Bankruptcy in the Pulp and Paper Industry: Market's Reaction & Prediction

Chun-Yu Ho*, Patrick McCarthy[, a], Yi Yang***, Xuan Ye******

CPBIS Working Paper[§]

Abstract:

This paper examines North American pulp and paper company bankruptcies that occurred between 1990 and 2009. We demonstrate that shareholders suffer substantial losses (37%) during the month a bankruptcy occurs. Encouragingly, we show that financial ratios are useful in predicting firm failure and that failed firms are less profitable, more liquidity constrained and higher in debt leverage. Using a binary logit model in the spirit of Ohlson (1980), we predict financial distress for pulp and paper firms one to two years ahead of the bankruptcy. We also adapt and re-estimate the empirical model on a sample of pulp and paper firms and perform in-sample and out-of-sample forecasts. For the out-of-sample analysis, our re-estimated Ohlson models correctly predict 93% of bankruptcy and non-bankruptcy outcomes.

Final Submission: 9 September 2012

Keywords: Forest Products, Pulp and Paper, Industry Studies, Bankruptcy, Corporate Finance

JEL Classification: G33, L67, L73, Q23

* School of Economics, Antai College of Economics and Management, Shanghai Jiao Tong University, Shanghai 200052, P.R. China.
** School of Economics and the Center for Paper Business and Industry Studies (CPBIS), Ga Tech, Atlanta GA., 30332
*** Capital One, McLean, VA., 22102.
**** PhD student, Stern School of Business, New York University, NY, 10012.
§ Research funded by the Center for Paper Business and Industry Studies, Ga Tech.

a Corresponding Author, e-mail: mccarthy@gatech.edu

1 Introduction

The pulp and paper industry is an important sector in the U.S. economy. According to the 2002 U.S. Economic Census, the value of shipments in 2002 dollars was $154 billion for the paper industry.[1] The industry accounted for 3.9% of the manufacturing shipments. The paper industry employed 491,000 workers (3.4% of the manufacturing industry) in 2002. However, the industry has been in decline. The 2007 U.S. Economic Census reports that the value of shipments in year 2007 decreased to $152 billion for the paper industry, representing 3.3% of manufacturing shipments.[2] Similarly, employment in the pulp and paper industry fell to 417,000 workers (3.1% of the manufacturing industry) in 2007.[3]

North American pulp and paper companies continue suffering through decreasing world market shares, falling demands, and the effects of technological changes.[4] Reflecting these longer term trends, there is an increasing number of pulp and paper firms filing for Chapter 11 bankruptcy protection.[5] Filing bankruptcy is often costly for shareholders because it increases the present value of bankruptcy costs and reveals the true value of a firm's assets. Direct (litigation and attorney fees) and indirect (profit loss and time involved) costs for reorganization process and a chance the shares will become worthless induce a negative market reaction to bankruptcy filing. The magnitude of such reaction in the stock price indicates the expected total cost of bankruptcy filing to shareholders.

Despite its importance in contributing to gross domestic product, employment, international trade, and producing a vast array of products that affect all aspects of daily life, there is no study on bankruptcy in the pulp and paper industry. This paper fills the existing knowledge gap and analyzes these failed firms in North America during a twenty year period, 1990-2009. We propose that an early warning signal for bankruptcy filing can be produced by a prediction model

[1] In this paper, we define the NAICS (North American Industry Classification System, 2007) code range within 322 (Paper manufacturing) as the pulp and paper industry. It consists of mills (NAICS 3221; Pulp, Paper, and Paperboard Mills) and paper manufacturing sectors (NAICS 3222; Converted Paper Product Manufacturing).
[2] We use GNP deflator to convert nominal value to real term in year 2002 dollars.
[3] The statistics can be downloaded from the website of US Census: http://www.census.gov/econ/census07.
[4] For example, recent evidence indicates that there is a shift in demand from North America to other parts of the world (McCarthy and Lei, 2010).
[5] Notable examples are: (1) Newsprint maker AbitibiBowater, with 25 pulp and paper plants and 30 wood product plants, filed for bankruptcy protection on April 16, 2009; (2) Smurfit-Stone, a major player in the packaging sector and the largest cardboard maker in North America, cited 'frozen credit markets' for its bankruptcy protection filing on January 27, 2009; (3) Chesapeake Corporation, a paperboard and packaging supplier, filed for bankruptcy in December, 2008; and (4) Tembec Industries, Inc., a lumber, pulp, and paper producer, filed for bankruptcy in September, 2008.

(such as logit model and MDA) consisting of financial ratios. Nearly bankrupt firms can use the relevant financial ratios as a guideline for restructuring their business to avoid bankruptcy in years ahead and to reduce losses for investors.

We report two new empirical findings in this study. First, we estimate the market's reaction to bankruptcy filings and provide suggestive evidence that a bankruptcy announcement provides additional information to market participants on firm value. Shareholders suffer substantial losses (37%) during the month a bankruptcy occurs. Second, we demonstrate that financial ratios are important in predicting bankruptcy. Failed firms are less profitable, more liquidity constrained and higher in debt leverage. Using a binary logit model in the spirit of Ohlson (1980), we predict financial distresses for pulp and paper companies one to two years ahead of the bankruptcy. Furthermore, in a validation analysis, our model achieves 93% accuracy rate in the out-of-sample forecasts for two bankruptcies and 42 non-bankruptcies in the two year period, 2007-2008.

This analysis contributes to the literature on firm dynamics in the pulp and paper industry by providing a bankruptcy prediction model based on publicly-available financial information. Li et al. (2004) and Sun (2006) analyze the survival of U.S. pulp and paper mills from 1970 to 2000 using a micro-capacity dataset. The survival rates of small and new mills are usually lower than those of the large and mature mills. Our work differs from the previous two works in an important aspect. Since we focus on a sample of pulp and paper firms listed on the stock exchange, we are able to associate the survival rates of those firms with financial information, which has implications for management and is absent in the previous two studies.

Moreover, we quantify the adverse valuation effect of a bankruptcy filing. Pesendorfer (2003) examines mergers and acquisitions (M&As) in the U.S. paper and paperboard industry in the 1980s, and shows that the efficiency of most acquiring firms improved after an acquisition. Mei and Sun (2008) examine 70 M&As for the period 1990-2004 and show that the average cumulative abnormal returns for targeting firms is about 4% over a 7-15 days event window.[6] Esteve-Perez et al. (2010) argue that, although both M&A and bankruptcy are important routes for firm exit, these two exit routes are very different and should be examined separately. The former method sells the firm as a whole to another firm, whereas the latter method sells the assets in the market. The choice of using M&A or bankruptcy as an exit strategy depends on

[6] Event study is also employed in Niquidet (2008) to quantify the change in forest policy of Canada.

various factors, including age, size, labor productivity and whether undertaking R&D and advertising activities. Interesting, our paper complements the previous work in showing that there are fewer bankruptcies than M&A for the period 1990-2004, and bankruptcy filing results in a negative market reaction.

2 Bankruptcy: Background and Literature

When a firm is unable to service its debt or pay its creditors, there are two common options to resolve the problem. First, the firm and its creditors can negotiate with its creditors to restructure debt payments. Private negotiation does not entail legal costs and is more cost-effective to resolve the problem if the firm and its creditors can easily reach a solution for debt restructure. Second, the firm or its creditors can file with a federal bankruptcy court for protection under either Chapter 7 or Chapter 11. In Chapter 7, the business ceases operations, a trustee sells all of its assets, and then distributes the proceeds to its creditors. Any residual amount is returned to the owners of the firm. In Chapter 11, the debtor usually proposes a plan of reorganization to stay in business and continues to operate the business during restructuring. A bankruptcy court oversees the reorganization of the firm's contractual and debt obligations and may grant complete or partial relief from most of the firm's debts and contracts. In this section, we concentrate on Chapter 11, which is the focus of our empirical analysis.

After filing bankruptcy, the U.S. Trustee, the bankruptcy arm of the Justice Department, will appoint one or more committees to represent the interests of creditors and stockholders in working with the firm to develop a plan of reorganization. The plan must be accepted by the creditors, bondholders, and stockholders, and confirmed by the court. However, even if creditors or stockholders vote to reject the plan, the court can disregard the vote and still confirm the plan if it finds that it treats creditors and stockholders fairly. Once the plan is confirmed, another more detailed report (Form 8-K) must be filed with the SEC containing a summary of the plan. Moreover, under Chapter 11, a firm usually keeps doing business and its stock and bonds may continue to trade in securities markets. Since it still trades, the firm must continue to file SEC reports with information about significant developments.

The main benefit of filing protection under Chapter 11 is that the firm can keep its assets to continue its business. The firm is granted a time period to successfully reconstruct its debt. Filing Chapter 11 often involves changes in management, organization and governance structure in order to improve resource allocation within the firm and create value. On the other hand, there are direct and indirect costs for filing Chapter 11. The direct costs are litigation and attorney fees, whereas the indirect costs include time involved and profit forgone. White (1984) shows that total cost for filing Chapter 11 ranges from 3% to 10% of debt value for direct costs plus significant indirect costs.

Firms choose to file Chapter 11 when the benefit outweighs cost. For example, benefits will likely outweigh costs when: 1) coordination among a firm's many creditors to reach a reorganization plan is difficult, making it more likely for firms to file protection under Chapter 11; 2) the firm wants to halt all creditors' collection efforts for months or years (as managers draft and then negotiate a plan of reorganization) in order to continue its business; and 3) the direct costs of filing Chapter 11 are substantial as is the case for less-capitalized firms.

Because of the huge potential cost of bankruptcy filing, researchers conduct event studies to examine market reactions to bankruptcy filings. More specifically, they estimate the abnormal return (AR) and cumulative abnormal return (CAR) for filing firms based on the event study methodology. The AR, i.e. the excess return over expected return, around an event is attributed to the occurrence of the event. Researchers use the AR over the event window to measure the impact of a bankruptcy announcement on firm value. Additionally, they employ the cumulative abnormal return (CAR), i.e. the abnormal return summed over the event window for each point in time, as an overall measure of the impact over a time period. Looking into U.S. listed firms, Clark and Weinstein (1983) and Lang and Stulz (1992) show, respectively, that there is a negative market reaction in response to a bankruptcy announcement during 1960-70's and 1970-80's.

