Is there a relation between the cost of debt and environmental performance?

An empirical investigation of the U.S. Pulp and Paper Industry, 1994-2005.

by

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Author's Declaration

I hereby declare that I am the sole author of this thesis. This is a true copy of the thesis, including any required final revisions, as accepted by my examiners.

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Abstract

This study shows an economically significant relation between a firm's environmental performance and its cost of debt. Firms that have poor environmental performance will face future environmental liabilities related to compliance and clean-up costs due to increasingly strict environmental laws and regulations. Under current U.S. law, environmental liabilities can impair the value of fixed assets, as environmental claims often take precedence over the claims of creditors. Thus, future environmental liabilities are of particular concern to creditors. Previous accounting research has shown that a firm's market value of equity is significantly affected by its environmental performance. However, the same has yet to be shown for a firm's cost of debt capital. This study focuses on a sample of U.S. pulp and paper firms. The results imply that the market applies an 'environmental risk' premium of thirty-eight basis points to the cost of debt capital for the average public firm in the U.S. pulp and paper industry, based on its environmental performance. Environmental performance is measured using the annual toxic release inventory of the United States Environmental Protection Agency. It is a measure of the amount of toxic chemicals released to land, air and water by a firm's operating facilities. This paper adds to the literature, providing evidence that environmental performance is a value relevant measure with regards to creditors. Thus, recent calls in the United States for greater cooperation between the Securities and Exchange Commission and the Environmental Protection Agency should be addressed. These calls are for the reporting, on a firm-wide basis, of quantifiable data that is already required by the Environmental Protection Agency but is not typically available in detail in firms' reports to investors.

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1 Introduction

The objective of this paper is to provide evidence as to whether environmental performance is a measurable component of polluting firms' cost of debt. Barth and McNichols (1994) find that unreported environmental liabilities significantly affect firms' equity values. Graham, Northcut and Maher (2001), and Graham and Maher (2006), find that firms' cost of debt on new bond issues is affected by unreported environmental liabilities. These studies use information from the U.S. Environmental Protection Agency (EPA) on what are known as Superfund sites. These sites are the result of a legacy of pollution that take a number of years to be identified and often take decades to clean-up. Thus, these papers relate to polluting activities that typically have taken place many years earlier. Other research focuses on environmental performance, which relates firm value to contemporary measures of a firm's polluting activities. Cormier and Magnan (1997), and Clarkson, Li and Richardson (2004), use measures of environmental performance to show that a firm's equity value in a given year is affected by its environmental performance in that same year.

Sharfman and Fernando (2008) look at environmental risk management and how it affects the weighted average cost of capital (WACC). They use a one-year cross-section of a sub-set of the S&P 500 and find that the more effectively a firm manages its environmental risk, the lower its WACC. However, they find a negative association between a firm's environmental risk management and their debt component of WACC. This result is mitigated by the fact that their measure of environmental risk management is not consistent with previous literature, is somewhat counter-intuitive and that industry effects are inadequately controlled for. This study extends Sharfman and Fernando (2008) by exploring a more powerful setting in which to examine a firm's cost of debt as they relate to environmental performance. It follows Clarkson, Li and Richardson (2004) in focusing on the U.S. pulp and paper industry. By using a single industry, significant inter-industry differences in operating activities and capital structure are controlled for. However, results that hold for the pulp and paper industry may not be generalisable to other industries.

The U.S. Pulp and Paper industry is a major polluter and has been the focus of a number of studies in the environmental accounting literature (from Bragdon and Marlin, 1972, to Clarkson, Li and Richardson, 2004). It is also the subject of a set of ever increasing cluster rules that require firms in the industry to progressively improve their pollution performance. This makes it an appropriate industry to study for the purposes of assessing the impact of environmental performance on a firm's cost of debt. I collect bond issue and trading data for firms in the U.S. pulp and paper industry from 1990 through 2006 by using a combination of the Mergent Fixed Income Securities Database (FISD) and the Trade Reporting and Compliance Engine (TRACE). This allows for the calculation of a market-based cost of debt for any of these firms that either issue debt or have their debt traded, in any given year over the sample period, as reported by these databases. To measure environmental performance (the independent variable of interest), I use the Toxic Release Inventory (TRI), reported annually by the U.S. Environmental Protection Agency (EPA).

Using the TRI as a proxy for environmental performance in the U.S. pulp and paper industry follows the methodology of Clarkson, Li and Richardson (2004). My results imply that in a given year, for each pound of toxic chemicals released per $1,000 of U.S. sales, the market applies a 17.13 basis point risk premium to the cost of debt capital (the average sample firm releases 2.2 pounds per $1,000 U.S. sales for an average premium of 37.69 basis points). I also find that the bond ratings of the sample firms are affected by their environmental performance. For each pound of toxic chemicals released per $1,000 of U.S. sales, the sample firms' bond ratings change by about one third of a rating point (for example, a rating point change would be a change from BBB+ to BBB).

A firm's environmental performance is becoming an increasingly important facet of its overall operations. The main contribution of this study is the evidence that environmental performance is relevant with respect to the value of outstanding debt. Thus, it should be part of a firm's external reporting requirements. The TRI is already mandatory reporting with respect to the U.S. EPA and is publicly available, on a facility by facility basis. However, attributing these facilities to their corporate parents can be a difficult and time consuming activity. Requiring firms to aggregate this information and include it in their annual reports creates minimal incremental reporting costs, yet would provide value-relevant information to all debt holders. This position is consistent with a 2004 United Sates Government Accountability Office (GAO) report. In this 2004 report, the GAO calls for more cooperation between the U.S. EPA and the U.S. Securities and Exchange Commission (SEC) to improve tracking and create more transparency with regards to environmental disclosure.

Creditors and bond raters can expect that the costs related to a firm's current and past environmental performance will not be fully captured in its financial statements. Thus, based on the evidence presented herein, it seems that they include environmental performance in their assessment of a firm's credit worthiness, over and above what may be evident in a firm's financial reports. In more general terms, this study contributes to the long line of research on the determinants of the cost of debt. It also contributes to the performance measurement literature. Environmental performance is a value-relevant performance measure and should be accounted for when assessing the actions of a firm's management.

The next section discusses the institutional and regulatory environment as it pertains to environmental liabilities. Section 3 presents my hypotheses and reviews the literature from which they are derived. In section 4, my empirical proxies and research design are presented. In section 5, I discuss sample selection and present preliminary descriptive statistics. The main results are presented and discussed in section 6. Section 7 contains a number of sensitivity analyses. Section 8 concludes and discusses limitations of this work.

2 Institutional and Regulatory Environment

2.1 Early institutional framework

The United States Environmental Protection Agency (EPA) was established in the early 1970s in response to the environmental movement in the United States, which took hold in the mid to late 1960s. This movement was quite strong and many parallels can be drawn between then and now with regards to environmental awareness. The general institutional environment was one in which governments and regulators were beginning to look for ways to hold firms accountable for their polluting activities. For example, at this time, the American Accounting Association established a committee which was given the charge "to develop measurement and reporting methods useful in communicating to internal and external users the effect of an organization's behaviour on the physical environment."[1] The committee's 1973 report concluded that more environmental disclosure would be required in the future and that environmental laws and regulations would have a material impact on firms' financial results. Thus, already in the early 1970s, environmental liabilities were beginning to be considered material with regards to a firm's ongoing operations. However, it was not until the Love Canal disaster of the late 1970s that the United States Congress gave the EPA its strongest law under which to force firms to address their environmental liabilities due to past pollution. This was through the so-called Superfund, established by the United States Congress after Love Canal much in the same way that Sarbanes-Oxley came after the Enron and related accounting scandals of recent years.

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[1] American Accounting Association committee on environmental effects of organizational behavior. Report of Committee on environmental effects of organizational behavior (1973), p. 75.

2.2 Current legal and regulatory environment in the United States

With the establishment of the United States EPA, and its related state level agencies, it became the primary agency responsible for environmental monitoring and enforcement in the United States. The most important laws the EPA operates under are the Resource Conservation and Recovery Act (RCRA) and the Comprehensive Environmental Response, Compensation and Liability Act (CERCLA, also known as the Superfund). These laws are the EPA's primary tools in cleaning up contaminated sites, holding parties responsible for these clean-ups, and forcing compliance with environmental laws and regulations. CERCLA is the specific law that came about as a direct result of the Love Canal disaster. The EPA identifies sites where hazardous waste exists and, if a particular site meets its threshold for taking action, the site becomes a so-called Superfund site.[2] When the EPA identifies a Superfund site, it will identify potentially responsible parties (PRPs). The PRPs will ultimately be held liable for the cost of site remediation and may also be assessed punitive damages.

Liability under CERCLA is joint, several and strict. Any current owner or operator of a contaminated site, or any owner or operator at the time the site was contaminated, can be held responsible for the entire clean-up costs. Negligence does not have to be proven to hold a party responsible for clean-up costs; the contamination only has to exist. Lenders have been held responsible for clean-up costs under CERCLA due to: foreclosure on a company's real assets, taking part in the operating of an insolvent company, and a lack of due diligence when providing funding to a polluting firm.

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[2] For a detailed discussion of the specific process as to Superfund sites see Barth and McNichols (1994), p.p. 180-183.

Turning to the pulp and paper industry in particular, the so-called cluster rules are a set of regulations addressing pollution in the industry. The cluster rules are in the process of being phased in, the phase in having begun in February, 1998. Full implementation will be completed by 2014. The first draft of these rules was released by the U.S. EPA in December 1993. At that time the EPA estimated compliance costs of $4 billion, but the American Forestry and Paper Association (AFPA) estimated compliance costs at $11.5 billion (Nichols, 1994; p. 81). After lobbying from the pulp and paper industry, the rules that came into effect in 1998 were described as more 'palatable' (Nichols, 1998, p. 71).[3] These rules apply to air and water emissions and effluent, and are technology based in nature. A particular feature, noted by Clarkson, Li and Richardson (2004), is the best available technology requirement for water effluent, where industry requirements are set by the best performers in the industry. Other concepts being applied are maximum achievable control technology (MACT) for air emissions, and best management practices (BMPs). The timelines involved allow firms to take a proactive, leading role in complying with the cluster rules, or to take a minimum compliance approach. Thus, the current legal environment is such that firms in the pulp and paper industry could have significant off-balance sheet environmental liabilities, based on their environmental performance. All government environmental litigation aside, the United States is an extremely litigious society. The threat that private litigation may exceed any government mandated clean-up costs always exists.

[3] For a detailed overview of the 'cluster rules' see Nichols (1998).

2.3 Accounting standards and environmental liabilities

There are many situations in which management may decide that a reasonable estimation cannot be made for an environmental liability. Under Financial Accounting Standards Board (FASB) Statement of Financial Accounting Standards No. 5, *Accounting for Contingencies* (SFAS 5), if a reasonable estimation cannot be made, the liability need not be recognised in the current period.[4] In the event that an amount is accrued, the potential for significant unreported liabilities still remains, as a variety of estimation techniques are allowed. When a range of possible liabilities is estimated, the most likely amount is recorded. In the case where each of the estimates is equally likely, it is acceptable to record the lowest amount (known minimum value).[5] In both cases, when the liability is finally realised it can be much greater than the one reported at the time of the pollution. Thus, if the market is to assess a risk premium based on the environmental performance of a polluting firm, the financial statements for the year in which the pollution occurs cannot be the sole information source.

The most recent financial reporting standard in the U.S. relating to environmental liabilities is FASB Statement of Financial Accounting Standards No. 143, *Accounting for Asset Retirement Obligations* (SFAS 143). SFAS 143 came into effect for fiscal years beginning after June 15, 2002. It requires the recognition of asset retirement obligations based on the concepts of FASB Statement of Financial Accounting Concepts No. 7, *Using Cash Flow Information and Present Value in Accounting.* Firms must now recognise an annual expense and liability based on expected obligations with regards to

[4] Under SFAS 5 an accrual is made if a contingent liability is likely and can be reasonably estimated.
[5] Interpretation No. 14 and Staff Accounting Bulletin No. 92 are the relevant guidance on this from FASB and the SEC respectively.

the de-commissioning of long-lived assets. From a 'fair value' perspective, this amount would be equal to the amount for which a third party will take over the liability.

However, third parties do not typically take over future environmental liabilities. If a third party market does not exist, the amount is based on discounting the expected future expense by the firm's cost of capital. Using present value accounting, the more financially distressed a firm is, the greater the rate at which the future obligation is discounted and the lower the liability it must report. Thus, based on SFAS 143, as a firm approaches bankruptcy, environmental liabilities due to the expected retirement of long-lived assets approach zero. This reporting may accurately reflect the liability from the aspect of the shareholder; however, from the perspective of a lender, the ability to make claims on a firm's assets will be affected by environmental liabilities. Another feature of SFAS 143 is that it only recognises asset retirement obligations as the result of operations up to the financial statement date. It does not reflect asset retirement obligations that will be incurred as a result of normal, ongoing operations related to a polluting asset over its remaining life. Current accounting standards and practice are such that a firm's future environmental liabilities can remain under reported, or un-reported, in their financial statements.

Several SEC rules exist regarding the disclosure of environmental liabilities. They are found in regulation S-K items 101, 103 and 303 covering a firm's business description, legal proceedings, and Management Discussion and Analysis (MD&A), respectively. Firms must disclose their compliance with environmental laws and any environmental contingencies which are reasonably likely to have a material financial impact on the firm. Potential liabilities that are material to the company's financial condition, or that exceed, in aggregate, ten percent of total assets must be disclosed.

For example, Westvaco Corporation's business description for 1996 discusses its exposure to environmental laws and regulations. It particularly touches on the expected impact of the cluster rules, providing a range of $175-400 million in capital expenditures to comply with the rules as they are implemented and additional annual operating costs of $25-50 million. In the same year, Mead Corporation does not mention the cluster rules and the expected implementation costs, but Mead does disclose the number of sites at which it has been named as a PRP at federal EPA Superfund sites and that a reserve of $38 million has been established to address remediation costs. Mead also explains that this estimate may be exceeded by up to $45 million. An example of disclosures related to item 103, legal proceedings can be found in Kimberley-Clark's 10-Ks. In 1994 it states that it is a PRP at 28 Superfund sites, whereas in the subsequent years it simply states that it is a PRP at 'a number' of sites. With regards to the MD&A, in 1999 Georgia Pacific's management states that capital expenditures to comply with the cluster rules are expected to be approximately $550 million through April 2006. In general, the contingent nature of expected environmental liability and compliance costs is evident in the financial reporting of firms in the pulp and paper industry.

This is supported by a number of studies. A 1993 GAO report found that many companies were not properly aggregating their environmental liabilities when determining materiality. The requirement of Regulation S-K mandating disclosure of environmental liabilities if they exceed ten percent of assets was often being applied on a case by case basis, rather than in aggregate. A 2004 report from the United States Government Accountability Office (GAO) calls for the SEC to create more transparency with regards to environmental liabilities. It complains of a lack of coordination between the SEC and EPA in aggregating already available public information, noting that minimal effort has been exerted towards improvement. A 2008 Ontario Securities Commission report finds that there is great disparity as to how firms disclose their environmental liabilities. Based on these reports, it can be expected that the costs related to a firm's current and past environmental performance will not be captured accurately in its financial statements.

3 Literature Review and Hypothesis Development

3.1 Market-based evidence of off-balance sheet environmental liabilities

Barth and McNichols (1994) use publicly available information to develop models they expect might have predictive power in determining the clean-up costs related to Superfund sites. The explanatory variables in their models are available prior to the EPA releasing publicly its own estimates of clean-up costs. The estimation equations, although with some significant results, show a low level of explanatory power. Thus, they conclude that recording Superfund site related accruals would not be required under SFAS 5 based on their estimation method, at least prior to the EPA releasing its cost estimates. However, they also use their explanatory variables as proxies for environmental liabilities in a market based model. Barth and McNichols find that a significant liability, which is highly correlated with their proxies, is imputed into share price. As their market model includes firms' book values of liabilities as a control variable, this environmental liability is over and above any already reported by the sample firms. The most significant proxy used in the model is the number of times a firm is listed as a potentially responsible party at Superfund sites (compared to the other proxies, which are monetary estimates of remediation costs). Their results estimate an average implicit liability of 28.6% of market value for firms that are named as potentially responsible parties on Superfund sites.

In a paper focusing on three specific industry segments, Cormier and Magnan (1997) use water-based pollution data available from the Ontario and Quebec governments to create a proxy for implicit environmental liabilities. Their pollution measure is based on a firm's conformity to existing government regulations. For the pulp and paper industry, Cormier and Magnan collect the Ontario and Quebec environment ministries' reports of the biochemical oxygen demand of water effluent from the operating facilities of their sample firms. Water that has a higher biochemical oxygen demand is more polluted. This is then scaled by the respective environment ministries' allowed levels to create a measure of how well these firms meet or exceed government regulations. Similar to Barth and McNichols (1994), Cormier and Magnan use the market value of equity as the dependent variable and then include their proxy for implicit environmental liabilities as an independent variable. An important difference exists between the proxies used by Barth and McNichols and Cormier and Magnan. Barth and McNichols use factors relating to Superfund sites. These are sites where an implicit environmental liability exists due to past environmental performance, often from many years previous. Cormier and Magnan are using a measure of current environmental performance as a proxy for implicit environmental liabilities.

The results of Cormier and Magnan (1997) suggest inter-industry differences. For their sample of pulp and paper firms, they find a significant link between environmental performance and the market value of equity. They find less significant results for the firms categorised as chemicals and oil refiners, and weak results for the firms categorised as steel, metals and mining. If within sample homogeneity is important, as suggested by the authors, a close inspection of the sample presents reasons for the variety of results.[6] The strength of the results for each industry category is consistent with the homogeneity

[6] For a full list of the sample firms used see: Cormier et al. (1993), Appendix 1.

of each category, indicating that the model may not be well-specified for heterogeneous groupings of firms.

Another paper exploring the market valuations in relation to environmental performance (as a proxy for implicit environmental liabilities) is Clarkson, Li and Richardson (2004). Clarkson, Li and Richardson use a modified version of the Ohlson (1995) model to show that the market positively values environmental capital expenditures for low polluting firms; whereas, environmental capital expenditures are valued at zero for high polluting firms. They look specifically at the U.S. pulp and paper industry, citing the EPA cluster rules and model specification (specifically noting Cormier and Magnan, 1997) as reasons for focusing on a single industry. They use the United States Environmental Protection Agency's (EPA's) toxic release inventory (TRI) to partition firms in the pulp and paper industry into high and low polluters. The TRI is a facility by facility report of the total toxic chemicals released to land, air and water. It is made available to the public by the EPA on an annual basis.

The results of Clarkson, Li and Richardson (2004) are consistent with their position: environmental capital expenditures made by low polluting firms are proactive measures that will provide future economic benefits; however, environmental capital expenditures made by high polluting firms provide no future economic benefit. In other words, when these firms make environmental capital expenditures, low polluting firms are creating an asset by proactively avoiding future liabilities and high polluting firms are just paying off current liabilities. Clarkson, Li and Richardson also find that the market assesses significant, unreported environmental liabilities when valuing the high polluting firms in their sample. Their estimate of unreported liabilities for these firms is equivalent to 16.6 percent of market capitalisation.

3.2 Environmental liabilities and the market value of debt

The regulatory and legal environment, as described in section 2, is certainly one in which a prudent lender should be concerned about a borrower's environmental performance. Under current common-law, environmental liabilities can impair the value of fixed assets, as environmental claims often take precedence over the claims of creditors. Graham and Maher (2006) look at bond ratings and bond issues from 1995-1998 for firms that are named as potentially responsible parties at EPA Superfund sites (357 firm-years). They collect these firms' environmental liability accruals as reported in their 10-Ks. They also collect the publicly available EPA Superfund site data, using four different measures of the expected clean-up costs. One is the number of times the EPA names a firm as a PRP (scaled by total assets), the other three are specific measures of the expected site clean-up costs. These are used in various models to test hypotheses as to whether they significantly affect bond rating and bond yield. The results suggest that bond rating and bond yield are affected by the number of times firms are named as a potentially responsible party at a Superfund site. They find weaker evidence using the specific monetary amounts reported by the EPA for Superfund clean-up costs. This is similar to the Barth and McNichols (1994) study on equity value, where the most significant proxy for Superfund site related environmental liabilities is also the number of times a firm is named as a PRP.

Graham and Maher (2006) find that when they include bond rating as an independent variable in their bond yield equation, it subsumes the significance of all of their environmental liability proxies. Evidence that bond rating would reflect unreported environmental liabilities can be found in the Standard and Poor's Corporate Rating Criteria (2006). Standard and Poor's states that it assesses a firm's environmental liabilities as they relate to accounting quality, asset specific values, liquidity, flexibility and asset retirement obligations (Standard and Poor's, 2006: pp. 24, 32, 33, 51, 67, 113 and 126) when establishing a firm's credit rating. Thus, any modelling of a firm's cost of debt as a function of environmental liabilities or performance should be done with the expectation that environmental liabilities and performance will be taken into account by the bond rating agencies.

