical analysis. Additionally, variations in quarterly income may not be significant enough to measurably affect bond pricing. Further, the detection of informed trading would not necessarily mean the presence of regulatory leakage - namely, the ability certain parties to get their hands on the filed reports after they're filed with the FDIC, but before they are officially released to the public. It is also possible that the informed parties get their information directly from company insiders, various statements by company employees, etc.

In examining the differences between public and private firm subsets, one may expect the presence of evidence of informed trading, if any, would be more pronounced in the privately-held firm sample, if the main motivation of the informed debt traders is to avoid attracting attention of regulators, who tend to focus on public companies. On the other hand, if the liquidity of the public debt of private firms is significantly impaired relative to that of the public ones, the public firm debt may be a more attractive trading venue, and thus exhibit stronger evidence of informed trading during the post-report-date time window.

Fundamentally, the question of the presence of informed trading here is an empirical one, and is addressed as such in this paper. Using a sample of 5793 firm-quarters for 195 reporting firms, 119 private and 76 public ones, I find significant evidence of informed trading during the 35-day window following the report period end date, both in the public and in the private firm subsamples. Specifically, for every extra billion dollars of unexpected earnings, bond price as a result of trading during the blackout window goes up on average by 0.1116 percent of par value. Further, this effect is somewhat smaller in magnitude for the publicly-traded firm sample. Finally, I find that the probability of trades occurring during the blackout window is significantly correlated with the absolute magnitude of unexpected earnings, and at the mean increases by 22.78 percent for a one billion dollar change in absolute surprise earnings.

My research contributes to existing literature in a number of substantial ways. First, I show that there is informed trading taking place in firms' publicly traded debt. Second, I find that this occurs both in firms with and firms without publicly traded equity. Further, the informed trading has a significant impact on the pricing of the affected debt instruments, with price changes being proportionally associated with the magnitude of unexpected future earnings surprises. Importantly, existing research on informed trading in the credit markets focuses on the trading activity in credit default swaps (CDSs)[23]; arguably the evidence from public debt market has broader impact, since CDS activity is still largely dominated by the banking and insurance sectors[24]. Though my sample is composed of financial institutions, the public debt market in general represents a much broader slice of the economy.

[23] Acharya and Johnson (2007), already mentioned above, find evidence of informed trading in CDS; Berndt and Ostrovnaya (2008) find significant incremental information flows from the CDS market into equity markets.

[24] Weistroffer (2009) provides descriptive statistics on the CDS market, reporting that banks and insurance companies have greater than 50% share of market activity in CDSs, and until the mid-2000s had >75%, with hedge funds only recently significantly expanding their activity in the market.

The remainder of this paper is organized as follows. Section 3.2 summarizes the major research targets for this paper. Section 3.3 details my data and sample selection procedures. Section 3.4 presents my research design and main empirical findings. Section 3.6 concludes.

3.2 Research Focus

The possibility of private information leakage leading to informed trading in public debt issues has not received much attention in the academic literature, and is my primary research focus. I investigate the incidence of informed trading in public debt issues using a sample of financial institutions with publicly traded debt. If information leakage does take place, and some market participants engage in informed trading, I would expect to see higher incidence of trade occurrence among firms with larger earnings surprises.

If informed trading does occur, the next aspect of the investigation is to determine its price impact on the affected securities. The natural expectation is that informed trading will impact the price in the direction of unexpected earnings, with the magnitude of the impact being positively associated with the magnitude of the earnings surprise.

Finally, most empirical academic research focuses on public-equity firms due to data availability. Here, by looking at the debt side of the markets, I have the opportunity to explore the differences, in any, between the firms with publicly traded equity and those without. Firms without public equity may exhibit differences is market depth and liquidity, regulatory attention, and other factors, which may moderate the incidence and impact of information leakage and informed trading.

3.3 Data

The data for this study come from a number sources. Regulatory filing information for commercial banks and bank holding companies is collected from the Reports of Condition and Income (Call Reports), for commercial banks, and the Y-9 family of reports, for bank holding companies. These reports are aggregated into datasets available from the Federal Reserve Bank of Chicago website[25]. The entity id *RSSD9001* is then matched to CUSIP numbers via name and address matching with the CUSIP Issuer database.

The data on the firms' bond issues and their characteristics is taken from the Mergent FISD database. This database contains information on all bond issues and their characteristics, including issue date, maturity, coupon and coupon frequency, call schedule, conversion features, and ratings from S&P, Fitch, and Moody's. Historical bond prices are from the TRACE database, which contains all reported bond trades starting from 2002, including trade execution date, price, and yield. Additional trade data is sourced from the FISD insurance bond transactions database.

The bond pricing information is then obtained by selecting trades within a 35 day window after the report period date for each firm-quarter. This time window accommodates both the FFIEC report release schedule, which states that reports

[25] http://www.chicagofed.org/webpages/banking/financial_institution_reports/

become available 40 days after the report period date[26], and also the public company quarterly report filings, which are observed to take place 35 days or more after the report period date. The "before" prices are obtained in a similar manner, selecting the latest trade within the 60 day window prior to the report period end date. The price and yield difference is then calculated between the "before" and "after" trades thus collected.

The initial sample of firms that I was able to match between the FDIC reports, CUSIP, and bond trades dataset contained 5793 firm-quarters for 195 reporting firms, 119 private and 76 public. Out of these, 2793 firm-quarters had the above bond pricing information, from 166 reporting firms, 98 private and 68 public.

3.3.1 Measuring unexpected earnings

I measure the unexpected earnings surprise as the residual from the regression of net income on the reported net income from one, four, and eight quarters ago[27]:

$$NI_{i,q} = \alpha + \alpha_1 NI_{i,q-1} + \alpha_2 NI_{i,q-4} + \alpha_3 NI_{i,q-8} + \varepsilon. \tag{20}$$

The mean unexpected earnings for the data sample is \$5084.17 dollars, and the mean absolute surprise is \$0.54 billion dollars.

[26] http://www2.fdic.gov/call_tfr_rpts/inform.html

[27] A similar approach is used by Anderson, Reeb, and Zhao (2011).

3.3.2 Control Variables

The effect of unexpected earnings on bond pricing may be affected by a number of firm characteristics. First, the debt of larger established firms may be less likely to be affected by variations in income. Alternatively, if the debt of larger firms is more liquid and thus more attractive to informed traders, the effect may be more pronounced. Second, higher firm leverage may reduce the firm's debt service cushion, possibly increasing the effect. Finally, the debt credit rating may also be expected to affect the debt's sensitivity to income variations. To account for these possibilities, I introduce control variables for firm leverage, size, and credit ratings.

I measure firm leverage using the book ratio of total liabilities to total assets,

$$Leverage = \frac{Total\ Assets - Total\ Equity}{Total\ Assets}, \tag{21}$$

and firm size as book value of assets,

$$Size = Total\ Assets. \tag{22}$$

These data items are collected from the call reports (commercial banks) and Y-9 reports (BHC) data for each of the reporting quarters.

I control for other sources of firm and issue-specific default risk using the firm's bond rating, using the latest issued credit rating for the traded bond issue (*Rating*). The character ratings are numerically operationalized by assigning an integer to each rating, with AAA corresponding to a numerical rating of 1, and D corresponding to 22.[28] Using this conversion, higher numbers mean higher default risk. The complete rating conversion chart is shown in Table 1. The rating used for each bond is the most recently issued rating prior to the issue-specific trade execution date used to determine the bond price. This procedure ensures that my rating measure incorporates the freshest possible information that bond ratings are supposed to reflect. Finally, *Public* is a dummy variable which is 1 for a firm that has publicly traded equity.

3.3.3 Descriptive and Univariate Statistics

Table 22 shows the summary statistics of the key variables in my sample. Included are the minimum, mean, median, maximum, and standard deviation.

Table 22: Summary Statistics, Chapter 3

This table shows summary statistics for the data used in the empirical analysis. The data set covers 2793 firm-quarters for 166 unique firms, from 2001 to 2010. The variables include: *Surprise*, the unexpected earning surprise; *Surprise.abs*, the absolute value of earnings surprise; *Yield*, the reported bond yield in percent; *Price*, the reported bond price as percent of par value; *PriceDiff*, the price difference between before and after trades around the report date; *YieldDiff*, the yield difference between the before and after trades around the report date; *Leverage*, firm leverage (total debt / total assets); *Size*, firm size (total book assets); *Rating*, numeric credit rating.

	Min.	Mean	Median	Max.	St. dev.
NI	−27.684	0.902	0.304	21.538	2.284
Surprise	−25.948	0.005	0.027	15.902	1.416
Surprise.abs	0.000	0.540	0.147	25.948	1.309
Yield	0.556	5.194	5.132	18.841	2.112
Price	40.000	101.639	101.012	137.860	8.312
PriceDiff	−10.000	0.002	0.000	9.965	2.237
YieldDiff	−24.058	0.063	0.000	15.558	1.090
Size	0.103	64.883	21.745	1674.523	148.369
Leverage	0.002	0.635	0.819	0.958	0.304
Rating	1.000	6.002	6.000	20.000	2.273

Firm size, as measured by total assets (in billions), has a mean of $64.88 billion, standard deviation of $148.37, with a minimum of $0.1, and a maximum of $1674.52.

[28]Same procedure as used in Reeb, Mansi, and Allee (2001) and Anderson, Mansi, and Reeb (2003)

Average leverage is 63.48%; and mean net income is $0.9 billion. As far as debt-specific measures go, the mean rating is 6, corresponding to a letter rating of A; mean price is 101.64 percent of par, and mean yield is 5.19 percent. The surprise earnings measure ranges from $-25.95 billion to $15.9 billion, with a mean of $0.01 billion and a standard deviation of $1.42. The mean absolute surprise is $0.54 billion.

The nature of the sample is such that only firms with publicly traded debt were selected, thus any results do not apply to firms without outstanding public debt. Within this sample, there is a wide cross sectional variation in the types and mix of public debt outstanding. The overall level of leverage ranges from almost none (less than 1 percent), to over 95 percent, with a mean of about 65 percent. Debt ratings range from AAA (lowest default risk tranche) down to CC (two tranches away from actual default). Bond prices are commensurately variable as well, with the sample ranging from 40 to 140 percent of par value. Of the 671 unique debt issues in the sample, 6 are exchangeable, 14 are convertible, 105 are callable, and 28 are putable. The offering sizes exhibit a lot of variation as well, with the minimum offering size being $0.845 million, median issue size of $300 million, mean of $557.29 million, and maximum of $4500 million. The average at-issue maturity is 9.67 years, with a minimum of 1 and a maximum of 60.04 years. 564 issues have a fixed coupon, 82 have variable coupons, and 25 have are zero-coupon bonds. There are 364, 90, 207, 3, and 1 senior, senior subordinate, subordinate, senior secured, and junior subordinate issues, respectively. The at-issue coupon amounts range from 0 to 10.25 percent, with a median of 5.5 and a mean of 5.21 percent.

3.4 Multivariate Empirical Results

3.4.1 Price Differences

The base-case model specification is a cross-sectional test of the relationship between bond price difference between trades before and after the report date, and the unexpected net income:

$$PriceDiff \sim \alpha_0 + \alpha_1 Surprise + \varepsilon \tag{23}$$

PriceDiff is the price difference between a bond trade within the 60 day window prior to the report date, and one in the 35 day window after the report date, which is within the "blackout window" where the regulatory report data is not yet released to the public, for each firm-quarter. *Surprise* is the unexpected earnings, measured as the residual in the regression of current quarter net income on net income reported one, four, and eight quarters ago. The coefficient of interest, α_1, if positive, will indicate that there is informed trading going on during the blackout window, with bond prices going up in trading when there is a positive surprise in earnings, and down when there is a negative one.

Column 1 of Table 23 presents the regression results following the specification shown in Eq. (23). The main finding is that firms with higher *Surprise* show a significant increase in the bond price. The coefficient on *Surprise* of 0.1092 is significant, and translates into 0.17 percent of face value change in bond price for a change of one standard deviation in *Surprise*. This suggests that there is indeed informed bond

Table 23: Multivariate Analysis: Price Delta and Surprise Earnings

This table shows the estimated coefficients of regressing the bond price changes on my measure of surprise earnings, and various controls. The dependent variable is *PriceDiff*, the price difference in bond trades before and after the report. The main independent variable is *Surprise*, the unexpected net income, which is the residual of the regression of current net income on net income reported one, four, and eight quarters ago.
The primary specification is:

$$PriceDiff \sim \alpha_0 + \alpha_1 Surprise + \varepsilon$$

These results are reported in Column 1. In Column 2 I add *Size*, measured by total assets in billions; in Column 3, I also include the *Leverage*, the book debt ratio; Column 4 adds *Rating*, which is the numerical bond rating. In Column 5 I include the *Public* dummy variable, which is 1 if the firm has publicly-traded equity. Finally, Column 6 includes quarter fixed effects to control for general market sentiment (coefficients not shown).

Significance levels: '***' 0.001 '**' 0.01 '*' 0.05 '†' 0.1 . Robust t-statistics using the Huber-White sandwich estimator of variance are listed in parentheses below each coefficient estimate.

	Dependent variable: PriceDiff					
	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	−0.109∗	−0.181∗∗∗	−0.068	−0.024	−0.060	−0.049
	(−2.39)	(−3.35)	(−0.63)	(−0.19)	(−0.25)	(−0.17)
Surprise	0.109∗∗	0.113∗∗	0.113∗∗	0.112∗∗	0.144	0.095∗∗
	(3.06)	(3.14)	(3.13)	(3.11)	(1.39)	(2.80)
Size		0.001†	0.001∗	0.001†	0.001†	0.001†
		(1.87)	(1.96)	(1.83)	(1.80)	(1.90)
Leverage			−0.191	−0.179	−0.144	−0.179
			(−1.20)	(−1.14)	(−0.53)	(−1.13)
Rating				−0.008	−0.007	−0.006
				(−0.54)	(−0.51)	(−0.45)
Public					0.026	
					(0.18)	
Surprise:Public					−0.037	
					(−0.33)	
N	2016	2016	2016	1984	1984	1984
R-squared	0.007	0.013	0.014	0.014	0.015	0.032
Adj. R-squared	0.006	0.012	0.013	0.012	0.012	0.016

trading taking place in the blackout window after the report period date.