Based on the event study methodology, we provide suggestive evidence that there is a negative market reaction to a bankruptcy announcement for pulp and paper firms. Figure 1 plots the CAR for filing firms in the pulp and paper industry over the event window twenty days before and five days after the announcement.[7] We report that shareholders incur 36.9% losses during the period one day before and after the bankruptcy announcement, which is comparable to that (47%) shown in Clark and Weinstein (1983). To put our results in perspective, we compute the valuation effects (i.e. the changes in market capitalization) on bankrupt firms. The average market capitalizations of filing firms in the pulp and paper industry is 0.13 million fifty days

[7] The estimation procedure is outlined in the Appendix 2

before the bankruptcy. The negative valuation impact on filing firms is about 0.07 (=0.13*0.369) million.

The substantial loss in shareholder wealth when a firm announces its bankruptcy filing draws the attention of economists to understand and predict bankruptcy choice. In a seminal work, Altman (1968) shows that a firm is more likely to fail if it is unprofitable, highly leveraged, and illiquid. Myers (1977) then provides a theoretical model which helps to explain these findings. The model predicts that investors will choose to liquidate a firm if its liquidation value exceeds its continuation value. If a profitable firm has a higher continuation value, one should find that it is less likely to go bankrupt than unprofitable firm.

Bulow and Shoven (1978) examine an insolvent firm's decision between liquidation and continuation, with a focus on the efficient timing of bankruptcy. This study assumes that a bank lender and equity holder have bankruptcy decision power but a bondholder does not have rights to restructure its debt. Consequently, the bankruptcy decision of a bank and equity holder is not based on maximizing total value of the firm, and can lead viable firms to shut down or non-viable firms to survive. Aivazian and Callen (1983) argue that allowing re-contracting among shareholders and bondholders can potentially overcome any inefficiency generated by bankruptcy, as long as bargaining costs are negligible. They claim that formal bankruptcy code, such as Chapter 11, may reduce transaction costs helping to generate efficient re-contracting outcomes in bankruptcy.

The theory suggests profitability determines bankruptcy decision. For example, a firm has a high bankruptcy probability if it faces very competitive input and output markets or it faces a drop in pulp prices because each leads to lower firm profits. Financial condition is also important to a bankruptcy decision because it informs on a firm's value and its ability to service debt. A firm is less likely to default on its debt if it has access to internal or external finance. A liquid firm has relatively easy access to internal finance, and so it is less likely to go bankrupt than an illiquid firm. Large firms are less likely to encounter market credit constraints for external finance because there is less information asymmetry for large firms. A highly-leveraged firm is more likely to file bankruptcy because creditors can file bankruptcy protection when the firm cannot service its debt. Therefore, profitability, liquidity, size and leverage relate to bankruptcy filing.

Moreover, macroeconomic variables are useful in predicting a bankruptcy decision because these factors affect firm's profitability and access to finance. For example, according to the U.S. Court, the number of Chapter 11 bankrupting filing increased from 5,163 in 2006 to 15,189 in 2009. In the aftermath of the financial crisis in 2007, the amount of loans and the cost of loans decreased and increased, respectively (Ivashina and Scharfte, 2010; Santos 2010). The adverse macroeconomic shock reduced a firm's profitability and made it more difficult for a firm to obtain funding to service its debt. Consequently, it the financial crisis raised bankruptcy filings after 2007.

3 A Model of Bankruptcy Prediction

In light of the adverse effect of bankruptcy filings on shareholders, a bankruptcy prediction model provides a warning system for managers to mitigate the chance of firm failure. There are many prediction models proposed in the bankruptcy literatures. Models based on accounting ratios are commonly used to measure firms' bankruptcy risks. The basis of this class of models is that financial ratios should systematically vary between bankrupt and non-bankrupt firms at least one year before a firm files for bankruptcy protection. Beaver (1966) pioneers the use of financial ratios for bankruptcy prediction, but his approach was restricted to univariate analysis. However, there is no consensus on which set of financial ratios to include in the bankruptcy studies. Boritz (1991), for example, suggests more than 65 financial ratios while Hamer (1983) argues that the ability of a model to predict firm failure is relatively independent of ratios used.

Altman (1968) develops an empirical framework for bankruptcy prediction using multiple discriminant analysis (MDA). Ohlson (1980), on the other hand, uses logit analysis, which overcomes several statistical problems inherent in the MDA approach, including the assumptions that the financial ratios of bankrupt and non-bankrupt groups are normally distributed and have the same variance-covariance matrix (Maddala, 1983 page 16-18). Hamer (1983) compares MDA with logit analysis for several datasets and concludes that both models are comparable in predicting firm failure. However, Begley et al. (1996) argues that Ohlson's model outperforms Altman's (1968) model. Logit analysis and MDA are two commonly used methods in the literature of bankruptcy prediction. In this paper, we employ the logit model based on financial ratios (including total assets) according to Ohlson (1980) as our main model and provide a robustness check with the MDA model of Altman (1968) (reported in Appendix 3). The results of both models point to the conclusion that financial ratios are useful in predicting bankruptcy in the years ahead, which provide confidence in our use of logit analysis and financial ratios.[8]

Ohlson (1980) uses a logit model to examine the probability of bankruptcy. Let y_i be the occurrence of bankruptcy for firm i, which equals 1 if a firm files for bankruptcy and 0 otherwise. The probability that firm i goes bankrupt is

$$P(y_i = 1 | X_i) = \frac{\exp(\beta_1 X_{1i} + \beta_2 X_{2i} + \cdots + \beta_{ki} X_{ki})}{1 + \exp(\beta_1 X_{1i} + \beta_2 X_{2i} + \cdots + \beta_{ki} X_{ki})} \tag{1}$$

where $\{\beta_1 \ldots, \beta_k\}$ are k parameters to be estimated, $\{X_1 \ldots, X_k\}$ are variables that determine bankruptcy, and the errors are logistically distributed. Listed below, Ohlson identifies nine financial ratios below to represent four general factors that affect bankruptcy: firm size (1), financial structure (2, 4), liquidity (3, 5, 6), and performance (7, 8, 9). From the logit model, the odds that firm i goes bankrupt are $\exp(\sum_{i=1}^{k} \beta_i X_i)$.[9]

(1) ln (Total Assets/GNP Price-level Index), a measure of real assets (RASSET) and firm size. Since total assets are reported in dollars, we deflate it with the GNP deflator with a base value of 100 for year 1968;
(2) Total Liabilities/Total Assets (TLTA), which measures overall debt leverage;
(3) Current Liabilities/Current Assets (CLCA), which measures short-term obligation for current assets;
(4) Net Liability (NLNEG), which is a dummy variable that equals one if a firm's total liabilities exceed total assets and 0 otherwise;
(5) Working Capital/Total Assets (WCTA), which measures liquidity relative to total assets and total debts;
(6) (Pretax Income + (Depreciation and Amortization))/Total Liabilities (FFOTL), which measures firm performance on recurring operations;[10]

---

[8] We focus on Ohlson's (1980) logit model rather than Atlman's (1968) MDA model because it allows us to use more observations of bankrupt firms. There are two bankrupt firms in our sample, namely Equitable Bag Co. Inc. and American Tissue Inc., which do not have market value of equity data for estimating Atlman's (1968) model.
[9] The odds of bankruptcy are $P(y_i = 1|X_i) /(1 - (P(y_i = 1|X_i))$ which, from equation (3) is $\exp(\beta_i)$, which implies that a unit increase in X_i increases the odds of bankruptcy by a factor of $\exp(\beta_i)$.
[10] Ohlson used (Funds provided by Operations/Total Liabilities). Funds provided by Operations is operating revenue which was not available. As a proxy, we used (Pretax Income + Depreciation and Amortization).

(7) Net Income/Total Assets (NITA), which profitability in the current year;

(8) Income Negative for Two Years (INTWO), which captures firms with extremely poor profitability. INTWO is a dummy variable which takes the value one if net income was negative for the last two years and 0 otherwise;

(9) Change in Net Income (CHIN), which measures income growth and is defined as $(N_{it} - N_{it-1})/(|N_{it}| + |N_{it-1}|)$, where N_{it} is net income for year t and the denominator acts to ensure positive income growth when $(N_{it} - N_{it-1})$ is positive, regardless of whether net income in year (t-1) is positive or negative.

Ohlson's O-score is the estimated probability of bankruptcy from the logit model,

$$\text{O-Score} = \hat{P}_i = \frac{\exp(\hat{\beta}_1 X_{1i} + \hat{\beta}_2 X_{2i} + \cdots + \hat{\beta}_{ki} X_{ki})}{1 + \exp(\hat{\beta}_1 X_{1i} + \hat{\beta}_2 X_{2i} + \cdots + \hat{\beta}_{ki} X_{ki})}$$

Ohlson estimates his models using 105 bankrupt and 2058 non-bankrupt firms in manufacturing industries. Equation (2) reports Ohlson's estimated logit (i.e. log odds) for predicting bankruptcy one-year ahead:

$$\ln[P_i/(1 - P_i)] = -1.32 - 0.41\ \text{RASSET} + 6.03\ \text{TLTA} - 1.43\ \text{WCTA} + 0.08\ \text{CLCA} - 1.72\ \text{NLNEG} - 2.37\ \text{NITA} - 1.83 - \text{FUTL} + 0.29\ \text{INTWO} - 0.52\ \text{CHIN} \qquad (2)$$

Ohlson finds that a cut-off value $P_{cutoff} = 0.038$ minimizes the sum of Type I (predicting a bankrupt firm to be healthy) and Type II (predicting a healthy firm to be bankrupt) errors for his sample. A higher P_{cutoff} indicates a higher probability of bankruptcy. If the predicted probability $\hat{P}_i$ for firm i from Ohlson's model is less than the cutoff P_{cutoff} point but the firm is bankrupt, this is a Type I error. A Type II error occurs when the predicted probability $\hat{P}_i$ is greater than the cut-off point P_{cutoff}, but the firm is not bankrupt.