This study is similar to that of Graham and Maher (2006) in that it uses measures of a firm's cost of debt as a dependent variable and EPA reported environmental data as an independent variable of interest. However, it differs significantly in that the independent variable of interest in this study is a measure of current environmental performance; whereas, Graham and Maher are using a proxy for environmental liabilities as they relate to Superfund sites. Typically, by the time a firm is named as a potentially responsible party at a Superfund site, many years have passed from the time of the polluting activities. It is the same distinction between the variables of interest from Barth and McNichols (1994) and Clarkson, Li and Richardson (2004). The potential exists that there is some overlap in these measures and thus, some redundancy in the studies.

However, the lag between current environmental performance and being named a potentially responsible party is long. Thus, these are separate and distinct measures with separate and distinct implications for the firms studied.

3.3 Environmental liabilities and the cost of capital

Sharfman and Fernando (2008) theorise that improved environmental risk management represents a lower risk strategy and that this lower risk should be reflected in cheaper equity, cheaper debt and higher leverage. Sharfman and Fernando start with a set of TRI based quantitative information acquired from the Investor Responsibility Research Center (IRRC). The IRRC collects and aggregates a number of items from the TRI database for S&P 500 firms, and then scales them by domestic sales. Sharfman and Fernando specifically collect total TRI emissions, total TRI emissions treated on site and total TRI re-used or recycled to create on-site energy (all scaled by domestic sales). These measures are then scaled by the IRRC report of total waste generated by the firm, including TRI emissions (scaled by U.S. sales). As both measures are scaled by domestic sales, domestic sales cancels out resulting in the various TRI measures being scaled by total waste generated (including TRI). These are meant to be measures of a firm's environmental risk management.

For a qualitative measure of environmental risk management, Sharfman and Fernando look to the Kinder, Lydenberg, Domini & Co. (KLD) social performance dataset. KLD is a social investment screening firm that provides environmental and social screening of the S&P 500 companies for its clients. KLD measure firms' strengths and weaknesses with regards to a broad range of environmental and social criteria. Sharfman and Fernando use the ratings of environmental strengths and environmental weaknesses as two separate measures. As a final step to develop a measure of environmental risk management, a factor analysis is done using all of the TRI measures and the two KLD measures. Sharfman and Fernando end up with a single variable using factor weightings on total TRI emissions as a percentage of waste generated, total TRI treated on-site for toxicity as a percentage of waste generated and the KLD environmental strengths measure. The sample is based on the S&P 500 and is ultimately limited to 267 firms, due to data limitations. These 267 firms represent 39 different two-digit SIC code groupings.

Firms and industries that systematically generate more waste and less TRI are considered to be doing a worse job of environmental risk management. The higher the TRI numbers used as a percent of total waste generated, the better the firm's rating for environmental risk management. If a firm were to lower its TRI emissions, but not correspondingly lower its other waste generated, the firm would be characterised as having worse environmental risk management. Conversely, a firm that increases its TRI emissions, while keeping all other waste generated constant, would be classified as a better manager of environmental risk.

Sharfman and Fernando establish models in which they use measures of cost of debt, cost of equity, weighted average cost of capital (WACC) and leverage as dependent variables, with their environmental risk management construct as the independent variable of interest. They rely on the Bloomberg Financial dataset for much of their cost of capital estimation, acquired directly from Bloomberg in March of 2004. They base their measure of cost of debt on Bloomberg's estimates of firm-specific marginal cost of borrowing. However, Sharfman and Fernando do not clearly describe how Bloomberg calculates this cost or at what point in time during their sample year (2002) it is calculated. The cost of equity is based on the capital asset pricing model (Sharpe, 1964; Lintner, 1965). The risk-free rate used in their analysis is based on a 10-year U.S. treasury bond, measured at the beginning of their sample year. Three measures of WACC are calculated. The first uses firm Beta from Compustat and a risk premium based on Fama and French (2002). The second is Bloomberg's firm-specific calculation of WACC and the third uses the Compustat Beta and Bloomberg's firm specific risk premium. They call these WACC-1, 2 and 3 respectively. A factor analysis is then used to create a weighting of the three, which they call WACC-4. All of their analyses are then run using only WACC-1 and WACC-4. When leverage is used as the dependent variable, it is calculated as long-term debt reported by Compustat, scaled by market capitalisation.

With regards to control variables, leverage is used in all models, except when it is the dependent variable. Size is controlled for using total market capitalisation. Industry is controlled for by using one indicator variable. Of the thirty-nine SIC codes represented in their sample, Sharfman and Fernando performed an analysis determining that six of the SIC codes represented were heterogeneous and that the remaining thirty-three represented a homogeneous grouping. The indicator variable was then used to identify firms from the heterogeneous grouping. Sharfman and Fernando explicitly state that this effectively parses out any inter-industry differences that might exist among their sample firms (Sharfman and Fernando; 2008, p. 579). Further control variables are leverage and market capitalisation. The results of Sharfman and Fernando indicate that firms with better environmental risk management have a lower WACC, lower cost of equity and higher leverage. However, they find the opposite results for cost of debt. Their model indicates that the worse a firm is at managing environmental risk, the lower its cost of debt.

There are a number of reasons to explore these results further. First, the measure of environmental management is one which includes two main measures that will result in firms that increase their release and use of toxic chemical being labelled as better environmental managers. The second is the single indicator variable used as a control for industry effects. With thirty-nine different industries in the sample of 267 firms, parsing out industry differences with a single indicator variable may not be adequate. Last, no control variables for things such as volatility and profitability are included in the model. In the study presented herein, the focus is on a single industry. This will control for significant inter-industry differences in capital structure, TRI and total waste generated. I also use control variables that reflect volatility and profitability, among others. The results of Sharfman and Fernando indicate that firms with higher TRI as a percentage of total waste have a higher cost of debt capital. These results are not necessarily inconsistent with the theory and results to be presented herein.

3.4 Environmental Liabilities and Agency Theory

A final theoretical point suggesting a link between environmental performance and the cost of debt capital can be found in agency theory. Agency theory, as per Jensen and Meckling (1976), dictates that it is optimal for bondholders to put restrictions on owner-managers so that they cannot take risks that will shift wealth from bondholders to shareholders. In polluting industries, environmentally proactive firms are working to address their future environmental liabilities on a timely basis; whereas, other firms are deferring this cost and will ultimately either shut down their higher polluting operations or face compliance costs that have no future economic benefit. Thus, an ex ante decision by management to take a proactive environmental strategy should be one that the debt market looks upon favourably. The firm's managers have given up the option to pollute, a higher risk strategy that might benefit shareholders, in favour of a lower polluting strategy that will help to secure the interests of bondholders.

3.5 Hypotheses

Based on the previous discussion, I advance the following two hypotheses, in alternate form:

> *H1: Firms in the pulp and paper industry with relatively superior environmental performance will have a higher bond rating; ceteris paribus.*
>
> *H2: Firms in the pulp and paper industry with relatively superior environmental performance will have a lower cost of debt; ceteris paribus.*

H1 is somewhat redundant after H2 has been explored. However, there are two important subtleties. The first is to test the expectation that the rating agencies include environmental performance in their bond ratings of polluting firms. The second is to predetermine whether bond rating can be used as a control variable in a model that also includes environmental performance. A number of papers exploring the determinants of firms' cost of debt include bond rating as a control variable, only to find that it subsumes the variable of interest. A case in point is Graham and Maher (2006), as discussed previously herein. Thus, the results of H1 will support the assertion that a model using cost of debt as a dependent variable cannot include bond rating as a control variable, without first addressing the relation between environmental performance and bond rating. H2 addresses the main objective of this paper, which is to directly explore the relation between a firm's cost of debt and its environmental performance.

4 Model Development

4.1 Bond rating

To use bond rating as a dependent variable, I convert firms' bond ratings into an ordinal scale. This is necessary in all cases where bond rating is used as a model variable, with the methodology of the conversion being the only difference. For example, Ortiz-Molina (2006) uses a scale of one to six, whereas Vasvari (2006) uses a scale of one to twenty-two. I use the finer partition based on the twenty-two point scale, so that the model can pick up changes within a particular letter rating, such as BBB to BBB+. For ease of comparison and for simplicity, I use the S&P bond rating. If it is not available prior to the bond trade used in the sample, I use the equivalent Moody's or Fitch rating. Thus, an S&P rating of AAA+ is coded as '1', AAA as '2', AAA– as '3', and so on. Using this coding, a lower number represents a better bond rating.

4.2 Firm specific cost of debt

To establish a firm specific cost of debt, so as to test H2, it is necessary to have an observable transaction. Trading in corporate debt has been an over-the-counter, opaque market for most of the twentieth century and observable transactions have historically not been readily available.[7] Thus, access to data has been a limitation when measuring a firm's cost of debt. One approach is to use new issues of corporate debt only. For example: Vasvari (2006) uses the floating rate on new, syndicated loans, and Ortiz-Molina (2006) uses the at-issue yield spread on new, fixed rate corporate bonds. Both papers explore aspects of the interaction of managerial incentives and a firm's cost of

[7] For a historical overview of the bond market microstructure see Biais and Green (2005). For a discussion of recent changes in transparency, see Edwards (2006).

debt. Graham and Maher (2006) also restrict their sample to firms issuing new debt. The drawback of using new debt issues to measure a firm's cost of debt is that it restricts the sample to firms issuing debt in a given year. This can lead to a sample selection bias, as debt issuing firms may exhibit systematically different characteristics from those that do not issue debt in a given year. Regardless of this potential bias, when focusing on a single industry, restricting the sample to new issuers is not feasible due to the limited sample size.

To capture a larger data set, Campbell and Taksler (2003) use bond trades as reported by the National Association of Insurance Commissioners (NAIC). The NAIC data includes bond trades by life insurance companies, property and casualty insurance companies, and health maintenance organisations. This allowed Campbell and Taksler to collect panel data to explore the interaction of equity volatility and corporate bond yield. The sample period over which Campbell and Taksler draw their data is 1995 to 1999. Over this same period, increased calls were made for more transparency in the debt market.[8] As a result, the Trade Reporting and Compliance Engine (TRACE) was established. It was phased in beginning in June 2002, and was in full implementation by the end of 2005. TRACE now reports virtually all over-the-counter trades, with the exception of private placements issued under rule 144A.[9] Thus, using data from the Mergent Fixed Income Securities Database (which reports NAIC trades), along with TRACE, the market prices for a large cross section of firms' bond trades is available. I use this data to calculate the cost of debt for firms in the pulp and paper industry. This blended approach creates a set of

[8] Edwards 2006, p. 33.
[9] Rule 144: Selling Restricted and Controlled Securities. Rule 144A identifies what sales produce restricted securities. For more detail see: http://www.sec.gov/investor/pubs/rule144.htm

panel data for U.S. pulp and paper firms with outstanding debt from 1994 through 2005. Only one bond trade per firm-year is used. The set of panel data is unbalanced as a result of mergers and acquisitions, and a few firms that do not have outstanding debt at the beginning of the sample period.

To control for changes in the market-wide cost of debt over time, I use the yield spread as a measure of firms' cost of debt. The yield spread is defined as the difference between the yield to maturity of a corporate bond, or note, and that of a government bond of similar maturity. For new issues, the Mergent Fixed Income Securities Database reports the yield spread; however, when using after-issue trade data from Mergent or TRACE, several calculations must be made. TRACE reports the yield to maturity of its bond trades. Thus, an appropriate government bond must be used to calculate the bond's yield spread. The U.S. Federal Reserve reports the yield on 1, 2, 5, 7, 10 and 20 year treasury bonds of constant maturity for the sample period of 1995 to 2006. It also reports 30 year yields covering January 1, 1995 to February 18, 2003; recommencing February 9, 2006. In the cases where the time to maturity is greater than 20 years and the bond transaction takes place between February 18, 2003 and February 9, 2006; a twenty year treasury bond is used as the benchmark. In the cases where the time to maturity falls between two of the benchmark treasury bonds, I use interpolation to apply an appropriate weighting of the two benchmarks. An example of the calculation using TRACE is presented in Appendix A.

For the NAIC trades, the yield to maturity must be calculated by equating the cash outflow to the discounted value of the future cash inflows. This is done by finding the discount rate that makes the present value of the par value of the bond plus the present value of the remaining coupon payments equal to the cash outflow on the date of the bond transaction. The following equation is used to do this:

$$\text{Cash Outflow}_t = \text{Par Value}/(1+r)^T + \sum \text{Coupon Payment}/(1+r)^{T-i} \quad (1)$$

Where, in the case of semi-annual Coupon payments:

T = 2*(Years to maturity)

i = 0, 1, 2, ….; for all T-i > 0.

Cash Outflow = Actual price paid for the bond (flat price) plus cash paid for accrued interest from last coupon date to the transaction date; based on a $100 par value

Par Value = $100.00

Coupon Payment = stated value of semi-annual bond coupon

r = the effective interest rate satisfying the stated equality, solved for iteratively

Once the yield to maturity is calculated, the yield spread can be calculated in the same manner as it is for the TRACE transactions.

For each sample firm, a bond transaction is selected that takes place closest to, but after, the three months following the firm's fiscal year end date. This allows adequate time for the release of the previous year's financial results. Only one bond trade per firm-year is used. Using this approach, the yield spreads for the sample are calculated based on NAIC transactions for 1995 through 2004. For 2005 and 2006, the TRACE transactions are primarily used. As convertible bonds have an embedded equity component, convertible bonds are not used in the sample. None of the bonds in the sample are putable or have a sinking fund provision and almost all are senior debt.

4.3 Proxy for environmental liabilities

In 1987, the EPA began collecting and reporting national data on the release of toxic chemicals, which is known as the Toxic Release Inventory (TRI). The TRI reports the amount of toxic chemicals released to land, air and water for all facilities operating in the United States. Since this data became available, a number of academic studies have used the TRI as a proxy for environmental performance (e.g. Klassen and Whybark, 1999; Klassen, 2001; King and Lennox, 2001; Clarkson, Li and Richardson 2004; Clarkson et al., 2006). In keeping with these studies, I use the TRI as a proxy for environmental performance.

Other papers using different versions of TRI based measures include Al-Tuwaijri, Christensen and Hughes (2004) and Sharfman and Fernando (2006). These two papers use a sample of S&P 500 firms, thus industry differences are important. Al-Tuwaijri, Christensen and Hughes control this by using the total TRI in the denominator of their proxy and TRI recycled as their numerator. Thus, they are measuring what percentage of total TRI is recycled by each firm in their sample. As inter-industry control is important when using an S&P 500 sample, this method works to control for inter-industry differences. I explored using this method for the pulp and paper industry; however, the numerator (TRI recycled) is typically at or near zero for the entire sample. Turning to Sharfman and Fernando (2006), they scale their TRI measures by total waste generated.

Again, this scaling is meant to provide comparability across industries. Sharfman and Fernando argue that the higher the percentage of TRI as a function of total waste, the better the firm is at managing environmental risk. I do not use this measure as I want to measure environmental performance and not environmental risk management.[10]

Clarkson, Li and Richardson (2004) scale total firm TRI by cost of goods sold. The objective of scaling is to create a measure that reflects each firm's toxic release per unit of production in each given year. However, scaling by cost of goods sold includes costs related to foreign operations. The TRI only reflects domestic U.S. operations. The more internationally diversified a firm is, the larger the denominator when scaling, and the lower its relative measure of TRI. This may lead to underestimating the amount of pollution an internationally diversified firm creates in relation to firms that operate primarily in the U.S. To address this, I scale firms' total TRI by U.S. sales (based on location of seller), eliminating the possibility that a firm with a higher degree of international diversification will have its environmental performance measure biased downward.

4.4 Control Variables

The primary reason for focusing on a single industry is to control for the overall economic and regulatory factors that are industry-specific. However, there are still a number of intra-industry factors that must be controlled for, while also maintaining as many degrees of freedom as possible, due to the restricted sample size.

[10] For a more in depth overview of TRI used as a proxy see Toffel and Marshall (2004).

To proxy for a firm's overall default risk I use the Altman Z-score (Altman, 1968). For public companies this is:

$$Z = 1.2X_1 + 1.4X_2 + 3.3X_3 + 0.6X_4 + 1.0X_5$$

Where (Compustat data items in brackets),

X_1 = Working Capital/Total Assets = (Item 4 - Item 5)/(Item 6)

X_2 = Retained Earnings/Total Assets = (Item 36)/(Item 6)

X_3 = EBIT/Total Assets = (Item 170 + Item 15)/(Item 6)

X_4 = Market Equity/Book Value Liabilities = (Item 199*Item 25)/(Item 5 + Item 9)

X_5 = Sales/Total Assets = (Item 12)/(Item 6)

The Altman Z-score is considered the 'tried and tested' model for bankruptcy prediction (Eidleman, 1995). It has been shown to be an effective predictor of bankruptcy since it has come into use. Several papers imply the model has not been as effective a predictor of bankruptcy in different time-frames and under different economic cycles over the past 30 years as it was in the period over which it was developed (e.g. Begley et al., 1996; Grice and Ingram, 2001). However, regardless of whether it is an accurate predictor of bankruptcy, it is used widely by banks, underwriters and rating agencies to asses a firm's credit worthiness. It also captures many of the underlying control variables that are used to model firm-specific cost of debt. The model is meant to represent: liquidity (X_1), profitability (X_2), productivity (X3), market value (X_4) and asset-turnover (X_5). Altman (2003, p. 8) notes that X_5 is of particular concern as asset-turnover can vary from industry to industry. Thus, using the Z-score as a proxy for default risk is more applicable in a single industry setting, where inter-industry differences in asset turnover are not a concern. Some examples of Z-score being used as a control variable can be found in the finance literature (e.g. Mackie-Mason, 1990; Lemmon et al., 2006). Higher values for each individual measure used in the Z-score reflect lower default risk. I expect that this will cause the coefficient on Z-score to be negative.

Campbell and Taksler (2003) study the increasing spread between U.S. Corporate bonds and U.S. Treasury bonds. This spread increases in the latter half of the 1990s. Campbell and Taksler find evidence that this is due to increased firm volatility. The same result is found by Mansi, Maxwell and Miller (2006). I am concerned about capturing firm volatility, given its demonstrated effect on yield spread. Thus, I include the annualised standard deviation of firms' mean returns for the year prior to the bond trade as a measure of firm-specific volatility. I expect that as volatility increases, yield spread will increase. To be consistent with this expectation, I also include volatility when using bond rating as a measure of firm specific cost of debt. If higher volatility results in a higher yield spread, it follows that it should affect bond rating. As the ordinal transformation of bond rating used herein increases as bond rating decreases, the predicted sign for the coefficient on volatility is positive for both yield spread and bond rating.

The resulting model to test H1 is:

$$\text{Bond Rating}_{it} = \alpha_0 + \alpha_1\text{TRI/US Sales}_{it} + \alpha_2\text{Z-Score}_{it} + \alpha_3\text{Volatility}_{it} + \varepsilon_{it} \qquad (2)$$

The predicted signs are $\alpha_1 > 0$, $\alpha_2 < 0$, $\alpha_3 > 0$.

To test H2, I use equation (2) as a starting point, replacing bond rating with yield spread and adding several more control variables that have been shown to affect a firm's yield spread. The first additional variable is derived from equation (2). As implied by H1, I expect that bond rating will take into account a firm's environmental performance and that using it as a control variable, when yield spread is the dependent variable, will subsume the power of the test variable (environmental performance). However, using bond rating as a control variable to test H2 would serve to capture many firm specific characteristics that might not be picked up in other model variables. To facilitate the use of bond rating as a control variable, I follow the methodology used by Datta, Iskandar-Datta and Patel (1999), as well as a number of subsequent papers using yield spread as a dependent variable (i.e. Anderson, Mansi and Reeb, 2003; Klock, Mansi and Maxwell, 2005; Ortiz-Molina, 2006). This approach imposes an orthogonal condition on bond rating by first regressing bond rating onto the variable of interest. The residual is then used as a measure of bond rating, incremental to the information content of the test variable already in the regression. Thus, a control variable that addresses bond raters' opinions as to the credit worthiness of each bond can be used, in the presence of other control variables that also act as determinants of the bond raters' opinions. Using this approach, I create a 'modified bond rating' as follows:

$$\text{Bond rating}_{it} = \alpha_1 + \alpha_0 + \alpha_1\text{TRI/US Sales}_{it} + \varepsilon_{it}$$

$$\text{Modified bond rating}_{it} = \varepsilon_{it} \qquad (3)$$

The only drawback is that equation (3) may be under-specified and that α_2 may be biased due to an omitted control variable. Thus, I also include Z-score and volatility in this first stage regression. The equation for the modified bond rating is equation (2), saving the residual as the modified bond rating:

$$\text{Bond Rating}_{it} = \alpha_0 + \alpha_1\text{TRI/US Sales}_{it} + \alpha_2\text{Z-Score}_{it} + \alpha_3\text{Volatility}_{it} + \varepsilon_{it}$$

$$\text{Modified bond rating}_{it} = \varepsilon_{it} \qquad (2a)$$

As the modified bond rating will have a mean of zero, with ratings below zero reflecting a better bond rating, I expect that the parameter estimate will be positive.