Among the control variables, *Size* appears to be positively associated with bond price changes, possibly due to higher liquidity in the debt of larger firms attracting more informed trading activity. The coefficients on *Leverage* and *Rating* are not significant. Column 5, which includes the interaction term between *Surprise* and *Public*, shows that the magnitude of the effect is smaller for publicly traded firms. This suggests the possibility that the informed traders favor the privately held firms, due to their receiving less scrutiny from the regulatory authorities, or that the lower liquidity of the market in that debt exhibits a greater price impact for a given volume of trade. Finally, Column 6 includes quarter fixed effects, to control for general market sentiment variation over time (time period coefficients not shown). The main coefficient of interest remains qualitatively unaffected.

3.4.2 Yield Spread Differences

As an alternative specification, I try the same regressions using the changes in bond yield spread rather than prices,

$$YieldDiff \sim \alpha_0 + \alpha_1 Surprise + \varepsilon. \tag{24}$$

These results are shown in Table 24, and are qualitatively similar to the prior specification. Note that since yields go down when prices go up, the coefficient here is negative, opposite to what we saw with the price regressions. Since the yield information is available for fewer data points, resulting in a reduction of sample size, the resulting general reduction in significance is not unexpected.

Table 24: Multivariate Analysis: Yield Delta and Surprise Earnings

This table shows the estimated coefficients of regressing the bond yield changes on my measure of surprise earnings, and various controls. The dependent variable is *YieldDiff*, the yield difference in bond trades before and after the report. The main independent variable is *Surprise*, the unexpected net income, which is the residual of the regression of current net income on net income reported one, four, and eight quarters ago.
The primary specification is:

$$YieldDiff \sim \alpha_0 + \alpha_1 Surprise + \varepsilon$$

These results are reported in Column 1. In Column 2 I add *Size*, measured by total assets in billions; in Column 3, I also include the *Leverage*, the book debt ratio; Column 4 adds *Rating*, which is the numerical bond rating. In Column 5 I include the *Public* dummy variable, which is 1 if the firm has publicly-traded equity. Finally, Column 6 includes quarter fixed effects to control for general market sentiment (coefficients not shown).

Significance levels: '***' 0.001 '**' 0.01 '*' 0.05 '†' 0.1 . Robust t-statistics using the Huber-White sandwich estimator of variance are listed in parentheses below each coefficient estimate.

	Dependent variable: YieldDiff					
	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	0.084	0.095	0.094	−0.151	−0.340	−0.100
	(1.52)	(1.44)	(0.48)	(−0.69)	(−1.24)	(−0.57)
Surprise	−0.056†	−0.057†	−0.057†	−0.055†	−0.124**	−0.034
	(−1.83)	(−1.85)	(−1.85)	(−1.79)	(−2.75)	(−1.13)
Size		−0.000	−0.000	−0.000	−0.000	−0.000
		(−0.90)	(−1.46)	(−0.15)	(−0.80)	(−1.43)
Leverage			0.002	0.042	0.230	0.067
			(0.01)	(0.18)	(0.90)	(0.29)
Rating				0.033	0.035†	0.029
				(1.62)	(1.70)	(1.30)
Public					0.141	
					(1.39)	
Surprise:Public					0.075	
					(1.35)	
N	1453	1453	1453	1429	1429	1429
R-squared	0.003	0.003	0.003	0.004	0.005	0.034
Adj. R-squared	0.002	0.001	0.001	0.001	0.001	0.011

3.4.3 Split Sample Regressions

Since it is not unlikely that the coefficients for the various controls will differ between the public and the private firms, I next try separate regressions for the public and private firm samples. Given the previous results, the expectation is that both sets will show a positive association between bond price and surprise earnings, but that the coefficient for the public firms will be somewhat smaller than that for the private ones. The results for these specifications are shown in Table 25 using *PriceDiff* as the dependent variable.

The coefficients of *Surprise* are positive across all specifications, though drop below the threshold of significance when using the robust sandwich estimator variance for the private firm sample (as shown). Those of the public sample remain significant, and are somewhat lower in magnitude than the private sample, which is consistent with the results obtained in the combined-sample regression using the *Public* dummy variable. It could be the case that the effect is more consistent, albeit smaller, in the public sample due to liquidity or other differences in the debt markets for publicly-traded firms.

Table 26 shows the same regressions repeated using *YieldDiff* as the dependent variable and is in general agreement with the combined-sample results. The coefficients on *Surprise* are negative rather than positive, since prices and yields move in opposite directions. The difference in significance, however, is reversed, relative to the *PriceDiff* regressions, and now private firms show greater significance for the coefficient while public firm results drop below the standard significance threshold. The results are still consistent in that the magnitude of the effect in greater among the privately held firms.

Table 25: Multivariate Analysis: Price Delta and Surprise Earnings, Split Sample

This table shows the estimated coefficients of regressing the bond price changes on my measure of surprise earnings, and various controls. The dependent variable is *PriceDiff*, the price difference in bond trades before and after the report. The main independent variable is *Surprise*, the unexpected net income, which is the residual of the regression of current net income on net income reported one, four, and eight quarters ago. *Size* is firm total assets, in billions. The primary specification is:

$$PriceDiff \sim \alpha_0 + \alpha_1 Surprise + \alpha_2 Size + \varepsilon$$

These results are reported in Column 1, for the private firm sample. In Column 2 I include the *Leverage*, the book debt ratio; Column 3 adds *Rating*, which is the numerical bond rating. Columns 4-6 repeat these specifications for the public firm sample.

Significance levels: '***' 0.001 '**' 0.01 '*' 0.05 '†' 0.1 . Robust t-statistics using the Huber-White sandwich estimator of variance are listed in parentheses below each coefficient estimate.

	Private			Public		
	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	−0.226**	0.203	0.285	−0.138†	−0.265	−0.155
	(−3.19)	(1.25)	(1.24)	(−1.69)	(−1.32)	(−0.70)
Surprise	0.155	0.155	0.144	0.107**	0.108**	0.108**
	(1.51)	(1.50)	(1.37)	(2.86)	(2.86)	(2.84)
Size	0.001†	0.001†	0.001†	0.001**	0.001	0.000
	(1.66)	(1.73)	(1.69)	(3.28)	(1.33)	(0.33)
Leverage		−0.512*	−0.603**		0.442	0.786
		(−2.53)	(−2.73)		(0.75)	(1.55)
Rating			−0.000			−0.030
			(−0.02)			(−1.08)
N	1152	1152	1139	864	864	845
R-squared	0.012	0.014	0.014	0.017	0.018	0.022
Adj. R-squared	0.01	0.011	0.011	0.014	0.014	0.017

Table 26: Multivariate Analysis: Yield Delta and Surprise Earnings, Split Sample

This table shows the estimated coefficients of regressing the bond price changes on my measure of surprise earnings, and various controls. The dependent variable is *YieldDiff*, the yield difference in bond trades before and after the report. The main independent variable is *Surprise*, the unexpected net income, which is the residual of the regression of current net income on net income reported one, four, and eight quarters ago. *Size* is firm total assets, in billions. The primary specification is:

$$YieldDiff \sim \alpha_0 + \alpha_1 Surprise + \alpha_2 Size + \varepsilon$$

These results are reported in Column 1, for the private firm sample. In Column 2 I include the *Leverage*, the book debt ratio; Column 3 adds *Rating*, which is the numerical bond rating. Columns 4-6 repeat these specifications for the public firm sample.

Significance levels: '***' 0.001 '**' 0.01 '*' 0.05 '†' 0.1 . Robust t-statistics using the Huber-White sandwich estimator of variance are listed in parentheses below each coefficient estimate.

	Private			Public		
	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	0.085*	0.136	−0.108	0.126	−0.017	−0.571
	(2.24)	(0.61)	(−0.61)	(0.83)	(−0.05)	(−1.15)
Surprise	−0.145**	−0.145**	−0.123**	−0.050	−0.049	−0.049
	(−2.79)	(−2.77)	(−2.76)	(−1.54)	(−1.53)	(−1.50)
Size	−0.000	−0.000	−0.000	−0.001	−0.001*	−0.000
	(−0.92)	(−0.89)	(−0.60)	(−1.08)	(−2.01)	(−0.83)
Leverage		−0.062	0.191		0.504	0.450
		(−0.25)	(1.45)		(0.66)	(0.56)
Rating			0.001			0.086†
			(0.05)			(1.90)
N	825	825	817	628	628	612
R-squared	0.007	0.007	0.009	0.003	0.004	0.007
Adj. R-squared	0.005	0.004	0.004	0	−0.001	0

3.4.4 Trade Occurrence

It may be argued that informed trading by a few informed parties that spread their trading around across different firms may not affect bond pricing very much, and thereby not show up as a significant response in empirical tests. To sidestep this issue, I attack the question in a more direct way, looking at only the probability of trade occurrence in the blackout window, rather than the price effect thereof. To this end, I employ a probit model, with the presence of bond trades in the blackout window (*BlackoutTrades*) being the dependent variable, and the *absolute value* of the unexpected earnings (*Surprise.abs*) as the main independent variable. If there is informed trading going on, the expectation is that the higher the magnitude of the surprise earnings, the greater the probability that there will be trades happening in the blackout window to capitalize on the private information. Thus, we expect the coefficient on *Surprise.abs* to be positive in the presence of informed trading.

The base probit model specification is

$$BlackoutTrades \sim \alpha_0 + \alpha_1 Surprise.abs + \varepsilon \tag{25}$$

and the results are shown in Table 27. The result strongly indicates that for firm-quarters with larger surprise earnings, the probability of trade occurrence in the blackout window is greater. Examining the Column 3 cross-sectional result, the probability of trades occurring during the blackout window at the mean increases by 22.78 percent for a one billion dollar change in absolute surprise earnings. Column 4, which includes the interaction term with the *Public* dummy variable, shows that the probability of trade occurrence in the blackout window is greater for the public firms than the private ones, for a given magnitude of earnings surprise. This suggests that the lower price and yield impacts among the public firms, relative to the private ones, that we observe in the earlier results may be due to deeper markets in public firm debt, which are better able to absorb the informed trades with a less significant associated price movement.

Table 27: Multivariate Analysis: Trade Occurrence and Absolute Earnings Surprise

This table shows the estimated coefficients of regressing a binary variable measuring trade occurrence in the blackout window, on the measure of absolute surprise earnings, and various controls, in a probit model. The dependent variable is *BlackoutTrades*, which is 1 if there are bond trades within the blackout window after report period date. The main independent variable is *Surprise.abs*, the absolute value of unexpected net income, which is the absolute value of the residual of the regression of current net income on net income reported one, four, and eight quarters ago.
The primary specification is:

$$BlackoutTrades \sim \alpha_0 + \alpha_1 Surprise.abs + \varepsilon$$

These results are reported in Column 1. In Column 2 I include *Size*, total assets in billions; in Column 3, I add *Leverage*, the book debt ratio. Column 4 adds the *Public* dummy and its interaction with *Surprise.abs*.

Significance levels: '***' 0.001 '**' 0.01 '*' 0.05 '†' 0.1 . z-statistics are listed in parentheses below each coefficient estimate.

	Dependent variable: BlackoutTrades			
	(1)	(2)	(3)	(4)
Intercept	0.046†	0.046†	−0.253∗∗∗	−0.759∗∗∗
	(1.88)	(1.89)	(−5.63)	(−8.27)
Surprise.abs	0.644∗∗∗	0.668∗∗∗	0.715∗∗∗	0.299∗∗∗
	(11.31)	(10.09)	(10.56)	(3.88)
Size		−0.000	−0.000∗	0.000
		(−0.65)	(−2.53)	(0.91)
Leverage			0.526∗∗∗	1.093∗∗∗
			(7.93)	(10.12)
Public				0.304∗∗∗
				(3.83)
Surprise.abs:Public				1.524∗∗∗
				(7.51)
N	3589	3589	3588	3588
AIC	4616.087	4617.64	4553.901	4404.753

As an alternative specification, I try separate regressions for the split private and public firm samples. These results are in Table 28, and show qualitatively similar results. The probability of blackout window trades is significantly higher for greater magnitude of surprise earnings, and for a given magnitude of surprise appears to be higher for the public firm sample.

Table 28: Multivariate Analysis: Trade Occurrence and Absolute Earnings Surprise, Split Sample

This table shows the estimated coefficients of regressing a binary variable measuring trade occurrence in the blackout window, on the measure of absolute surprise earnings, and various controls, in a probit model. The dependent variable is *BlackoutTrades*, which is 1 if there are bond trades within the blackout window after report period date. The main independent variable is *Surprise.abs*, the absolute value of unexpected net income, which is the absolute value of the residual of the regression of current net income on net income reported one, four, and eight quarters ago.
The primary specification is:

$$BlackoutTrades \sim \alpha_0 + \alpha_1 Surprise.abs + \varepsilon$$

These results are reported in Column 1, for the private firm sample. In Column 2 I include *Size*, total assets in billions; in Column 3, I add *Leverage*, the book debt ratio. Columns 4-6 repeat these for the public sample.

Significance levels: '***' 0.001 '**' 0.01 '*' 0.05 '†' 0.1 . z-statistics are listed in parentheses below each coefficient estimate.

