Predicting Bankruptcy:
Ask the Employees*

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Abstract

The purpose of the paper is to show how employees' attitudes predict bankruptcy throughout various years (phases) of the bankruptcy process – from two and three years before (1), one year before (2), and from the time of filing to the time of liquidation/reorganization (3). We find that our prediction model, inclusive of employees' attitudes, more accurately predicts bankruptcy two to three years before bankruptcy filings, while the other models are more accurate in the year prior to bankruptcy. While already-established statistical models' predictive power is higher (than our model) one year before bankruptcy filings, our model's predictive power is higher (than statistical models) two and three years before bankruptcy filings. Moreover, the addition of employee satisfaction into already-established models improves their predictive performance. We create CatBoost, Random Forest, Support Vector Machine, and Logistic Regression models, and an Autoencoder Anomaly Detection model (GenAI model), all consisting of reviews, and show that textual reviews are in themselves strong predictors of bankruptcy. In survival analyses, we show that employee satisfaction (both in terms of aggregated and individual rating categories) one, two, and three years before bankruptcy filings is a strong predictor whether a company would emerge from bankruptcy successfully. Our paper is the first paper to show that not only is employee satisfaction a predictor of bankruptcy in addition to financial and market data, but that it also is a more powerful predictor of bankruptcy emergence than financial and market data.

Keywords: bankruptcy filing and emergence prediction models, employees' attitudes, in and out-of-sample tests, survival analyses, CatBoost, Random Forest, SVM, Autoencoder Anomaly Detection, Glassdoor
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I. Introduction

The purpose of the paper is to test the predictive performance of established bankruptcy prediction models against a new model inclusive of employee information. We track employees' attitudes from before bankruptcy filings to after bankruptcy filings and test their predictability of bankruptcy across the three phases of the bankruptcy process – two and three years before (1), one year before (2), and from the time of filing to the time of liquidation/reorganization (3). We show that before bankruptcy filings, employees have insider information on where the company is headed. Well before bankruptcy or even negative financial performance, managers and employees may be aware of significant problems within their companies. Although managers may be reluctant to disclose this information, employees may reveal problems through dissatisfaction with their jobs and the firm, although we don't necessarily know what the underlying cause for their dissatisfaction is and how they are going to express their dissatisfaction. This employee insider information, however, shows up as a more powerful predictor of bankruptcy, in comparison to financial statement data, two and three years prior to bankruptcy filings. In the year before the bankruptcy, employee insider information is overwhelmed by financial statement data. From the time of bankruptcy filing to the time of liquidation/restructuring, employee insider information overwhelms financial and market data to predict whether the company will emerge from bankruptcy. We empirically test our model for predictability, not causation, similar to what prior bankruptcy prediction literature does. Whether employees are less satisfied because of an impending bankruptcy or whether employee satisfaction impacts the chances of bankruptcy is an interesting topic for further studies.

Our paper argues that employee satisfaction serves as an early indicator of financial distress, enhances bankruptcy prediction when combined with financial metrics, and plays a critical role in determining post-filing outcomes by influencing human capital retention, organizational resilience, and the success of restructuring efforts. Employees possess unique insider knowledge about operational inefficiencies, management challenges, and workplace dynamics that often signal financial distress before it appears in financial statements. They observe early warning signs, such as reduced investment and leadership shifts, which financial metrics may not immediately capture. Employee satisfaction reflects both explicit operational changes and implicit workplace sentiment, offering a complementary dimension to financial indicators. As bankruptcy approaches, financial signals become more prominent, but employee sentiment remains crucial for understanding organizational resilience, innovation potential, and human capital quality. This perspective fills a gap in bankruptcy research by linking employee satisfaction to post-filing outcomes, where retention and morale influence successful reorganization. When combined with financial metrics, employee satisfaction enhances the prediction of both bankruptcy and a firm's likelihood of successful emergence.

We document that employee satisfaction is a strong predictor of bankruptcy in all three phases of the bankruptcy process – from two and three years before, one year before, and while in bankruptcy. Specifically, we find that our employee satisfaction model predicts bankruptcy more accurately than existing financial information-based models at two and three years before filing, while financial models dominate in the year immediately preceding bankruptcy. This finding addresses a significant limitation of traditional bankruptcy prediction models, which lose predictive power as the time horizon extends beyond one year before filing. We also demonstrate that incorporating employee satisfaction metrics into established financial models significantly improves their predictive performance across all time horizons, as evidenced by improvements in Adjusted R-Squared, ROC curves, optimal threshold points, and classification error rates. For the post-filing phase, we find that employee satisfaction serves as a powerful predictor of bankruptcy emergence, with companies maintaining higher employee satisfaction significantly more likely to successfully reorganize rather than liquidate.