A measure that is not incorporated into bond rating is time to maturity. For each individual firm, I expect that the yield spread will increase as the time to maturity increases. However, when comparing the yield spreads of different firms, bonds of longer duration may be associated with stronger firms and thus with lower yield spreads. A lower yield spread for longer maturity bonds may also be due to the fact that my sample period covers a number of years (around 2000 to 2003) in which it was common to see an inverted yield curve. With regards to bond rating, I expect that stronger firms will have access to longer term debt. However, as my selection of bonds is based on the closest trade to a specific point in time, the sample bonds are not necessarily a reflection of the average time to maturity of a firm's bonds. A final point with regards to maturity is the possibility that firms that are under-performing may have higher yields on longer maturity bonds, as bond holders might have a more positive outlook on the weaker firms long-term prospects. Thus, I make no directional predictions as to the relation between time to maturity and yield spread.

As noted previously herein, Campbell and Taksler (2003) attribute much of the increase in the average spread of corporate bonds over treasury bonds in the late 1990s to increased stock market volatility. However, liquidity has also been shown to be a major factor in pricing corporate bonds relative to treasury bonds (i.e. Chen et al., 2007). To address this, I include the spread between the average Moody's Aaa corporate bond yield and the ten-year treasury bond yield on the day of the bond trade I use in my sample. In periods of tighter liquidity, the treasury spread of average bond yields tend to increase to compensate. Thus, I expect the yield spread of the sample bonds to increase as the spread between the average corporate and Treasury bond increases.

The resulting model to test H2 is:

$$\begin{aligned}\text{Yield Spread}_{it} = \;& \alpha_0 + \alpha_1\text{TRI/US Sales}_{it} + \alpha_2 \text{ Modified Bond Rating}_{it} + \alpha_3\text{Z-Score}_{it} \\ & + \alpha_4\text{Volatility}_{it} + \alpha_5\text{Maturity}_{it} + \alpha_6\text{AaaSpread}_{it} + \varepsilon_{it} \qquad (4)\end{aligned}$$

The predicted signs are $\alpha_1 > 0$, $\alpha_2 > 0$, $\alpha_3 < 0$, $\alpha_4 > 0$, $\alpha_5 = ?$, and $\alpha_6 > 0$.

With a minimum of variables, the models control for firm-specific default risk. Using yield spread also controls for changes in the risk-free interest rate over the time-series of the sample. Keeping the number of parameters to a minimum allows for more power in the regressions and more flexibility in choosing econometric techniques.

5 Sample selection and descriptive statistics

Clarkson, Li and Richardson (2004) identify forty-four firms that operate pulp and paper mills in the United States. They identify fifteen firms for which the pulp and paper operations are not a major part of operations. After eliminating these firms, they are left with twenty-nine firms that have significant operations in the pulp and paper industry. Their sample period goes from 1989 to 2000 and includes 256 firm-year observations of unbalanced panel data. This provides a reasonable benchmark as to the number of firms and firm-year observations I collect.

The sample period of this study differs from that of Clarkson, Li and Richardson (2004), as it is more recent and covers more closely the years in which the cluster rules come into effect. The fiscal years over which the sample is gathered are from 1994 to 2005 (12 years). The sample firms' bond trades, from which the annual costs of debt are calculated, are the bond trade closest to, but after, the three months following fiscal year-end.[11] Typically, this is on or after April 1st, as most firms have a December year-end. Only one bond trade is used per firm-year. All of the control variables, except for volatility, are measured at fiscal year-end. Volatility is based on the calendar year prior to the date of the bond trade.

The starting point for creating a list of sample firms is the U.S. Environmental Protection Agency's Toxic Release Inventory database.[12] Preliminary data for each year is publicly available in the September following the end of each reporting year on a facility by

[11] In three instances this restriction is violated and a trade within the three months after fiscal year-end is used, so as not to lose a firm-year observation.
[12] http://www.epa.gov/enviro/index.html

facility basis.[13] A complete report is released in the following March, covering the calendar year two years previous. This data can be accessed on an industry by industry basis, my focus being SIC 26, Paper and Allied Products. In this study, I match the TRI from a given sample year to all other variables from the same year. This means that the actual TRI data is not publicly released and I am making the assumption that relative environmental performance is recognised prior to the TRI data being officially released. Any positive results imply that bond holders and raters are close enough to the ongoing activities of a firm so as to assess whether the firm has technology in place so as to release less toxic chemicals and that it is making capital expenditures that will reduce these releases. The matching of TRI to the same fiscal year in which it occurs follows the methodology of Clarkson, Li and Richardson (2004). Clarkson, Li and Richardson also look at a one-year lag variable for TRI as a sensitivity analysis. This will also be addressed in the sensitivity analysis presented herein.

Within SIC 26, approximately five to six hundred facilities per year reported their releases of toxic chemicals to the EPA for a total of 6,443 facility reports over the twelve year time-series. Facility name, address, city, county, state, zip code, latitude, longitude and two EPA designated identification numbers are given for each facility. The facility name may, or may not, be indicative of the corporate ownership of the facility. Based on the facility names and some preliminary web searching, I identify forty-five distinct firms and aggregate individual facilities to these firms. These forty-five firms represent 84% of the toxic chemicals released by firms in SIC 26 as reported to the EPA from 1994 to

[13] Firms must report their facility data to the EPA by the beginning of July each year.

2005. Many of the facilities that are not assigned to a firm are owned by firms in the packaging and laminating business and not directly related to the pulp and paper sector.

At this point it is important to account for the way in which the EPA handles its TRI data on a time-series basis. If a facility is acquired by another firm, the entire time-series for the facility is transferred to the acquiring firm. For example, Domtar Inc. is not a major pulp and paper firm in the United States until it purchases four large facilities in 2001 from Georgia Pacific. However, the current data for these four facilities attributes the entire time-series of the annual TRI data to Domtar. If I do not address this, I will attribute the TRI of these facilities to Domtar from 1994-2005, when they should be attributed to Domtar from 2001-2005 and to Georgia-Pacific previous to that. This is also the case for mergers. For example, Mead Corp and Westvaco merge in 2002 to become Mead Westvaco. After the merger, the EPA data reports the facilities under the Mead Westvaco facility names. For the period 1994-2001, each of the Mead Westvaco facilities must be attributed to Mead or Westvaco on a facility by facility basis. Furthermore, all of these facilities must be tracked back in time to establish whether they were acquired from other companies between 1994 and 2001. This process must be done for all firms from the original forty-five identified firms, across the more than five hundred facilities reported each year, over the twelve year time-series.

To do this, I first look to the firms' lists of properties as described in Part II of each 10-K ('Properties').[14] The detail given by each firm differs greatly. Some firms identify each

[14] For Canadian companies, annual reports are sourced from Sedar and for other non-U.S. firms annual reports are sourced from company websites.

of their production facilities by city and state, some only give the number of facilities per state and some give almost no information. In many cases, a review of Part I of the 10-K ('Business') will reveal information about facilities. Alternatively, the MD&A might also discuss facilities. The notes to the financial statements also cover acquisitions and disposals. As a last resort, a web search using the facility name and related firm will often result in information on the disposal or acquisition of a particular facility.

The result of this search, and re-assigning facilities to their appropriate corporate owner over the twelve year time-series, increases the number of specifically identified firms to seventy-one, representing eighty-nine percent of the Toxic Release Inventory for the sample period. This is indicative of the rationalisation in the pulp and paper industry that has occurred over the past decade or so. A good example is International Paper. Based on the 2005 EPA TRI data, International Paper released 50.6 million pounds of toxic chemicals in 1994. However, since 1994, International Paper acquired four major firms within the pulp and paper industry. Attributing the relevant facilities to these four firms reduces International Paper's 1994 TRI to 30.1 million. Over the sample period, as International Paper makes various acquisitions (and some disposals), its TRI increases to 57.5 million pounds in 2005. The described methodology of tracking facilities over the sample period and re-assigning them appropriately will certainly include a number of errors; however, these errors will create much less noise than not tracking facility disposals and acquisitions at all.

At this point, a number of firms that are clearly not predominantly in the pulp and paper industry are dropped as sample candidates. These are firms such as Proctor and Gamble and 3M. This reduces the number of firms to sixty-five and pulls two percent from the total TRI. The required control variables are not available for seventeen firms, as they are privately held. Despite the fact that this represents a relatively large number of firms, they account for only seven percent of the total TRI. A further three small firms that are taken over early in the time-series are eliminated. Foreign firms that operate primarily outside the U.S. are also removed from the sample, removing nine firms and five percent of the TRI. This leaves thirty-six firms representing seventy-five percent of the EPA reported TRI over the twelve year time-series. Merged with the bond trades and control data, the sample includes twenty-six firms and 205 firm-year observations.

The reduction in firms is primarily attributable to firms that do not have available bond trade data. However, they represent a relatively small amount of the TRI releases over the sample period. Another firm-year is ultimately eliminated as an outlier based on an OLS regression and a Cook's D of 1.137. This observation is from a firm that is clearly approaching bankruptcy, as the yield spread for the outlying firm-year is over 1,200 basis points. Less extreme outliers are addressed as part of the sensitivity analyses presented in section 7. Thus, the final sample is twenty-six firms and 204 firm-year observation representing sixty-four percent of the total TRI emissions of SIC 26 from 1994 through 2005. This sample size is comparable to that of Clarkson, Li and Richardson (2004), particularly given that their sample covers a number of years prior to mine and the rationalisation that occurred in the industry over both sample periods.

Table 1 presents the sample descriptive statistics. Yield spread, total TRI and time to maturity indicate a positively skewed distribution. For yield spread, this is due to more clustering at the lower end, with the higher yield spreads being more spread out. Total TRI is affected by a few very large firms creating a large proportion of the total industry TRI. For instance, in 2005 International Paper released 57.5 million pounds of toxic chemicals, compared to the median of 4.6 million pounds. Time to maturity is affected by a number of bonds in the twenty to thirty year range and tighter clustering around the seven to ten year range. The other variables exhibit minimal skewness, with a relatively small difference between mean and median.

Table 2 presents the Pearson correlations for the sample (Spearman correlations are similar and unreported). Bond rating is also presented for comparison to modified bond rating. The correlations between yield spread and the independent variables in equation (4) are as predicted by the theory and hypotheses discussed previously herein. The orthogonal condition placed between bond rating and the three variables; TRI/US Sales, volatility and Z-score is evident.

6 <u>Results</u>

6.1 Econometric approach

As the data used for this analysis is both time-series and cross-sectional (panel data), I expect that if standard OLS is used, the error term will be a compound one that includes the usual error term as well as fixed and random effects reflecting firm and year specific characteristics that are not sufficiently captured in the model. These specific characteristics may be material with regards to environmental performance. I will take a number of approaches to estimate the model parameters and deal with the error terms from which to make inferences. The main approach uses clustered standard errors (Huber, 1967; Rogers, 1993; Petersen, 2008a, 2008b) based on firm and controls for fixed year effects with a set of year-specific indicator variables. Clustered standard errors are also known as Rogers standard errors and are White (1984) standard errors corrected for within cluster correlation. The parameter estimates will be identical to OLS, but the standard errors will be larger. Clustering by firm is described as one-dimensional clustering in Petersen (2008a, 2008b). As the pulp and paper industry has gone through significant changes over the twelve year time-series, the year-specific indicator should address this second dimension of correlation. This is one of the methods suggested by Petersen (2008b) as a way to deal with two cross-sections of correlated error-terms. In the panel data setting used, this is a relatively conservative approach to making inferences. Other approaches are also presented for comparison; including OLS, two-way fixed-effects, random effects (FGLS), between group estimation, Fama-MacBeth and annual regression methods.

6.2 Bond rating as dependent variable

I follow the method as described above to run equation (2), clustering by firm to address correlation in the residuals due to re-sampling the same firms over a number of years and using year-specific indicators to address year-specific fixed effects. The resulting parameter estimates and related statistics are presented in table 3, panel A. The parameter estimate for environmental performance is significant (p-value = 0.0373, one-tailed) and large enough to be economically relevant. It indicates that the market assesses a rating change of 0.30 for each pound of toxic chemicals released per $1,000 U.S. sales, based on the 22 point bond scale used. The results for Z-score and volatility also indicate they affect bond rating as predicted in Equation (2). The parameter estimate for Z-score is negative 1.25 and significant at the 1% level. The impact of volatility is also significant at the 1% level and similar in economic relevance.

To present another method of estimation meant to address panel data situations, I take a two-way fixed effects approach. This approach simply includes a set of firm and year indicators. This takes up a number of degrees of freedom and will greatly increase the R-squared of the model (as is expected when 25 firm and 11 year indicators enter the model). Table 3; panel B, presents the results of running equation (2) in this way. An F-test indicates that fixed effects are present. The parameter estimate for the environmental performance variable is again statistically and economically significant. However, the parameter is lower, at a rating change of 0.23 for each pound of toxic release per $1,000 of U.S. Sales. This might be a result of the lower power of the regression with the added independent variables. The R-squared, at ninety-five percent, is much larger, as predicted.

Taking into account firm and year effects results in marginal significance for Z-score, with a parameter of just -0.14 compared to -1.25 when using a clustering approach and a p-value of 0.0991. The Z-score variable is meant to capture firm-specific characteristics. Thus, it is not surprising that Z-score becomes marginal in a model that includes firm indicator variables. Volatility is significant at the greater than 1% level; however, its magnitude is reduced to 3.28 compared to 22.28 when clustering by firm. As volatility is included in the model partly to address the systematic time-series changes in volatility documented by Campbell and Taksler (2003), this result is also plausible.

To clearly demonstrate how clustering is a method of efficiency gain, I also run equation (2) using standard OLS regression, except that I continue to control for fixed year effects with the set of year-specific indicators. Table 3; panel C, presents the OLS results, with year fixed effects. The parameters of panel C are identical to panel A. However, the significance levels are much higher when the standard errors are not corrected for correlation in the residuals. This clearly shows that the main approach, based on clustered (or Rogers) standard errors is a more conservative approach and results in more reliable inferences.

For another approach to estimation I look to Clarkson, Li and Richardson (2004). They use an estimated GLS approach as their main technique in addressing their sample of unbalanced panel data. Taking the same approach with this sample provides results that are consistent with those already presented. However, based on a Hausman Test (Hausman [1978]), the random effects a GLS approach is meant to address are highly correlated with the regressors. This indicates that an estimated GLS should not be used for equation (3) as it yields biased and inconsistent parameter estimates.

The overall results of table 3 provide strong evidence that a firm's bond rating is affected by environmental performance, supporting H1. With the results of estimating equation (2) in hand, I move on to the main hypothesis, modelled in equation (4).

6.3 Yield spread as dependent variable

Using the same approach as with the bond rating model, I start by running equation (4) clustering by firm to address within firm correlation in the residuals and year-specific indicators to pick up year fixed effects. The results presented in table 4; panel A, reject the null hypothesis of no association between environmental performance and yield spread at conventional levels. This supports the prediction of H2. The parameter estimate implies a 17.13 basis point 'environmental risk' premium for each pound of TRI per $1,000 of U.S. sales. All of the other variables behave as expected. Z-Score and volatility are incrementally significant to the modified bond rating, which is consistent with the orthogonal condition imposed to create the modified bond rating. It is interesting to note that the bond rating variable and volatility are similar in their affect on yield spread. This is remarkably consistent with the findings of Campbell and Taksler (2003), who also find that volatility explains as much about cross-sectional variations in bond yield as bond rating does. The usual association between maturity and yield spread is significant, indicating that firm and year effects have adequately been controlled. It is interesting to note that the strongest year effects are found in the years 2004 and 2005. These two year indicators are positive and significant at the ten percent and five percent level, respectively. This may by indicative of the merger and acquisition activity that took place in the industry over the sample period. By these years, many of the weaker firms have dropped out of the sample and in 2005 one of the largest sample firms, Georgia Pacific, is taken private.

A Hausman Test indicates that a two-way random effects model is appropriate for this setting. Thus, I use estimated GLS, based on Wansbeek and Kapteyn (1989), as another method of testing H2. Table 4; panel B, presents the results of a two-way random effects approach for making inferences based on equation (4). Again, the results are highly significant with a coefficient of 21.20 basis points, or an average 'environmental risk' premium of 46.64 basis points. The control variables continue to be significant, consistent with the discussion presented above.

For comparison purposes, I also run standard OLS with White's standard errors. Table 4; panel C, presents the results with year-specific indicator variables. Again, the under-stated error-term is evident with the stronger results compared to clustering. Two-way fixed effects results are similar to those already presented.

6.4 Time-series average, annual regressions and Fama-MacBeth

As a way to try and eliminate time-series problems, I take the time-series average of the independent and dependent variables for each firm that enters the sample. I used each average as a single observation in a classical OLS regression (a 'between-groups' estimator). This reduces the sample size from 204 to 26. This setting will indicate whether a better long-term average environmental performance will result in lower average yield spreads. The results are presented in table 5. Again, the main result holds, indicating a yield spread of 31.43 basis points for each pound of toxic chemicals released per $1,000 in U.S. sales (p-value = 0.0062).

I also run a series of annual regressions. The parameter estimates for environmental performance in each annual regression are presented in table 6. In seven of the twelve years, the parameter estimate for the environmental performance variable is significant at the 10% or greater level. The years of significance are in two groups, 1995-1998 and 2003-2005. In the years between 1998 and 2003 a great deal of consolidation occurred in the pulp and paper business. In those years there is a great deal of noise in the data. The data gathering methodology is such that all of an acquired firm's TRI was added to the new parent's total TRI for the entire year of the acquisition. This may not have coincided perfectly with the attribution of the sales from the acquired company. This potential measurement error works against H2. With small annual sample sizes, noise that is acceptable in a larger sample may show up and result in insignificant estimates for the years in which mergers and acquisition are more prevalent.

With a set of annual cross-sectional regressions, the next logical approach is to use that of Fama and MacBeth (1973). However, the issue of possible noise in the years with more mergers and acquisitions is one to which this method is also sensitive. The results based on Fama and MacBeth (1973) are presented in table 7. Taking the time-series average of the annual parameter estimates for the environmental performance variable results in a parameter estimate of 18.10 basis points. I then use the standard deviation of the annual slopes to calculate the t-value for making inferences. With a standard deviation of 21.38 basis points, the t-value is less than 1.00, clearly making the estimate statistically insignificant. The years 1999-2002 are very much driving the deviations of the annual slopes.

This is consistent with greater noise being in the data those years. It is also consistent with the possibility that the association between environmental performance and yield spread is not strong enough to infer that a relation exists. However, it is interesting to note that the variable Aaa spread also becomes insignificant in the Fama-MacBeth approach. As previously described herein, Aaa spread is the difference between a Moody's rated Aaa bond yield and the yield of a ten year treasury bond. Like environmental performance, the annual slopes show too much variance from year to year, which works against finding results using Fama-MacBeth.

The Fama-MacBeth approach should also be adjusted for serial correlation. For instance, in Fama and French (2002), an AR(1) process with a correlation of 0.75 is assumed. They take a somewhat informal approach to addressing this by increasing the required t-stat by a factor of 2.5. Thus, the required t-stat for significance at the five percent level is approximately 5.00 (two-tailed). The highest t-stat in the results presented in table 7 is the t-stat for modified bond rating, at 1.85. Thus, any adjustment for serial correlation may serve to make inferences for all parameters in the model insignificant.

7 Sensitivity analysis

7.1 Alternate specification

To address the possibility that equation (4) is not well specified, I look to a setting that uses other control variables. The model presented in equation (4) is used so as to be as parsimonious as possible with the specification. As parsimony is the stated objective, I am using a non-nested test, rather than a 'kitchen sink' approach to test whether equation (4) is appropriate.[15] The alternate model is based on a survey of the literature using the cost of debt as a dependent variable. The papers include: Sengupta (1998), Campbell and Taksler (2003), Ortiz-Molina (2006), Vasvari (2006), and Sengupta and Wang (2006). The objective is to create an alternate (non-nested) specification that does not include bond rating and Z-Score. This specification is as follows:

$$\begin{aligned}\text{Yield Spread} = \quad & \alpha_0 + \alpha_1\text{TRI/US Sales} + \alpha_2\text{Leverage} + \alpha_3\text{Coverage} + \\ & \alpha_4\text{Current} + \alpha_5\text{Volatility} + \alpha_6\text{Size} + \varepsilon \qquad (5)\end{aligned}$$

The predicted signs are $\alpha_1 > 0$, $\alpha_2 > 0$, $\alpha_3 < 0$, $\alpha_4 < 0$, $\alpha_5 > 0$ and $\alpha_6 < 0$; where leverage is defined as total debt divided by total assets, coverage is defined as earnings before interest and taxes divided by interest expense, current is current assets minus current liabilities then scaled by total assets (X1 from the Z-score), volatility is as defined previously, and size is the total market value of equity.[16] For reference table 8 presents the Pearson correlation matrix for the variables in the main model, equation (4), and those

[15] I also run a model using the 'kitchen sink' approach with all variables from both equations (4) and (5). The main results remain unchanged. I also run a version of both models including asset newness (total assets over undepreciated total assets). This is meant to control for the possibility that the results are simply related to the firms that have most recently made capital expenditures. The main results remain unchanged.