	Private			Public		
	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	0.116∗∗∗	0.112∗∗∗	−0.699∗∗∗	−0.172∗∗∗	−0.337∗∗∗	−0.559∗∗∗
	(3.74)	(3.57)	(−6.65)	(−4.05)	(−7.26)	(−8.09)
Surprise.abs	0.378∗∗∗	0.291∗∗∗	0.323∗∗∗	1.859∗∗∗	0.450∗	0.567∗∗
	(6.10)	(3.75)	(4.15)	(10.18)	(2.17)	(2.59)
Size		0.000†	0.000		0.058∗∗∗	0.053∗∗∗
		(1.66)	(0.49)		(8.50)	(7.55)
Leverage			1.020∗∗∗			0.918∗∗∗
			(8.10)			(4.28)
N	2057	2057	2057	1532	1532	1531
AIC	2746.671	2745.705	2674.446	1775.407	1668.842	1650.648

Overall, the results are consistent across all specifications. Price and yield changes are in evidence that are correlated with surprise earnings, indicating that price changes as a result of trading in the blackout window reflect the not-yet-public report data. Additionally, the probability of bond trade occurrence during the blackout time window is significantly higher in the presence of surprise earnings, further suggesting that there is informed trading activity taking place. Moreover, both public and private firm samples show qualitatively similar behavior. All the results suggest that there is informed debt trading taking place in the sample of financial firms used for this study.

3.5 Additional Specifications

One criticism that can be leveled at the analysis above is that the binary variable for trade occurrence discards a lot of information contained in the actual trade frequencies. Additionally, trading during the blackout window could be at least in part associated with the baseline liquidity during the prior months. Further, trading may also be expected to be influenced by changes in macroeconomic variables around the report period date. To this end, I try several alternative specifications for investigating changes in trading activity during the blackout window. First, rather than using a binary variable for trade occurrence, I introduce a trade frequency measure for the dependent variable, which is the average number of trades per day during the blackout period, *BlackoutTradeFreq*. Second, I also include variables for the baseline liquidity in the form of average trade frequency during the 60 days prior to the report period date (*BaselineLiquidity*). Finally, I introduce a couple of variables to measure relevant macroeconomic changes around the report period date. The change in the 10-year treasury yields (*RateChange*) is a measure of changes of interest rates in the economy, and is calculated as the change from 30 days before to 30 days after the report period date. Further, I include the change in the yield spread between AAA and BBB-rated bonds (*RiskChange*), as a measure of the changes in the general appetite for risk in the economy. These macroeconomic variables should adequately capture the relevant changes in economic environment that would affect the pricing of a wide spectrum of debt instruments. The base model falling out of the discussion above is thus as follows:

$$\begin{aligned} BlackoutTradeFreq \sim \alpha_0 + \alpha_1 Surprise.abs + \alpha_2 BaselineLiquidity + \\ + RateChange + RiskChange + \varepsilon \end{aligned} \tag{26}$$

The result of this regression is presented in Table 29 in Column 1. These results are qualitatively similar to earlier specifications, wherein a greater magnitude of future earnings surprise is positively associated with increased trading activity during the blackout window, and is more so for publicly-traded firms.

An additional consideration is that of our measure of earnings surprise. Specifically, it may be reasonable to suggest that the impact of earnings surprise depends on its relative magnitude, as compared to overall firm size. I repeat the previous results using *Surprise.pct.abs*, which is the absolute value of earnings surprise, scaled by firm total assets to see if measuring earnings surprise on a relative basis changes the findings. The results are shown in Table 30. Using the surprise earnings as percent of total assets as the measure of surprise, we retain the signs, but lose significance of the coefficient across all specifications. The only consistently significant variable is the *BaselineLiquidity* measure.

The controls for baseline liquidity, changes in market environment, as well as trying the relative measure of earnings surprise (scaled by total assets) seem like useful

Table 29: Multivariate Analysis: Blackout Trade Frequency vs. Absolute Earnings Surprise

This table shows the estimated coefficients of regressing the trade frequency during the blackout window on my measure of absolute surprise earnings, and various controls. The dependent variable is *BlackoutTradeFreq*, the average daily trade frequency during the post-report blackout window. The main independent variable is *Surprise.abs*, the absolute value of unexpected net income, which is the residual of the regression of current net income on net income reported one, four, and eight quarters ago. *BaselineLiquidity* is the average daily trade frequency during the 60 day window prior to report date; *RateChange* is the change in the 10 year treasury yield in the two-month window surrounding the report date; *RiskChange* is the change in the yield spread between AAA and BBB-rated bonds; *Size* is firm total assets, in billions; *Leverage* is book leverage; *Public* is a binary variable which is 1 for firms with publicly-traded equity.
The primary specification is:

$$BlackoutTradeFreq \sim \alpha_0 + \alpha_1 Surprise.abs + \alpha_2 BaselineLiquidity + \\ + RateChange + RiskChange + \varepsilon$$

These results are reported in Column 1. In Column 2 I add *Size*; in Column 3, *Leverage*; in Column 4, *Public*, the publicly traded firm binary flag; and in Column 5, the interaction term between *Public* and *Surprise.abs*.

Significance levels: '***' 0.001 '**' 0.01 '*' 0.05 '†' 0.1 . Robust t-statistics using the Huber-White sandwich estimator of variance are listed in parentheses below each coefficient estimate.

	Dependent variable: BlackoutTradeFreq				
	(1)	(2)	(3)	(4)	(5)
Intercept	−0.000	0.163	0.092	−3.087*	−2.277†
	(−0.00)	(0.72)	(0.27)	(−2.26)	(−1.84)
Surprise.abs	3.274†	3.490†	3.491†	3.413†	−0.048
	(1.95)	(1.92)	(1.92)	(1.89)	(−0.09)
BaselineLiquidity	0.857***	0.857***	0.857***	0.854***	0.846***
	(24.54)	(24.83)	(24.81)	(24.90)	(22.46)
RateChange	0.631	0.631	0.629	0.598	0.528
	(0.70)	(0.70)	(0.69)	(0.66)	(0.59)
RiskChange	0.129	0.149	0.149	0.109	−0.180
	(0.07)	(0.08)	(0.08)	(0.06)	(−0.10)
Size		−0.004	−0.004	−0.004	0.002
		(−1.35)	(−1.35)	(−1.26)	(1.07)
Leverage			0.123	3.500*	3.050*
			(0.36)	(2.28)	(2.14)
Public				2.848*	1.979†
				(2.34)	(1.66)
Surprise.abs:Public					3.889†
					(1.92)
N	3415	3415	3415	3415	3415
R-squared	0.88	0.88	0.88	0.88	0.881
Adj. R-squared	0.88	0.88	0.88	0.88	0.881

Table 30: Multivariate Analysis: Blackout Trade Frequency vs. Absolute Percent Earnings Surprise

This table shows the estimated coefficients of regressing the trade frequency during the blackout window on my measure of absolute surprise earnings scaled by firm assets, and various controls. The dependent variable is *BlackoutTradeFreq*, the average daily trade frequency during the post-report blackout window. The main independent variable is *Surprise.pct.abs*, the absolute value of unexpected net income, which is the residual of the regression of current net income on net income reported one, four, and eight quarters ago, scaled by firm total assets. *BaselineLiquidity* is the average daily trade frequency during the 60 day window prior to report date; *RateChange* is the change in the 10 year treasury yield in the two-month window surrounding the report date; *RiskChange* is the change in the yield spread between AAA and BBB-rated bonds; *Size* is firm total assets, in billions; *Leverage* is book leverage; *Public* is a binary variable which is 1 for firms with publicly-traded equity.
The primary specification is:

$$\begin{gathered} BlackoutTradeFreq \sim \alpha_0 + \alpha_1 Surprise.pct.abs + \alpha_2 BaselineLiquidity + \\ + RateChange + RiskChange + \varepsilon \end{gathered}$$

These results are reported in Column 1. In Column 2 I add *Size*; in Column 3, *Leverage*; in Column 4, *Public*, the publicly traded firm binary flag; and in Column 5, the interaction term between *Public* and *Surprise.pct.abs*.

Significance levels: '***' 0.001 '**' 0.01 '*' 0.05 '†' 0.1 . Robust t-statistics using the Huber-White sandwich estimator of variance are listed in parentheses below each coefficient estimate.

	Dependent variable: BlackoutTradeFreq				
	(1)	(2)	(3)	(4)	(5)
Intercept	0.722∗∗	0.544∗∗	0.565†	−3.776∗	−3.899†
	(3.08)	(2.96)	(1.66)	(−1.98)	(−1.94)
Surprise.pct.abs	7.980	9.613	9.511	9.019	12.922
	(1.15)	(1.27)	(1.27)	(1.22)	(1.59)
BaselineLiquidity	0.888∗∗∗	0.886∗∗∗	0.886∗∗∗	0.881∗∗∗	0.881∗∗∗
	(47.59)	(45.60)	(45.38)	(44.35)	(44.58)
RateChange	0.341	0.378	0.378	0.341	0.334
	(0.51)	(0.56)	(0.56)	(0.51)	(0.50)
RiskChange	0.835	0.792	0.791	0.717	0.725
	(0.53)	(0.50)	(0.50)	(0.46)	(0.47)
Size		0.003	0.003	0.003	0.003
		(1.31)	(1.27)	(1.32)	(1.33)
Leverage			−0.034	4.569∗	4.675∗
			(−0.09)	(2.12)	(2.08)
Public				3.883∗	4.055∗
				(2.20)	(2.10)
Surprise.pct.abs:Public					−6.674
					(−0.49)
N	3415	3415	3415	3415	3415
R-squared	0.877	0.877	0.877	0.877	0.877
Adj. R-squared	0.877	0.877	0.877	0.877	0.877

alternatives to try for bond price changes as well. The prevailing liquidity may certainly impact the magnitude of price changes all else equal; changes in macroeconomic conditions would probably explain at least some part of the contemporaneous price changes; and the relative measure of earnings surprise seems like it should capture more adequately the actual magnitude of impact of the unexpected earnings. To this end, the new base specification for the price delta regressions is:

$$
\begin{aligned}
PriceDiff \sim \alpha_0 + \alpha_1 Surprise.pct + \alpha_2 BaselineLiquidity + \\
+ RateChange + RiskChange + \varepsilon
\end{aligned}
\tag{27}
$$

The results of this specification are shown in Column 1 of Table 31. Column 2 adds a control for *Size*; Column 3, *Leverage*; Column 4, *Rating*; Column 5, *Public*; Column 6, interaction between *Public* and *Surprise.pct*. The general pattern of coefficients remains qualitatively similar to that of earlier specifications, with future earnings surprises being positively associated with price changes due to trading within the blackout window. Table 32 repeats the same using the yield differences, *YieldDiff*, and shows the same qualitative pattern of coefficients.

3.6 Conclusions

Informed trading has the potential to be a highly profitable activity, so any regulatory efforts to prevent it are bound to fall short of perfection. Rational market participants would be expected to take advantage of the opportunity to the extent that the benefits

Table 31: Multivariate Analysis: Price Delta vs. Percent Earnings Surprise

This table shows the estimated coefficients of regressing the price delta on my measure of surprise earnings scaled by firm assets, and various controls. The dependent variable is *PriceDiff*, the bond price difference between pre- and during-blackout window trades. The main independent variable is *Surprise.pct*, the unexpected net income, which is the residual of the regression of current net income on net income reported one, four, and eight quarters ago, scaled by firm total assets. *BaselineLiquidity* is the average daily trade frequency during the 60 day window prior to report date; *RateChange* is the change in the 10 year treasury yield in the two-month window surrounding the report date; *RiskChange* is the change in the yield spread between AAA and BBB-rated bonds; *Size* is firm total assets, in billions; *Leverage* is book leverage; *Rating* is the numeric bond rating; *Public* is a binary variable which is 1 for firms with publicly-traded equity.
The primary specification is:

$$PriceDiff \sim \alpha_0 + \alpha_1 Surprise.pct + \alpha_2 BaselineLiquidity + \\ + RateChange + RiskChange + \varepsilon$$

These results are reported in Column 1. In Column 2 I add *Size*; in Column 3, *Leverage*; in Column 4, *Rating*; in Column 5, *Public*, the publicly traded firm binary flag; and in Column 6, the interaction term between *Public* and *Surprise.pct*.

Significance levels: '***' 0.001 '**' 0.01 '*' 0.05 '†' 0.1 . Robust t-statistics using the Huber-White sandwich estimator of variance are listed in parentheses below each coefficient estimate.