4 Data

Our empirical analysis utilizes a sample of publicly listed firms from COMPUSTAT North America and the Center for Research on Security Prices (CRSP) databases, Wharton Research

Data Services (WRDS). We focus on pulp and paper firms (NAICS 322) between 1990 and 2009 which covers three sectors including pulp and paper mills, paperboard mills, and converted paper product manufacturing. We collect the daily stock prices of individual firms from CRSP, and use these to compute the daily returns for analyzing the market's reaction to a firm's bankruptcy filing. Using COMPUSTAT, we collect annual financial and related data from a firm's balance sheet and income statement to compute the financial ratios for building a bankruptcy prediction model.

We define the bankruptcy date according to the date of bankruptcy filing reported in BankruptcyData.com.[11] Events included correspond to filing Chapter 11 bankruptcy protection (corporation reorganization and restructuring).[12] Our sample includes 122 individual firms, 12 of which filed for bankruptcy during the sample period. Table A1-1 in Appendix 1 provides the list of bankrupt firms in the pulp and paper industry from 1990 to 2009, including their filing dates and 4-digit NAICS codes. There are 27 filings of Chapter 11 bankruptcy protection over that period in which 5 and 8 bankruptcies filed in year 2000 and 2009, respectively. Although there are idiosyncrasies in determining the bankruptcy decision, bankruptcy filing increases during economic recessions. Moreover, the more recent bankruptcy filings are in pulp, paper and paperboard sector of the industry.

Our sample covers about 5% of total firms in the pulp and paper industry (SIC 322) in which there are 3,808, 3,537 and 3,242 in years 1997, 2002 and 2007, respectively, according to U.S. Economic Census. Therefore, our sample of listed firms cannot capture the bankruptcy probability of private firms, which are smaller in size and young in age. Esteve-Perez et al. (2010) point out that the choice of bankruptcy filing as an exit strategy decreases as firm size increases. As a result, our empirical results need to be interpreted with caution because we may underestimate the effect of financial and macroeconomic conditions on bankruptcy probability.

5 Descriptive Statistics

Our 122 individual sample firms give us a sample of 1,047 firm-years that have data on O-

---

[11] We cross-check the year of bankruptcy with the year of deletion reported in LoPucki's Bankruptcy Research Database (BRD) and COMPUSTAT (footnote 34). Source of BRD: http://lopucki.law.ucla.edu, provided by Lynn M. LoPucki.

[12] We cross checked these data with COMPUSTAT (footnote 35, reason of deletion).

Score over the period 1990-2005.[13] For compiling the sample for the prediction model, we removed the firm-years after they filed Chapter 11.[14] Also, in order to include only those firms that survived throughout a fiscal year, we use data one year before the year of bankruptcy.

Table 1 presents the descriptive statistics for our bankrupt firms and their matched non-bankrupt counterparts. For each bankrupt firm in the pulp and paper sector (NAICS 322), we find two non-bankrupt firms in this same sector which have total assets that are next bigger and next smaller than the bankrupt firm. We then match the financial ratios of the bankrupt firm with the simple average of the two selected non-bankrupt firms. Since data are through 2005 and some pulp and paper firms went bankrupt after that year, the number of observations for one and two years before the bankruptcy are less than the number of observations three years prior to the bankruptcy. For example, Chesapeake went bankrupt in 2008. To predict bankruptcy one year ahead requires data for 2007, which is unavailable. But we can predict bankruptcy two years ahead because we have 2006 data available. On the other hand, there are several firms that only have data for two sample years, thus the observations on three years prior to the bankruptcy for those failed firms are unavailable. Consequently, the number of observations for three years before the bankruptcy is less than the number of observations two years prior to the bankruptcy.

We compare the financial ratios of bankrupt and matched non-bankrupt firms for one to three years prior to the bankruptcy. The financial ratios are classified into four groups reflecting size, liquidity, profit and leverage. Tables A1-2 in Appendix 1 reports the data sources and defines the variables in the logit models.

From the t-statistics, there is no significant difference in the level of real total assets size, i.e. firm size, between the bankrupt and non-bankrupt firms. The failed firms are more liquidity constrained relative to the non-failed firms. And the failed firms have fewer current assets to meet their short term obligation of current liability. Figure 2 indicates that the ratio of current liabilities to current assets (CLCA) increases from 67% to 242% when the failed firms approach bankruptcy. On the other hand, for non-failed firms, this ratio hovers around 46-60%. Additionally, the failed firms have lower ratios of net working capital to total assets (WCTA) and ratios of funds provided by operations to total liabilities (FFOTL), which are about zero.

[13] Although the price information is available until 2009, the balance sheet information for estimating the prediction model ended in 2006. Therefore, the last year of the model uses the information in 2005 to predict the bankruptcy in 2006

[14] We also deleted a non-bankrupt firm, EarthShell Corp., which we regard as an outlier due to its small total assets.

Not surprisingly, non-failed firms are more profitable and the pattern of net income to total assets (NITA) indicates that the failed firms consistently lose money several years before bankruptcy. Figure 3 shows that, as a ratio of total assets, net income declines from -3% to less than -15% as the year of bankruptcy approaches, while the non-bankrupt firms maintain net income at 1-4% of their total assets. Consistent with these results are INTWO and CHIN.

Table 1

Descriptive Statistics and Means Tests for Bankrupt (B) and Non-Bankrupt (NB) Firms

	1st year Before (obs = 9)			2nd year Before (0bs = 10)			3rd year Before (0bs = 9)		
Variable	B	NB	t-stat	B	NB	t-stat	B	NB	t-stat
Size Related									
RASSET	0.15	0.17	-0.10	0.26	0.24	0.10	0.55	0.47	0.16
	[0.48]	[0.55]		[0.54]	[0.54]		[0.98]	[1.06]	
Liquidity Related									
WCTA	-0.34	0.20	-3.42	0.09	0.15	-2.23	0.12	0.19	-1.19
	[0.47]	[0.05]		[0.05]	[0.07]		[0.09]	[0.15]	
CLCA	2.42	0.46	3.14	0.71	0.60	1.84	0.67	0.53	1.27
	[1.87]	[0.06]		[0.15]	[0.11]		[0.26]	[0.19]	
FFOTL	-0.07	0.18	-2.33	0.02	0.20	-2.90	0.07	0.19	-1.33
	[0.17]	[0.27]		[0.18]	[0.10]		[0.19]	[0.19]	
Profit Related									
NITA	-0.15	0.01	-2.30	-0.06	0.04	-3.60	-0.03	0.02	-1.39
	[0.20]	[0.10]		[0.08]	[0.04]		[0.10]	[0.03]	
INTWO	0.33	0.06	1.58	0.20	0.05	1.05	0.44	0.00	2.53
	[0.50]	[0.17]		[0.42]	[0.16]		[0.53]	[0.00]	
CHIN	-0.12	0.10	-0.85	-0.32	0.10	-1.28	-0.08	-0.21	0.42
	[0.59]	[0.51]		[0.85]	[0.18]		[0.84]	[0.39]	
Leverage Related									
TLTA	1.01	0.67	3.52	0.84	0.67	2.44	0.74	0.62	1.14
	[0.21]	[0.20]		[0.19]	[0.10]		[0.19]	[0.24]	
NLNEG	0.44	0.11	1.76	0.10	0.05	0.45	0.11	0.06	0.45
	[0.53]	[0.22]		[0.32]	[0.16]		[0.33]	[0.17]	

RASSET - Log(Real Total Assets)
WCTA - Net Working Capital/Total Assets#
CLCA - Current Liabilities/Current Assets
FFOTL - (Pretax Income + Depreciation and Amortization)/Total Liabilities
NITA - Net Income/Total Assets
INTWO - Negative Income, Two Years Dummy Variable
CHIN - Change in Net Income
TLTA - Total Liabilities/Total Assets
NLNEG - Net Liability Dummy Variable
Standard Deviations are shown in []

Turning to a firm's capital structure, we see that the failed firms have ratios of total liability to total assets (TLTA) one and two years before bankruptcy that are significantly higher than those of the non-failed firms. For the failed firms, TLTA increases from 74% to 101% as bankruptcy approaches, which is much higher than the TLTAs of the non-bankrupt firms. Figure 4 illustrates that TLTAs of bankrupt and non-bankrupt firms diverge as early as three years before bankruptcy, which is consistent with the previous results. Moreover, total liability of a failed firm is likely to be larger than its total asset in the year before bankruptcy (NLNEG). This suggests that those firms that rely on debt finance have a high risk of failure when profitability and liquidity decline during economic downturns. In particular, the failed firms have difficulty meeting their debt obligations for both short and long term debts.

Table 2 Correlation Matrix for Variable used in Ohlson (1980)

	RASSET	TLTA	WCTA	CLCA	NITA	FFOTL	INTWO	NLNEG	CHIN
RASSET	1								
TLTA	0.20	1							
WCTA	-0.34	-0.51	1						
CLCA	0.05	0.31	-0.71	1					
NITA	0.08	-0.33	0.28	-0.30	1				
FFOTL	-0.18	-0.38	0.38	-0.22	0.53	1			
INTWO	-0.06	0.31	-0.14	0.18	-0.30	-0.15	1		
NLNEG	-0.04	0.63	-0.19	0.22	-0.23	-0.10	0.26	1	
CHIN	-0.02	-0.04	0.08	-0.05	0.31	0.13	0.22	0.01	1

Table 2 reports the correlation coefficients for variables in our sample used in Ohlson's models.[15] The financial state variables TLTA, NLNEG, WCTA and CLCA are uncorrelated with the performance variables NITA, FFOTL, INTWO and CHIN. However, there are high correlations between WCTA and TLTA, between WCTA and CLCA, between NLNEG and TLTA and between FFOTL and NITA. This suggests that (1) NLNEG and CLCA may not be statistically significant in the logit regression model and (2) NITA provides little independent information in the statistical analysis conditional on FFOTL. These results support the hypothesis that liquidity, profitability and leverage are important in analyzing the bankruptcy occurrences.

5.1 Descriptive Statistics by Sectors

We categorize our sample into two sectors, pulp and paper mills and converted paper. Table

[15] Ohlson (1980) only reported correlation coefficients larger than 0.20.