[16] I also run a regression with the log of the book value of total assets as a measure of size as opposed to market value, with similar results.

in the alternate model, equation (5). Leverage, interest coverage, current ratio and size are all correlated with bond rating and Z-score as expected. This supports the use of a bond rating variable and Z-score in equation (4) to capture the affects of these variables on yield spread. With regards to yield spread; leverage, interest coverage and size are correlated as expected; however, the current ratio is not significantly correlated with yield spread.

Table 9; panel A, presents the regression results for equation (5), based on standard errors clustered by firm and using year fixed effects. The results continue to support the hypothesized relationship between environmental performance and the cost of debt. The parameter estimate for the environmental performance variable is 18.99 with a p-value of 0.004. Table 9; panel B, presents the results using estimated GLS. Results are similar.

To establish whether equation (4) or equation (5) is the most appropriate, I apply the Davidson and MacKinnon non-nested J test.[17] I run the following regressions:

$$\begin{aligned}\text{Yield Spread} = \quad & \alpha_0 + \alpha_1\text{TRI/US Sales} + \alpha_2\text{ Modified Bond Rating} + \alpha_3\text{Z-Score} \\ & + \alpha_4\text{Volatility} + \alpha_5\text{Maturity} + \alpha_6\text{AaaSpread} + \\ & \beta_1\text{Predicted Value of Eq'n (5)} + \varepsilon \qquad \text{(4a)}\end{aligned}$$

$$\begin{aligned}\text{Yield Spread} = \quad & \alpha_0 + \alpha_1\text{TRI/US Sales} + \alpha_2\text{Leverage} + \alpha_3\text{Coverage} + \alpha_4\text{Current} \\ & + \alpha_5\text{Volatility} + \alpha_6\text{Size} + \beta_2\text{Predicted Value of Eq'n (4)} + \varepsilon \qquad \text{(5a)}\end{aligned}$$

[17] See Greene 2003, p. 155.

If $\beta_1 = 0$ and $\beta_2 \neq 0$, then equation (4) is a more appropriate model. If $\beta_1 \neq 0$ and $\beta_2 = 0$, then equation (5) is a more appropriate model. If a model's predicted value provides explanatory power when included in a competing model while the competing model's predicted value does not do the same in reverse, the given model is a better specification. In other words, the given model provides all of the explanatory power of the competing model, and then some. The results are presented in table 10. The regression results are such that $\beta_1 = 0.323$, with p-value 0.1553 and $\beta_2 = 1.00$, with p-value < 0.0001. Thus, based on the Davidson MacKinnon J test, I can conclude that equation (4) is a better specification than equation (5).

7.2 Outliers

As discussed in the sample selection process presented in section 5, one outlier was eliminated from all analyses due to an extremely high yield spread of over 1,200 basis points and a Cook's D of 1.137. Chen et al. (2003) suggest that the conventional level of Cook's D is 4/N. I take two approaches to this. As Chen at al. (2003) are not discussing panel data, my first approach is to calculate the cut-off level based on the number of sample firms. This is consistent with the principle approach of clustering based on firm. The resulting cut-off point for each observation-wise statistic is then 4/26 or 0.154. No observation used in the full sample result in a Cook's D greater than 0.154 and thus, the main results hold as already presented. However, based on the total number of 204 firm-year observations, the cut-off point is 4/204 of 0.020. Observation-wise analysis identifies fourteen firm-year observations with Cook's Ds greater than 0.020.

Table 11 presents the results of running equation (4) after eliminating the fourteen identified outliers based on the 0.020 Cook's D cut-off point. The results are similar to those presented using the full sample, except that they are more statistically significant. Thus, I conclude that the main results are not being driven by outliers.

7.3 Bond-specific features

To further refine equation (4), I also explore a version which includes some of the bond specific characteristics. Vasvari (2006) uses a covenant index, which is the sum of all covenants attached to each specific bond. My data source for covenants is Mergent FISD, which records the covenants for most, but not all, bonds in the sample. Including the covenant index in the regression reduces the sample size to 188 firm-years. None of the bonds in the sample are putable and only sixteen are not senior, but ninety-five of the 204 bond observations are callable. I run equation (4) including the covenant index and the callable indicator separately and also with them both in the same regression. As a call option is a benefit to the lender, I expect it to be priced into the bond yield and a positive co-efficient is expected for the callable bond feature. For the covenant index, I expect a negative co-efficient as covenants are designed to favour the bond holder. The results are presented in Table 12.

The results are not significant at any level for the call or covenant index variables. The covenant index can be explained by a very high degree of correlation between the modified bond rating and covenant index. The Pearson correlation co-efficient between the modified bond rating variable and the covenant index is 0.55. A bond rating is meant to measure both firm and bond characteristics and it appears to be doing this here. More covenants are also associated with weaker firms, which would lead to a high degree of correlation between a poorer bond rating and the number of covenants attached to the bond. The results for the call feature might indicate that the higher cash flows that are typically required for callable bonds outweigh the negative aspect of the call. Regardless, the main results hold in all settings.

7.4 Non-pulp and paper operating segments

The proxy for environmental performance is each firm's total toxic release inventory scaled by domestic sales, based on location of seller. A possible problem with this scaling may arise due to the number of firms operating in more than just the pulp and paper segment. Although non-U.S. sales are eliminated from the denominator, domestic sales from non pulp and paper segments are not.

As a first approach to adjust for non pulp and paper operating segments, I scale TRI by each firm's pulp and paper sales only. As this is from firms' own reports of operating segments, it will be somewhat imprecise, as firms' methods of reporting segment sales change over time and differ between each other. This denominator will also pick up non U.S. sales of pulp and paper. The results of replacing TRI scaled by U.S. sales with this new environmental performance proxy are presented in table 13, panel A. The regression results of scaling by firm wide pulp and paper sales indicate a smaller parameter estimate on the environmental performance variable. In table 13; panel A, the parameter estimate for environmental performance is 8.58 basis points. In panel B, using FGLS, the parameter estimate is 12.88 basis points. The two estimates are significant at the less than ten percent and five percent levels respectively.

I also run a regression with the percentage of a firm's total sales that are not pulp and paper sales used as a control variable (non-pulp and paper sales divided by total sales). These results are presented in table 13, panel C. Including the percentage of total sales that are non-pulp and paper as a control variable has no effect on the results.

As a final approach to control for non-pulp and paper operations, I divide the sample into two groups based on the median level of non-pulp and paper sales. An indicator variable, High Non-P&P, is then assigned to firms above the median, with a '0' assigned to those below the median. I then interact the TRI/US Sales variable with the indicator variable (TRI/US Sales*High Non-P&P) and include the indicator and interaction variable in equation (4). I expect that firms with more non-pulp and paper sales will be less exposed to the cluster rules and that the interaction variable will have a moderating effect on the environmental performance variable (TRI/US Sales) and that the parameter estimate will be negative. The results are presented in table 13, panel D. The parameter estimate for TRI/US Sales*High Non-P&P is negative as predicted, however it is not significant at any conventional level. For an F-test to check the joint significance of adding the parameter estimates for TRI/US Sales and the interaction variable (H_0: $\alpha_1 + \alpha_8 = 0$) I run the model using two-way random effects (FGLS). The results indicate that the combined parameter estimates are statistically significant and that the moderating effect of parsing out the firms with high non-pulp and paper sales does not affect the results.

7.5 Non-U.S. segments

Firms that have a higher percentage of non-U.S. sales may face less exposure to the cluster rules and they face a less stringent overall environmental regime. This would be particularly true with respect to private litigation, either by individuals or environmental groups. For instance, compared to Canada, the U.S. is a much more litigious society. The U.S. is also much more populous, thus TRI releases are likely to affect a much larger population base. Thus, with the specific mandate of the cluster rules and a more litigious 'tradition' in the United States, I expect that firms with more operations outside the U.S. will have less overall exposure to U.S. domestic issues and that the U.S. based environmental performance proxy (TRI/US Sales) will be less significant. It could also be argued that the diversification of firms with operations outside the U.S. essentially 'dilutes' the effect of TRI.

To address this, I take the same approach as just previously presented herein for non-pulp and paper operations. I divide the sample firms up based on median non-U.S. sales and assign an indicator variable (High non-US) of '1' to firms above the median and '0' for those below the median. I then create an interaction variable using the indicator variable (High non-US) and the environmental performance measure (TRI/US Sales). I expect that the parameter estimate of the interaction variable (TRI/US Sales*High non-US) will be negative, supporting the expectation that less exposure to the U.S. cluster rules and overall U.S. environmental pressures mitigates the effect of U.S. based environmental performance.

The results are presented in table 14. The parameter estimate for the interaction variable (TRI/US Sales*High non-US) is negative and significant at the five percent level (α_8 = –18.50, p-value = 0.0489). As in the previous section, for an F-test to check the joint significance of adding the parameter estimates for TRI/US Sales and the interaction variable (H_0: $\alpha_1 + \alpha_8 = 0$) I run the model using two-way random effects (FGLS). The results indicate that the combined parameter estimates are statistically significant. Thus, the effect of parsing out the firms with high non-U.S. sales indicates that firms with more internationally diversified operations are less exposed to their environmental performance in the U.S. as compared to firms with all, or most, of their operations in the U.S. However, their cost of debt is still significantly affected by their environmental performance in the U.S.

Another possible aspect of a firm's geographic operations that might affect its environmental performance is the state (within the United States) in which its operations are located. Some states (i.e. California) have stronger state-based enforcement of environmental laws and regulations. I run equation (4) clustering in two dimensions, by firm and by state and controlling for year-effects with year indicators. The main results (unreported) remain similar to those already presented. However, this regression is based on the state in which the sample firms are incorporated, which may be different from where its operating facilities are. To address this, some sort of control must be developed to reflect the actual states in which operations occur. I do not develop such a control variable and the relation between environmental performance and the state in which its operations are located remains an open question (and also the way in which that relation might affect yield spread). Regardless, the data I am using is from the U.S. EPA, which is a national agency and is mandated to enforce its rules equally throughout the U.S. Thus, I expect that any state-based results would be incremental to the main results already presented herein.

7.6 Changes

A changes model will result in less power, but serves as an excellent control for correlation in the residuals. Taking first differences creates much more independence in the time-series data. It also serves to address the potential problem of omitted variables. Thus, OLS is an appropriate method to use in a changes model, as long as heteroscedasticity is controlled for by using White's standard errors.

The process of generating data for a changes model is less than straight-forward. This is because of the thinness of the trading data for the bond market. For each given bond in the sample I need to find a trade of the same bond in the previous year. Thus, I am trying to find a match for the firm's specific bond trade from year *t*, in year *t–1*. For many of the bond trades, a trade of the same bond in the previous year is not available on the Mergent FISD database. If a trade in the previous year cannot be found, I look to the firm's bond trade in year *t–1* and try to find a matching trade in year *t*. The yield spreads are then calculated as described in section 4.2. The final changes sample includes 165 paired bond trades. They are not perfectly matched with regards to time to maturity. The difference in time between the two bond trade observations ranges from about six to eighteen months. This range is the result of the matching bond trades occurring at any time in the matching year as opposed to occurring exactly one year apart. Bond trades that occur closer to six months apart will work against finding results in the changes model.

The change in environmental performance (TRI/US Sales) represents the difference between two adjacent calendar year's environmental performance variable. The corresponding change variables are calculated based either on the year-end or on the time of the corresponding bond trade. For the bond rating of the matching bond, I pick up the most recent bond rating prior to the trade of the matching bond trade date. I then run equation (2a) to get the matching modified bond rating. I calculate the matching volatility and the Moody's Aaa yield spread based on the matching bond trade date and the Z-Score is based on the fiscal year. All matching data is used for first differencing against the data from the sample year. Thus, the changes model is:

$$\begin{aligned} \Delta\text{Yield Spread}_{it} = {} & \alpha_0 + \alpha_1\Delta\text{TRI/U.S. Sales}_{it} + \alpha_2\Delta\text{Modified Bond Rating}_{it} + \\ & \alpha_3\Delta\text{Z-Score}_{it} + \alpha_4\Delta\text{Volatility}_{it} + \alpha_5\Delta\text{Maturity}_{it} + \\ & \alpha_6\Delta\text{Aaa Spread}_{it} + \varepsilon \end{aligned} \tag{6}$$

Table 15 presents the OLS regression results for equation (6). The parameter estimate for change in TRI/U.S. Sales is 13.01 basis points for each pound of change in toxic releases per thousand dollars of U.S. sales. The estimate is significant at the less than 10% level (p-value = 0.0843). Although this level of significance is marginal, the changes setting is one that has lower power and the sample size is small. Thus, these results continue to provide evidence inferring that H2 is true and that there is a significant relation between a firm's cost of debt and its environmental performance.

7.7 Duration

Years to maturity and Aaa spread are included in the model partly to control for bond specific and market wide liquidity. Another possible control for liquidity is duration. Duration puts a heavier weight on cash flows that come earlier in the bonds life. The closer in time that a bond's cash flow will occur, the more liquid the bond, as it is less sensitive to longer-term interest rate risk. All of the bonds used in this study pay regular coupons, with higher coupon paying bonds having relatively shorter durations. Non-coupon paying bonds would have durations that are equal to their maturity. However, with coupon paying bonds, duration will be less than maturity. The concept of duration was first introduced by economist Frederick Macauley in his 1938 book, "Some theoretical problems suggested by the movements of interest rates, bond yields & stock prices in the United States since 1856". The results are presented in table 16. Duration performs in a similar way to maturity, being positively associated with yield spread. The main result, the parameter estimate for environmental performance, is unaffected.[18]

[18] As a further control for liquidity I also include the issue size of each particular bond in the model, with insignificant results for issue size and no change to the main results.

7.8 Bond Rating

Graham and Maher (2006) hypothesise that their various measures of Superfund site related liabilities will have an effect on the cost of debt over and above that impounded in a firm's bond rating. As discussed in section 3.2, the main variable of interest that Graham and Maher use is the number of times a firm has been named as a Potentially Responsible Party (PRP) at U.S. EPA Superfund sites. When they include their PRP measure in a cost of debt regression, it is a significant variable. However, when Graham and Maher include bond rating and their Superfund liability variable in the same regression, their Superfund liability variable is no longer significant. Graham and Maher conclude that bond rating adequately captures these liabilities.

Using the EPA's TRI data rather than the Superfund data, I am capturing a contemporaneous measure of environmental performance. Over the twelve year sample period, the bond ratings are updated only once every few years. Thus, although the rating agencies clearly state that they incorporate environmental performance into their ratings (i.e. Standard and Poor's, 2006: pp. 24, 32, 33, 51, 67, 113 and 126) and the results of equation (2) show that this is likely true, 'stale' bond ratings may not perfectly incorporate current-year environmental performance. To explore whether this may be the case, I run equation (4) replacing the modified bond rating variable with the actual bond rating, converted as previously described herein, to a scale of one to twenty-two where AAA+ = 1, AAA = 2....CCC– = 21, D = 22.

The results are presented in table 17, panel A. The results indicate that the proxy for environmental performance provides information beyond that already impounded in bond rating. The results are significant at the ten percent level and still remain economically significant (6.73 basis points, p-value= 0.0865). It is interesting to note that Z-score is completely subsumed by the bond rating variable (p-value = 0.2584). Z-score and the underlying variables that make up Z-score are likely well known to bond raters; whereas, bond raters may not be as keenly aware of environmental performance in a given year (or consider that it warrants a change of bond rating). With regards to Graham and Maher (2006) and bond rating subsuming their proxy for Superfund related liabilities, the time-lag between a firm's act of polluting and the time at which it is taken to task may be relevant.

There is now a long history around Superfund sites and a firm will be listed as a potentially responsible party (PRP) for many years in a row for the same site. This makes it a much more straight-forward liability for a bond rater to consider. However, the toxic release inventory measure used herein is a measure of a firm's toxic chemical releases concurrent to the financial statement information used in the model, and within approximately six months of the bond trade information used in the model. This leaves much less time for a bond rating to be changed in reaction to a firm's environmental performance. Thus, Superfund related liabilities and those related to current environmental performance may be unrelated when it comes to cost of debt. This will be addressed in more detail in a following section.

In Campbell and Taksler (2003), it is noted that trades by the National Association of Insurance Companies (NAIC) may be affected by the difference in reserve ratio requirements for insurance companies when they trade in non-investment grade (junk) bonds. When a bond rating goes from BBB– to BB+, the reserve ratio requirement goes from one percent to five percent (Campbell and Taksler, 2003, p. 2326). As discussed in section 4.2, the bond trades in the sample used herein are all NAIC trades for the period from 1994 through 2003. In 2004 and 2005, the trades are from the Trade Reporting and Compliance Engine (TRACE), which captures a much larger portion of the bond market, but still includes many NAIC trades. To control for the possible non-linear effect on yield spread as a bond approaches non-investment grade, I use a logarithmic transformation of the bond rating.

However, as the current numerical scaling used has a lower number associated with a better bond rating (AAA+ = 1, AAA = 2) I reverse the order, with D = 1, CCC– = 2..... AAA = 21 AAA+ = 22. Taking the log of this reversed bond scale will result in a greater spread between each change in bond rating as it approaches non-investment grade (junk) and beyond. I use this log of the reversed bond scale in equation (4), with the results presented in Table 17, panel B. The log of the reversed bond scale is significant at the five percent level, but is not as strong a variable as the linear bond scale used previously. However, the environmental performance measure picks up more economic significance and is more statistically significant than the log version of the bond scale. Although this provides stronger support for H2, using Equation (4) with the actual bond scale as opposed to the log may be a better specification.

As a final step to address the possible non-linear break between investment and non-investment grade bonds, I divide my sample into two groups. One consists of all firm-year observations in which the bond traded was of investment grade (BBB– or better), the other consists of non-investment grade bonds (BB+ or worse). I run regressions using equation (4) for both groups separately. Campbell and Taksler (2003) use only investment grade bonds in their sample, thus the reduced sample based on investment grade bonds only, is consistent with their approach. The results are presented in Table 18, panels A and B. The breaking up of the sample greatly reduces the sample size, making inferences somewhat more tenuous. The investment grade bond sub-sample consists of 156 firm-year observations and 21 firms. The non-investment grade bond sub-sample consists of 48 firm-year observations and 11 firms.

The results for the investment grade bond sub-sample indicate that environmental performance affects yield spread for this group. The parameter estimate is economically significant at 7.93 basis points and significant at the ten percent level ($p = 0.0754$). Again, given the small sample size, this continues to support the assertion of H2, that environmental performance affects yield spread. The results of the non-investment grade sample are interesting in that the only variable that retains any significance is the Z-score. With such a small sample it is difficult to come to any conclusions, but it is not surprising that once a bond reaches non-investment, or junk, status the yield spread is dominated by the underlying variables in the Z-score.

7.9 PRP versus TRI as a measure of environmental performance

When a pollution measure is based on TRI its purpose is to measure some form of environmental performance (i.e. Klassen, 2001; Clarkson, Li and Richardson, 2004; Al-Tuwarji et al., 2004). This measure is meant to be a function of a firm's current activities. The Superfund related literature discussed in section 3.1 characterises the Superfund site related measures as ones that measure part of a firm's environmental liabilities (i.e. Barth and McNichols, 1994; Graham and Maher, 2006). The most significant measure used is the number of times a firm is named as a potentially responsible party, or PRP. I am unaware of any cases in which TRI and PRP have been used in the same model. It is possible that these two measures are proxies for the same thing.

However, there are many reasons to believe that this is not the case, particularly with regards to the pulp and paper industry. Most PRPs are named on sites which are related to soil and groundwater contamination. Of the 1,156 Superfund sites studied in Barth and McNichols (1994, p.189) only twelve were related to waterways or creeks. Barth and McNichols also list the most predominate industries in their sample. SIC 26, paper and allied products, is not one of them. In the pulp and paper industry most of the pollution is either sent up the smokestack or down the river. For example, in 2000 the total TRI for SIC 26, paper and allied products; was 253 million pounds. Of that, 205 million pounds were released to the air, 22 million pounds were released to surface water, 17 million pounds were disposed of on land and the remaining 8 million pounds were sent off-site. A review of industry 10-Ks indicates that with only a couple exceptions, the PRPs in the pulp and paper industry are related to landfill sites as opposed to air and water emissions. This might be a reason why the cluster rules have been specifically developed to address air and water pollution.