	Dependent variable: PriceDiff					
	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	−0.172∗∗	−0.227∗∗	−0.206	−0.062	−0.211	−0.233
	(−2.59)	(−3.10)	(−1.19)	(−0.22)	(−0.31)	(−0.34)
Surprise.pct	4.742†	4.663†	4.668†	6.181∗	6.187∗	0.437
	(1.68)	(1.65)	(1.67)	(2.56)	(2.56)	(0.18)
BaselineLiquidity	0.001∗∗	0.000	0.000	0.000	0.000	0.000
	(2.67)	(0.84)	(0.75)	(0.65)	(0.30)	(0.29)
RateChange	−0.467†	−0.460†	−0.460†	−0.417	−0.420	−0.402
	(−1.70)	(−1.68)	(−1.68)	(−1.55)	(−1.57)	(−1.50)
RiskChange	−0.682	−0.695†	−0.696†	−0.882∗	−0.888∗	−0.887∗
	(−1.63)	(−1.66)	(−1.66)	(−2.15)	(−2.16)	(−2.16)
Size		0.001	0.001	0.001	0.001	0.001
		(1.54)	(1.51)	(1.31)	(1.32)	(1.33)
Leverage			−0.035	0.019	0.186	0.197
			(−0.15)	(0.08)	(0.28)	(0.30)
Rating				−0.028	−0.029	−0.027
				(−0.88)	(−0.95)	(−0.91)
Public					0.121	0.135
					(0.31)	(0.34)
Surprise.pct:Public						8.416∗
						(2.21)
N	1981	1981	1981	1950	1950	1950
R-squared	0.009	0.012	0.012	0.017	0.017	0.019
Adj. R-squared	0.007	0.009	0.009	0.013	0.013	0.014

Table 32: Multivariate Analysis: Yield Delta vs. Percent Earnings Surprise

This table shows the estimated coefficients of regressing the price delta on my measure of surprise earnings scaled by firm assets, and various controls. The dependent variable is *YieldDiff*, the bond yield difference between pre- and during-blackout window trades. The main independent variable is *Surprise.pct*, the unexpected net income, which is the residual of the regression of current net income on net income reported one, four, and eight quarters ago, scaled by firm total assets. *BaselineLiquidity* is the average daily trade frequency during the 60 day window prior to report date; *RateChange* is the change in the 10 year treasury yield in the two-month window surrounding the report date; *RiskChange* is the change in the yield spread between AAA and BBB-rated bonds; *Size* is firm total assets, in billions; *Leverage* is book leverage; *Rating* is the numeric bond rating; *Public* is a binary variable which is 1 for firms with publicly-traded equity.
The primary specification is:

$$YieldDiff \sim \alpha_0 + \alpha_1 Surprise.pct + \alpha_2 BaselineLiquidity + \\ + RateChange + RiskChange + \varepsilon$$

These results are reported in Column 1. In Column 2 I add *Size*; in Column 3, *Leverage*; in Column 4, *Rating*; in Column 5, *Public*, the publicly traded firm binary flag; and in Column 6, the interaction term between *Public* and *Surprise.pct*.

Significance levels: '***' 0.001 '**' 0.01 '*' 0.05 '†' 0.1 . Robust t-statistics using the Huber-White sandwich estimator of variance are listed in parentheses below each coefficient estimate.

	Dependent variable: YieldDiff					
	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	0.076*	0.082*	0.121	−0.039	−0.138	−0.155
	(2.07)	(2.00)	(1.08)	(−0.23)	(−0.62)	(−0.70)
Surprise.pct	−6.363**	−6.351**	−6.323**	−7.303***	−7.297***	−9.710***
	(−2.95)	(−2.94)	(−2.92)	(−3.63)	(−3.62)	(−3.60)
BaselineLiquidity	−0.000**	−0.000**	−0.000*	−0.000†	−0.000†	−0.000†
	(−2.83)	(−2.65)	(−2.27)	(−1.65)	(−1.80)	(−1.84)
RateChange	−0.082	−0.084	−0.083	−0.057	−0.058	−0.052
	(−0.75)	(−0.76)	(−0.75)	(−0.61)	(−0.62)	(−0.54)
RiskChange	0.072	0.073	0.072	0.115	0.111	0.110
	(0.22)	(0.22)	(0.22)	(0.33)	(0.32)	(0.32)
Size		−0.000	−0.000	0.000	0.000	0.000
		(−0.73)	(−0.49)	(0.32)	(0.33)	(0.36)
Leverage			−0.064	−0.054	0.051	0.060
			(−0.44)	(−0.36)	(0.24)	(0.28)
Rating				0.021	0.021	0.022
				(1.42)	(1.45)	(1.58)
Public					0.076	0.089
					(0.71)	(0.83)
Surprise.pct:Public						3.670
						(1.08)
N	1434	1434	1434	1410	1410	1410
R-squared	0.027	0.027	0.027	0.036	0.036	0.038
Adj. R-squared	0.024	0.024	0.023	0.031	0.031	0.032

outweigh the potential costs, and with the costs being primarily regulatory, one would expect to see informed trading to take place in less scrutinized areas of the market. To this end, I attempt to empirically detect informed trading in the debt markets, focusing specifically on privately held financial firms which provide regular financial report data in the form of FDIC call reports.

Using a sample of financial firms matched from the call/Y-9 report data to the Mergent FISD database and the TRACE bond pricing database, I find that there is evidence to support the suggestion that informed trading in debt markets does take place. Looking at bond trades within the 35 day window between the creation of report and its official availability to the public, I find evidence of price changes due to trades in this blackout window being correlated with unexpected earnings surprises. Additionally, I find that the probability of the very occurrence of bond trades in the blackout window is strongly associated with the absolute magnitude of the earnings surprise for the report period. Further, there is empirical evidence that suggests an effect differential between private firms and firms with publicly traded equity, wherein the magnitude of the pricing effect is greater in the private firm sample, while the probability of trade occurrence is higher among the publicly traded firms. One possibility is that this is due to greater market depth for the public debt of firms with public equity.

It is possible that the observed effects are due not to private information leakage, but to public statements by firm executives made around the time of report filing, or the inference of the expected results from other publicly available data. While

I cannot say where and to whom the information leakage is taking place based on the tests in this study, the results do indicate that there may be a need for greater regulatory scrutiny of debt markets with regard to informed trading.

When thinking about public firms, one usually has in mind firms with publicly traded equity. However, any security issued by a firm for public ownership effectively makes the firm a "publicly traded" firm, inasmuch as some instrument secured against the interest of a company (a "security") is publicly traded. The Securities Act of 1933 and the Securities Exchange Act of 1934 are quite explicitly broad and vague on what constitutes a "security" and thus falls under the purview of SEC regulation. The empirical results obtained in this paper strongly suggest that informed trading is quite active in publicly held debt securities, and raise the question of why the relative frequency of SEC enforcement actions in the debt markets is so low compared to equity markets.

The basic reasoning behind the insider trading laws is to prevent the exploitation of outside traders by informed insiders, regardless of the type of security traded. Without such protection, it is argued, outsider investors will be loath to participate in the marketplace, thereby reducing the efficiency of capital allocation in the economy. This idea has been backed up empirically by Bhattacharya and Daouk (2002), who find in a cross-country study that enforcement of insider trading laws significantly lowers the cost of equity. Pointing toward a similar result, Fishman and Hagerty (1992) develop a theoretical model, showing that insider trading leads to less efficient stock prices, by deterring traders from acquiring information.

The other side of the coin is that trading on private information - or any kind of real information, is the process by which information gets incorporated into market price. Laws preventing trading on any subset of such information decrease market efficiency by preventing information from entering the market.[29] Without laws regulating informed trading, maybe rather than seeing large price jumps in stocks on days when big news is announced, we would see a gradual price drift in the weeks or months preceding the announcement, as informed traders act on their information. After all, the large price jumps on announcement days benefit those first to see the news release and first to pull the trigger, which is usually professional institutional investors, rather than small retail investors. With that being the case, are the retail investors really being protected by insider trading laws?

One might hypothesize that insider trading regulations may be deliberately lighter-handed than those in the equity markets, to allow private information to be incorporated into equity prices via these other markets as side channels. There is no argument that the vast majority of retail investors are only active in the equity markets, with instruments such as credit default swaps, and to a lesser extent, public corporate debt, being almost exclusively the domain of institutional investors. By allowing institutional investors leeway to trade on private information in these other markets, and letting the resulting price discovery filter sideways to the equity markets (Berndt and Ostrovnaya (2008) provide empirical evidence that these information flows do

[29]In his rather well-known book, Manne (1966) argues this position at length. Boudreaux (2009) is of similar opinion, as is Milton Friedman (Harris, 2003, Chapter 29). Leland (1992) builds a theoretical model that shows that when insider trading is permitted, stock prices better reflect information, real investment rises, and owners and insider benefit while outsiders are hurt. In the model, the total welfare depends on some factors of the economic environment.

occur), maybe the regulators are striking a balance between protecting the outsiders from insider exploitation, and increased market efficiency from information entering the markets.

Whatever the regulatory goals may be, the empirical results in the present paper, together with research on informed trading in other non-equity markets, show that informed trading does take place in these instruments, which indicates that the relative lack of SEC enforcement is not due to the absence of informed trading, but is rather a regulatory choice. The empirical evidence presented herein will, it is hoped, help make this choice a more informed one.

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Appendices

A High CI Examples

Included below are some samples of competitive discussion in annual reports from firms with relatively high amount of such discussion, labeled by year, firm name, and CIK code.

Discussion of competition in the 2005 10-K annual report by Vasco Data Security International Inc. CIK 1044777. Word count of 1151.

> COMPETITION The market for computer and network security solutions is very competitive and, like most technology-driven markets, is subject to rapid change and constantly evolving products and services. Our main competitor is RSA Security. Additional competitors are ActivIdentity, Xiring, Todos Data Systems and Kobil Systems. There are many other companies such as Secure Computing, SafeNet, Entrust, and Aladdin Knowledge Systems that offer authentication hardware, software and services that range from simple locking mechanisms to sophisticated encryption technologies. We believe that competition in this market is likely to intensify as a result of increasing demand for security products.
>
> We believe that the principal competitive factors affecting the market for computer and network security products include the strength and effectiveness of the solution, technical features, ease of use, quality/reliability, customer service and support, name recognition, customer base, distribution channels and price. Although we believe that our products currently compete favorably with respect to such factors, other than name recognition in certain markets, there can be no assurance that we can maintain our competitive position against current and potential competitors, especially those with significantly greater financial, marketing, service, support, technical and other competitive resources.
>
> Some of our present and potential competitors have significantly greater financial, technical, marketing, purchasing and other resources than we do, and as a result, may be able to respond more quickly to new or emerging technologies and changes in customer requirements, or to devote greater resources to the development, promotion and sale of products, or to deliver competitive products at a lower end-user price. Current and potential

competitors have established or may establish cooperative relationships among themselves or with third parties to increase the ability of their products to address the needs of our prospective customers. It is possible that new competitors or alliances may emerge and rapidly acquire significant market share. Accordingly, VASCO has, and will continue to forge its own partnerships to offer a broader range of products and capabilities to the market.

Our products are designed to allow authorized users access to a computing environment, in some cases using patented technology as a replacement for the static password. Although certain of our security token technologies are patented, there are other organizations that offer token-type password generators incorporating challenge-response or response-only approaches that employ different technological solutions and compete with us for market share.

The market for computer and network security products is highly competitive. Our competitors include organizations that provide computer and network security products based upon approaches similar to and different from those that we employ such as RSA Security, ActivIdentity, Xiring, Todos Data Systems and Kobil Systems Many of our competitors have significantly greater financial, marketing, technical and other competitive resources than we do. As a result, our competitors may be able to adapt more quickly to new or emerging technologies and changes in customer requirements, or to devote greater resources to the promotion and sale of their products.

TECHNOLOGICAL CHANGES OCCUR RAPIDLY IN OUR INDUSTRY AND OUR DEVELOPMENT OF NEW PRODUCTS IS CRITICAL TO MAINTAIN OUR REVENUES.

The introduction by our competitors of products embodying new technologies and the emergence of new industry standards could render our existing products obsolete and unmarketable. Our future revenue growth and operating profit will depend in part upon our ability to enhance our current products and develop innovative products to distinguish ourselves from the competition and to meet customers' changing needs in the data security industry. We cannot assure you that security-related product developments and technology innovations by others will not adversely affect our competitive position or that we will be able to successfully anticipate or adapt to changing technology, industry standards or customer requirements on a timely basis.

Part of our business strategy is to enter into strategic alliances and other cooperative arrangements with other companies in our industry. We currently are involved in cooperative efforts with respect to incorporation of our products into products of others, research and development efforts, marketing efforts and reseller arrangements. None of these relationships are exclusive, and some of our strategic partners also have cooperative relationships with certain of our competitors. If we are unable to enter cooperative arrangements in the future or if we lose any of our current strategic or cooperative relationships, our business could be harmed. We do not control the time and resources devoted to such activities by parties with whom we have relationships. In addition, we may not have the resources available to satisfy our commitments, which may adversely affect these relationships. These relationships may not continue, may not be commercially successful, or may require our expenditure of significant financial, personnel and administrative resources from time to time. Further, certain of our products and services compete with the products and services of our strategic partners.

There has been substantial litigation in the technology industry regarding intellectual property rights, and we may have to litigate to protect our proprietary technology. We expect that companies in the computer and information security market will increasingly be subject to infringement claims as the number of products and competitors increases. Any such claims or litigation may be time-consuming and costly, cause product shipment delays, require us to redesign our products or require us to enter into royalty or licensing agreements, any of which could reduce revenue and increase our operating costs.

OUR PATENTS MAY NOT PROVIDE US WITH COMPETITIVE ADVANTAGES.

We hold several patents in the U. S. and in some European countries, which cover multiple aspects of our technology. The majority of our patents cover the Digipass product line. These patents expire between 2006 and 2022, with one patent expiring in 2006. In addition to the issued patents, we also have several patents pending in the U. S. and other countries. There can be no assurance that we will continue to develop proprietary products or technologies that are patentable, that any issued patent will provide us with any competitive advantages or will not be challenged by third parties, or that patents of others will not hinder our competitive advantage. Although certain of our security token technologies are patented, there are other organizations that offer token-type password generators incorporating challenge-response or response-only approaches that employ different technological solutions and compete with us for market share.

In the future, as in the past, our quarterly operating results may vary significantly resulting in a volatile stock price. Factors affecting our operating results include: The level of competition; The size, timing, cancellation or rescheduling of significant orders; New product announcements or introductions by current competitors; Technological changes in the market for data security products including the adoption of new technologies and standards; Changes in pricing by current competitors; Our ability to develop, introduce and market new products and product enhancements on a timely basis, if at all; Our success in expanding our sales and marketing programs; Market acceptance of new products and product enhancements; Changes in foreign currency exchange rates; and General economic trends.

Discussion of competition in the 2008 10-K annual report by ev3 Inc., CIK 1318310.