3 reports the descriptive statistics of bankrupt and non-bankrupt firms in these sectors one year before bankruptcy.[16] Firms in the mill sector are larger than those in the converted paper sector.[17]

Table 3
Descriptive Statistics and Means Tests: Bankrupt (B) and Non-Bankrupt (NB) Firms Across Sectors and in the 1st year Before Bankruptcy

	Mills (Obs=4)			Converted Paper (Obs=5)		
	B	NB	t-stat	B	NB	t-stat
Size Related						
RASSETS	0.24	0.34	-0.60	0.07	0.04	0.08
	[0.20]	[0.29]		[0.64]	[0.72]	
Liquidity						
WCTA	-0.14	0.19	-1.16	-0.49	0.20	-4.47
	[0.58]	[0.03]		[0.34]	[0.06]	
CLCA	1.81	0.44	1.13	2.91	0.47	3.87
	[2.41]	[0.07]		[1.41]	[0.06]	
FFOTL	0.01	0.02	-0.07	-0.13	0.31	-3.73
	[0.17]	[0.28]		[0.16]	[0.21]	
Profitability						
NITA	-0.09	-0.04	-0.51	-0.21	0.05	-2.67
	[0.18]	[0.14]		[0.21]	[0.02]	
INTWO	0.50	0.13	1.19	0.20	0.00	1.00
	[0.58]	[0.25]		[0.45]	[0.00]	
CHIN	0.26	-0.18	1.07	-0.42	0.32	-2.94
	[0.57]	[0.59]		[0.44]	[0.36]	
Leverage						
TLTA	1.05	0.75	1.79	0.98	0.60	3.13
	[0.31]	[0.11]		[0.11]	[0.25]	
NLNEG	0.50	0.13	1.19	0.40	0.10	1.13
	[0.58]	[0.25]		[0.55]	[0.22]	

Std. deviations are shown in []

T-stat is a two-sided test for the null of equality between bankrupt firms and non-bankrupt firms

Profitability is lower for a bankrupt firm than its non-bankrupt counterpart. Moreover, the bankrupt firms in the converted paper sector are less profitable than those in the mills sector. In addition, bankrupt firms in the mills sector are more leveraged than those in the converted paper sector (see TLTA). And liquidity of a bankrupt firm is lower than that of its non-bankrupt counterpart, particularly in the converted paper sector (see WCTA, CLCA and FFOTL). These results are again consistent with expectations that poor profitability, high leverage, and tight liquidity are important features of bankrupt firms across the two sectors.

[16] The results in years 2 and 3 are qualitatively similar to those in year 1. Descriptive statistics for two and three years before bankruptcy are available upon request.

[17] In terms of total assets (1 year before bankruptcy), the firm size of bankrupt mills is 1,669 million and that of non-bankrupt mills is 1755. On the other hand, the firm size of bankrupt converted paper firms is 438 million and that of non-bankrupt converted paper firms is 445.

6 Empirical Results

In this section, we re-estimate the Ohlson (1980) model on our sample of 1,047 firm-year observations and discuss their results.[18] And we extend Ohlson's model to include real GDP growth (RGDPG) and real interest rate of 2-year Treasury bond (Rinterest) to control for aggregate fluctuations. To capture sectoral heterogeneity, we include a dummy variable which equals 1 if the firm has a pulping mill and 0 otherwise. Table 4 reports the estimates of Ohlson's original model and our re-estimated model.

Table 4 Logit Estimates and their Marginal Effects

	Original Model		Re-estimated Model		
Variable	Coefficient	Std. Error	Coefficient	Std. Error	Marginal Effect
RASSET	-0.41*	0.11	0.11	0.15	0.00
WCTA	-1.43**	0.76	-4.35*	1.48	-0.05
CLCA	0.08	0.11	0.17	0.25	0.00
FFOTL	-1.83*	0.78	-1.82*	0.91	-0.02
NITA	-2.37**	1.28	1.82	1.90	0.02
INTWO	0.29	0.36	0.39	0.82	0.00
CHIN	-0.52*	0.24	-1.13**	0.63	-0.01
TLTA	6.03*	0.91	2.13**	1.25	0.02
NLNEG	-1.72*	0.7	-0.05	1.29	0.00
RGDPG			50.67*	23.53	0.54
Rinterest			-20.27	26.64	-0.22
Mills			-0.86	1.00	-0.01
Constant	-1.32	1.36	-5.88*	1.15	
# Observations	2163		1047		
Log-Likelihood	0.839		0.306		

Std. errors are clustered by firm. * and ** denote significance levels at 5% and 10%, respectively

Note: We compute marginal effects by taking the simple average of marginal effects at every observation. For the discrete explanatory variables, we compute the change in bankruptcy probability when the corresponding indicator switches from the value zero to one.

Our model predicts bankruptcy in the following one or two years. The empirical results of the re-estimated model indicate that firms with higher WCTA, FFOTL and CHIN and lower TLTA are less vulnerable to bankruptcy. Table 4 also reports the average of sample enumerated marginal effects (i.e. partial derivative) of the probability of bankruptcy with respect to each explanatory variable. When there is a 1% increase in WCTA, FFOTL and CHIN, the probability of bankruptcy decreases by 5%, 2% and 1%, respectively. On the other hand, a 1% increase in

[18] STATA was used to for all estimation results reported. Our model corresponds to Ohlson's Model III.

TLTA raises the probability of bankruptcy by 2%.

Contrasting our estimates with Ohlson (1980) highlights several differences. Knowing that the firm has enough liquidity (WCTA and FFOTL), high profit growth (CHIN) and low leverage (TLTA) is useful for predicting bankruptcy in our sample and is consistent with Ohlson's original model. Moreover, NLNEG is significant in predicting bankruptcy in Ohlson (1980) for manufacturing firms; in our results NLNEG also has the expected sign for predicting bankruptcy. However, the result on net profit per unit assets (NITA) is less consistent with those in Ohlson (1980).The logit regression results also provide guidelines for remediating ahead of time potential financial distress, guidelines which confirm common notions about bankruptcy. Capital structure, debt leverage and profitability are important in detecting bankruptcy. Keeping total liabilities low relative to total assets, maintaining positive profit growth, higher working capital relative to total asset, and increasing income from recurring operations all work to firm lower bankruptcy risks. [19]

7 Predicting Bankruptcy

To assess the classification accuracy of the logit model, we perform in-sample and out-of-sample predictions for recent bankruptcy events to further assess our models. For each type of prediction, we compute the O-scores (i.e. predicted probabilities) for the original and re-estimated models. For the in-sample predictions, we report the cutoff point for the re-estimated Ohlson models that minimize misclassification and combined errors, respectively.[20] We then analyze the predictions for the groups of bankrupt and non-bankruptcy firms.

Following Ohlson (1980), we use the sum of Type I and Type II error rates (the combined error) to deduce the optimal probability cutoff for the logit model.[21] For one-year-ahead

[19] We also experiment with the specifications with interaction terms between financial ratios and macro variables. However, they do not improve the model and are dropped from the final estimation results.

[20] The distinction between in-sample and out-of-sample refers to whether the prediction sample for the re-estimated model is the estimation sample or a validation sample. All predictions based upon Ohlson's original models are out-of-sample. Thus, using the estimation sample, Tables 5 – 6 compare Ohlson's out-of-sample predictions with our in-sample predictions. And Table 7 compares Ohlson's out-of-sample prediction with our out-of-sample predictions.

[21] Ohlson's approach is the Receiver Operating Characteristic (ROC) goodness of fit method. Let α be the Type I error and β be the Type II error. The ROC curve plots the true positive (predict distressed firm to be bankrupt, which equals $(1 - \alpha)$ and is referred to as the 'sensitivity of a classification') against false positive (predict healthy firm to be bankrupt, which equals 1 – true negative and is referred to as the 'specificity of a classification'). A 45^{o} line represents randomness where the sum of α and β equals 1. The difference between a ROC curve and a 45^{o} line for a specified Type II error is (1- Type I error). Therefore, the cutoff t for minimizing the combined error is equivalent to

predictions, the optimal cutoff proposed in Ohlson (1980) is 0.038, whereas the optimal cutoff from our re-estimated model is 0.14. Our cutoff value is higher than Ohlson's original model because there is a smaller proportion of bankrupt firms in our sample.[22]

For the re-estimated model, Table 5 reports Type I and Type II errors of 44% and 1%, respectively. The misclassification rate is 4%. Although Ohlson's original model achieves a lower Type I error for the in-sample predictions, the re-estimated model out-performs Ohlson's original model in terms of both Type II and misclassification errors.

Table 5 Classification Errors of Ohlson Model for the In-Sample Predictions

Error	No. of Firms	O-score (Ohlson, 1980)	O-score (Re-estimated)
Type I	11	0.00	0.44
Type II	111	0.99	0.01
Misclassification Error	122	0.98	0.04

Authors' calculations; Ohlson's O-Score is 0.038; Our O-Score cutoff is 0.14

We use the coefficients reported in Ohlson (1980) to compute the O-score for our sample. Using this measure, Table 6 indicates that the average O-score of bankrupt firms is larger than that of the non-bankrupt firms, ranging from 0.90 to 0.98 and which significantly exceeds the cutoff point (0.038) proposed in Ohlson (1980). However, the O-score for non-bankrupt firms is 0.73 which is also greater than the 0.038 cutoff point of bankruptcy, indicating that there are Type II errors in this model.