Another reason to conclude that the TRI and PRP measures are different is the time-lag between when a firm's activities lead to site contamination and when it is named as a PRP. For example, Wausau Paper is related to only one remediation site (and only at the State level), which is a landfill. The contamination at the site goes back to pre-1986 and remains unresolved in 2005. Another example is Domtar, which is a PRP at a number of sites, as reported in its annual reports from 2000 to 2005. It states in each year's annual report that these sites relate to their wood-preserving business, which was divested in 1993. An extreme example is Union Camp Corporation, which reported in 1995 that it might be responsible for part of a $35 million clean-up at a Superfund site in Louisiana. The site had been in operation from 1882 to 1972. American Creosoting operated on the site from 1933 to 1958. Union Camp bought the assets of American Creosoting in 1956 and sold them in 1962. In March 1996, Union Camp was named a PRP on the site.

In the sample firms' 10-Ks, environmental costs due to the cluster rules are typically described as material. However, all but one firm claim that liabilities related to Superfund sites are immaterial. The cluster rules relate to air and water quality and are discussed by all firms in the years from 1994 through the late nineties and beyond, as the rules were first introduced. For example, in 2001 Westvaco reported that it had made expenditures of $110 million to comply with cluster rule regulations and expected to have to make a further $70 million of expenditures in the coming years. It also reports that it is named as a PRP at a number of environmental waste sites and that it has accrued $5 million dollars to cover its share of anticipated clean-up costs. Willamette Industries is not named as a PRP in any year, but estimated that compliance with the cluster rules will require $120 million in capital expenditures.

As a final point, it should be noted that the Superfund based studies are top-down, multi-industry studies. This may create a selection and survivorship bias. Barth and McNichols (1994) create their sample through searching on *Nexis*. This may result in larger firms being picked up in the sample and many smaller PRPs not being included in the sample. Graham and Maher (2006) use new bond issuers from March 1, 1995 to February 28, 1998. This may also pick up only large firms. The results of Graham and Maher (2006) show that a PRP designation leads to a higher yield spread for firms issuing new debt. Graham and Maher start with the list of 36,429 PRPs listed on the U.S. EPA database for the period of their sample (1995-1998). After matching this to firms issuing new debt over this period and to firms with the required Compustat data, the final sample represents 357 new bond issues.

The one industry sample that I use in this study, captures as much of a single industry as is possible given the data limitations. Of the pollutants released over the twelve year sample period, I capture more than sixty percent of the total releases in the industry. The sample period represents a time over which significant consolidation occurred in the pulp and paper industry. I expect that as weaker firms are acquired, the stronger firms will increase the number of times that they are named as PRPs. When International Paper took over Union Camp in 1999, it also took over as PRP on the Superfund sites related to Union Camp. Thus, it is possible that in a one industry, longitudinal study a higher incidence of being named as PRP may indicate that the firm is more financially sound. This would be reflected in a firm's cost of debt. The pulp and paper sample used in this paper picks up a time-series in a single industry. Over the sample period, there is much consolidation. As a polluting industry consolidates, the stronger firms will absorb the weaker ones. However, they will also absorb the PRP designations.

To investigate this, I review the 10-Ks of all of the sample firms from 1994 to 2005. It is a requirement that firms state whether or not they are involved at a Superfund site as a PRP under legal proceedings. There is also typically a subsequent note to the financial statements stating the amount accrued relating to these sites and a statement as to whether the impact will be material. Of the 204 firm-years reviewed, the number of times that a firm is named as a PRP is given 130 times by eighteen different firms. This includes 58 firm-years in which a sample firm is not named as a PRP. In the remaining 74 firm-years, the number of times a firm is named as a PRP is characterised by one of four descriptive words. The firms describe themselves as being named as PRPs at several, various, a number of, or numerous Superfund sites. Some firms change from presenting an actual number to a description, over the sample period, and vice versa. For example, in 1997 Weyerhaeuser states that it is named as a PRP at 43 sites; then from 1998 to 2001 it states that it is named as a PRP at numerous sites. In 2002 and beyond, it switches back to presenting a specific number (79 sites).

Including this data in the main model (equation 4) would provide evidence as to whether there is a strong survivorship bias in a multi-year, one industry study with regards to Superfund sites. I utilise the data in two ways. The first is to include only the firms that specifically state the number of sites at which they are PRPs. The second is based on an estimate of the number of times a firm is named as a PRP for those firms that do not specifically report it. The estimated number of times a firm is named as a PRP is based first on adjacent years, if the firm reports the actual number in adjacent years. Firms that do not report the specifics will use certain words to describe the number of times they are named as a PRP. Thus, when no adjacent data exists I convert the following descriptive words to a number as follows: numerous = 50, a number = 20 and several = 10. The firm-year data is presented in Table 19.

How to scale the PRP data is again a question, as scaling was a question when dealing with the TRI data in the discussion presented in section 4.3. Barth and McNichols (1994) use a market value of equity model and scale all of their variables by the number of shares outstanding to control for heteroscedasticity. Graham and Maher scale their PRP measure by total assets in their cost of debt model. I have been scaling the TRI based measure by U.S. sales as previously described herein. As equation (4) is a cost of debt model and not a market value of equity model, I scale the PRP number by total assets, to be consistent with Graham and Maher and also by U.S. Sales, to be consistent with this study.

The Pearson correlations between the number of times a firm is named as a PRP (without any scaling) and the same number scaled by total assets and U.S. sales are presented in table 20. I also present the scaled data, using the larger sample from the estimated times a firm is named as a PRP, in table 20. Significantly negative correlations exist between the scaled PRP measures and yield spread, TRI/U.S. Sales and bond rating. There is also a very strong relation between the number of times a firm is named as a PRP and firm size (market value of equity). A significant correlation also exists between size and PRP scaled by U.S. sales. These univariate associations support the position that industry survivors will pick up PRP designations as a polluting industry consolidates.

Including the respective PRP measures in equation (4) results in the following model:

$$\begin{aligned}\text{Yield Spread} = \quad & \alpha_0 + \alpha_1\text{TRI/US Sales} + \alpha_2 \text{ Modified Bond Rating} + \alpha_3\text{Z-Score} + \\ & \alpha_4\text{Volatility} + \alpha_5\text{Maturity} + \alpha_6\text{AaaSpread} + \alpha_7\text{PRP/Total Assets (US Sales)} \\ & \text{or } \alpha_7\text{PRPest/Total Assets (US Sales)} + \varepsilon \qquad (7)\end{aligned}$$

The predicted signs are $\alpha_1 > 0$, $\alpha_2 > 0$, $\alpha_3 < 0$, $\alpha_4 > 0$, $\alpha_5 = ?$, $\alpha_6 > 0$ and $\alpha_7 = ?$.

The variables for α_1 through α_6 are as described in section 4. PRP/Total Assets (US Sales) is the number of times a firm reports itself as being named a PRP, scaled by total assets (U.S. sales); PRPest/Total Assets (US Sales) uses the actual number reported and an estimate for years where specific numbers are not reported, scaled by total assets (U.S. sales). The results for the PRP measures scaled by total assets are presented in table 21, panels A and B. The results when PRP is scaled by U.S. sales are similar. In all cases, the sign on the PRP variable is negative; however it is insignificant at conventional levels. If a negative parameter estimate is predicted and one-tailed test is used, the parameter estimates presented are significantly less than zero at the ten percent level. Thus, if the results are to indicate anything, they indicate that in the pulp and paper industry, carrying more PRP related liabilities is typical of the surviving firms in the industry.

The environmental performance variable (TRI/US Sales), when in the same regression as the PRP variables, is of a reduced magnitude but remains significant at the less than five percent level. Thus, I conclude that the measure of environmental performance based on the TRI is a different measure than the number of times a firm is named as a PRP.

7.10 TRI Lag

As a final sensitivity check, I look to a one year lag of the main environmental performance variable, TRI/US Sales. The first time that the raw TRI becomes available is in the September of the calendar year following the year in which the polluting activity occurred. It is not until March of the second year following the polluting activity that the full detailed data is available on the EPA's TRI database. Thus, in March 2008 the full online TRI data is released for calendar year 2006. The assumption up to this point has been that the market is aware of a firm's environmental performance prior to the release of the TRI data. The results already presented herein are consistent with this assumption. However, whether a firm's yield spread is affected by its environmental performance from the previous year would serve to see if there is a lag effect. Thus, I run equation (4) using the TRI from the previous year. The resulting equation is:

$$\begin{aligned}\text{Yield Spread}_{it} = \quad & \alpha_0 + \alpha_1\text{TRI/US Sales}_{it-1} + \alpha_2 \text{ Modified Bond Rating}_{it} + \\ & \alpha_3\text{Z-Score}_{it} + \alpha_4\text{Volatility}_{it} + \alpha_5\text{Maturity}_{it} \\ & + \alpha_6\text{AaaSpread}_{it} + \varepsilon \qquad (8)\end{aligned}$$

This lag approach also serves to address possible concerns over endogeneity. Relatively better environmental performance may just be a function of other variables that affect the cost of debt. Going back in time by a one-year lag creates a greater degree of separation between the proxy for environmental performance and any potentially related variables. In a given year, a firm that has superior economic performance may also have the ability invest more heavily in environmental technology. The TRI proxy used in equation (4) already has a certain amount of lag, as environmental performance in a given year will be the result of decisions made in years previous. Increasing the lag by another year will result in a proxy for environmental performance that is less related to contemporaneous firm level results. Thus, the lag variable can be characterised as an instrumental variable that is independent of any other variables used (or omitted) in the model.[19]

Table 22 presents the results of equation (8). The results show that the lag measure of environmental performance is also significant (α_1 = 14.46, p-value = 0.0016). This result

[19] As a further method to address potential omitted variables, I create a return on assets indicator variable using X_3 from the Z-score calculation (EBIT/Total Assets). The assumption is that better managers will generate a better return. Firm-years above the median are coded as 1, zero otherwise. Including this indicator variable in equation (4) leaves the original results unchanged.

is similar to that using the TRI from the current year. The Pearson correlation between the TRI/US Sales$_{it-1}$ and the TRI/US Sales$_{it}$ has a correlation of 0.885 (p-value < 0.0001). This high degree of correlation implies that either measure works well as a proxy for environmental performance. However, it is not surprising that there is a high degree of correlation from one year to the next. A twenty percent reduction in TRI, holding sales constant, would be considered a major improvement in environmental performance. Yet this also implies a correlation of 0.8, which is considered a high level of year to year correlation. This may be the reason that the changes model presented in section 7.6 herein has significant results, despite the very high degree of correlation from year to year in the measure of environmental performance.

These results do raise the question as to just how the market picks up on changes and trends in firm level environmental performance. I am using the EPA's TRI data as a proxy for environmental performance. As this information is released to the public in detailed form almost fifteen months after the year-end in which the pollution occurs, the information dynamics must be such that a firm's environmental performance is evident to the public at an earlier point in time. To investigate this, I contacted a senior analyst at Jantzi Research. Jantzi Research is the leading research firm in Canada on social and environmental investing. They also work in concert with KLD Research and Analytics, the leading research firm in the United States in the same area. The analyst stated that they do follow closely the emissions data, particularly trends, but that it is used more as a back-up to more timely firm based research. Thus, if a particular firm is very weak in its reporting, giving very little detail as to its environmental initiatives (i.e. environmental capital expenditures) and overall performance in its own reports, they would expect to see higher emissions reported when the data is released. The opposite would be true if a firm was reporting that it was taking initiatives to improve its performance and reporting that it was cleaning up its emissions. This serves to support the use of the EPA's TRI data as an ex-post measure of environmental performance in a given year, while assuming that the market can pick up on relative environmental performance on a timelier basis.

Overall, the sensitivity analyses presented in section 7 continue to indicate that hypothesis two should not be rejected. Thus, the conclusion that a lower yield spread for lower polluting firms still holds. The fact that the main results still hold using an alternate specification, changes model, controlling for foreign operations, bond characteristics, and so on, provides strong evidence as to the robustness of the results presented herein.

8 Conclusions and Limitations

The results presented in the previous sections provide evidence that higher polluting firms are deemed a riskier investment by the debt market. The main results imply that this risk is priced at a premium of 17.13 basis points in yield spread for each pound of toxic chemicals released per $1,000 U.S. sales (the average sample firm releases 2.2 pounds per $1,000 U.S. sales). This represents a material effect on the cost of debt capital that is consistent with the results found when exploring firm value and environmental liabilities. Given that bond holders and shareholders often have conflicting goals, these results could not be taken as a given before this study was undertaken. Thus, as pervious research has shown that equity holders value relatively superior environmental performance (i.e. Cormier and Magnan, 1997; Clarkson, Li and Richardson, 2004), this study serves to provide evidence that bond holders' and shareholders' interests are aligned when it comes to environmental performance, with relatively better environmental performance seen as a benefit for both types of investors. It also reinforces the use of environmental performance as a measure of management performance. Managers tend to pay attention to the items on which they are measured. If environmental performance is made an important aspect of the way in which managers are judged, it will serve to benefit all investors (and the general public as well).

A potential weakness of this study is that it focuses on one industry and one country. There is now increasingly robust data from which to work. The European Union has begun to report its version of the TRI for firms operating within the EU. Canada and Mexico are also tracking similar data. In 2006, the U.S. Supreme Court struck down an attempt by the Bush administration to rule that CO_2 emissions are not pollutants and thus, could not be tracked by the EPA (as they would then be outside of the EPA's jurisdiction). The EPA can now treat CO_2 as a pollutant and track its release, which will provide an opportunity to include greenhouse gases in measures of environmental performance. Thus, expanding the scope of this study by continually updating the data, including other polluting industries in the sample, and expanding the sample to firms' operations outside the U.S. is a logical next step.

Model specification has been a cause for debate in the environmental accounting and finance literature. This is due to the possibility that a firm's financial performance and environmental performance are jointly determined. There are also latent variables that might be the underlying cause of environmental performance, such as managerial competency and attitude. Thus, it cannot be ruled out that superior environmental performance is simply an artefact of other firm-specific characteristics.

In any case, industry-wide and firm-specific environmental performance is now a mainstream issue. If superior environmental performance is an indicator of other underlying firm characteristics, it is important firm-specific information in which investors will be interested. Given the difficulty in aggregating firms' EPA toxic release inventory data, recent calls for more cooperation between the EPA and the SEC are well founded. The results of this paper indicate that the debt market is capable of aggregating this information; however, it is not readily accessible to the general public on a firm by firm basis. It would take almost no effort for firms to be required to aggregate and report publicly their firm-wide release of polluting chemicals, including CO_2 and related gases. It already has to be reported to the EPA on a facility by facility basis. However, for a concerned citizen or individual investor to do this is an extremely onerous task. Thus, as this information is most likely value-relevant, calls for it to be made public on a firm-wide basis should be heeded by regulators.

Appendix

Appendix A: Yield spread calculation for TRACE transactions

a.	Trade execution date as per TRACE:	May 2, 2005
b.	Maturity Date of the bond as per FISD:	November 11, 2011
c.	Time to maturity of bond (b-a):	6.54 Years
d.	Yield to Maturity of bond as per TRACE:	8.25%
e.	Yield to Maturity of 7 yr. Treasury Bond; May 2, 2005 as per Federal Reserve:	5.03%
f.	Yield to Maturity of 5 yr. Treasury Bond; May 2, 2005 as per Federal Reserve:	4.98 %
g.	Weight of 7 year bond ([6.54 years-5 years] over 2 years):	0.77
h.	Weight of 5 year bond ([7 years-6.54 years] over 2 years):	0.23
i.	Weighted Average Benchmark Treasury (e*g + f*h):	5.02%
j.	Yield Spread (d-e):	3.23%

Table 1: Descriptive statistics and variable definition

Panel A: Descriptive Statistics

	N	MEAN	Median	STD	MIN	MAX
Yield Spread	204	199	143	143	9	723
TRI (‘000s)	204	9,422	4,624	11,295	174	58,221
TRI/US Sales	204	2.20	2.07	1.40	0.09	7.93
Bond Rating	204	11.13	11.00	3.06	5.00	19.00
Modified Bond Rating	204	0.01	-0.16	2.08	-3.64	5.83
Z-Score	204	2.28	2.12	1.13	-0.97	5.97
Volatility	204	22.81%	21.41%	8.68%	8.42%	54.73%
Maturity	204	12.67	9.05	8.65	0.72	30.09
Aaa Spread	204	159	135	62	78	346

Table 1, panel B: Variable Definitions

Yield Spread	The basis point spread (100 basis points = 1%) between the yield to maturity of the sample bond and the comparable treasury bond.
TRI (‘000s)	The total annual pounds of toxic chemicals released to land, air or water as per the United States Environmental Protection Agency (Toxic Release Inventory), presented in thousands of pounds.
TRI/US Sales	Pounds of toxic chemicals released (TRI) per $1,000 of U. S. sales, based on location of seller.
Bond Rating	A firm’s S&P bond rating converted to an ordinal from 1 to 22, where AAA+ = 1, AAA = 2, etc. In two cases Moody’s rating was used, Fitch in one case.
Modified Bond Rating	The residual of regressing bond rating onto TRI/US Sales + Z-Score + Volatility; as described in Section 4.2 herein.
Z-Score	Altman’s Z-Score, where Z = 1.2*(Working Capital/Total Assets) + 1.4*(Retained Earnings/Total Assets) + 3.3*EBIT/Total Assets + 0.6*(Market Value of Equity/Book Value of Total Liabilities) + Sales/Total Assets.
Volatility	The annualised standard deviation of the sample firms’ mean returns for the year prior to the bond trade used to calculate Yield Spread.
Maturity	Bond specific time to maturity in years from the trade date used to calculate Yield Spread.
Aaa Spread	The spread (in basis points) between the average Moody’s Aaa bond yield and the ten-year treasury bond yield, on the date of the bond transaction used to calculate yield spread.

Table 2: Pearson Correlation Matrix

	Yield Spread	TRI	TRI/US Sales	Bond Rating	Modified Rating	Volatility	Z-Score	Maturity
TRI	-0.0322							
p-value	0.6475							
TRI/US Sales	0.35686	0.12462						
p-value	<.0001	0.0758						
Bond Rating	0.77576	0.03962	0.43102					
p-value	<.0001	0.5736	<.0001					
Modified Rating	0.43012	-0.16019	0.00378	0.68129				
p-value	<.0001	0.0221	0.9572	<.0001				
Volatility	0.60223	-0.11335	0.11681	0.47883	0.09173			
p-value	<.0001	0.1065	0.0962	<.0001	0.1919	0.0059		
Z-Score	-0.46737	-0.27532	-0.47752	-0.65123	-0.0058	-0.19203		
p-value	<.0001	<.0001	<.0001	<.0001	0.9344	0.0059	0.2715	
Maturity	-0.13205	0.07016	0.01938	-0.24204	-0.22202	-0.19242	0.07734	
p-value	0.0597	0.3187	0.7832	0.0005	0.0014	0.0058	0.2715	
Aaa Spread	0.2581	-0.00668	-0.00667	0.07155	-0.1568	0.30935	-0.1292	-0.0852
p-value	0.0002	0.9245	0.9246	0.3092	0.0251	<.0001	0.0656	0.2259

Variables as per Table 1, Panel B.

Table 3: Bond rating as dependent variable

Panel A

Model: **Bond Rating = $\alpha_0 + \alpha_1$TRI/US Sales + α_2Z-Score + α_3Volatility + ε**

Method: **Cluster in one-dimension (Firm), One-way fixed effects (Year). N = 204 firm-years, 26 firms.**

Variable	Predicted Sign	Estimate	Error	t-value	Pr > |t|	R-squared
Intercept		8.32	1.02	8.17	<.0001	0.732
TRI/US Sales	+	0.30	0.16	1.86	0.0373	
Z-score	–	-1.25	0.21	-5.95	<.0001	
Volatility	+	22.28	2.74	8.14	<.0001	
Y95		0.44	0.35	1.27	0.2150	
Y96		0.99	0.44	2.24	0.0344	
Y97		-0.36	0.49	-0.73	0.4744	
Y98		-1.63	0.50	-3.27	0.0032	
Y99		-2.14	0.50	-4.26	0.0003	
Y00		-1.95	0.61	-3.18	0.0039	
Y01		-0.67	0.63	-1.06	0.2990	
Y02		-1.06	0.67	-1.57	0.1295	
Y03		1.59	0.43	3.68	0.0011	
Y04		1.99	0.49	4.08	0.0004	
Y05		2.61	0.55	4.72	<.0001	

N.B. Where the sign of a parameter is predicted, t-tests are one-tailed. Variables are as per Table 1, Panel B, except for year indicators. Year indicators are binary variables, years 1995 through 2005, for comparison against the base year of 1994.