Word count of 6258.

ev3 Inc. is a leading global endovascular company focused on identifying and treating peripheral vascular disease, including in particular lower extremity arterial disease, and neurovascular disease. Since our founding in 2000, we have been dedicated to developing innovative, breakthrough and clinically proven technologies and solutions for the treatment of peripheral vascular and neurovascular diseases, a strategy that we believe is uncommon in the medical device industry. We believe our unique approach of focusing on emerging and under-innovated opportunities which treat peripheral vascular and neurovascular disease allows us to compete with smaller companies that have narrow product lines and lack an international sales force and infrastructure, yet also compete with larger companies that do not have our focus and agility.

The competitive strengths that have been responsible for our past success and the strategies that we believe will drive our future growth include: targeting under-innovated and emerging markets; leveraging our products across major endovascular sub-markets; investing in clinical research to demonstrate the benefits of our products; expanding our business through product innovation and strategic acquisitions; driving our global organization and presence; and leading our business by an experienced management team.

Although our stents, like some of our competitors stents, have been cleared by the FDA for the palliative treatment of malignant neoplasms in the biliary tree, they are used by physicians not only in the biliary duct, which transports bile from the liver and gall bladder to the small intestines, but also off label in various other locations in the body, including renal arteries, which transport blood from the aorta to the kidneys; iliac, femoral and popliteal arteries, which are major arteries in the legs and subclavian arteries, which are major vessels of the upper body, originating at the aortic arch. We believe that our portfolio of self-expanding stents is differentiated from our competitors offerings due to their fracture resistance, flexibility and lengths, and that both our self-expanding and balloon expandable stent platforms provide advanced radiopacity (visibility under fluoroscopy), placement accuracy, deliverability and strong clinical performance.

ProtÃ©gÃ© EverFlex, ProtÃ©gÃ© GPS and ProtÃ©gÃ© GPS BIGGS. Our self-expanding stent portfolio includes our ProtÃ©gÃ© EverFlex Self-Expanding Stent and our ProtÃ©gÃ© GPS Self-Expanding Stent, all of which are shape memory Nitinol stents that expand to a predetermined diameter upon deployment. Nitinol is a highly flexible metal with shape retention and fatigue resistance properties. We offer a number of sizes of the EverFlex and ProtÃ©gÃ© GPS stents. The EverFlex stent has enhanced flexibility and resistance to fractures, which we believe provides superior performance in vessels that are subjected to repeated flexing and bending. Designed specifically for use in the superficial femoral artery where peripheral artery disease is often present, the EverFlex stent encompasses a unique spiral cell geometry constructed to withstand the extreme movement of the SFA. Although not a substitute for clinical performance, our internal bench testing has provided us with data suggesting that our EverFlex stent may be up to five to 10 times more durable than stents offered by our competitors. We believe the design of our EverFlex stents is unique in that it features: Spiral cell interconnections that greatly enhance flexibility; New wave peak structure that more efficiently distributes stress and resists compression; and Longer lengths (up to 200 mm and all 6 French compatible), which minimize the need for overlapping stents when treating long lesions.

We are subject to various environmental health and safety laws, directives and regulations both in the U.S. and abroad. Our operations, like those of other medical device companies, involve the use of substances regulated under environmental laws, primarily in manufacturing and sterilization processes. We do not expect that compliance with environmental protection laws will have a material impact on our capital expenditures, earnings or competitive position. Given the scope and nature of these laws, however, there can be no assurance that environmental laws will not have a material impact on our results of operations. Our leased Redwood City facility sits on property formerly occupied by Rohm & Haas and Occidental Chemical Company and contains residual contamination in soil and groundwater from these past industrial operations. Rohm & Haas and Occidental Chemical Company previously performed soil remediation on the property under the supervision of the California Regional Water Quality Control Board. Rohm & Haas has indemnified the owner of the facility and its tenants against costs associated with the residual contamination.

Competition The markets in which we compete are highly competitive, subject to change and impacted by new product introductions and other activities of industry participants. We compete primarily on the basis of our ability to treat vascular diseases and disorders safely and effectively. Our success can be impacted by the ease and predictability of product use, adequate third-party reimbursement, brand name recognition and cost. We believe we compete favorably with respect to these factors, although there can be no assurance that we will be able to continue to do so in the future or that new products that perform better than those we offer will not be introduced. Because of the size of the peripheral vascular and neurovascular markets, competitors and potential competitors have historically dedicated and will continue to dedicate significant resources to aggressively promote their products and develop new and improved products.

Our competitors range from small start-up companies to much larger companies. The larger companies with which we compete include Abbott Laboratories, Boston Scientific Corporation, Cook Incorporated, Cordis Corporation (a Johnson & Johnson company) and Medtronic, Inc. All of these larger companies have substantially greater capital resources, larger customer bases, broader product lines, larger sales forces, greater marketing and management resources, larger research and development staffs and larger facilities than ours and have established reputations and relationships with our target customers, as well as worldwide distribution channels that are more effective than ours. We also compete, however, and in some cases even more intensely, with smaller manufacturers. In the peripheral vascular market, we compete against, among others: C.R. Bard, Inc., MEDRAD, Inc., Cardiovascular Systems, Inc., Pathway Medical Technologies, Inc., Idev Technologies, Inc., Invatec s.r.l. and Spectranetics Corporation. In the neurovascular market, we compete against, among others: Balt Extrusion, Inc., Terumo/MicroVention, Inc. and Micrus Corporation. In addition, we compete with a number of drug therapy treatments manufactured by major pharmaceutical companies, including Otsuka Pharmaceutical, the manufacturer of Pletal, and Sanofi Aventis, the manufacturer of Plavix.

Many of our physician customers like to experiment with new technologies. Within the atherectomy market, although we believe our SilverHawk plaque excision products compete favorably against other competing technologies, surgical procedures and pharmaceutical products, recently introduced atherectomy products have adversely affected and may continue to adversely affect future sales of our atherectomy products, at least in the short term while physician customers experiment with such new products. Within the peripheral vascular stent market, we may experience increased competition from C. R. Bard Inc. which recently announced that the FDA approved certain of its stents for use in the superficial femoral arteries and proximal popliteal arteries, if physicians decide to use C. R. Bard Inc. s FDA cleared stents rather than our stents off-label.

Since a significant portion of our sales are derived from products that physicians in the past have elected to use and may continue to elect to use off-label, ultimately, if physicians cease or lessen their use of our products for other than FDA-approved indications, sales of our products likely would decline, which could materially adversely affect our net sales and operating results. In addition, if we are perceived not to be in compliance with all of the restrictions limiting the promotion of our products for off-label use, we could be subject to various enforcement measures, including investigations, administrative proceedings and federal and state court litigation, which likely would be costly to defend and harmful to our business. If the FDA or another governmental authority ultimately concludes we are not in compliance with such restrictions, we could be subject to significant liability, including civil and administrative remedies, injunctions against sales for off-label uses, significant monetary and punitive penalties and criminal sanctions, any or all of which would be harmful to our business. Finally, if one or more of our competitors obtains FDA approval or clearance for a product to be used for a specific indication that was previously considered off-label for such product, it is possible that physicians would be more likely to use the competitor s FDA approved or cleared product rather than our products off-label, which would adversely affect the sales of our affected products. For example, C. R. Bard Inc. recently announced that the FDA cleared certain of its stents for use in the superficial femoral arteries and proximal popliteal arteries. If physicians decide to use C. R. Bard Inc. s FDA cleared stents rather than our stents off-label, sales of our stents could suffer.

If we fail to comply with laws prohibiting kickbacks and false or fraudulent claims and other similar laws, we could be subject to criminal and civil penalties and exclusion from governmental health care programs, which could have a material adverse effect on our business and operating results.

We are subject to various federal, state and foreign laws concerning health care fraud and abuse, including false claims laws, anti-kickback laws, physician self-referral laws and other similar laws. Many of these laws constrain the sales, marketing and other promotional activities of manufacturers of medical devices by limiting the kinds of financial arrangements, including sales programs, with physicians, hospitals, laboratories and other potential purchasers of medical devices. The scope of these laws and related regulations are very broad and many of their provisions have not been uniformly or definitively interpreted by existing case law or regulations, and thus are subject to evolving interpretations. There is very little precedent related to these laws and regulations. All of our financial relationships with health care providers and others who provide products or services to federal health care program beneficiaries are potentially governed by these laws. While we have established policies and procedures based on the AdvaMed Code of Ethics on Interactions with Health Care Professionals and implemented a broad-based corporate compliance program in order to inform our employees regarding these laws and maintain compliance with them, no assurance can be given that we will not be subject to investigations or litigation alleging violations of these laws. Increased funding for enforcement of these laws and regulations has resulted in greater scrutiny of financial relationships with physicians and marketing practices and resulted in several governmental investigations by various governmental authorities, including investigations of the sales practices of several of our competitors. Any investigation or litigation against us, even if we were to successfully defend against it, would likely be time-consuming and costly for us to defend. It also would likely divert the attention of our management from the operation of our business, cause adverse publicity and damage our reputation. If our arrangements were found to have violated any of these laws, we and our officers and employees could be subject to severe criminal and/or civil penalties, including fines, imprisonment and exclusion from participation in government health care programs, which could have a material adverse effect on our reputation, business and operating results. Similarly, if the physicians or other providers or entities with which we do business are found to be non-compliant with such laws, they may be subject to sanctions, which also could have a negative impact on us. If as a result of any investigation or evolving interpretation of these laws, our business practices or those of our competitors are found to be unlawful or otherwise challenged as or determined to be unlawful, we would be required or advised to change such practices, which could have a material adverse effect on our business and operating results.

Some of our products are emerging technologies or have only recently been introduced into the market. If physicians do not recommend and endorse them or if our working relationships with physicians deteriorate, our products may not be accepted in the marketplace, which would adversely affect our business and operating results.

In order for us to sell our products, physicians must recommend and endorse them. We may not obtain the necessary recommendations or endorsements from physicians. Acceptance of our products depends on educating the medical community as to the distinctive characteristics, perceived benefits, safety, clinical efficacy and cost-effectiveness of our products compared to products of our competitors, and on training physicians in the proper application of our products. We often need to invest in significant training and education of our sales representatives or our physician customers to achieve market acceptance of our products with no assurance of success. For example, the future success of our SilverHawk products is dependent in part upon us educating first our sales representatives and second, physicians, and in particular interventional cardiologists, vascular surgeons, as well as general practitioners and other physicians, about screening for peripheral artery disease, or PAD, referral opportunities and the benefits of our SilverHawk products in relating to competitive products and other treatment options. If we are not successful in obtaining the recommendations or endorsements of physicians for our products, if customers prefer our competitors products or if our products otherwise do not gain market acceptance, our business could be adversely affected.

The medical device industry is characterized by extensive research and development and rapid and significant technological change. The peripheral vascular and neurovascular markets in which we compete are in particular highly competitive and new technologies and products are often introduced. Therefore, product life cycles are relatively short. Developments by other companies of new or improved products, processes or technologies may make our products or proposed products obsolete or less competitive and may negatively impact our net sales. For example, new procedures and medications that are more effective or less invasive or expensive could be developed that replace or reduce the importance of current procedures that use our products or may cause our customers to cease, delay or defer purchasing our products, which would adversely affect our business and operating results.

Product development involves a high degree of risk, and we cannot provide assurance that our product development efforts will result in any commercially successful products. Many of our clinical trials have durations of several years and it is possible that such trials may not be successful or that competing therapies, such as drug therapies, may be introduced while our products are still undergoing clinical trials. New products and technologies introduced by competitors may reach the market earlier, may be more effective or less invasive or expensive than our products or render our products obsolete, all of which would harm our business and operating results.

We sell our products to customers in the United States, Europe and elsewhere throughout the world. Although most of our sales are made in U.S. dollars, a significant portion of our sales are made in Euros. Approximately 24% and 27% of our net sales were denominated in foreign currencies in 2008 and 2007, respectively. Our principal exposure to movements in foreign currency exchange rates relate to non-U.S. dollar denominated sales in Europe and throughout the world, as well as non-U.S. dollar denominated operating expenses incurred in Europe and throughout the world. Our reported net earnings may be significantly affected by fluctuations in currency exchange rates, with earnings generally decreasing with a strengthening U.S. dollar and increasing with a weaker U.S. dollar. For sales not denominated in U.S. dollars, if there is an increase in the rate at which a foreign currency is exchanged for U.S. dollars, it will require more of the foreign currency to equal a specified amount of U.S. dollars than before the rate increase. In such cases, we will receive less in U.S. dollars than we did before the exchange rate increase went into effect. Thus, a strengthening U.S. dollar relative to the foreign currencies in which we transact business will adversely affect the U.S. dollar value of our foreign currency-denominated sales and earnings. Although we may raise international pricing in such circumstances, such price increases may potentially reduce demand for our products, and thus in most circumstances, due to competition or other reasons, we may decide not to raise local prices to the full extent of the U.S. dollar s strengthening or at all. A weakening of the U.S dollar relative to the foreign currencies in which we transact business is generally beneficial to our foreign currency-denominated sales and earnings. However, it may cause us to reduce our international pricing, thereby limiting the benefit. Additionally, strengthening of foreign currencies also may increase our operating costs or costs of product components denominated in those currencies, thus adversely affecting our gross margins. If we price our products in U.S. dollars and competitors price their products in local currency, an increase in the relative strength of the U.S. dollar could result in our price not being competitive in a market where business is transacted in the local currency.

The medical device industry is litigious with respect to patents and other intellectual property rights. Companies operating in our industry routinely seek patent protection for their product designs, and many of our principal competitors have large patent portfolios. Companies in the medical device industry have used intellectual property litigation to gain a competitive advantage, including aggressively challenging the patent rights of other companies in order to prevent the marketing of new products. The fact that we have patents issued to us for our products does not mean that we will always be able to successfully defend our patents and proprietary rights against challenges or claims of infringement by our competitors. Whether a product infringes a patent involves complex legal and factual issues, the determination of which is often uncertain. We have incurred in the past significant costs in connection with patent litigation, including most recently in connection with our previous litigation with the Regents of the University of California and Boston Scientific Corporation. We continue to face the risk of claims that we have infringed on third parties intellectual property rights.