Table 6 In-Sample O-Score for Bankrupt (B) and Non-Bankrupt (NB) Firms

	1st year Before Bankruptcy (N=9)	2nd year Before Bankruptcy (N=7)	3rd year Before Bankruptcy (N=9)	No Bankruptcy (N=1068)
Original	0.98	0.90	0.90	0.73
Re-estimated	0.32	0.05	0.01	0.01

Authors' calculations; the cutoff of the original model is 0.038; the cutoff of our model is 0.14. The re-estimated

finding the a $\beta(t)$, $\hat{\beta}(t)$, that maximizes the distance between ROC curve and 45^o line, that is, it maximizes $(1 - \alpha(t) - \hat{\beta}(t))$ or minimizes the Type I error

[22] The set of non-bankrupt firms included all available firms (except utilities) in COMPUSTAT over the period 1970 – 1976, which numbered 2,058 firms, Adding the 105 bankrupt firms over the period gives Ohlson a total sample of 2,163 observations. Bankrupt firms comprised approximately 5% of the sample. In our sample, we combine all non-bankrupt firms in the pulp and paper sector (NAICS 322) during 1980 – 2005 with bankrupt firms in this sector during the same period for a total sample of 1,706. Only 13 (0.008%) of these firms were bankrupt.

model correctly predicts bankruptcy one year before the occurrence because the average O-score of bankrupt firms exceeds the cutoff (0.14). Moreover, the O-score increases as bankruptcy nears, which suggests that the probability of bankruptcy increases. On average, there is no misclassification error in this model because the O-scores of non-failed firms remain below 0.01 which are lower than the cutoff point.

7.1 Out-of-Sample Predictions

Another assessment of our model is out-of-sample predictions. We use our model, estimated on sample data for the 1990-2005, to predict two bankruptcies and 42 non-bankruptcies that occurred between 2007 and 2008. We compute the O-scores for each of these firms in 2006 using the original and re-estimated models. We then use these scores to predict bankruptcy or non-bankruptcy for the two year period 2007-2008. Table 7 reports the Type I, Type II and total misclassification errors for the two models.

Table 7 Prediction Errors for the Out-of-Sample Forecast in Year 2006

Error	No. of Firms	O score (1980)	O score (Our)
Type I (bankrupt firm is predicted to be healthy)	2	0.00	1.00
Type II (healthy firm is predicted to be bankrupt)	42	1.00	0.02
Misclassification Error	44	0.91	0.07

Authors' calculations; the cutoff of the original O-Score model is 0.038; the cutoff of our O-Score model is 0.14.

The original Ohlson (1980) model correctly predicts the two bankruptcies, i.e. Type I error is zero. However, the cutoff point for the original model is too low which gives the Type II error at unity. The re-estimated model predicts 0% of the bankruptcies in advance. Encouragingly, the Type II error for re-estimated model decreases to 2%. The misclassification errors for original and re-estimated models of Ohlson (1980) are 91% and 7%, respectively. As a result, based on the misclassifications, we infer that the re-estimated model of Ohlson (1980) provides a better performance for the out-of-sample forecast than the original model. The re-estimated model out-performs the original model in terms of the Type II and misclassification errors.

8 Conclusions

Our study provides a method for detecting potential bankruptcy in the future and a guideline for remedying those financial distressed firms ahead of time. In this paper, we examine the financial characteristics of failed firms in the North America pulp and paper industry during year 1990-2009. We demonstrate that shareholders suffer substantial losses (37%) during the month a bankruptcy occurs. Encouragingly, we show that failed firms are less profitable, more liquidity constrained and higher in debt leverage. Using the bankruptcy prediction models proposed by Ohlson (1980), we report that the failed firms have higher O scores than the non-failed firms for one to two years before the bankruptcy. Therefore, those models are ready to predict bankruptcy for firms in the pulp and paper industry. We also improve those models by re-estimating them with a sample of firms in the pulp and paper industry. In particular, on average, the misclassification errors for the in-sample predictions are lower because of the low Type II error. Furthermore, we perform out-of-sample forecasts for two bankruptcies and 42 non-bankruptcies occurred between year 2007 and 2008. Based on the criterion of misclassification rate, the results suggest that the re-estimated models of Ohlson (1980) perform better than Ohlson's original models for our sample. Since our empirical results are based on a sample of listed firms, future research can extend our work by exploring the bankruptcy behavior of private firms.

References

Altman, E., 1968. Financial Ratios, Discriminant Analysis and the Prediction of Corporate Bankruptcy. *J Finance* 23, 589–609

Aivazian, V. A., et J. L. Callen (1983), Reorganization in Bankruptcy and the Issue of Strategic Risk. *J Bank Financ* 7: 119-133.

Begley, J., Ming, J., Watts, S., 1986. Bankruptcy Classification Errors in the 1980s: An Empirical Analysis of Altman's and Ohlson's Models. *Rev Account Stud*, 1, 267-284

Beaver, W., 1966. Financial Ratios as Predictors of Bankruptcy. *J Account Res* 6, 71–102

Beaver, W. 1968. Market Prices, Financial Ratios, and the Prediction of Failure. *J Account Res,* 8, 179–192

Boritz, J., 1991. The "Going Concern" assumption: accounting and auditing implications. research report, Canadian Institute of Chartered Accountants (CICA), Toronto, Canada.

Bulow, J., and Shoven, J. (1978). The bankruptcy decision. The Bell J Econ 9(2):437–456.

Clark, T.A., and M.I. Weinstein, 1983. The Behavior of the Common Stock of Bankrupt firms. *J Financ*, 38, 489-504.

Esteve-Pérez S, Sanchis-Llopis A, Sanchis-Llopis JA (2010) A competing risks analysis of firms' exit. *Emp Econ* 38:281–304.

Hamer, M., 1983. Failure prediction: sensitivity of classification accuracy to alternative statistical methods and variable sets. *J Account. and Public Policy*. 2: 289-307.

Hillegeist, S., Keating, E., Cram, D., Lundstedt, K., 2004. Assessing the Probability of Bankruptcy. *Rev Account Stud* 9, 5-34.

Ivashina, V. and Scharfstein, D. (2010). Bank lending during the financial crisis of 2008. *J Financ Econ*, 97 (3):319–338.

Lang, L.H.P., and R.M. Stulz, 1992. Contagion and Competitive Intra-industry Effects of Bankruptcy Announcements. *J Financ Econ*, 32, 45-60.

Li, X., Buongiorno, J., Ince, P.J., 2004. Effects of size and age on the survival and growth of pulp and paper mills. *J For Econ*, 10, 3–19.

MacKinlay, A.C., 1997. Event studies in economics and finance, *J Econ Lit*, 35, 13-39.

Maddala, G. S. *1983*. *Limited-Dependent and Qualitative Variables in Econometrics*, New York: Cambridge University Press.

McCarthy, P. and L. Lei, 2010. Regional demands for pulp and paper products. *J For Econ*, 16, 127–144.

Mei, B., Sun, C., 2008. Event analysis of the impact of mergers and acquisitions on the financial performance of the U.S. forest products industry. *For Policy and Econ*, 10, 286–294.

Myers, S. November (1977). Determinants of corporate borrowing. *J Financ Econ* 5(2):147–175.

Niquidet, K., 2008. Revitalized? An event study of forest policy reform in British Columbia. *J For Econ*, 14, 227–241.

Ohanian, N.K., 1994. Vertical integration in the U.S. pulp and paper industry, 1900–1940. *Rev Econ and Stat*, 76, 202–207.

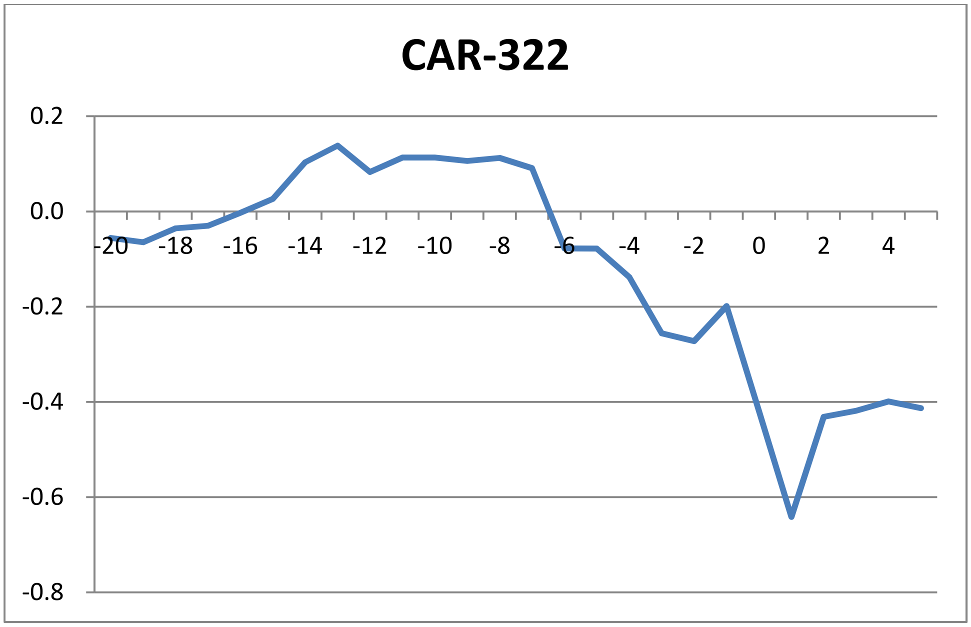
Ohlson, J., 1980. Financial Ratios and the Probabilistic Prediction of Bankruptcy. *J Account. Res,* 19, 109–131

Pesendorfer, M., 2003. Horizontal mergers in the paper industry. *Rand J Econ*, 34, 495–515.

Santos, J. (2010). Bank corporate loan pricing following the subprime crisis. *Rev Financ Stud*, 24(6), 1916-1943.