Table 3, panel B						
Model: **Bond Rating$_{it}$ = α_0 + α_1TRI/US Sales + α_2Z-Score + α_3Volatility + ε**						
Method: **Two-way fixed effects (Firm and Year). N = 204 firm-years, 26 firms.**						
Variable	**Predicted Sign**	**Estimate**	**Error**	**t-value**	**Pr > |t|**	**R-squared**
Intercept		18.70	0.66	28.23	<.0001	0.9510
TRI/US Sales	+	0.23	0.09	2.59	0.0053	
Z-score	–	-0.14	0.11	-1.29	0.0991	
Volatility	+	3.28	1.37	2.39	0.0089	
N.B. Where the sign of a parameter is predicted, t-tests are one-tailed. Variables are as per Table 1, Panel B. Firm and year parameter estimates not reported.						

Table 3, panel C						
Model: **Bond Rating = α_0 + α_1TRI/US Sales + α_2Z-Score + α_3Volatility + ε**						
Method: **OLS with year fixed effects. N = 204 firm-years, 26 firms.**						
Variable	**Predicted Sign**	**Estimate**	**Error**	**t-value**	**Pr > |t|**	**R-squared**
Intercept		8.32	0.67	12.45	<.0001	0.7122
TRI/US Sales	+	0.30	0.09	3.19	0.0009	
Z-score	–	-1.25	0.12	-10.29	<.0001	
Volatility	+	22.28	1.71	13.04	<.0001	
N.B. Where the sign of a parameter is predicted, t-tests are one-tailed. Errors are White's standard errors. Variables are as per Table 1, Panel B. Fixed-effects parameter estimates not reported.						

Table 4: Yield spread as dependent variable

Panel A

Model: **Yield Spread = $\alpha_0 + \alpha_1$TRI/US Sales + α_2Modified Bond Rating + α_3Z-Score + α_4Volatility + α_5Maturity + α_6Aaa Spread + ε**

Method: **Cluster in one-dimension (Firm), One-way fixed effects (Year). N = 204 firm-years, 26 firms.**

Variable	Predicted Sign	Estimate	Error	t-value	Pr > |t|	R-squared
Intercept		-66.98	63.36	-1.06	0.3006	0.7896
TRI/US Sales	+	17.13	5.03	3.41	0.0011	
Modified Bond Rating	+	30.16	6.19	4.87	<.0001	
Z-Score	–	-37.26	11.16	-3.34	0.0013	
Volatility	+	642.31	166.80	3.85	0.0004	
Maturity		1.76	0.66	2.68	0.0128	
Aaa Spread	+	0.85	0.39	2.18	0.0194	
Y95		-3.30	18.36	-0.18	0.8586	
Y96		9.28	19.02	0.49	0.6299	
Y97		22.32	19.59	1.14	0.2652	
Y98		1.20	22.67	0.05	0.9583	
Y99		65.47	39.23	1.67	0.1076	
Y00		-1.67	48.37	-0.03	0.9727	
Y01		-12.80	40.69	-0.31	0.7557	
Y02		-59.71	66.93	-0.89	0.3808	
Y03		-61.01	44.58	-1.37	0.1833	
Y04		44.95	25.35	1.77	0.0884	
Y05		91.21	33.90	2.69	0.0125	

N.B. Where the sign of a parameter is predicted, t-tests are one-tailed. Variables are as per Table 1, Panel B, except year indicators. Year indicators are binary variables, years 1995 through 2005, for comparison against the base year of 1994.

Table 4, panel B

Model: **Yield Spread = α_0 + α_1TRI/US Sales + α_2Modified Bond Rating + α_3Z-Score + α_4Volatility + α_5Maturity + α_6Aaa Spread + ε**

Method: **Two way random effects, year and firm (FGLS).**

Variable	Predicted Sign	Estimate	Error	t-value	Pr > |t|	R-squared
Intercept		-32.87	45.72	-0.72	0.4731	0.4735
TRI/US Sales	+	21.20	6.43	3.30	0.0006	
Modified Bond Rating	+	31.39	4.18	7.52	<.0001	
Z-Score	-	-50.75	8.18	-6.20	<.0001	
Volatility	+	805.97	101.80	7.92	<.0001	
Maturity		2.30	0.78	2.95	0.0036	
Aaa Spread	+	0.50	0.16	3.21	0.0008	

N.B. Where the sign of a parameter is predicted, t-tests are one-tailed. Variables are as per Table 1, Panel B.

Table 4, panel C

Model: **Yield Spread = α_0 + α_1TRI/US Sales + α_2Modified Bond Rating + α_3Z-Score + α_4Volatility + α_5Maturity + α_6Aaa Spread + ε**

Method: **OLS with year fixed effects.**

Variable	Predicted Sign	Estimate	Error	t-value	Pr > |t|	R-squared
Intercept		-66.98	46.76	-1.43	0.1537	0.6950
TRI/US Sales	+	17.13	4.56	3.76	0.0002	
Modified Bond Rating	+	30.16	3.53	8.54	<.0001	
Z-Score	-	-37.26	5.89	-6.33	<.0001	
Volatility	+	642.31	94.89	6.77	<.0001	
Maturity		1.76	0.69	2.54	0.0118	
Aaa Spread	+	0.85	0.26	3.24	0.0014	

N.B. Where the sign of a parameter is predicted, t-tests are one-tailed. Variables are as per Table 1, Panel B. Errors are White's standard errors. Fixed-effects parameter estimates not reported.

Table 5: Yield spread as dependent variable, between groups OLS

Model: $\textbf{Yield Spread}_i = \alpha_0 + \alpha_1\textbf{TRI/US Sales}_i + \alpha_2\textbf{Modified Bond Rating}_i + \alpha_3\textbf{Z-Score}_i + \alpha_4\textbf{Volatility}_i + \alpha_5\textbf{Maturity}_i + \alpha_6\textbf{Aaa Spread}_i + \varepsilon_i$

Method: **Between groups OLS (by firm, n = 26).**

Variable	Predicted Sign	Estimate	Error	t-value	Pr > |t|	R-squared
Intercept		-59.78	92.52	-0.65	0.5259	0.7852
TRI/US Sales	+	31.43	11.38	2.76	0.0062	
Modified Bond Rating	+	41.59	11.38	3.65	0.0009	
Z-Score	-	-21.36	14.09	-1.52	0.0730	
Volatility	+	539.43	246.93	2.18	0.0209	
Maturity		1.07	2.05	0.52	0.6085	
Aaa Spread	+	0.60	0.47	1.28	0.1075	

N.B. Where the sign of a parameter is predicted, t-tests are one-tailed. Variables are as per Table 1, Panel B.

Table 6: Annual Regressions

Model: **Yield Spread = $\alpha_0 + \alpha_1$TRI/US Sales + α_2Modified Bond Rating + α_3Z-Score + α_4Volatility + α_5Maturity + α_6Aaa Spread + ε**

Method: **OLS by year.**

1994 (N= 17)

Variable	Predicted Sign	Estimate	Error	t-value	Pr > |t|	R-squared
Intercept		192.56	169.03	1.14	0.2812	0.7797
TRI/US Sales	+	-12.24	10.08	-1.21	0.7476	
Modified Bond Rating	+	23.07	8.06	2.86	0.0085	
Z-Score	–	-55.38	11.06	-5.01	0.0003	
Volatility	+	527.62	314.24	1.68	0.0621	
Maturity		0.82	1.33	0.62	0.5496	
Aaa Spread	+	-0.12	1.08	-0.11	0.9171	

1995 (N = 19)

Variable	Predicted Sign	Estimate	Error	t-value	Pr > |t|	R-squared
Intercept		-92.29	232.49	-0.40	0.6984	0.7002
TRI/US Sales		**48.87**	**21.72**	**2.25**	**0.0220**	
Modified Bond Rating	+	14.94	14.07	1.06	0.1546	
Z-Score	–	-26.93	20.38	-1.32	0.1056	
Volatility	+	1001.43	277.89	3.60	0.0018	
Maturity		2.35	2.38	0.99	0.3440	
Aaa Spread	+	-0.38	1.85	-0.20	0.8428	

1996 (N = 19)

Variable	Predicted Sign	Estimate	Error	t-value	Pr > |t|	R-squared
Intercept		-334.05	390.46	-0.86	0.409	0.4444
TRI/US Sales		**34.89**	**21.45**	**1.63**	**0.0649**	
Modified Bond Rating	+	16.39	15.06	1.09	0.1490	
Z-Score	–	-45.39	26.78	-1.69	0.0580	
Volatility	+	772.93	509.54	1.52	0.0776	
Maturity		0.25	2.13	0.12	0.9077	
Aaa Spread	+	3.53	3.82	0.92	0.1872	

N.B. Where the sign of a parameter is predicted, t-tests are one-tailed. Variables are as per Table 1, Panel B. Errors are White's standard errors. Fixed-effects parameter estimates not reported. TRI/US Sales presented in bold if significant at the < 10% level.

Table 6, continued: Annual Regressions

Model: **Yield Spread = α_0 + α_1TRI/US Sales + α_2Modified Bond Rating + α_3Z-Score + α_4Volatility + α_5Maturity + α_6Aaa Spread + ε**

Method: **OLS by year.**

1997 (N = 20)

Variable	**Predicted Sign**	**Estimate**	**Error**	**t-value**	**Pr > |t|**	**R-squared**
Intercept		-70.87262	156.3734	-0.45	0.6579	0.6908
TRI/US Sales		**25.44567**	**18.79228**	**1.35**	**0.0994**	
Modified Bond Rating	+	38.15645	14.66995	2.6	0.0110	
Z-Score	-	-29.89624	17.76494	-1.68	0.0581	
Volatility	+	746.71311	554.6442	1.35	0.1006	
Maturity		2.2605	2.64399	0.85	0.4081	
Aaa Spread	+	0.54932	0.54437	1.01	0.1657	

1998 (N = 20)

Variable	**Predicted Sign**	**Estimate**	**Error**	**t-value**	**Pr > |t|**	**R-squared**
Intercept		-539.33	453.50	-1.19	0.2556	0.7069
TRI/US Sales		**35.14**	**17.96**	**1.96**	**0.0361**	
Modified Bond Rating	+	23.66	18.39	1.29	0.11035	
Z-Score	–	-25.05	28.36	-0.88	0.1966	
Volatility	+	971.63	395.79	2.45	0.01445	
Maturity		-0.14	2.67	-0.05	0.9584	
Aaa Spread	+	3.01	3.03	0.99	0.169	

1999 (N = 19)

Variable	**Predicted Sign**	**Estimate**	**Error**	**t-value**	**Pr > |t|**	**R-squared**
Intercept		-82.82	222.85	-0.37	0.7166	0.5468
TRI/US Sales		-20.55	22.06	-0.93	0.1850	
Modified Bond Rating	+	26.43	16.78	1.57	0.0707	
Z-Score	–	-42.86	23.43	-1.83	0.0462	
Volatility	+	437.29	547.40	0.80	0.2200	
Maturity		5.62	2.69	2.09	0.0585	
Aaa Spread	+	2.19	0.92	2.40	0.0169	

N.B. Where the sign of a parameter is predicted, t-tests are one-tailed. Variables are as per Table 1, Panel B. Errors are White's standard errors. Fixed-effects parameter estimates not reported. TRI/US Sales presented in bold if significant at the < 10% level.

Table 6, continued: Annual Regressions						
Model:	**Yield Spread = α_0 + α_1TRI/US Sales + α_2Modified Bond Rating + α_3Z-Score + α_4Volatility + α_5Maturity + α_6Aaa Spread + ε**					
Method:	**OLS by year.**					
2000 (N = 16)						
Variable	**Predicted Sign**	**Estimate**	**Error**	**t-value**	**Pr > |t|**	**R-squared**
Intercept		504.95	283.52	1.78	0.1086	0.5487
TRI/US Sales		0.89	14.58	0.06	0.4765	
Modified Bond Rating	+	36.19	10.33	3.5	0.0034	
Z-Score	–	-51.03	18.09	-2.82	0.0100	
Volatility	+	-160.17	244.59	-0.65	0.2645	
Maturity		2.65	1.91	1.39	0.1992	
Aaa Spread	+	-0.29	1.07	-0.27	0.7935	
2001 (N = 15)						
Variable	**Predicted Sign**	**Estimate**	**Error**	**t-value**	**Pr > |t|**	**R-squared**
Intercept		-65.81	115.64	-0.57	0.5849	0.7114
TRI/US Sales		-1.06	13.56	-0.08	0.4699	
Modified Bond Rating	+	0.65	11.74	0.06	0.4786	
Z-Score	–	-59.57	22.16	-2.69	0.0138	
Volatility	+	518.15	201.45	2.57	0.0165	
Maturity		1.23	2.11	0.58	0.5758	
Aaa Spread	+	1.29	0.42	3.10	0.0074	
2002 (N = 15)						
Variable	**Predicted Sign**	**Estimate**	**Error**	**t-value**	**Pr > |t|**	**R-squared**
Intercept		-804.67	652.17	-1.23	0.2523	0.5573
TRI/US Sales		23.59	20.38	1.16	0.1402	
Modified Bond Rating	+	48.79	19.22	2.54	0.0174	
Z-Score	–	-39.79	41.49	-0.96	0.1828	
Volatility	+	1051.35	367.97	2.86	0.0106	
Maturity		-1.46	5.01	-0.29	0.7781	
Aaa Spread	+	3.03	2.42	1.25	0.1227	

N.B. Where the sign of a parameter is predicted, t-tests are one-tailed. Variables are as per Table 1, Panel B. Errors are White's standard errors. Fixed-effects parameter estimates not reported. TRI/US Sales presented in bold if significant at the < 10% level.

Table 6, continued: Annual Regressions

Model: Yield Spread = α_0 + α_1TRI/US Sales + α_2Modified Bond Rating + α_3Z-Score + α_4Volatility + α_5Maturity + α_6Aaa Spread + ε

Method: OLS by year.

Variable	Predicted Sign	Estimate	Error	t-value	Pr > |t|	R-squared
2003 (N = 15)						
Intercept		324.56	214.95	1.51	0.1695	0.7728
TRI/US Sales		**22.05**	**14.73**	**1.50**	**0.0865**	
Modified Bond Rating	+	55.39	13.73	4.04	0.0019	
Z-Score	–	1.66	19.84	0.08	0.9353	
Volatility	+	-7.71	354.63	-0.02	0.9832	
Maturity		10.58	3.12	3.39	0.0095	
Aaa Spread	+	-1.47	0.91	-1.62	0.0720	
2004 (N = 15)						
Variable	**Predicted Sign**	**Estimate**	**Error**	**t-value**	**Pr > |t|**	**R-squared**
Intercept		137.84	287.86	0.48	0.6449	0.8145
TRI/US Sales		**34.77**	**11.46**	**3.03**	**0.0081**	
Modified Bond Rating	+	50.31	10.56	4.76	0.0007	
Z-Score	-	-0.35	18.21	-0.02	0.9852	
Volatility	+	567.64	338.11	1.68	0.1317	
Maturity		6.56	3.46	1.89	0.0947	
Aaa Spread	+	-1.89	1.98	-0.96	0.1833	
2005 (N = 14)						
Variable	**Predicted Sign**	**Estimate**	**Error**	**t-value**	**Pr > |t|**	**R-squared**
Intercept		-664.16	451.63	-1.47	0.1849	0.8526
TRI/US Sales		**25.44**	**12.58**	**2.02**	**0.0415**	
Modified Bond Rating	+	27.03	8.70	3.11	0.0086	
Z-Score	-	-9.50	24.69	-0.38	0.7119	
Volatility	+	872.98	446.11	1.96	0.0912	
Maturity		7.20	3.65	1.97	0.0897	
Aaa Spread	+	6.97	5.13	1.36	0.1083	

N.B. Where the sign of a parameter is predicted, t-tests are one-tailed. Variables are as per Table 1, Panel B. Errors are White's standard errors. Fixed-effects parameter estimates not reported. TRI/US Sales presented in bold if significant at the < 10% level.

Table 7: Fama-MacBeth

Model: $\textbf{Yield Spread}_t = \alpha_0 + \alpha_1\textbf{TRI/US Sales}_t + \alpha_2\textbf{Modified Bond Rating}_t + \alpha_3\textbf{Z-Score}_t + \alpha_4\textbf{Volatility}_t + \alpha_5\textbf{Maturity}_t + \alpha_6\textbf{Aaa Spread}_t + \varepsilon_t$

Method: **Fama-MacBeth (1973).**

Variable	Predicted Sign	Estimate	Error	t-value	Pr > |t|
Intercept		-124.51	398.43	-0.31	0.7600
TRI/US Sales		18.10	21.38	0.85	0.2069
Modified Bond Rating	+	30.09	16.23	1.85	0.0443
Z-Score	–	-32.01	20.77	-1.54	0.0747
Volatility	+	608.32	383.13	1.59	0.0692
Maturity		3.16	3.57	0.88	0.3940
Aaa Spread	+	1.37	2.51	0.54	0.2980

N.B. Where the sign of a parameter is predicted, t-tests are one-tailed. Variables are as per Table 1, Panel B. Error terms are not adjusted for serial correlation.

Table 8: Pearson Correlation Matrix with alternate variables

	Yield Spread	TRI/US Sales	Bond Scale	Mod. Bond Rating	Volatility	Z-score	Maturity	Aaa Spread	Leverage	Coverage	Current
TRI/US Sales	0.3569										
	<.0001										
Bond Scale	0.7758	0.4310									
	<.0001	<.0001									
Mod. Bond Rating	0.4301	0.0038	0.6813								
	<.0001	0.9572	<.0001								
Volatility	0.6022	0.1168	0.4788	0.0917							
	<.0001	0.0962	<.0001	0.1919							
Z-score	-0.4674	-0.4775	-0.6512	-0.0058	-0.1920						
	<.0001	<.0001	<.0001	0.9344	0.0059						
Maturity	-0.1321	0.0194	-0.2420	-0.2220	-0.1924	0.0773					
	0.0597	0.7832	0.0005	0.0014	0.0058	0.2715					
Aaa Spread	0.2581	-0.0067	0.0716	-0.1568	0.3094	-0.1292	-0.0852				
	0.0002	0.9246	0.3092	0.0251	<.0001	0.0656	0.2259				
Leverage	0.5241	0.2697	0.6350	0.3151	0.3885	-0.5455	-0.1317	0.0325			
	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	0.0605	0.6446			
Coverage	-0.3980	-0.3633	-0.5232	0.0212	-0.1704	0.8355	0.0653	-0.0910	-0.3585		
	<.0001	<.0001	<.0001	0.7633	0.0148	<.0001	0.3535	0.1954	<.0001		
Current Ratio	0.0495	0.0348	0.1750	0.3569	0.1795	0.2140	-0.1694	-0.1362	-0.0433	0.0912	
	0.4822	0.6210	0.0123	<.0001	0.0102	0.0021	0.0154	0.0522	0.5390	0.1945	
Size	-0.2780	-0.3051	-0.4885	-0.2491	-0.2480	0.4203	0.0717	0.0538	-0.2491	0.3751	-0.3819
	<.0001	<.0001	<.0001	0.0003	0.0003	<.0001	0.3083	0.4445	0.0003	<.0001	<.0001

Table 8, Panel B: Variable definitions	
TRI/US Sales, Bond Scale, Mod. Bond Rating, Volatility, Z-score, Maturity and Aaa spread are as described in table 1; panel B.	
Alternate variables not described in table 1, panel B are:	
Leverage	Total debt divided by total assets
Coverage	Earnings before interest and taxes divided by interest expense (times interest earned)
Current	(Current assets minus current liabilities) divided by total assets
Size	Total market value of equity

Table 9: Alternate regression
Panel A

Model: **Yield Spread =** $\alpha_0 + \alpha_1$**TRI/US Sales** $+ \alpha_2$**Leverage** $+ \alpha_3$**Coverage** $+ \alpha_4$**Current** $+ \alpha_5$**Volatility** $+ \alpha_6$**Size** $+ \varepsilon$

Method: **Cluster in one-dimension (Firm), One-way fixed effects (Year). N = 204 firm-years, 26 firms.**

Variable	Predicted Sign	Estimate	Error	t-value	Pr > |t|	R-squared
Intercept		-117.47	38.19	-3.08	0.005	0.6202
TRI/US Sales	+	18.99	6.65	2.86	0.009	
Leverage	+	170.81	70.42	2.43	0.023	
Coverage	–	-2.60	2.61	-0.99	0.330	
Current	–	-188.94	167.53	-1.13	0.270	
Volatility	+	854.22	182.77	4.67	<.0001	
Size	–	-0.0014	0.0015	-0.94	0.358	
Y95		12.98	15.29	0.85	0.404	
Y96		31.81	19.97	1.59	0.124	
Y97		21.15	25.73	0.82	0.419	
Y98		-11.31	23.66	-0.48	0.637	
Y99		29.42	38.82	0.76	0.456	
Y00		61.12	40.14	1.52	0.140	
Y01		74.66	30.70	2.43	0.023	
Y02		54.98	37.24	1.48	0.152	
Y03		90.24	26.23	3.44	0.002	
Y04		119.69	26.93	4.44	0.000	
Y05		147.68	27.39	5.39	<.0001	

Variables are: Yield Spread = The basis point spread (100 basis points = 1%) between the yield to maturity of the sample bond and the comparable treasury bond; TRI is the pounds of toxic chemicals released to land, air or water per thousand dollars of U.S. Sales; Leverage = total debt divided by total assets; Coverage = earnings before interest and taxes divided by interest expense; Current = (current assets minus current liabilities) divided by total assets; Volatility = annualised standard deviation of the sample firms' mean returns for the year prior to the bond trade used to calculate yield spread.; Size = total market value of equity. N.B. Where the sign of a parameter is predicted, t-tests are one-tailed.