From time to time, in the ordinary course of business, we receive notices from third parties alleging infringement or misappropriation of the patent, trademark or other intellectual property rights of third parties by us or our customers in connection with the use of our products or we otherwise may become aware of possible infringement claims against us. We routinely analyze such claims and determine how best to respond in light of the circumstances existing at the time, including the importance of the intellectual property right to us and the third party, the relative strength of our position of non-infringement or non-misappropriation and the product or products incorporating the intellectual property right at issue. For example, we are aware of patents held by Abbott Laboratories that may be asserted against our FoxHollow subsidiary in litigation that could be costly and limit our ability to sell the SilverHawk or other products. One of FoxHollow s founders, John B. Simpson, Ph.D., M.D. founded a company prior to founding FoxHollow that developed an atherectomy device that is currently sold by Abbott, and he is a listed inventor on several patents covering that device. Abbott's device is currently marketed and sold for use in coronary arteries. Although we are not currently aware of any claims Abbott has made or intends to make against FoxHollow, because of a doctrine known as assignor estoppel, if any of Dr. Simpson s earlier patents are asserted against FoxHollow by Abbott, we may be prevented from asserting an invalidity defense regarding those patents, and our defense may be compromised. Abbott has significantly greater financial resources than us to pursue patent litigation and could assert these patent families against us at any time. Any adverse determinations in such litigation could prevent us from manufacturing or selling our SilverHawk or other products, which would have a significant adverse impact on our business.

We also may be unaware of intellectual property rights of others that may cover some of our technology. Prior to launching major new products in our key markets, we normally evaluate existing intellectual property rights. However, our competitors may have filed for patent protection which is not as yet a matter of public knowledge or claim trademark rights that have not been revealed through our availability searches. Our efforts to identify and avoid infringing on third parties intellectual property rights may not always be successful.

Any claims of patent or other intellectual property infringement, even those without merit, could: be expensive and time consuming to defend; result in us being required to pay significant damages to third parties; cause us to cease making or selling products that incorporate the challenged intellectual property; require us to redesign, reengineer or rebrand our products, if feasible; require us to enter into license agreements in order to obtain the right to use a third party s intellectual property, which agreements may require us to pay significant license fees, including royalties, or may not be available on terms acceptable to us or at all and which licenses may be non-exclusive, which could provide our competitors access to the same technologies; divert the attention of our management and other personnel from other business issues; or result in our customers or potential customers deferring or limiting their purchase or use of the affected products until resolution of the litigation.

In addition, new patents obtained by our competitors could threaten a product s continued life in the market even after it has already been introduced. Any of these adverse consequences could have a material adverse effect on our business, operating results and financial condition.

If our patents and other intellectual property rights do not adequately protect our products, we may lose market share to our competitors, which would harm our business.

Our future success depends significantly on our ability to protect our proprietary rights to the technologies used in our products. We rely on patent protection, as well as a combination of copyright and trademark laws and nondisclosure, confidentiality and other contractual arrangements to protect our proprietary technology. However, these legal means afford only limited protection and may not adequately protect our rights or permit us to gain or keep any competitive advantage. In addition, we cannot be assured that any of our pending patent applications will result in the issuance of a patent to us. The United States Patent and Trademark Office, or PTO, may deny or require significant narrowing of claims in our pending patent applications, and patents issued as a result of the pending patent applications, if any, may not provide us with significant commercial protection or be issued in a form that is advantageous to us. We could also incur substantial costs in proceedings before the PTO. These proceedings could result in adverse decisions as to the priority of our inventions and the narrowing or invalidation of claims in issued patents. Our issued patents and those that may be issued in the future may be challenged, invalidated or circumvented, which could limit our ability to stop competitors from marketing related products. Litigation also may be necessary to enforce patent rights we hold or to protect trade secrets or techniques we own. Intellectual property litigation is costly and may adversely affect our operating results. Although we have taken steps to protect our intellectual property and proprietary technology, there is no assurance that third parties will not be able to design around our patents. We also rely on unpatented proprietary technology. In addition, we rely on the use of registered trademarks with respect to the brand names of some of our products. We also rely on common law trademark protection for some brand names, which are not protected to the same extent as our rights in the use of our registered trademarks. We cannot assure you that we will be able to meaningfully protect all of our rights in our unpatented proprietary technology or that others will not independently develop substantially equivalent proprietary products or processes or otherwise gain access to our unpatented proprietary technology. We seek to protect our know-how and other unpatented proprietary technology, in part with confidentiality agreements and intellectual property assignment agreements with our employees, independent distributors and consultants. However, such agreements may not be enforceable or may not provide meaningful protection for our proprietary information in the event of unauthorized use or disclosure or other breaches of the agreements or in the event that our competitors discover or independently develop similar or identical designs or other proprietary information. For example, we are currently involved in litigation with Cardiovascular Systems, Inc. in which we allege misappropriation and use of our confidential information by CSI and certain of CSI s employees who were formerly employees of FoxHollow. The complaint also alleges that certain of CSI s employees violated their employment agreements with FoxHollow requiring them to refrain from soliciting FoxHollow employees.

Furthermore, the laws of foreign countries may not protect our intellectual property rights to the same extent as the laws of the United States. For example, foreign countries generally do not allow patents to cover methods for performing surgical procedures. If we cannot adequately protect our intellectual property rights in these foreign countries, our competitors may be able to compete more directly with us, which could adversely affect our competitive position and business.

We rely on our manufacturing facilities in Plymouth, Minnesota and Irvine, California. Any damage or destruction to our facilities and the manufacturing equipment we use to produce our products would be difficult to replace and could require substantial lead-time to repair or replace. Our facilities may be affected by natural or man-made disasters. In the event that one of our facilities was affected by a disaster, we would be forced to rely on third-party manufacturers if we could not shift production to our other manufacturing facility. In the case of a device with a premarket approval application, we might in such event be required to obtain prior FDA or notified body approval of an alternate manufacturing facility, which could delay or prevent our marketing of the affected product until such approval is obtained. Although we believe that we possess adequate insurance for damage to our property and the disruption of our business from casualties, such insurance may not be sufficient to cover all of our potential losses and may not continue to be available to us on acceptable terms, or at all. It is also possible that one of our competitors could claim that our manufacturing process violates an existing patent. If we were unsuccessful in defending such a claim, we might be forced to stop production at one of our manufacturing facilities in the United States and to seek alternative facilities. Even if we were able to identify such alternative facilities, we might incur additional costs and experience a disruption in the supply of our products until those facilities are available. Any disruption in our manufacturing capacity could have an adverse impact on our ability to produce sufficient inventory of our products or may require us to incur additional expenses in order to produce sufficient inventory, and therefore would adversely affect our net sales and operating results.

We have limited experience in manufacturing our products in commercial quantities and therefore may encounter unforeseen situations that could result in delays or shortfalls. Manufacturers often experience difficulties in increasing production, including problems with production yields and quality control and assurance. Any disruption or delay at our manufacturing facilities, any inability to accurately predict the number of products to manufacture or to expand our manufacturing capabilities if necessary could impair our ability to meet the demand of our customers and these customers may cancel orders or purchase products from our competitors, which could adversely affect our business and operating results.

In order to build our core technology platforms, we have acquired several businesses since our inception. For example, most recently, in October 2007, we completed our acquisition of FoxHollow. In September 2006, FoxHollow acquired Kerberos Proximal Solutions, Inc. In January 2006, we acquired the outstanding shares of Micro Therapeutics, Inc. that we did not already own. We expect to continue to actively pursue additional targeted acquisitions of, investments in or alliances with, other companies and businesses in the future as a component of our business strategy. Our ability to grow through future acquisitions, investments and alliances will depend upon our ability to identify, negotiate, complete and integrate attractive candidates on favorable terms and to obtain any necessary financing. Our inability to complete one or more acquisitions, investments or alliances could impair our ability to develop our product lines and to compete against many industry participants, many of whom have product lines broader than ours. Acquisitions, investments and alliances involve risks, including: difficulties in integrating any acquired companies, personnel and products into our existing business; delays in realizing projected efficiencies, cost savings, revenue synergies and other benefits of the acquired company or products; inaccurate assessment of the future market size or market acceptance of any acquired products or technologies or the hurdles in obtaining regulatory approvals of such products; inaccurate assessment of undisclosed, contingent or other liabilities or problems; diversion of our management s time and attention from other business concerns; limited or no direct prior experience in new markets or countries we may enter;

higher costs of integration than we anticipated; adverse accounting consequences under recently revised accounting rules; or difficulties in retaining key employees of the acquired business who are necessary to manage the acquired business.

Because healthcare costs have risen significantly over the past decade, numerous initiatives and reforms initiated by legislators, regulators and third-party payors to curb these costs have resulted in a consolidation trend in the healthcare industry to create new companies with greater market power, including hospitals. As the healthcare industry consolidates, competition to provide products and services to industry participants has become and will continue to become more intense. This in turn has resulted and will likely continue to result in greater pricing pressures and the exclusion of certain suppliers from important market segments as group purchasing organizations, independent delivery networks and large single accounts continue to use their market power to consolidate purchasing decisions for some of our hospital customers. We expect that market demand, government regulation, third-party reimbursement policies and societal pressures will continue to change the worldwide healthcare industry, resulting in further business consolidations and alliances, which may increase competition, exert further downward pressure on the prices of their products and may adversely impact our business, financial condition or operating results.

Our quarterly operating and financial results may fluctuate from period to period due to a combination of factors, many of which are beyond our control. These include: the seasonality of our product sales, which typically results in higher demand in our fourth fiscal quarter and lower sales volumes in our third fiscal quarter; the mix of our products sold; demand for, and pricing of, our products and the products of our competitors; timing of or failure to obtain regulatory approvals for products; costs, benefits and timing of new product introductions by us and our competitors; increased competition; the timing and extent of promotional pricing or volume discounts; the timing of larger orders by customers and the timing of shipment of such orders; field inventory levels; changes in average selling prices; the availability and cost of components and materials; fluctuations in foreign currency exchange rates; the possible deferral of revenue under our revenue recognition policies; the timing of operating expenses in anticipation of sales; unanticipated expenses; costs related to acquisitions of technologies or businesses; restructuring, impairment and other special charges; and fluctuations in investment returns on invested cash balances.

The design, manufacture and sale of medical devices expose us to significant risk of product liability claims, some of which may have a negative impact on our business. Most of our products were developed relatively recently and defects or risks that we have not yet identified may give rise to product liability claims. Our product liability insurance coverage may be inadequate to protect us from any liabilities we may incur or we may not be able to maintain adequate product liability insurance at acceptable rates. If a product liability claim or series of claims is brought against us for uninsured liabilities or in excess of our insurance coverage and it is ultimately determined that we are liable, our business could suffer. Additionally, we could experience a material design defect or manufacturing failure in our products, a quality system failure, other safety issues or heightened regulatory scrutiny that would warrant a recall of some of our products. A recall of our products could also result in increased product liability claims. Further, while we train our physician customers on the proper usage of our products, there can be no assurance that they will implement our instructions accurately. If our products are used incorrectly by our customers, injury may result and this could give rise to product liability claims against us. Even a meritless or unsuccessful product liability claim could harm our reputation in the industry, lead to significant legal fees and could result in the diversion of management s attention from managing our business and may have a negative impact on our business and our operating results. In addition, successful product liability claims against one of our competitors could cause claims to be made against us.

We face competition from other companies, which could adversely impact our business and operating results.

The markets in which we compete are highly competitive, subject to change and significantly affected by new product introductions and other activities of industry participants. Because of the size of the peripheral vascular and neurovascular markets, competitors and potential competitors have historically dedicated and will continue to dedicate significant resources to aggressively promote their products and develop new and improved products. Our competitors and potential competitors may develop technologies and products that are safer, more effective, easier to use, less expensive or more readily accepted than ours. Their products could make our technology and products obsolete or noncompetitive. None of our customers have long-term purchase agreements with us and may at any time switch to the use of our competitors products. Many of our physician customers like to experiment with new technologies. Within the atherectomy market, although we believe our atherectomy plaque excision products compete favorably against other competing technologies, surgical procedures and pharmaceutical products, recently introduced atherectomy products by our competitors have adversely affected and may continue to adversely affect future sales of our atherectomy products, at least in the short term while physician customers experiment with such new products.

Within the peripheral vascular stent market, we may experience increased competition from C. R. Bard Inc. which recently announced that the FDA cleared certain of its stents for use in the superficial femoral arteries and proximal popliteal arteries, if physicians decide to use C. R. Bard Inc. s FDA cleared stents rather than our stents off-label.

Our competitors range from small start-up companies to much larger companies. The larger companies with which we compete include Abbott Laboratories, Boston Scientific Corporation, Cook Incorporated, Cordis Corporation (a Johnson & Johnson company) and Medtronic, Inc. All of these larger companies have substantially greater capital resources, larger customer bases, broader product lines, larger sales forces, greater marketing and management resources, larger research and development staffs and larger facilities than ours and have established reputations and relationships with our target customers, as well as worldwide distribution channels that are more effective than ours. We also compete, however, and in some cases even more intensely, with smaller manufacturers. In the peripheral vascular market, we compete against, among others: C.R. Bard, Inc., MEDRAD, Inc., Cardiovascular Systems, Inc., Pathway Medical Technologies, Inc., Idev Technologies, Inc., Invatec s.r.l. and Spectranetics Corporation. In the neurovascular market, we compete against, among others: Balt Extrusion, Inc., Terumo/MicroVention, Inc. and Micrus Corporation. In addition, we compete with a number of drug therapy treatments manufactured by major pharmaceutical companies, including Otsuka Pharmaceutical, the manufacturer of Pletal, and Sanofi Aventis, the manufacturer of Plavix.