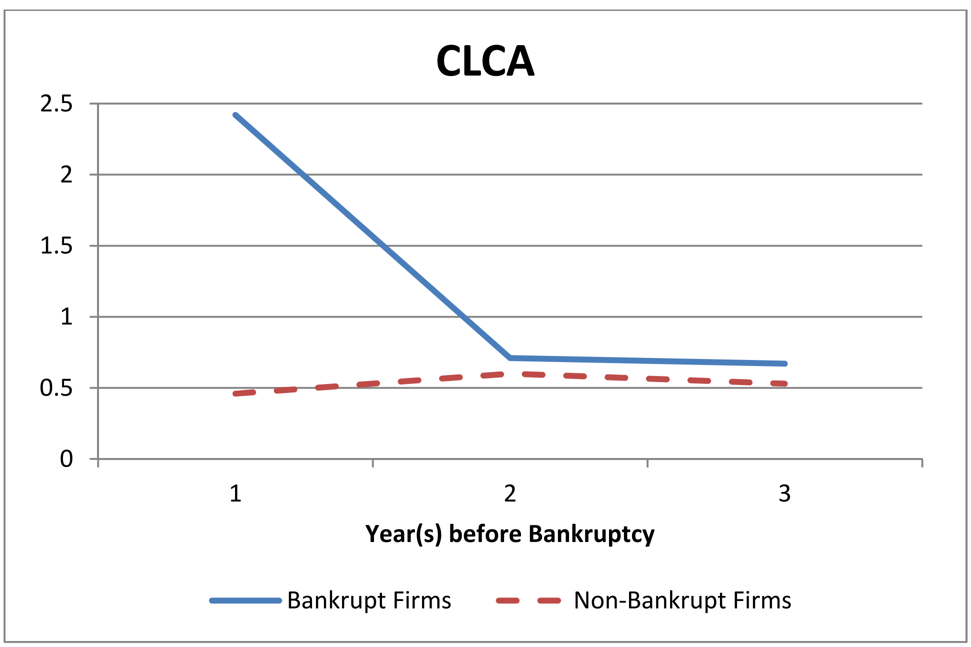
Sun, C., 2006. Lifetimes of US paper and allied products mills: insights from a duration analysis. *South J App Forestry*, 30, 5–12.

Fig 1 CAR(-20,+5) for Filing Firms in the Industry 322



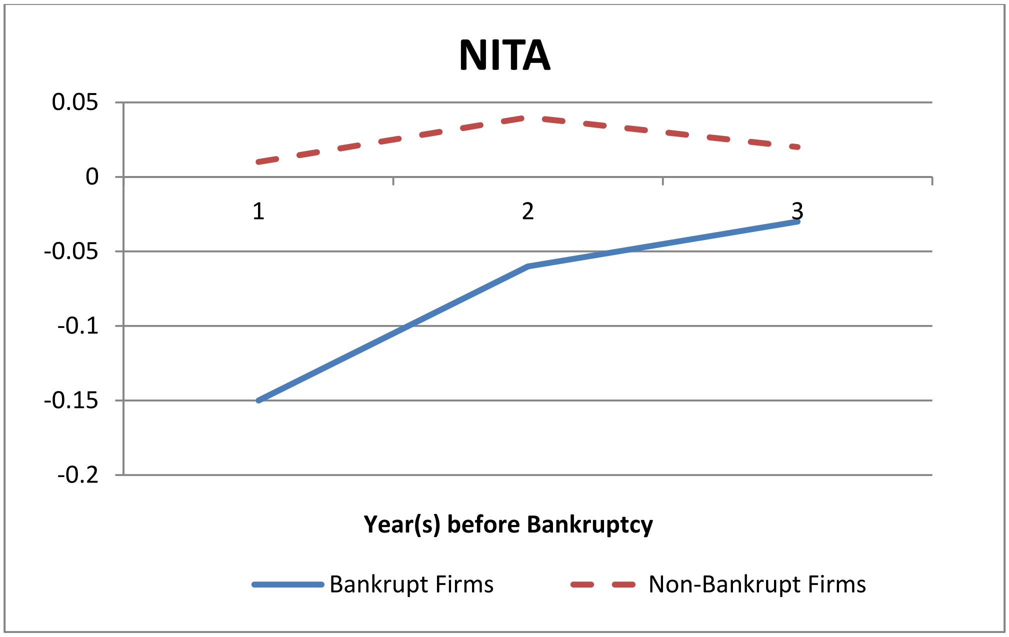
Note: Event window is (-20,+5), i.e. 20 days before and 5 days after the bankruptcy announcement. Day 0 is the announcement day. Sources: CRSP and author calculation.

Fig 2 CLCA for Bankrupt and Non-Bankrupt Firms



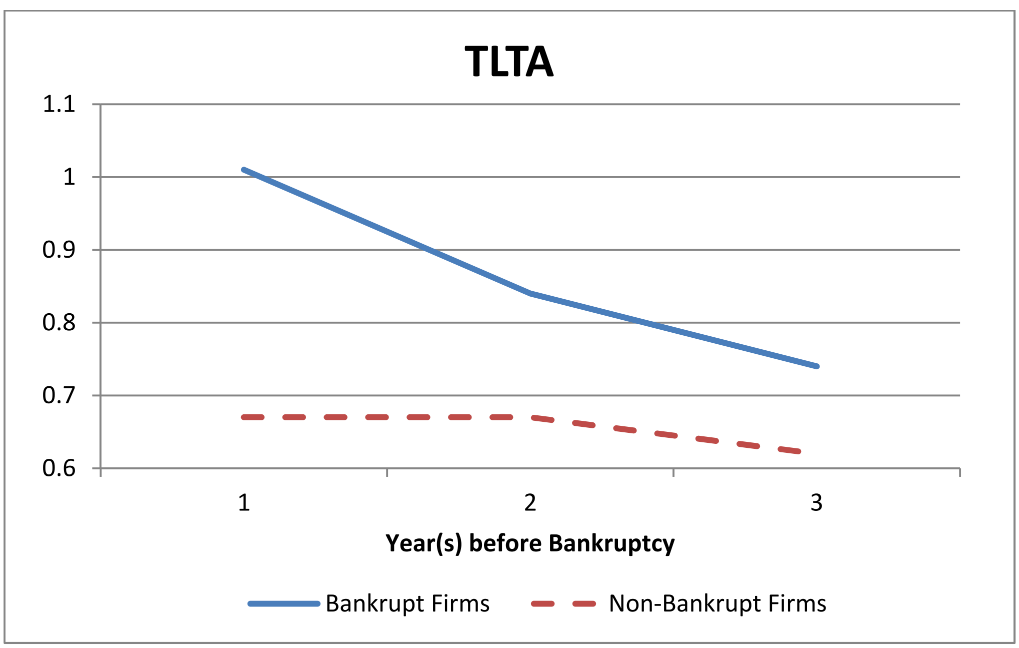
Sources: COMPUSTAT and author calculation.

Fig 3 NITA for Bankrupt and Non-Bankrupt Firms



Sources: COMPUSTAT and author calculation.

Fig 4 TLTA for Bankrupt and Non-Bankrupt Firms



Sources: COMPUSTAT and author calculation.

Appendix 1 Tables

Table A1-1: List of Bankrupt Pulp & Paper Firms 1990-2009

Filing Year	Filing Date	Company Name	Sample	Sector
1992	September 11	Gaylord Container Corp.	*$	3222
1994	October 14	Equitable Bag Co., Inc.	*	3222
1998	January 6	Paragon Trade Brands, Inc.	#$	3222
2000	January 14	American Pad & Paper Company	#	3222
2000	March 15	Crown Vantage Inc.	#	3221
2000	October 10	Drypers Corp.	#	3222
2001	September 10	American Tissue, Inc.	*	3221
2004	March 30	Fibermark Inc.	#	3221
2007	November 19	Pope & Talbot, Inc.	#	3221
2008	December 29	Chesapeake Corporation	#	3221
2009	January 26	Smurfit-Stone Container Corporation	#$	3221
2009	June 1	Caraustar Industries, Inc.	#$	3221

Note: # Data available in COMPUSTAT; * Data available in COMPUSTAT for only two years - Those firms do not have O-Scores 3 years before the bankruptcy; $ Data available in CRSP for estimating CAR over the period twenty days before and five days after the announcement. Source: Bankruptcy.com & sector codes obtained from COMPUSTAT.

List of Bankrupt Pulp & Paper Firms 1990-2009

Reported in BankruptcyData.com, but there is no data in COMPUSTAT & CRSP

Filing Year	Filing Date	Company Name	Sector
1991	May 24	Consolidated Packaging Corp.	3222
2000	September 22	Eastern Pulp and Paper Corp.	3221
2000	January 5	Imperial Home Decor Group Inc.	3222
2001	June 11	Langston Corporation	3332
2001	December 2	Enron (energy, pulp & paper)	2111/2212
2003	January 9	Great Northern Paper	3222
2006	January 3	Pliant Corporation	3261
2007	January 29	Port Townsend Paper Corp.	3221
2008	September 4	Tembec Industries, Inc.	3221
2009	February 11	Pliant Corporation	3261
2009	February 13	Marathon Pulp Inc.(Parent firm: Howe Sound Pulp and Paper)	3211/3221
2009	April 16	Abitibibowater Inc.	3221
2009	June 18	Fraser Papers	3221
2009	June 25	Grant Forest Products Inc.	3212
2009	December 31	Blue Heron Paper	3221

Table A1-2: Financial ratios used in the prediction model of Ohlson (1980)

Variables	Abbreviations	Definitions in COMPUSTAT
Total Assets / GDP Deflator	RASSET	ln(data6/gnpdfl*)
Total liabilities / Total Assets	TLTA	data181/ data6
Working Capital / Total Assets	WCTA	data179/ data6
Current Liability / Current Assets	CLCA	data5/ data4
Total liabilities > Total Assets	NLNEG	1 if data181> data6; 0 if else
Net Income / Total Assets	NITA	data172/ data6
Lag one and two years of Net Income < 0	INTWO	1 if (data172[_n-1]<0) & (data172[_n-2]<0); 0 if else
Funds provided by operations/Total liabilities	FFOTL	(data170 + data14)/ data181
Net income increase rate	CHIN	(data172 - data172[_n-1]) / (abs(data172) + abs(data172[_n-1]))

Source: COMPUSTAT

Appendix 2 An Event Study Model for Bankruptcy Announcement

The basis of event study is the efficient market hypothesis which states that stock prices fully reflect all publicly available information and expectations about the future. The abnormal return, i.e. the excess return over expected return, around an event is attributed to the occurrence of an event. Therefore, we use the abnormal return (AR) over the event window to measure the impact of a bankruptcy announcement on firm value. Additionally, we employ the cumulative abnormal return (CAR), i.e. the abnormal return summed over the event window for each point in time, as an overall measure of the impact over a time period. MacKinlay (1997) provides an excellent review of this methodology.