Table 9, panel B : Alternate Regression

Model: **Yield Spread =** $\alpha_0 + \alpha_1$**TRI/US Sales** $+ \alpha_2$**Leverage** $+ \alpha_3$**Coverage** $+ \alpha_4$**Current** $+ \alpha_5$**Volatility** $+ \alpha_6$**Size** $+ \varepsilon$

Method: **Two way random effects, year and firm (FGLS).**

Variable	Predicted Sign	Estimate	Error	t-value	Pr > |t|	R-squared
Intercept		-64.86	39.40	-1.65	0.1013	0.3697
TRI/US Sales		20.74	6.77	3.06	0.0013	
Leverage	+	184.78	44.75	4.13	<.0001	
Coverage	–	-2.88	2.33	-1.24	0.1084	
Current	–	67.58	152.00	0.44	0.3285	
Volatility	+	702.23	116.10	6.05	<.0001	
Size	–	-0.0008	0.0017	-0.46	0.3230	

Variables are: Yield Spread = The basis point spread (100 basis points = 1%) between the yield to maturity of the sample bond and the comparable treasury bond; TRI is the pounds of toxic chemicals released to land, air or water per thousand dollars of U.S. Sales; Leverage = total debt divided by total assets; Coverage = earnings before interest and taxes divided by interest expense; Current = (current assets minus current liabilities) divided by total assets; Volatility = annualised standard deviation of the sample firms' mean returns for the year prior to the bond trade used to calculate yield spread.; Size = total market value of equity. N.B. Where the sign of a parameter is predicted, t-tests are one-tailed.

Table 10: Davidson MacKinnon J Test

Panel A: Equation 4a

Model: Yield Spread = α_0 + α_1TRI/US Sales + α_2Modified Bond Rating + α_3Z-Score + α_4Volatility + α_5Maturity + α_6Aaa Spread + β_1Predicted Value of Eq'n (5) + ε

Method: OLS

Variable	Predicted Sign	Estimate	Error	t-value	Pr > |t|	Adj. R-squared
Intercept		-16.55	33.48	-0.49	0.6216	0.6727
TRI/US Sales	+	11.40	6.09	1.87	0.0315	
Modified Bond Rating	+	28.29	3.02	9.38	<.0001	
Z-Score	–	-25.24	9.65	-2.61	0.0048	
Volatility	–	468.14	211.74	2.21	0.0141	
Maturity	+	1.35	0.70	1.94	0.0539	
Aaa Spread		0.37	0.10	3.72	0.0002	
Predict Value Eq'n 5		0.32	0.23	1.43	0.1553	

N.B. Where the sign of a parameter is predicted, t-tests are one-tailed. Variables as per table 1, panel B. Predict Value Eq'n 5 is the predicted value from a regression of equation 5. Errors are White's standard errors.

Table 10, panel B: Equation 5a

Model: Yield Spread = α_0 + α_1TRI/US Sales + α_2Leverage + α_3Coverage + α_4Current + α_5Volatility + α_6Size + β_2Predicted Value of Eq'n (4) + ε

Method: OLS

Variable	Predicted Sign	Estimate	Error	t-value	Pr > |t|	Adj. R-squared
Intercept		12.80	22.58	0.57	0.5716	0.6721
TRI/US Sales	+	-0.39	4.80	-0.08	0.9346	
Leverage	+	3.35	36.19	0.09	0.4632	
Coverage	–	-0.44	1.91	-0.23	0.4089	
Current	–	-245.39	106.25	-2.31	0.0110	
Volatility	+	22.03	103.78	0.21	0.4161	
Predict Value Eq'n 4		1.00	0.10	10.01	<.0001	

N.B. Where the sign of a parameter is predicted, t-tests are one-tailed. Variables as per table 8. Predict Value Eq'n 4 is the predicted value from a regression of equation 4.

Table 11: Outliers

Equation (4) without sample outliers based on Cook's D of 0.020

Model: **Yield Spread = α_0 + α_1TRI/US Sales + α_2Modified Bond Rating + α_3Z-Score + α_4Volatility + α_5Maturity + α_6Aaa Spread + ε**

Method: **Cluster in one-dimension (Firm), One-way fixed effects (Year). N = 190 firm-years, 26 firms.**

Variable	Predicted Sign	Estimate	Error	t-value	Pr > |t|	R-squared
						0.7971
Intercept		-56.68	30.54	-1.86	0.0753	
TRI/US Sales	+	17.78	3.32	5.36	<.0001	
Modified Bond Rating	+	26.55	3.23	8.22	<.0001	
Z-Score	-	-35.98	8.46	-4.25	0.0002	
Volatility	+	511.34	126.30	4.05	0.0002	
Maturity		2.31	0.54	4.27	0.0002	
Aaa Spread	+	0.82	0.19	4.23	0.0002	
Y95		3.65	16.63	0.22	0.8283	
Y96		-3.64	12.25	-0.3	0.7691	
Y97		14.04	19.94	0.7	0.4878	
Y98		-9.62	19.51	-0.49	0.6261	
Y99		77.30	27.64	2.8	0.0098	
Y00		4.32	27.74	0.16	0.8776	
Y01		-6.51	25.17	-0.26	0.7982	
Y02		-66.68	43.42	-1.54	0.1372	
Y03		-72.07	28.90	-2.49	0.0196	
Y04		44.10	24.92	1.77	0.0890	
Y05		105.85	21.70	4.88	<.0001	

N.B. Where the sign of a parameter is predicted, t-tests are one-tailed. Variables are as per Table 1, Panel B, except year indicators. Year indicators are binary variables, years 1995 through 2005, for comparison against the base year of 1994.

Table 12: Bond specific features

Panel A: Call

Model: **Yield Spread = α_0 + α_1TRI/US Sales + α_2Modified Bond Rating + α_3Z-Score + α_4Volatility + α_5Maturity + α_6Aaa Spread + α_7Call + ε**

Method: **Cluster in one-dimension (Firm), One-way fixed effects (Year). N = 204 firm-years, 26 firms.**

Variable	Predicted Sign	Estimate	Error	t-value	Pr > |t|	R-Squared
Intercept		-65.37	63.70	-1.03	0.3146	0.7209
TRI/US Sales	+	16.82	5.01	3.35	0.0025	
Modified Bond Rating	+	29.82	6.47	4.61	0.0001	
Z-Score	–	-37.23	10.88	-3.42	0.0022	
Volatility	+	633.35	164.57	3.85	0.0007	
Maturity		1.70	0.74	2.3	0.0303	
Aaa Spread	+	0.84	0.39	2.16	0.0406	
Call	+	6.46	17.49	0.37	0.3300	

N.B. Where the sign of a parameter is predicted, t-tests are one-tailed. Variables as per table 1, panel B. Call is an indicator variable indicating the bond is callable.

Table 12, Panel B : Covenant Index

Model: **Yield Spread = α_0 + α_1TRI/US Sales + α_2Modified Bond Rating + α_3Z-Score + α_4Volatility + α_5Maturity + α_6Aaa Spread + Cov Index + ε**

Method: **Cluster in one-dimension (Firm), One-way fixed effects (Year). N = 188 firm-years, 26 firms.**

Variable	Predicted Sign	Estimate	Error	t-value	Pr > |t|	R-Squared
Intercept		-122.21	87.09	-1.4	0.1728	0.7357
TRI/US Sales	+	15.15	5.54	2.74	0.0057	
Modified Bond Rating	+	24.26	6.51	3.73	0.0005	
Z-Score	–	-35.45	11.96	-2.96	0.0033	
Volatility	+	638.04	165.45	3.86	0.0004	
Maturity		2.17	0.85	2.56	0.0168	
Aaa Spread	+	0.97	0.47	2.08	0.0239	
Cov Index		4.99	4.45	1.12	0.1365	

N.B. Where the sign of a parameter is predicted, t-tests are one-tailed. Variables as per table 1, panel B. Cov Index is the number of covenants attached to each respective bond.

Table 12, Panel C : Call and Covenant Index

Model: Yield Spread = α_0 + α_1TRI/US Sales + α_2Modified Bond Rating + α_3Z-Score + α_4Volatility + α_5Maturity + α_6Aaa Spread + α_7Cov Index + ε

Method: Cluster in one-dimension (Firm), One-way fixed effects (Year). N = 188 firm-years, 26 firms.

Variable	Predicted Sign	Estimate	Error	t-value	Pr > |t|	R-Squared
Intercept		-116.22	89.08	-1.30	0.2039	0.7367
TRI/US Sales	+	14.80	5.47	2.70	0.0061	
Modified Bond Rating	+	24.08	6.69	3.60	0.0007	
Z-Score	–	-35.76	11.49	-3.11	0.0023	
Volatility	+	626.01	161.60	3.87	0.0004	
Maturity		2.05	0.96	2.15	0.0419	
Aaa Spread	+	0.97	0.47	2.06	0.0252	
Call	+	10.47	19.06	0.55	0.1469	
Cov Index		4.51	4.61	0.98	0.1687	

N.B. Where the sign of a parameter is predicted, t-tests are one-tailed. Variables as per table 1, panel B. Call is an indicator variable indicating the bond is callable. Cov Index is the number of covenants attached to each respective bond. Fixed effects year indicators are not reported.

Table 13: Addressing non-pulp and paper sales

Panel A : TRI scaled by pulp and paper segment sales

Model: **Yield Spread = α_0 + α_1TRI/P&P Sales + α_2Modified Bond Rating + α_3Z-Score + α_4Volatility + α_5Maturity + α_6Aaa Spread + ε**

Method: **Cluster in one-dimension (Firm), One-way fixed effects (Year). N = 204 firm-years, 26 firms.**

Variable	Predicted Sign	Estimate	Error	t-value	Pr > |t|	R-Squared
Intercept		-59.29	67.23	-0.88	0.3862	0.7048
TRI/P&P Sales	+	8.58	6.48	1.32	0.0988	
Modified Bond Rating	+	29.41	5.92	4.97	<.0001	
Z-Score	–	-43.21	11.35	-3.81	0.0004	
Volatility	+	704.09	158.83	4.43	0.0001	
Maturity		2.00	0.75	2.68	0.0130	
Aaa Spread	+	0.89	0.40	2.25	0.0169	

N.B. Where the sign of a parameter is predicted, t-tests are one-tailed. Variables as per table 1, panel B. TRI/P&P Sales is total TRI scaled by a firms' pulp and paper sales. Fixed effects year indicators are not reported.

Table 13, Panel B : TRI scaled by pulp and paper segment sales

Model: **Yield Spread = α_0 + α_1TRI/P&P Sales + α_2Modified Bond Rating + α_3Z-Score + α_4Volatility + α_5Maturity + α_6Aaa Spread + ε**

Method: **Two way random effects, year and firm (FGLS).**

Variable	Predicted Sign	Estimate	Error	t-value	Pr > |t|	R-Squared
Intercept		-13.20	46.82	-0.28	0.7783	0.4796
TRI/P&P Sales	+	12.88	6.60	1.95	0.0261	
Modified Bond Rating	+	30.37	4.08	7.44	<.0001	
Z-Score	–	-52.63	7.78	-6.77	<.0001	
Volatility	+	824.97	101.40	8.14	<.0001	
Maturity		2.25	0.79	2.85	0.0049	
Aaa Spread	+	0.51	0.16	3.14	0.0010	

N.B. Where the sign of a parameter is predicted, t-tests are one-tailed. Variables as per table 1, panel B. TRI/P&P Sales is total TRI scaled by a firms' pulp and paper sales.

Table 13, Panel C: Percent non-pulp and paper sales

Model: Yield Spread = α_0 + α_1TRI/U.S. Sales + α_2Modified Bond Rating + α_3Z-Score + α_4Volatility + α_5Maturity + α_6Aaa Spread + α_7Percent non P&P + ε

Method: Cluster in one-dimension (Firm), One-way fixed effects (Year). N = 204 firm-years, 26 firms.

Variable	Predicted Sign	Estimate	Error	t-value	Pr > |t|	R-Squared
Intercept		-82.05	67.90	-1.21	0.2382	0.7213
TRI/US Sales	+	17.71	5.09	3.48	0.0009	
Modified Bond Rating	+	30.35	6.23	4.87	<.0001	
Z-Score	–	-35.63	11.27	-3.16	0.0021	
Volatility	+	667.43	170.19	3.92	0.0003	
Maturity		1.70	0.63	2.68	0.0127	
Aaa Spread	+	0.86	0.39	2.20	0.0188	
Percent non P&P		22.43	35.57	0.63	0.5341	

N.B. Where the sign of a parameter is predicted, t-tests are one-tailed. Variables as per table 1, panel B. Percent non P&P is non pulp and paper sales divided by total sales. Fixed effects year indicators are not reported.

Table 13, Panel D: Interaction of TRI and non-pulp and paper indicator

Model: Yield Spread = α_0 + α_1TRI/U.S. Sales + α_2Modified Bond Rating + α_3Z-Score + α_4Volatility + α_5Maturity + α_6Aaa Spread + α_7High Non-P&P + α_8TRI/US Sales*High Non-P&P + ε

Method: Cluster in one-dimension (Firm), One-way fixed effects (Year). N = 204 firm-years, 26 firms.

Variable	Predicted Sign	Estimate	Error	t-value	Pr > |t|	R-Squared
Intercept		-94.34	75.00	-1.26	0.2201	0.7233
TRI/US Sales	+	22.26	8.46	2.63	0.0072	
Modified Bond Rating	+	30.15	6.16	4.90	<.0001	
Z-Score	–	-34.21	11.87	-2.88	0.0040	
Volatility	+	656.81	166.94	3.93	0.0003	
Maturity	?	1.56	0.63	2.48	0.0204	
Aaa Spread	+	0.88	0.41	2.16	0.0205	
High Non-P&P	?	32.27	28.51	1.13	0.2685	
TRI/US Sales*High Non-P&P	–	-10.52	10.02	-1.05	0.1520	

N.B. Where the sign of a parameter is predicted, t-tests are one-tailed. Variables as per table 1, panel B; except Non-P&P Indicator which is an indicator variable of '1' if a firm is above the sample median for non-pulp and paper sales, '0' otherwise and TRI/US Sales*High Non-P&P, which is an interaction variable between TRI/US Sales and High Non-P&P Indicator. Fixed effects year indicators are not reported.

Table 14: Non U.S. sales

Model: **Yield Spread = α_0 + α_1TRI/U.S. Sales + α_2Modified Bond Rating + α_3Z-Score + α_4Volatility + α_5Maturity + α_6Aaa Spread + α_7High Non-US + α_8TRI/US Sales*High Non-US + ε**

Method: **Cluster in one-dimension (Firm), One-way fixed effects (Year). N = 204 firm-years, 26 firms.**

Variable	Predicted Sign	Estimate	Error	t-value	Pr > |t|	R-Squared
Intercept		-97.85	75.90	-1.29	0.2091	0.7269
TRI/US Sales	+	29.10	7.74	3.76	0.0005	
Modified Bond Rating	+	29.94	6.41	4.67	<.0001	
Z-Score	–	-38.89	10.43	-3.73	0.0005	
Volatility	+	677.66	154.85	4.38	0.0001	
Maturity	?	1.85	0.70	2.64	0.0141	
Aaa Spread	+	0.86	0.41	2.09	0.0237	
High Non-US	?	35.25	33.22	1.06	0.2987	
TRI/US Sales*High Non-US	–	-18.50	10.75	-1.72	0.0489	
Y95		-2.75	17.96	-0.15	0.8797	
Y96		12.20	19.19	0.64	0.5308	
Y97		23.10	20.15	1.15	0.2624	
Y98		-1.76	22.73	-0.08	0.9390	
Y99		64.17	36.89	1.74	0.0942	
Y00		0.10	50.93	0.00	0.9985	
Y01		-9.35	43.70	-0.21	0.8324	
Y02		-57.86	71.59	-0.81	0.4266	
Y03		-54.93	48.08	-1.14	0.2641	
Y04		52.31	30.42	1.72	0.0979	
Y05		98.13	36.76	2.67	0.0131	

N.B. Where the sign of a parameter is predicted, t-tests are one-tailed. Variables as per table 1, panel B. High Non U.S. indicates that the firm-year's sales are above the sample median. High Non-US*TRI/US Sales is the interaction of these two individual variables.

Table 15: Changes model

Model: Δ**Yield Spread** = $\alpha_0 + \alpha_1\Delta$**TRI/U.S. Sales** + $\alpha_2\Delta$**Modified Bond Rating** + $\alpha_3\Delta$**Z-Score** + $\alpha_4\Delta$**Volatility** + $\alpha_5\Delta$**Maturity** + $\alpha_6\Delta$**Aaa Spread** + ε

Method: **OLS.**

Variable	Predicted Sign	Estimate	Error	t-value	Pr > |t|	Adj. R-Squared
Intercept		-58.95	22.79	-2.59	0.0106	0.2430
ΔTRI/US Sales	+	13.01	9.41	1.38	0.0843	
ΔModified Bond Rating	+	20.94	8.55	2.45	0.0077	
ΔZ-Score	–	-25.16	15.35	-1.64	0.0516	
ΔVolatility	+	658.56	125.00	5.27	<.0001	
ΔMaturity		-85.56	23.66	-3.62	0.0004	
ΔAaa Spread	+	0.25	0.11	2.23	0.0137	

N.B. Where the sign of a parameter is predicted, t-tests are one-tailed. Variables are first differences of the variables described in table 1, panel B. Errors are White's standard errors.

Table 16: Duration

Model: **Yield Spread** = $\alpha_0 + \alpha_1$**TRI/U.S. Sales** + α_2**Modified Bond Rating** + α_3**Z-Score** + α_4**Volatility** + α_5**Duration** + α_6**Aaa Spread** + ε

Method: **Cluster in one-dimension (Firm), One-way fixed effects (Year). N = 204 firm-years, 26 firms.**

Variable	Predicted Sign	Estimate	Error	t-value	Pr > |t|	R-Squared
Intercept		-67.38	64.04	-1.05	0.3028	0.7168
TRI/US Sales	+	17.31	5.24	3.31	0.0015	
Modified Bond Rating	+	29.57	6.30	4.7	<.0001	
Z-Score	–	-37.71	10.99	-3.43	0.0011	
Volatility	+	637.71	169.11	3.77	0.0005	
Duration		3.84	1.78	2.15	0.0410	
Aaa Spread	+	0.83	0.39	2.12	0.0219	

N.B. Where the sign of a parameter is predicted, t-tests are one-tailed. Variables as per table 1, panel B. Duration is Macauley's duration index. Fixed effects year indicators are not reported.

Table 17: Bond Rating as control variable

Panel A: Bond Rating as 1 to 22 scale, where AAA+ = 1, AAA = 2, etc.

Model: Yield Spread = α_0 + α_1TRI/U.S. Sales + α_2Bond Rating + α_3Z-Score + α_4Volatility + α_5Maturity + α_6Aaa Spread + ε

Method: Cluster in one-dimension (Firm), One-way fixed effects (Year). N = 204 firm-years, 26 firms.

Variable	Predicted Sign	Estimate	Error	t-value	Pr > |t|	R-Squared
						0.7358
Intercept		-426.52	63.82	-6.68	<.0001	
TRI/US Sales	+	6.73	4.79	1.40	0.0865	
Bond Rating	+	32.30	6.06	5.33	<.0001	
Z-Score	–	8.04	12.22	0.66	0.2584	
Volatility	+	309.54	198.73	1.56	0.0660	
Maturity		1.79	0.60	2.97	0.0064	
Aaa Spread	+	0.84	0.38	2.19	0.0192	

N.B. Where the sign of a parameter is predicted, t-tests are one-tailed. Variables as per table 1, panel B. Bond Rating is the bond rating after being transformed to a scale of 1 to 22 where AAA+ = 1, AAA = 2, etc. Fixed effects year indicators are not reported.