We also compete with other manufacturers of medical devices for clinical sites to conduct human trials. If we are not able to locate clinical sites on a timely or cost-effective basis, this could impede our ability to conduct trials of our products and, therefore, our ability to obtain required regulatory clearance or approval.

Certain of our principal stockholders, including Warburg Pincus, may make investments in companies and from time to time acquire and hold interests in businesses that compete directly or indirectly with us. These other investments may: create competing financial demands on our principal stockholders; create potential conflicts of interest; and require efforts consistent with applicable law to keep the other businesses separate from our operations. the introduction of new products or product enhancements by us or our competitors; changes in our growth rate or our competitors growth rates; strategic actions by us or our competitors, such as acquisitions or restructurings; our ability to develop, obtain regulatory clearance or approval for, and market new and enhanced products on a timely basis; loss of any of key management personnel; disputes or

> other developments with respect to intellectual property rights; product liability claims or other litigation; public concern as to the safety or efficacy of our products; the public's reaction to our press releases and other public announcements and our filings with the SEC; sales of common stock by us, our significant stockholders, executive officers or directors; changes in stock market analyst recommendations or earnings estimates regarding our common stock, other comparable companies or our industry generally; changes in expectations or future performance; new laws or regulations or new interpretations of existing laws or regulations applicable to our business; and changes in health care policy in the United States and internationally, including changes in the availability of third-party reimbursement.

Discussion of competition in the 2005 10-K annual report by RCN Corp., CIK 1041858. Word count of 5066.

> RCN's revenues are generated primarily by the monthly fees paid by customers for its services. RCN prices its services to promote sales of bundled packages. RCN offers bundles of two or more services with tiered features and prices to meet the demands of a variety of customers. RCN also sells individual services at prices competitive to those of the incumbent providers. The prices RCN charges vary based on the level of service the customer chooses. An installation fee, which is typically waived for a bundled installation, is charged to new and reconnected customers. RCN also charges monthly fees for cable customer premises equipment.
>
> Customer service is an essential element of RCN's operations and strategy for customer retention. RCN provides customer service 24 hours a day, seven days a week via the Internet. RCN also operates a centralized customer call center in Wilkes-Barre, PA, which handles customer service transactions for all of RCN's products. In 2005, RCN opened a multilingual call center in Herndon, VA. This center also operates as a back-up site, in the event of a disaster, to the main call center in Wilkes-Barre, PA. RCN's customer service operations utilize technologically advanced equipment that RCN believes enhances interactions with its customers through more intelligent call routing, data management, forecasting and scheduling capabilities. RCN also provides answers to frequently asked questions and equipment troubleshooting on RCN's website (www.rcn.com). RCN believes that providing customers with the convenience of a single point of contact for all customer service issues for RCN's video, data and voice services gives RCN a competitive advantage and complements RCN's bundling strategy.

As of December 31, 2005, RCN had approximately 130 franchise and open video system ("OVS") agreements, permits and similar authorizations issued by local and state governmental authorities. Each license is awarded by a governmental authority, which often must approve any transfer to another party. Most licenses are subject to termination proceedings in the event of a material breach. In addition, most licenses require RCN to pay the granting authority a fee of up to 5.0% of gross cable service revenues, as defined in the various agreements. RCN is entitled to and generally does pass this fee through to the customer. RCN is also obligated to pay contributions in support of public, educational and governmental ("PEG") channels that match those provided by its incumbent cable operator competitors. These contributions are most often based on a percent of RCN's gross revenues and are in the range of 1% to 3% percent of gross cable service revenues, but can also include "in kind" services and facilities such as the dedication of fiber facilities for use by the franchise authority and other PEG entities.

Prior to the scheduled expiration of most licenses, RCN initiates renewal proceedings with the granting authorities. The Cable Television Consumer Protection and Competition Act of 1992 (the "1992 Cable Act") provides for an orderly license renewal process in which granting authorities may not unreasonably withhold renewals. Historically, RCN has been able to renew its licenses generally at or before their stated expirations and without incurring significant costs, although any particular license may not be renewed on commercially favorable terms or otherwise.

Competition RCN competes with a wide range of service providers in each market, including incumbent local telephone carriers ("ILECs"), incumbent multiple system cable operators ("MSOs"), competitive local exchange carriers ("CLECs"), Direct Broadcast Satellite ("DBS") providers, interexchange carriers ("IXCs") and dial-up Internet service providers. These companies represent RCN's primary competition in the delivery of "last mile" connections for video, data and voice services.

RCN's principal competitors are ILECs and MSOs that are larger than RCN and have greater financial resources. These incumbents have numerous advantages as a result of their historically monopolistic control of their respective markets, economies of scale and scope, control of limited conduit and pole space, well-established customer and vendor relationships, and, in the case of MSOs, vertically integrated ownership of programming content. In addition, MSOs, ILECs and some CLECs have begun, either using their own networks or through joint marketing alliances, to provide a bundle of each of the services offered by RCN together, in some cases, with wireless phone service. This development is likely to place increased competitive pressure on RCN.

RCN's video service competes in each of its markets with incumbent MSOs, including Service Electric in Lehigh Valley, PA, Time Warner in New York, Cox in Virginia, and Comcast in the rest of its markets. In addition, RCN's video services face competition from a variety of other methods of receiving and distributing television signals, and from alternative sources of news, information and entertainment, including Internet services, newspapers, radio, movie theatres and live theatre, sports, and music. Competitive programming sources include over-the-air television digital and analog broadcast programming, DBS, interactive online computer services, and home video products. Home video products include videotape cassette recorders, digital video disk players, and streaming personal computer applications. RCN also faces competition from private satellite master antenna television ("SMATV") systems that serve condominiums, apartment and office complexes and private residential developments.

DBS is a signifigcant competitor to cable systems, particularly those located in suburban and rural areas with large percentages of single family homes where their satellite dishes can be installed, such as the Company's system in eastern Pennsylvania. The DBS industry has grown rapidly over the last several years, far exceeding the growth rate of the cable television industry. DBS service allows the subscriber to receive video services directly via satellite using a relatively small dish antenna. The two largest DBS providers are DirecTV, Inc., an affiliate of News Corp. ("DirecTV"), and EchoStar Communications Corp. ("EchoStar"), which operates the Dish Network.

Video compression technology and high powered satellites allow DBS providers to offer more than 200 digital channels from a single transponder satellite, thereby surpassing the typical analog cable system. DBS providers are able to offer service nationwide and are able to establish a national image and branding with standardized offerings, which leads to greater efficiencies and lower costs in the lower tiers of service. RCN believes that its higher tier products, particularly its bundled premium packages, are price-competitive with DBS packages and that many consumers prefer RCN as a result of its ability to economically bundle its cable television packages with high-speed Internet and local and long distance telephone services. RCN believes that this ability to bundle, combined with its introduction of additional new products that DBS cannot currently offer (such as local HDTV and local interactive television), differentiates RCN from DBS competitors and could enable RCN to win customers who might otherwise subscribe to DBS. However, recent joint marketing arrangements between DBS providers and ILECs in some of RCN's markets allow similar bundling of services by DBS providers. Both DirecTV and EchoStar have entered into joint marketing agreements with major telecommunications companies to offer bundled packages combining phone service, digital subscriber line service and DBS services. Moreover, DBS providers operate in a largely unregulated marketplace and are not subject to local franchise requirements and are not obligated to collect and pay license and other franchise-related fees to local authorities, which gives them a cost advantage over RCN and other cable operators.

In addition, certain ILECs and CLECs provide, or have announced plans to provide, video services within and outside of their telephone service areas through a variety of methods, including cable networks, satellite program distribution, and wireless transmission facilities. Such carriers are seeking relief in federal and state legislatures from the local franchise process which, if successful, would permit them to enter the video market more quickly and possibly without some of the obligations imposed in RCN's franchises. The ILECs entering the video market are larger than RCN and have greater financial resources and well-established customer relationships that will make them formidable competitors to RCN's bundled service offerings.

The Internet access market is highly competitive and increasingly price-sensitive. Competition in this market has intensified, particularly among cable operators and ILECs who continue to make significant progress using their local distribution facilities to offer high speed Internet services over their local cable and telephone facilities. RCN must therefore compete with both ILECs and MSOs for subscribers to its high speed Internet service. In certain areas, CLECs are also starting to penetrate this market with facilities-based high speed Internet services. Other competitors to RCN's high speed Internet services include local, regional and national ISPs who offer service using the facilities of other companies such as CLECs and ILECs.

ILECs typically compete with RCN by providing broadband Internet service over digital subscriber lines ("DSL") that utilize their existing copper lines and plant. DSL service provides Internet access to subscribers at data transmission speeds greater than those available over conventional telephone lines. DSL service therefore is competitive with high-speed Internet access over cable systems. Although the availability of DSL service is restricted by certain distance and other network limitations, most ILECs that already have facilities, an existing customer base, and other operational functions in place (such as billing, service personnel, etc.) offer DSL service throughout most of the service areas served by RCN. RCN expects DSL to remain a significant competitor to RCN's data services. In addition, while DSL service typically provides lower access speeds than RCN's higher tiers of high-speed Internet service, the further deployment of fiber-optic cable by ILECs and CLECs into their networks will enable them to provide higher bandwidth Internet service than provided over traditional DSL lines.

In some of RCN's service areas ILECs are also deploying advanced fiber optic facilities that will enable them to offer Internet services at speeds considerably higher than their existing DSL service and more competitive with RCN's high speed connections. These fiber networks will also allow the ILECs to offer cable or Internet-based video programming services in competition with RCN's cable and OVS service. Such networks have already come on line in limited areas but to date have been largely limited to telephone and high speed data service. Therefore, although the service currently provides some competition to RCN's voice and data services, it does not yet provide significant competition to RCN's bundled product offerings since the ILEC services do not yet include the full bundle of voice, data and video services offered by RCN over its networks. However, as these ILEC fiber networks are deployed more widely, and particularly as they are expanded to include video programming (assuming corresponding video licenses are obtained), the competitive impact on RCN will increase.

With the recent consolidation among ISPs, competition is becoming concentrated to the larger national and regional providers of Internet access. Although RCN does not expect significant new entrants into the Internet access market in the near future, new technologies are being introduced which will provide customers other choices for Internet access. Many competitors have broader brand recognition and spend significantly more marketing dollars for customer acquisition. RCN competes directly or indirectly with: Internet access (including DSL service) offered by regional Bell operating companies ("RBOCs"); high-speed services offered by incumbent cable providers and other regional cable providers offering high-speed Internet access over a cable modem; fixed wireless Internet access services offered by certain telecommunications providers; and mobile wireless Internet access services offered by cellular providers.

The voice service market, especially long distance, is characterized by intense price competition. RCN competes with the ILECs for the provision of voice services, including Verizon in the northeast corridor, and SBC in California and Chicago (both of which currently dominate their respective local telephone markets), as well as other CLECs and long distance service providers. Other local and long distance voice services competitors include, MSO's who are entering the voice market in some locations, wireless service providers, and VoIP providers. VoIP is a significant competitive service that an increasing number of companies in the industry are offering over high speed Internet service connections, including the facilities provided by RCN.

RCN expects to continue to face significant competition in all markets from the ILECs, CLECs, MSO's, VoIP providers and wireless providers, for both local and long distance service. In addition, the telecommunications industry has been characterized by increasing consolidation, which could lead to increased pressure from larger competitors as they achieve greater scale through acquisitions.

RCN's cable television systems are subject to regulation under the 1992 Cable Act. The 1992 Cable Act regulates, among other things, rates for cable services in communities that are not subject to "effective competition," certain programming requirements, and broadcast signal carriage requirements that allow local commercial television broadcast stations to require a cable system to carry the station. Local commercial television broadcast stations may elect once every three years to require a cable system to carry the station ("must-carry"), subject to certain exceptions, or to withhold consent and negotiate the terms of carriage ("retransmission consent"). A cable system generally is required to devote up to one-third of its activated channel capacity for the carriage of local commercial television stations whether under the must carry or retransmission consent requirements of the 1992 Cable Act. The 1992 Cable Act also permits LFAs to require cable operators to set aside certain channels for public access, educational and governmental ("PEG") programming. Cable systems with 36 or more channels must designate a portion of their channel capacity for commercial leased access by third parties to provide programming that may compete with services offered by the cable operator. Local non-commercial television stations are also given mandatory carriage rights.

In the event the City of Chicago were ultimately to prevail on its complaint, RCN-Chicago would need to pay the 5% franchise fee on its cable modem revenues and therefore to pass through the additional fees to its cable modem Internet service customers, which would raise their rates as compared to the high-speed Internet services provided by ILECs and therefore could have an adverse effect on RCN-Chicago's ability to compete with such providers. In the event that these fees are assessed retroactively, RCN-Chicago would likely not be able to recover these costs from its customers. However, because any adverse result will affect all of RCN-Chicago's cable competitors in the Chicago market, such a ruling would likely not have a disproportional effect on RCN's ability to compete with other cable operators in the Chicago market. RCN also notes that the United States Supreme Court in the Brand X decision upheld the FCC's classification of cable modem service as an information service, rather than a cable or telecommunications service, for federal regulatory purposes. However, the scope of state and local authority to regulate cable modem service as an information service is a question of nationwide significance to LFAs and cable television franchisees, and is the subject of both pending litigation and FCC rulemaking. The ultimate result of all these actions will likely determine whether and to what extent RCN's cable modem Internet access service is subject to state and local regulation, in addition to any obligations that may be imposed by the FCC. RCN cannot predict the outcome of such legal and regulatory proceedings. The ultimate result of all of these actions, including the action brought by the City of Chicago, will likely determine whether RCN's cable modem Internet service gross revenues will be required to be included for purposes of franchise fee payments, and RCN cannot assure you that it will not be subject to gross revenue fees or other regulation of its cable modem Internet access services in the future.