There are several important timings for conducting an event study. The announcement of bankruptcy occurs at time 0, t_0. The estimation period for the return model is between t_{-250} and t_{-50}, that is, between 250 and 50 days before the announcement. To isolate the effect of a bankruptcy announcement on the expected return, the estimation period precedes the event window. The event window for analyzing the abnormal return is between t_{-20} and t_5, between 20 days before and 5 days after the announcement. We also look at the sub-periods within this window.

Calculating the impact of a bankruptcy announcement on firm value requires knowledge of the firm's expected stock price had there been no announcement. For each firm i, we use the market model (or Capital Asset Pricing Model, CAPM) to estimate the return over the estimation period as follows

$$R_{it} = \alpha_i + \beta_i R_{mt} + \varepsilon_{it} \qquad \text{(A2-1)}$$

where α_i and β_i are the parameters to be estimated. R_{it} and R_{mt} is firm i's return and the market return at time t, respectively. The CRSP value-weighted index (excluding dividend) is the proxy for the market portfolio when estimating the parameters of market model. We assume $E[\varepsilon_{it}] = 0$ and $Var[\varepsilon_{it}] = \sigma_{i\varepsilon}^2$ which implies that the expected return of firm i at time t is $E[R_{it}| R_{mt}] = \alpha_i + \beta_i R_{mt}$. Given the market model, the abnormal return AR_{it} over the event window is

$$AR_{it} = R_{it} - E[R_{it}| R_{mt}] \sim N(0,\sigma_{i\varepsilon}^2)$$

For a given K period, the cumulative abnormal return $CAR_i(t,t+K)$ is defined as

$$CAR_i(t,t+K) = \sum_{k=0,..,K} AR_{it+k}$$

Assuming that there is no correlation between AR_{it}'s over time, then it follows that $CAR_i(t,t+K) \sim N(0, \sigma^2(CAR_i(t,t+K)))$ where $\sigma^2(CAR_i(t,t+K))=(K+1)\sigma_{i\varepsilon}^2$. We adopt the null hypothesis that $CAR_i(t,t+K) = 0$ to test the significance of the bankruptcy announcement on stock return. Since there are multiple bankruptcy announcements in our sample, we improve the power of our tests on AR and $CAR_i(t,t+K)$ by aggregating AR_{it} and $CAR_i(t,t+K)$ across firms (n=1,..,N):

$$\overline{AR_t} = \frac{1}{N}\sum_{n=1}^{N} AR_{nt} \sim N\left(0, \frac{1}{N^2}\sum_{n=1}^{N}\sigma_{n\varepsilon}^2\right)$$

$$\overline{CAR(t,t+K)} = \frac{1}{N}\sum_{n=1}^{N} CAR_n(t,t+K) \sim N\left(0, \frac{1}{N^2}\sum_{n=1}^{N}\sigma^2(CAR_n(t,t+K))\right)$$

We have 12 bankrupt firms in our sample for the prediction model, which are about 10% of our sample firms. The low bankruptcy rate in the pulp and paper industry, which is capital-intensive, associates with a risk of losing a large fixed asset. The sample for the event study is further limited by trading suspension before filing bankruptcy. Only 4 out of 12 bankrupt firms (2 in mills sector and 2 in paper manufacturing sector) provided enough data for estimating AR and CAR around the bankruptcy announcement. The equities of 8 firms did not trade in the over-the-counter (OTC) market after their delisting from the stock exchange. As a result, we end up with a sample of 4 firms for the event study. Therefore, our results from the event study are primarily suggestive.

Table A2-1 reports the descriptive statistics on the bankrupt firms included in our event study. The market capitalizations of those firms usually decrease over the period between 250

Table A2-1: Descriptive Statistics for each Bankrupt Firm

Filing Year	Company Name	NAICS	α	β	MCap1	MCap2	Return1	Return2
1992	Gaylord Container Corp.	3222	0.002	0.589	0.027	0.038	0.003	0.010
1998	Paragon Trade Brands, Inc.	3222	-0.003	0.512*	0.350	0.216	-0.002	-0.036
2009	Smurfit-Stone Container Corporation	3221	0.003	1.387*	2.457	0.254	-0.008	-0.033
2009	Caraustar Industries, Inc.	3221	0.003	1.042*	0.070	0.003	0.000	-0.026

Note: The parameters α and β correspond to those in Equation (A2-1). MCap1 = Market capitalization computed at t=-250, and MCap2 = Market capitalization computed at t=-50. Return1 is the average daily return for the estimation period = (-250,-50) and Return2 is the average daily return for the event window = (-20,5). Unit: Million for market capitalization and %/100 for daily return. The asterisks * and ** indicate the significant level at 5% and 10% levels, respectively. Sources: CRSP and author calculation.

and 50 days before the announcement. The average daily returns around the bankruptcy announcement are often more negative than those over the period between 250 and 50 days before the announcement.

Table A2-2 reports the estimates of AR for the date of bankruptcy announcement and the surrounding days. For the mills sector, shareholders suffer 42.8% losses in wealth on the announcement day. Moreover, there is a 20.1% loss in shareholders' wealth 1 day after the announcement. Similarly, for the paper manufacturing sector, there are 20.1% and 24.4% losses in shareholders' wealth 3 days before and 1 day after the announcement, respectively. There is an interesting reversal of stock return 2 days after the announcement for the mills sector and 2-5 days after the announcement for the paper manufacturing sector. This suggests that there are market overreactions to the bankruptcy announcement which induce investors to hold those surviving firms in hopes of benefitting from the reorganization.

Table A2-2: Abnormal Return (AR) for Days (-5,5)

Day relative to bankruptcy	Filing-322	Filing-3221	Filing-3222
	Average AR (N=4)	Average AR (N=2)	Average AR (N=2)
-5	-0.000	-0.015	0.014
-4	-0.060	-0.116	-0.003
-3	-0.118	-0.035	-0.201**
-2	-0.017	-0.033	-0.001
-1	0.074	0.191**	-0.044
0	-0.220*	-0.428*	-0.012
1	-0.223*	-0.201**	-0.244*
2	0.210*	0.367*	0.054
3	0.013	-0.093	0.118
4	0.020	-0.055	0.094
5	-0.014	-0.107	0.079

Note: Authors' calculations; Standard error for filing firm-322, filing firm-3221 and filing firm-3222 are 0.075, 0.110 and 0.103, respectively. The asterisks * and ** indicate the significant level at 5% and 10% levels, respectively. Source: CRSP

As shown in Table A2-3, the CAR for the filing firm during the month of bankruptcy is negative. The cumulative losses are 52.4% and 14.7% for the mills and paper manufacturing

Table A2-3: Cumulative Abnormal Return (CAR) for Filing Firm

	Filing-322 (N=4)		Filing-3221 (N=2)		Filing-3222 (N=2)	
Window	Average CAR	SD	Average CAR	SD	Average CAR	SD
-20, +5	-0.413	0.385	-0.752	0.562	-0.074	0.526
-20, -6	-0.078	0.292	-0.228	0.427	0.073	0.399
-5,+5	-0.335	0.250	-0.524	0.365	-0.147	0.342
-2,+2	-0.178	0.169	-0.103	0.246	-0.248	0.231
-1,+1	-0.369*	0.131	-0.438*	0.191	-0.301**	0.179
0	-0.220*	0.075	-0.428*	0.110	-0.012	0.103

Note: Authors' calculations; The asterisks * and ** indicate the significant level at 5% and 10% levels, respectively.
Source: CRSP

sectors during the period five days before and after the announcement, respectively. Similarly, the cumulative losses are 43.8% and 30.1% for the mills and paper manufacturing sectors during the periods one day before and after the announcement, respectively.

To put our results in perspective, we compare the valuation effects (i.e. the changes in market capitalization) on bankrupt firms across two sectors. The average market capitalizations of filing firms in the mills and paper manufacturing sectors are both 0.13 million fifty days before the bankruptcy. The negative valuation impacts on filing firms are 0.07 (=0.13*0.524) millions for the mills sector and 0.02 (=0.13*0.147) millions for the paper manufacturing sector. The valuation effect on a bankrupt firm in mills sector is three times as large as that in paper manufacturing sector. We suggest the stronger reaction in the mills sector relates to the timing of bankruptcy. Firms in paper manufacturing sector filed bankruptcy in 1990s, but firms in mills sector filed bankruptcy after 2008 (see Table 13). The tight credit condition in the financial crisis imposes a larger financial cost on the shareholders because investors are less optimistic on the prospect of a distressed firm.

Appendix 3 Alternative Model of Bankruptcy Prediction

We perform a robustness check of using financial information to predict bankruptcy with an alternative model. Altman (1968) employs multiple discriminant analysis (MDA) to distinguish between bankrupt and non-bankrupt firms based on a set of predetermined financial variables. MDA is a statistical technique which allows the researcher to study the difference between two or more groups of objects with respect to several variables simultaneously. MDA employs sample data to construct a model which is used to classify the observations into one of several groups. In the case of two groups consisting of bankrupt firms and non-bankrupt firms, MDA transforms a set of classification variables (financial ratios in this analysis) into a single discriminant Z-score which the analyst uses to classify the firms. The multivariate discriminant model is

$$Z_i = \alpha_1 X_{1i} + \alpha_2 X_{2i} + \ldots + \alpha_n X_{ni} \qquad i = 1, \ldots, n \qquad \text{(A3-1)}$$

where $\{\alpha_1, \alpha_2, \ldots, \alpha_n\}$ are a set of n discriminant function coefficients, $\{X_{1i}, X_{2i}, \ldots, X_{ni}\}$ are classifying variables, i.e. financial ratios for our study, for firm i, and Z_i is the discriminant score for firm i. If Z_b be the mean value of the Z scores in the bankrupt group and Z_{nb} is the mean of the Z scores in the non-bankrupt group, then the cutoff is the value that maximizes the between group variance relative to the within group variance. The analysis classifies firm i into one of the two groups depending upon whether the firm's estimated Z-score, $\hat{Z}_i$, is greater or less than the estimated cut-off point, $\hat{D}_{cutoff}$.