Table 17, Panel B: Log of reversed bond scale (i.e. log of AAA+ = 22, AAA = 21, etc.)

Model: Yield Spread = α_0 + α_1TRI/U.S. Sales + α_2Log of Bond Rating + α_3Z-Score + α_4Volatility + α_5Maturity + α_6Aaa Spread + ε

Method: Cluster in one-dimension (Firm), One-way fixed effects (Year). N = 204 firm-years, 26 firms.

Variable	Predicted Sign	Estimate	Error	t-value	Pr > |t|	R-Squared
						0.6736
Intercept		276.40	267.23	1.03	0.3109	
TRI/US Sales	+	12.68	5.46	2.32	0.0143	
Log of Bond Rating	–	-369.52	210.40	-1.76	0.0457	
Z-Score	–	-13.34	11.37	-1.17	0.1261	
Volatility	+	671.15	249.42	2.69	0.0063	
Maturity		1.59	0.78	2.03	0.0528	
Aaa Spread	+	0.86	0.40	2.17	0.0200	

N.B. Where the sign of a parameter is predicted, t-tests are one-tailed. Variables as per table 1, panel B. Log of Bond Rating is the log of the bond rating after being transformed to a scale of 1 to 22 where D = 1, CCC– = 2.....AAA+ = 22 etc. Fixed effects year indicators are not reported.

Table 18: Investment Grade Bonds Only

Panel A: Equation (4) with investment grade bonds only

Model: **Yield Spread = α_0 + α_1TRI/U.S. Sales + α_2Modified Bond Rating + α_3Z-Score + α_4Volatility + α_5Maturity + α_6Aaa Spread + ε**

Method: **Cluster in one-dimension (Firm), One-way fixed effects (Year). N = 156 firm-years, 21 firms.**

Variable	Predicted Sign	Estimate	Error	t-value	Pr > |t|	R-Squared
						0.6843
Intercept		-129.27	61.76	-2.09	0.0493	
TRI/US Sales	+	7.93	5.31	1.49	0.0754	
Modified Bond Rating	+	13.55	3.26	4.16	0.0003	
Z-Score	–	-19.65	7.35	-2.67	0.0073	
Volatility	+	288.58	122.15	2.36	0.0142	
Maturity		2.59	0.62	4.21	0.0004	
Aaa Spread	+	1.31	0.50	2.63	0.0080	

N.B. Where the sign of a parameter is predicted, t-tests are one-tailed. Variables as per table 1, panel B. Fixed effects year indicators are not reported.

Table 18, Panel B: Equation (4) with non-investment grade bonds only

Model: **Yield Spread = α_0 + α_1TRI/U.S. Sales + α_2Modified Bond Rating + α_3Z-Score + α_4Volatility + α_5Maturity + α_6Aaa Spread + ε**

Method: **Cluster in one-dimension (Firm), One-way fixed effects (Year). N = 48 firm-years, 11 firms.**

Variable	Predicted Sign	Estimate	Error	t-value	Pr > |t|	R-Squared
						0.5183
Intercept		252.60	94.25	2.68	0.0231	
TRI/US Sales	+	1.15	7.92	0.14	0.4439	
Modified Bond Rating	–	-3.08	10.31	-0.30	0.7713	
Z-Score	–	-40.67	17.23	-2.36	0.0200	
Volatility	+	308.27	257.81	1.20	0.1297	
Maturity		-6.12	3.66	-1.67	0.1255	
Aaa Spread	+	0.38	0.38	1.01	0.1675	

N.B. Where the sign of a parameter is predicted, t-tests are one-tailed. Variables as per table 1, panel B. Fixed effects year indicators are not reported.

Table 19: Firm specific reports on # of times named as a PRP			
Firm	**Year**	**PRP from 10-K**	**PRP Estimate**
Abitibi Con	1998	0	0
Abitibi Con	1999	0	0
Abitibi Con	2000	0	0
Abitibi Con	2001	0	0
Abitibi Con	2002	0	0
Abitibi Con	2003	0	0
Abitibi Con	2004	0	0
Abitibi Con	2005	0	0
Bowater	1994	2	2
Bowater	1995	0	0
Bowater	1996	0	0
Bowater	1997	0	0
Bowater	1998	0	0
Bowater	1999	0	0
Bowater	2000	0	0
Bowater	2001	3	3
Bowater	2002	3	3
Bowater	2003	4	4
Bowater	2004	3	3
Bowater	2005	3	3
DOMTAR INC	2001	A number	20
DOMTAR INC	2002	A number	20
DOMTAR INC	2003	A number	20
DOMTAR INC	2004	A number	20
DOMTAR INC	2005	A number	20
GEORGIA-PACIFIC CORP	1994	Numerous	200
GEORGIA-PACIFIC CORP	1995	Numerous	200
GEORGIA-PACIFIC CORP	1996	200	200
GEORGIA-PACIFIC CORP	1997	208	208
GEORGIA-PACIFIC CORP	1998	173	173
GEORGIA-PACIFIC CORP	1999	173	173
GEORGIA-PACIFIC CORP	2000	194	194
GEORGIA-PACIFIC CORP	2001	170	170
GEORGIA-PACIFIC CORP	2002	172	172
GEORGIA-PACIFIC CORP	2003	171	171
GEORGIA-PACIFIC CORP	2004	171	171

Table 19, Cont'd – Firm specific reports on # of times names as a Potentially Responsible Party			
Firm	**Year**	**PRP from 10-K**	**PRP Estimate**
RAYONIER INC	1994	4	4
RAYONIER INC	1995	4	4
RAYONIER INC	1996	6	6
RAYONIER INC	1997	8	8
RAYONIER INC	1998	8	8
RAYONIER INC	1999	7	7
INTL PAPER CO	1994	71	71
INTL PAPER CO	1995	68	68
INTL PAPER CO	1996	73	73
INTL PAPER CO	1997	73	73
INTL PAPER CO	1998	71	71
INTL PAPER CO	1999	108	108
INTL PAPER CO	2000	97	97
INTL PAPER CO	2001	114	114
INTL PAPER CO	2002	117	117
INTL PAPER CO	2003	117	117
INTL PAPER CO	2004	88	88
INTL PAPER CO	2005	90	90
JAMES RIVER	1995	50	50
JAMES RIVER	1996	50	50
FORT JAMES CORP	1997	Various	10
FORT JAMES CORP	1998	Various	10
FORT JAMES CORP	1999	Various	10
SMURFIT-STONE CORP	1998	A number	20
SMURFIT-STONE CORP	1999	A number	20
SMURFIT-STONE CORP	2000	A number	20
SMURFIT-STONE CORP	2001	A number	20
SMURFIT-STONE CORP	2002	A number	20
SMURFIT-STONE CORP	2003	A number	20
SMURFIT-STONE CORP	2004	A number	20
SMURFIT-STONE CORP	2005	A number	20

Table 19, Cont'd. – Firm specific reports on # of times names as a Potentially Responsible Party			
Firm	**Year**	**PRP from 10-K**	**PRP Estimate**
KIMBERLY-CLARK CORP	1994	28	28
KIMBERLY-CLARK CORP	1995	A number	28
KIMBERLY-CLARK CORP	1996	A number	28
KIMBERLY-CLARK CORP	1997	A number	28
KIMBERLY-CLARK CORP	1998	A number	28
KIMBERLY-CLARK CORP	1999	A number	28
KIMBERLY-CLARK CORP	2000	A number	28
KIMBERLY-CLARK CORP	2001	A number	28
KIMBERLY-CLARK CORP	2002	A number	28
KIMBERLY-CLARK CORP	2003	A number	28
KIMBERLY-CLARK CORP	2004	A number	28
KIMBERLY-CLARK CORP	2005	A number	28
POTLATCH CORP	1994	0	0
POTLATCH CORP	1995	0	0
POTLATCH CORP	1996	0	0
POTLATCH CORP	1997	0	0
POTLATCH CORP	1998	0	0
POTLATCH CORP	1999	0	0
POTLATCH CORP	2000	0	0
POTLATCH CORP	2001	0	0
POTLATCH CORP	2002	0	0
POTLATCH CORP	2003	0	0
POTLATCH CORP	2004	0	0
POTLATCH CORP	2005	0	0
SONOCO PRODUCTS CO	1994	Several	10
SONOCO PRODUCTS CO	1995	Several	10
SONOCO PRODUCTS CO	1996	Several	10
SONOCO PRODUCTS CO	1997	Several	10
SONOCO PRODUCTS CO	1998	Several	10
SONOCO PRODUCTS CO	1999	Several	10
SONOCO PRODUCTS CO	2000	Several	10
SONOCO PRODUCTS CO	2001	Several	10
SONOCO PRODUCTS CO	2002	Several	10
SONOCO PRODUCTS CO	2003	Several	10
SONOCO PRODUCTS CO	2004	Several	10
SONOCO PRODUCTS CO	2005	Several	10

Table 19, Cont'd. – Firm specific reports on # of times names as a Potentially Responsible Party			
Firm	**Year**	**PRP from 10-K**	**PRP Estimate**
STONE CONTAINER CORP	1994	A number	20
STONE CONTAINER CORP	1995	A number	20
STONE CONTAINER CORP	1996	A number	20
STONE CONTAINER CORP	1997	A number	20
TEMPLE-INLAND INC	1994	numerous	9
TEMPLE-INLAND INC	1995	numerous	9
TEMPLE-INLAND INC	1996	numerous	9
TEMPLE-INLAND INC	1997	numerous	9
TEMPLE-INLAND INC	1998	numerous	9
TEMPLE-INLAND INC	1999	numerous	9
TEMPLE-INLAND INC	2000	9	9
TEMPLE-INLAND INC	2001	9	9
TEMPLE-INLAND INC	2002	8	8
TEMPLE-INLAND INC	2003	5	5
TEMPLE-INLAND INC	2004	6	6
TEMPLE-INLAND INC	2005	4	4
WAUSAU PAPER CORP	1997	0	0
WAUSAU PAPER CORP	1998	0	0
WAUSAU PAPER CORP	1999	0	0
WAUSAU PAPER CORP	2000	0	0
WAUSAU PAPER CORP	2001	0	0
WAUSAU PAPER CORP	2002	0	0
WAUSAU PAPER CORP	2003	0	0
WAUSAU PAPER CORP	2004	0	0
WAUSAU PAPER CORP	2005	0	0
WESTVACO	1994	several	10
WESTVACO	1995	several	10
WESTVACO	1996	several	10
WESTVACO	1997	several	10
WESTVACO	1998	several	10
WESTVACO	1999	A number	20
WESTVACO	2000	A number	20
WESTVACO	2001	A number	20
MEADWESTVACO CORP	2002	numerous	50
MEADWESTVACO CORP	2003	numerous	50
MEADWESTVACO CORP	2004	numerous	50
MEADWESTVACO CORP	2005	numerous	50

Table 19, Cont'd. – Firm specific reports on # of times names as a Potentially Responsible Party			
Firm	**Year**	**PRP from 10-K**	**PRP Estimate**
MEAD CORP	1994	31	31
MEAD CORP	1995	22	22
MEAD CORP	1996	18	18
MEAD CORP	1997	25	25
MEAD CORP	1998	26	26
MEAD CORP	1999	26	26
MEAD CORP	2000	26	26
WEYERHAEUSER CO	1994	36	36
WEYERHAEUSER CO	1995	41	41
WEYERHAEUSER CO	1996	43	43
WEYERHAEUSER CO	1997	43	43
WEYERHAEUSER CO	1998	numerous	50
WEYERHAEUSER CO	1999	numerous	50
WEYERHAEUSER CO	2000	numerous	50
WEYERHAEUSER CO	2001	numerous	50
WEYERHAEUSER CO	2002	79	79
WEYERHAEUSER CO	2003	73	73
WEYERHAEUSER CO	2004	67	67
WEYERHAEUSER CO	2005	70	70
ROCK-TENN CO	1994	8	8
ROCK-TENN CO	1995	8	8
ROCK-TENN CO	1996	8	8
ROCK-TENN CO	1997	10	10
ROCK-TENN CO	1998	9	9
ROCK-TENN CO	1999	9	9
ROCK-TENN CO	2000	8	8
ROCK-TENN CO	2001	8	8
ROCK-TENN CO	2002	10	10
ROCK-TENN CO	2003	11	11
ROCK-TENN CO	2004	9	9
ROCK-TENN CO	2005	10	10

Table 19, Cont'd. – Firm specific reports on # of times names as a Potentially Responsible Party			
Firm	**Year**	**PRP from 10-K**	**PRP Estimate**
BUCKEYE TECHNOLOGIES	1996	0	0
BUCKEYE TECHNOLOGIES	1997	0	0
BUCKEYE TECHNOLOGIES	1998	0	0
BUCKEYE TECHNOLOGIES	1999	0	0
BUCKEYE TECHNOLOGIES	2000	0	0
BUCKEYE TECHNOLOGIES	2001	0	0
BUCKEYE TECHNOLOGIES	2002	0	0
BUCKEYE TECHNOLOGIES	2003	0	0
BUCKEYE TECHNOLOGIES	2004	0	0
BUCKEYE TECHNOLOGIES	2005	0	0
FORT HOWARD CORP	1994	1	1
FORT HOWARD CORP	1995	2	2
UNION CAMP CORP	1994	A number	14
UNION CAMP CORP	1995	A number	14
UNION CAMP CORP	1996	14	14
UNION CAMP CORP	1997	14	14
CHAMPION INTERNATIONAL	1994	A number	20
CHAMPION INTERNATIONAL	1995	A number	20
CHAMPION INTERNATIONAL	1996	A number	20
CHAMPION INTERNATIONAL	1997	A number	20
CHAMPION INTERNATIONAL	1998	A number	20
WILLAMETTE INDUSTRIES	1994	0	0
WILLAMETTE INDUSTRIES	1995	0	0
WILLAMETTE INDUSTRIES	1996	0	0
WILLAMETTE INDUSTRIES	1997	0	0
WILLAMETTE INDUSTRIES	1998	0	0
WILLAMETTE INDUSTRIES	1999	0	0
WILLAMETTE INDUSTRIES	2000	0	0
GAYLORD CONTAINER CP	1995	0	0
GAYLORD CONTAINER CP	1996	0	0
GAYLORD CONTAINER CP	1997	0	0
GAYLORD CONTAINER CP	1998	0	0
GAYLORD CONTAINER CP	1999	0	0

Table 20: PRP Pearson Correlations					
Variable	# of times PRP	PRP / Total Assets	PRP Est / Tot Assets	PRP / US Sales	PRP Est / US Sales
Yield Spread	-0.0579	-0.1923	-0.1524	-0.2333	-0.1645
p-value	0.5128	0.0284	0.0295	0.0076	0.0187
TRI/US Sales	-0.1966	-0.4351	-0.3356	-0.4044	-0.1993
p-value	0.0250	<.0001	<.0001	<.0001	0.0043
Bond Scale	-0.1010	-0.1194	-0.0622	-0.1863	-0.0864
p-value	0.2527	0.1759	0.3771	0.0339	0.2194
Modified Bond Rating	-0.1641	0.1313	0.1389	-0.0202	-0.0148
p-value	0.0622	0.1365	0.0476	0.8200	0.8334
Volatility	-0.0900	-0.0030	-0.0444	-0.1152	-0.1427
p-value	0.3088	0.9730	0.5284	0.1919	0.0418
Z-Score	-0.1413	0.2569	0.1754	0.1041	0.0153
p-value	0.1088	0.0032	0.0121	0.2386	0.8279
Maturity	0.2484	0.0845	0.1272	0.0820	0.1029
p-value	0.0044	0.3392	0.0699	0.3536	0.1432
Aaa Spread	0.0527	-0.0927	-0.0759	-0.0610	-0.0090
p-value	0.5513	0.2943	0.2807	0.4908	0.8979
Leverage	-0.0814	-0.1656	-0.1129	-0.1779	-0.1237
p-value	0.3570	0.0598	0.1080	0.0429	0.0780
Coverage	-0.1343	0.2674	0.1662	0.1253	0.0126
p-value	0.1277	0.0021	0.0175	0.1553	0.8580
Current	-0.2789	-0.0405	-0.0327	-0.1667	-0.1384
p-value	0.0013	0.6472	0.6423	0.0580	0.0484
Size	0.6315	0.1166	0.0190	0.2911	0.0909
p-value	<.0001	0.1866	0.7875	0.0008	0.1962

# of time PRP is the number of times a firm has been named as a PRP (n=130). PRP/Total Assets is the number of times a firm is named as a PRP scaled by total assets (n = 130). (U.S. sales). PRP Est/Tot Assets is the number of times a firms is named as a PRP, including an estimate for firms that do not explicitly report, scales by total assets (n=204). PRP/US Sales and PRP Est/US Sales are the same measures, scaled by U.S. sales rather than total assets. All other variables are as previously described herein.

Table 21: PRP as a control variable

Panel A: Number of times named as PRP, scaled by total assets

Model: **Yield Spread = $\alpha_0 + \alpha_1$TRI/U.S. Sales + α_2Modified Bond Rating + α_3Z-Score + α_4Volatility + α_5Duration + α_6Aaa Spread + α_7PRP/Total Assets + ε**

Method: **Cluster in one-dimension (Firm), One-way fixed effects (Year). N = 130 firm-years, 18 firms.**

Variable	Predicted Sign	Estimate	Error	t-value	Pr > |t|	R-Squared
Intercept		11.99	76.51	0.16	0.8773	0.7629
TRI/US Sales	+	9.85	4.44	2.22	0.0203	
Modified Bond Rating	+	33.14	7.76	4.27	0.0003	
Z-Score	–	-50.41	5.47	-9.21	<.0001	
Volatility	+	593.21	169.02	3.51	0.0014	
Maturity		2.15	0.66	3.24	0.0048	
Aaa Spread	+	0.78	0.47	1.65	0.1182	
PRP/Total Assets		-2839.02	2151.06	-1.32	0.2044	

N.B. Where the sign of a parameter is predicted, t-tests are one-tailed. Variables as per table 1, panel B. PRP/Total Assets is the number of times a firm is named as a potentially responsible party on a U.S. EPA Superfund site, scaled by total assets. Fixed effects year indicators are not reported.

Table 21, panel B: Estimate of number of times named as PRP, scaled by total assets

Model: **Yield Spread = $\alpha_0 + \alpha_1$TRI/U.S. Sales + α_2Modified Bond Rating + α_3Z-Score + α_4Volatility + α_5Duration + α_6Aaa Spread + α_7PRP Est/Total Assets + ε**

Method: **Cluster in one-dimension (Firm), One-way fixed effects (Year). N = 204 firm-years, 26 firms.**

Variable	Predicted Sign	Estimate	Error	t-value	Pr > |t|	R-Squared
Intercept		-47.49	61.93	-0.77	0.4504	0.7256
TRI/US Sales	+	14.26	5.50	2.59	0.0078	
Modified Bond Rating	+	31.48	6.27	5.02	<.0001	
Z-Score	–	-37.47	10.43	-3.59	0.0007	
Volatility	+	642.18	148.49	4.32	0.0001	
Maturity		1.97	0.77	2.55	0.0086	
Aaa Spread	+	0.84	0.39	2.15	0.0206	
PRP Est/Total Assets		-3199.32	2317.69	-1.38	0.1797	

N.B. Where the sign of a parameter is predicted, t-tests are one-tailed. Variables as per table 1, panel B. PRP Est/Total Assets is the number of times a firm is named as a potentially responsible party on a U.S. EPA Superfund site, scaled by total assets. For firms that do not report the specific number, an estimate is used. Fixed effects year indicators are not reported.

Table 22: Lag of TRI/US Sales

Model: **Yield Spread$_{it}$ = α_0 + α_1TRI/U.S. Sales$_{it-1}$ + α_2Modified Bond Rating$_{it}$ + α_3Z-Score$_{it}$ + α_4Volatility$_{it}$ + α_5Maturity$_{it}$ + α_6Aaa Spread$_{it}$ + ε**

Method: **Cluster in one-dimension (Firm), One-way fixed effects (Year). N = 178 firm-years, 26 firms.**

Variable	Predicted Sign	Estimate	Error	t-value	Pr > |t|	R-Squared
Intercept		-58.78	63.87	-0.92	0.3662	0.7073
Lag TRI/US Sales	+	14.46	4.43	3.26	0.0016	
Modified Bond Rating	+	30.89	6.69	4.62	0.0001	
Z-Score	–	-36.86	11.52	-3.2	0.0019	
Volatility	+	589.76	183.47	3.21	0.0018	
Maturity		2.00	0.79	2.54	0.0178	
Aaa Spread	+	0.81	0.41	1.99	0.0286	

N.B. Where the sign of a parameter is predicted, t-tests are one-tailed. Variables as per table 1, panel B. Lag TRI/US Sales is TRI/US Sales for the calendar year prior to the fiscal year for each sample firm-year. Fixed effects year indicators are not reported.

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