Cable television systems, where effective competition has not been demonstrated to exist, are subject to rate regulation of the basic service tier. None of the municipalities in which RCN holds a cable franchise are currently attempting to impose rate regulation on RCN. As required by the 1996 Act, rates were deregulated for all cable programming services except limited basic service on March 31, 1999. In the event that a municipality in which RCN holds a cable franchise were to attempt to impose rate regulation, it would be necessary for RCN to demonstrate that effective competition exists in its franchise area. RCN believes that effective competition can be demonstrated as to RCN with respect to all of RCN's cable franchises, since in each case there is an existing incumbent cable operator serving the same area.

The 1996 Act gives RCN important rights to connect with the networks of ILECs in the areas where it operates (primarily Verizon and SBC). This law, among other things, requires ILECs to provide nondiscriminatory access and interconnection to potential competitors, such as cable operators, wireless telecommunications providers and long distance companies. These obligations include the following: Interconnection-Requires the ILECs to permit their competitors to interconnect with ILEC facilities at any technically feasible point in the ILEC's network. Reciprocal Compensation-Requires all ILECs and CLECs to complete calls originated by competing local exchange carriers under reciprocal arrangements at prices set by the FCC, PUCs or negotiated prices.

Regulations promulgated by the FCC to implement these provisions of the law require local exchange carriers to provide competitors more access to UNEs at prices based on incremental cost studies. The FCC began to re-examine its rules regarding access to UNEs in late 2001. In orders released in 2003 and 2005, the FCC adopted significant changes to its UNE rules. Because RCN built its own networks rather than relying on the ILECs' facilities, these changes may affect RCN less than they do some of its competitors. The most recent rulings eliminate a form of competition known as "UNE-P," which included an unbundled local switching element. Although RCN has never used the UNE-P, it was subject to competition from telephone companies that did use it, so the elimination of this form of competition may benefit RCN. The new rules did, however, increase RCN's cost for accessing certain databases used in providing local telephone service (such as the calling party name database used to provide Caller ID with Name service on calls received from the ILECs), and may also increase RCN's cost to lease loop facilities in certain markets (primarily New York City). Depending on how the new rules are interpreted by the FCC and PUCs, RCN may also incur increased costs for some of the facilities used to exchange local telephone calls with the ILECs. The FCC rules are the subject of a current court proceeding, which could result in further changes in RCN's access to UNEs.

The 1996 Act generally preempts state statutes and regulations that restrict the provision of competitive services. As a result of this preemption, RCN will be generally free to provide the full range of local, long distance, and data services in any state. This preemption also increases the amount of competition to which RCN may be subject. In addition, the cost of enforcing federal preemption against certain state policies and programs may be large and may cause considerable delay.

Under the 1996 Act, PUCs have jurisdiction over the terms and conditions of interconnection agreements between ILECs and other carriers such as RCN. In each state, RCN has the option of adopting the terms of an agreement negotiated by another carrier, but RCN cannot be certain that other agreements with suitable terms will be available for adoption in all cases. If no such agreement is available, RCN can negotiate a new agreement with the ILEC, and in the event of an impasse either RCN or the ILEC may request binding arbitration by the PUC. While current FCC rules and regulations require the ILEC to provide interconnection and network elements on an individual and combined basis, RCN cannot assure you that the ILECs will provide these components in a manner and at a price that will support competitive operations. RCN cannot assure you that the outcome of any arbitration proceeding would be favorable to RCN, and there is considerable legal uncertainty as to how interconnection agreements are to be enforced before PUCs and where appeals of PUCs' interconnection agreement determinations may be heard.

RCN is subject to numerous local, state and federal taxes and regulatory fees, including, but not limited to, the federal excise tax, FCC universal service fund contributions and regulatory fees, and numerous PUC regulatory fees. RCN has procedures in place to ensure that it properly collects taxes and fees from its customers and remits such taxes and fees to the appropriate entity pursuant to applicable law and/or regulation.

If RCN's collection procedures prove to be insufficient or if a taxing or regulatory authority determines that RCN's remittances were inadequate, RCN could be required to make additional payments, which could have a material adverse effect on its business.

In a number of jurisdictions, local authorities have attempted to impose right-of-way fees on RCN over and above the gross revenues fees paid pursuant to RCN's cable franchises or OVS agreements or which are not imposed on the incumbent local telephone companies, which RCN believes are in violation of federal law. A number of FCC and judicial decisions have addressed the issues posed by the imposition of right-of-way fees on CLECs and on video distributors. To date the state of the law is uncertain and may remain so for some time. In New York City, RCN and other competitive telecommunications carriers have entered into agreements that provide for the payment of a percentage of their gross telecommunications revenues to the City of New York. Similar fees are not paid by Verizon, which is the incumbent local telephone company in the City of New York. This has had a negative impact on RCN's ability to provide local telephone service in competition with Verizon. If RCN were required to pay local right-of-way fees that are excessive or discriminatory in other cities, this could have similar adverse effects on its local telephone business activities in those markets.

Under the Pole Attachment Act, the FCC is required to regulate the rates, terms and conditions imposed by utilities for cable systems' and telecommunications providers' use of utility pole and conduit space unless state authorities can demonstrate that they adequately regulate pole attachment rates, terms and conditions. In the absence of state regulation, the FCC administers pole attachment rates on a formula basis. RCN is subject in some instances to pole attachment practices and fees that RCN believes are in violation of applicable federal law. RCN has attempted to resolve certain of these matters informally. In some cases, utility companies have increased pole attachment fees for cable systems that have installed fiber-optic cables and that are using these cables for the distribution of non-video services. The 1996 Act amendments to the Pole Attachment Act modified the prior pole attachment provisions by establishing a new formula for setting rates for attachment of telecommunications wiring, and requires that utilities provide cable systems and telecommunications carriers with nondiscriminatory access to any pole, conduit or right-of-way, owned or controlled by the utility if the facility is carrying cable or telecommunications wires already. The FCC adopted regulations to govern the charges for pole attachments used by companies providing telecommunications services, including cable operators. The United States Supreme Court and Court of Appeals for the District of Columbia Circuit both issued rulings in 2002 upholding aspects of the

FCC's pole attachment rules favorable to RCN. In a ruling of particular importance to RCN, the Supreme Court held that broadband service providers who co-mingled video, telecommunications, and Internet services over their networks are entitled to the protections of the Pole Attachment Act. This ruling ensures that RCN will have the benefit of the FCC's rate formula for pole attachments. Notwithstanding this Supreme Court decision, RCN cannot predict whether utility companies will seek to raise the rates that RCN pays for pole attachments or whether such increases would materially affect the costs of RCN.

The 1992 Cable Act, the 1996 Act and FCC regulations preclude any cable operator or satellite video programmer affiliated with a cable company, or with a common carrier providing video programming directly to its subscribers, from favoring an affiliated company over competitors. In certain circumstances, these programmers are required to sell their programming to other multi-channel video distributors. The provisions limit the ability of program suppliers affiliated with cable companies or with common carriers providing satellite delivered video programming directly to their subscribers to offer exclusive programming arrangements to their affiliates. The FCC's Cable Service Bureau, however, has ruled that, except in limited circumstances, these statutory and regulatory limitations do not apply to programming which is distributed other than by satellite. Although RCN typically has been able to negotiate viable agreements to carry such programming, absent a change in the law pertaining to programming which is distributed other than by satellite, RCN will not have guaranteed access to certain non-satellite delivered programming, which could impact its ability to compete effectively in those markets.

Despite these reductions, we remain highly leveraged. This amount of leverage may have important consequences for us, including: placing us at a competitive disadvantage compared to our competitors that have less debt; and

In each of our markets we face significant competition from larger incumbent cable and telephone companies and DBS companies, high-speed data service providers and other telecommunication providers. These incumbents have numerous advantages, which result from their historically monopolistic control of their respective markets. These competitive advantages include: significant control over limited conduit and pole space (in the case of incumbent cable and telephone companies); and making it difficult for us to obtain additional financing in the future for working capital, capital expenditures and other purposes.

In addition, a continuing trend toward business combinations and alliances in the telecommunications industry may also create significant new competitors. We cannot predict the extent to which competition from such future competitors will impact our operations. Increased competition could lead to price reductions, fewer bundled sales, under-utilization of resources, reduced operating margins and loss of market share. Business combinations and joint ventures may also impact our ability to access new technology or other resources.

We may be unable to successfully anticipate and respond to various competitive factors affecting our industry, including regulatory changes that may affect our competitors differently from us, new technologies and services that may be introduced, changes in consumer preferences, demographic trends and discount pricing strategies by competitors.

These regulations are subject to change from time to time and new regulations are adopted periodically by both federal and other regulatory agencies. In addition, many of the existing regulations and requirements are currently the subject of judicial proceedings, legislative hearings and administrative proposals that could change the operations of communications companies. We cannot predict the ultimate outcome of these proceedings or how those outcomes may impact our business. Regulations, or interpretations of those regulations, that enhance the ability of our competitors could adversely affect our competitive position. Our ability to compete successfully will depend on the nature and timing of these legislative changes, regulations and interpretations and whether they are favorable to us or our competitors. See “Business-Regulation” for more information.

The cost of acquiring programming is a significant portion of the operating costs for our cable television business. These costs have increased each year and we expect them to continue to increase, especially the costs associated with sports programming. Many of our programming contracts cover multiple years and provide for future increases in the fees we must pay. Historically, we have absorbed increased programming costs in large part through increased prices to our customers. However, we cannot assure you that competitive and other marketplace factors will permit us to continue to pass through these costs. In order to minimize the negative impact that increased programming costs may have on our margins, we may pursue a variety of strategies, including moving some programming to premium tiers or migrating some programming from our analog service to our digital service. Despite our efforts to manage programming expenses, we cannot assure you that the rising cost of programming will not adversely affect our cash flow and operating margins.

We are not large enough to negotiate programming contracts as favorable as some of our larger competitors.

Programming costs are generally directly related to the number of subscribers to which the programming is provided, with discounts available to large MSOs and DBS providers based on their high subscriber levels. As a result, larger cable and DBS systems generally pay lower per subscriber programming costs. We have attempted to obtain volume discounts through our membership in the NCTC. Despite these efforts, we believe that our per subscriber programming costs are significantly higher than large MSOs and DBS providers with which we compete in some of our markets. This may put us at a competitive disadvantage in terms of maintaining our operating results while remaining competitive with prices offered by these providers.

In 2002, we obtained new OVS certifications from the FCC for Boston and San Francisco, and since that time we have entered into OVS agreements with those cities and terminated our cable franchises. We subsequently completed a new open enrollment period for both cities and did not receive any requests for carriage by any VPP or from any of the incumbent cable operators in those markets. We believe that we are operating in conformity with all applicable provisions of the law and will continue to defend our OVS systems against what we believe are anti-competitive requests for data or carriage by competing in-region cable operators. We believe that Time Warner's request for data regarding our Boston system in connection with its initial OVS open enrollment period has been rendered moot by the subsequent open enrollment period, in which Time Warner did not renew its claim. However, we cannot assure you that the FCC will resolve the Time Warner request for OVS data in our favor, or that other incumbents will not file similar requests in other markets during any subsequent open enrollment periods. If the FCC were to grant such a request, and require us to share such system data with local competitors, such an action could have a significant adverse effect on our company and our business. The FCC has the authority to enforce its OVS regulations by imposing substantial fines, issuing cease and desist orders and/or imposing other administrative sanctions, such as revoking FCC certifications.

We rely on other companies to connect our local telephone customers with customers of other local telephone providers. We presently have the right to interconnect with the networks of Verizon, SBC and other ILECs. If any of these interconnection agreements are not renewed, we will have to negotiate new interconnection agreements with the respective carriers. A renegotiated agreement could be on terms less favorable than current terms.

It is generally expected that the 1996 Act will continue to undergo considerable interpretation and implementation, which could have a negative impact on our interconnection agreements with Verizon and SBC. It is also possible that further amendments to the Communications Act may be enacted which could have a negative impact on our interconnection

> agreements with Verizon and SBC. The contractual arrangements for interconnection and access to UNEs with incumbent carriers generally contain provisions for incorporating changes in governing law. As a resulting, future FCC, PUC and/or court decisions may negatively impact the rates, terms and conditions of the interconnection services we have obtained and may seek to obtain under these agreements, which could adversely affect our business, financial condition or results of operations. Our ability to compete successfully will depend on the nature and timing of any such legislative changes, regulations and interpretations and whether they are favorable to us or to our competitors. See "Business-Regulation," page 28.

B Low CI Examples

Included below are some samples of competitive discussion in annual reports from firms with relatively low amount of such discussion, labeled by year, firm name, and CIK code.

Discussion of competition in the 2002 10-K annual report by A. M. Castle & Co., CIK 18172. Word count of 24.

> The Company encounters strong competition both from other metals and plastics distributors and from large distribution organizations, some of which have substantially greater resources.

Discussion of competition in the 1999 10-K annual report by Penn Virginia Corp., CIK 77159. Word count of 28.

> The energy industry is highly competitive. Many of the Company's competitors are large, well-established companies with substantially larger operating staffs, greater capital resources and established long-term strategic positions.

Discussion of competition in the 2001 10-K annual report by LSI Industries Inc., CIK 763532. Word count of 47.

> LSI Industries encounters strong competition in all markets served by the Company's product lines. The Company has many competitors, some of

which have greater financial and other resources. The Company considers product quality and performance, price, customer service, prompt delivery, and reputation to be important competitive factors.