In his paper, Altman (1968) identifies 22 accounting and non-accounting variables, in various combinations, as predictors of failure. However, he recommended a combination of five financial ratios for predicting bankruptcy. The set of variables includes:

(1) Net Working Capital/Total Assets (WCTA), which measures net liquidity relative to the total assets;

(2) Retained Earnings/Total Assets (RETA), which measures cumulative profitability over the life of the firm;

(3) Earnings before Interest and Taxes/Total Assets (EBITTA), which measures profitability independent of any tax or leverage factors;

(4) Market Value of Equity/Book Value of Total Liabilities (MVTL), which measures a firm's solvency; and

(5) Sales/Total Assets (SALETA), which measures the sales generating ability of a firm's assets.

These five variables can be categorized into three broad groups: Financial Structure (4), Liquidity (1) and Performance (2, 3 and 5). The data sources of those variables are reported in the Table A3-1.

Table A3-1: Financial ratios used in the prediction model of Altman (1968)

Variables	**Abbreviations**	**Definitions in COMPUSTAT**
Working Capital / Total Assets	WCTA	data179/ data6
Retained Earnings / Total Assets	RETA	data36/data6
Earnings before Interest and Tax (EBIT) / Total Asset	EBITTA	data178/data6
Market Value Equity / Total liabilities	MVTL	(data24*data25)/data181
Sales / Total Assets	SALETA	data12/data6

Source: COMPUSTAT

Altman (1968) estimates his models using 33 bankrupt and 33 paired non-bankrupt firms in manufacturing industries during 1946-1965. His results demonstrate that, with the exception of (Sales/Total Assets), these financial ratios differ across bankrupt and non-bankrupt groups. More specifically, the mean values of the ratios are significantly smaller for Altman's bankrupt group than for his non-bankrupt group. Equation (A2) gives Altman's estimated MDA model for predicting bankruptcy:

$$Z_i = 1.2*WCTA + 1.4*RETA + 3.3*EBITTA + 0.6*MVTL + 1.0*SALETA \qquad \text{(A3-2)}$$

Altman (1968) proposes a classification method based on the cutoff Z-score ($\hat{D}_{cutoff}$ = 2.675) that minimizes the combined errors, i.e. the sum of Type 1 (predicting no bankruptcy for a firm that declares bankruptcy) and Type 2 errors (predicting bankruptcy for a firm that is solvent). Firms with Z-scores < (>) 2.675 were classified as bankrupt (non-bankrupt). Moreover, Altman (1968) finds that all firms in his sample with the Z-scores greater than 2.99 clearly fall into the non-bankrupt group, while all those with the Z scores less than 1.81 declare bankruptcy within the following year. When the Z-score is larger than 2.99 (non-bankruptcy range), we infer that there is no risk of bankruptcy. On the other hand, when the Z-score falls below 1.81 (bankruptcy range), we infer that there is a high risk of bankruptcy. If the Z-score falls in the closed range [1.81, 2.99] we do not have enough information to predict bankruptcy.

Table A3-2 reports the correlation coefficients for variables in our sample used in with Altman's (1968) model.[23] The coefficients of the financial state variables (WCTA and MVTA) are uncorrelated with those of the performance variables (RETA, EBITTA, SALETA). Also, there is a high correlation between RETA and EBITTA and between RETA and SALETA.

Table A3-2: Correlation Matrix for Variable used in Altman (1968)

	WCTA	RETA	EBITTA	MVTL	SALETA
WCTA	1				
RETA	0.34	1			
EBITTA	0.22	0.54	1		
MVTL	0.42	0.01	0.03	1	
SALETA	0.03	-0.50	-0.05	-0.00	1

A3.1 Estimating Altman's Model with our sample

As in our empirical analysis on Ohlson's (1980) model, we re-estimate Altman's (1968) model on our sample of firms and discuss their results.[24] For our sample of pulp and paper firms, data of bankruptcy firms are obtained one year before the firm's filing. For each of these 9 bankrupt firms, a non-bankrupt firm is paired when it has the next smaller total asset.[25] Re-estimating this model gives

$$\text{Z-Score}_{\text{Pulp \& Paper Data}} = 2.0*\text{WCTA}-1.3*\text{RETA}-6.2*\text{EBITTA}+1.8*\text{MVTL}+1.9*\text{SALETA}+1.0$$

Similar to Begley et al. (1996) and Hillegeist et al. (2004), Altman's (1968) original model does not carry over to our sample. Increasing earnings before tax and amortization (EBITTA) has stronger effects on reducing bankruptcy in our sample than those suggested by the Altman's original model. On the other hand, the effects from increasing retained earnings (RETA) or

[23] Altman (1968) does not report correlation coefficients in his study.
[24] STATA was used to for all estimation results reported.
[25] For example, if one firm goes bankrupt in 1991, then we use 1990 for that firm. Alternatively, if another firm goes bankrupt in 2000, then we use 1999 data for this firm.

increasing solvency (MVTA) are weaker in our sample than those shown in Altman (1968). The negligible coefficient on liquidity (WCTA) is consistent with the high correlation (Table A3-2) between liquidity (WCTA) and profitability (RETA & EBITTA). Sales (SALETA) has an opposite sign with a similar magnitude, which indicates that for our sample profit is more pivotal in determining bankruptcy than sales.[26] Our results suggest that to lower bankruptcy risks, it is important to improve liquidity, enhance profitability and reduce leverage.

To assess the classification accuracy of the MDA model, we perform in-sample and out-of-sample predictions for recent bankruptcy events to further assess our models. For each type of prediction, we compute the Z-scores for Altman's original and re-estimated model. For the in-sample predictions, we report the cutoff point for the re-estimated Altman models for minimizing the misclassification and combined errors, respectively. Then, we analyze the Z-score predictions for the groups of bankrupt and non-bankruptcy firms.

A3.2 In-Sample Predictions: MDA Model

For our model, the cutoff Z-score is $\hat{D}_{cutoff}$ = -0.119. The minimum Z-score of all non-bankrupt firms is 0.091 and the maximum Z-score for all bankrupt firms is -0.328, so there is no 'gray area' for the cutoff point. For the re-estimated model with cutoff $\hat{D}_{cutoff}$ = -0.119, Type I (predicting a healthy firm to be bankrupt) and Type II (predicting a bankrupt firm to be healthy) errors are 0% and 0% for the re-estimated model, respectively. Table A3-3 reports the misclassification errors for the original and re-estimated models are 21% and 0%, respectively.[27]

Table A3-3: Classification Errors of Altman Model for the In-Sample Predictions

Error	No. of Firms	Z-Score (1968)	Z-Score (Our)
Type I	7	0.00	0.00
Type II	7	0.42	0.00
Misclassification Error	14	0.21	0.00

Authors' calculations; Altman's Z-Score is 2.675; Our Z-Score cutoff is -0.119. There are 2 out of these 9 firms do not have Z-Scores, and they are: Equitable Bag Co. Inc. and American Tissue Inc. As a result, there are only 7 bankrupt firms.

[26] This puzzling feature is also reported in Hillegeist et al. (2004) with a sample of manufacturing industries.
[27] Based the cutoff, D_{cutoff}, a misclassification error occurs when an observation is forecast as bankrupt (not bankrupt) when the firm is actually nonbankrupt (bankrupt).

Although multiple discriminant analysis aims to minimize in-sample misclassification errors, our re-estimated model has both fewer in sample Type I and Type II misclassification errors than Altman's original model, an expected result since predictions based upon Altman's model are out-of-sample predictions.

Using the average Z-score of bankrupt and non-bankrupt firms, the results presented in Table A3-4 indicate that the Z-score is useful in predicting bankruptcy for the pulp and paper firms in our sample. First, we apply the coefficients reported in Altman (1968) to compute the Z-score for our sample. For the original model, the cutoff point is 2.68. The average Z-scores of the ten failed firms for one, two, and three year horizons before bankruptcy fall below the cutoff point. However, the average Z-scores for non-bankrupt firms fall in the range of bankruptcy one, two and three year before bankruptcy. On average, there are Type II errors in predicting healthy firms to file bankruptcy.

Table A3-4: In-Sample Z-Score for Bankrupt (B) and Non-Bankrupt (NB) Firms

	1st year Before Bankruptcy		2nd year Before Bankruptcy		3rd year Before Bankruptcy	
Model	B (7)	NB (7)	B (8)	NB (8)	B (7)	NB (7)
Original	0.41	2.43	0.49	2.92	1.96	2.71
Re-Estimated	-1.36	0.38	-0.30	0.78	0.21	1.15

Authors' calculations; the cutoff of the original model is 2.68; the cutoff of our model is -0.119.

On the other hand, our re-estimated model predicts bankruptcy two years before the occurrence. Moreover, the Z-score is decreasing as the bankruptcy nears, which suggests that the probability of bankruptcy is increasing. Encouragingly, on average, there is no Type II error in this model because the Z-scores of non-failed firms remain higher than the cutoff.

A3.3 Out-of-Sample Predictions

Another assessment of our model is out-of-sample predictions. We estimated our model on sample data for the 1990-2005 to predict two bankruptcies and 42 non-bankruptcies that occurred between 2007 and 2008. We compute the Z-scores for each of these firms in 2006 using the original and re-estimated models. We then use these scores to predict bankruptcy or non-bankruptcy for the two year period 2007-2008. Table A3-5 reports the Type I, Type II and total misclassification errors for the two models.

Table A3-5: Prediction Errors for the Out-of-Sample Forecast in Year 2006

Error	No. of Firms	Z score (1968)	Z score (Our)
Type I (bankrupt firm is predicted to be healthy)	2	0.00	0.00
Type II (healthy firm is predicted to be bankrupt)	42	0.31	0.07
Misclassification Error	44	0.30	0.07

Authors' calculations; the cutoff of the original model Z-Score is 2.68; the cutoff of our Z-Score model is -0.119.

Z scores for original and re-estimated Altman models reflect Type I errors at 0% and Type II errors at 31% and 7%, respectively, for the original and re-estimated models. The misclassification errors, which suppose all events are equally likely, are 30% for the original model and 7% for the re-estimated model. As in the case of logit model, based on the misclassifications, the re-estimated model of Altman (1968) provides a better performance for the out-of-sample forecast than the original model. The re-estimated model out-performs the original models in terms of the Type II and misclassification errors.

We conclude that financial information is useful for bankruptcy prediction, which is robust to the specification and statistical technique employed in the analysis.