Our analysis is structured in three main sections. First, we test four established bankruptcy prediction models (Altman's, Ohlson's, Zmijewski's, and Shumway's) against our employee satisfaction model using one-year pre-bankruptcy data. Ohlson's model demonstrates superior in-sample performance with the highest Adjusted R-Squared (0.754) and ROC value (0.950), while our employee satisfaction model shows the strongest out-of-sample forecast accuracy. This pattern confirms our hypothesis that by one year before bankruptcy filing, financial indicators effectively capture company distress, yet employee satisfaction continues to provide complementary predictive value, particularly in out-of-sample tests where it outperforms traditional models.

When we incorporate employee satisfaction into the traditional financial models, we observe consistent improvements in their predictive accuracy. The addition of employee satisfaction enhances model fit across all four established models, as evidenced by increases in both Pseudo and Adjusted R-Squared values. Particularly notable is the dramatic improvement in Zmijewski's model, where the Wald Chi-Square statistic increases substantially from 62.20 to 167.70. ROC curves for all models show improvement after incorporating employee satisfaction, and classification error analyses reveal reduced total error rates, especially in the 85th-95th percentile threshold range. Out-of-sample tests further confirm these improvements, with reduced Chi-Square statistics in all models after adding employee satisfaction metrics. These findings strongly support our second hypothesis that employee satisfaction provides complementary information that enhances traditional bankruptcy prediction models.

Second, we extend our analysis to two and three years before bankruptcy, finding that our employee satisfaction model substantially outperforms traditional financial models at these longer horizons. The employee satisfaction model maintains remarkably stable ROC values across all three pre-bankruptcy years (0.9640 at two years and 0.9368 at three years before bankruptcy), while Altman's model shows substantial deterioration (0.7726 at two years and 0.6935 at three years before bankruptcy). These results confirm our hypothesis that employees detect problems within their organizations well before these issues manifest in financial statements, providing an early warning system that traditional models cannot match. We also compare the Employees' model to the other models with information two and three years before bankruptcy. The Employees' model demonstrates the most consistent performance across all time horizons, with the smallest decay in predictive power from one to three years before bankruptcy. While Ohlson's model excels at identifying bankruptcies one year before occurrence, it struggles at longer horizons. The Employees' model maintains a more balanced trade-off between sensitivity and specificity across all time periods. Two and three years before bankruptcy, the Employees' model substantially outperforms traditional financial models in sensitivity, making it the most effective early warning system.

Third, we perform additional survival analyses to examine predictions of companies' emergence from bankruptcies. In our sample, we have 219 company reorganizations (Chapter 11 filings) and 108 company failures (Chapter 7 filings). We use a Cox proportional hazards model to test whether employee satisfaction, financial and market data increase the hazard of bankruptcy emergence. We test whether the company would emerge from bankruptcy given their time of filing to their time of liquidation/restructuring. Our results suggest a complex temporal relationship between employee satisfaction and bankruptcy emergence. While higher employee satisfaction one year before filing may delay emergence, possibly due to reorganization efforts prioritizing employee concerns, higher satisfaction two years before filing appears to facilitate eventual emergence. This pattern suggests that the timing of employee satisfaction measurements relative to bankruptcy filing is crucial in understanding its impact on corporate restructuring outcomes.

To provide additional insights into the predictive power of employee satisfaction reviews for one year before, we apply advanced machine learning techniques to analyze employee reviews. Using CatBoost, Random Forest, Support Vector Machine, Logistic Regression, and Autoencoder Anomaly Detection models, we demonstrate that textual analysis of employee reviews provides substantial predictive power beyond numerical satisfaction ratings. The Support Vector Machine model achieves the highest discriminative ability (AUC = 0.9567), confirming that qualitative employee feedback contains rich signals about impending financial distress. These machine learning models effectively capture complex linguistic patterns in employee sentiment that prove valuable for bankruptcy prediction even without incorporating financial statement data. We conduct additional robustness tests, such as information content tests, likelihood ratio tests, and incremental predictive power tests which provide robust statistical evidence that employee satisfaction contains valuable predictive information for bankruptcy risk, both aa a standalone predictor and as a complement to traditional financial indicators.

Overall, our paper provides novel insights into how employee satisfaction shows up as a predictor of bankruptcy in various years (phases) of the bankruptcy process. Since prior literature has proved that companies' financial and market information can predict bankruptcy, we don't contradict other papers' findings, but rather improve on other papers by arguing that employee satisfaction shows up as a predictor of bankruptcy prior to financial and market information, that employee satisfaction improves other models' performance in the year prior to the bankruptcy (where their predictive power is the highest), and that employee satisfaction is a more powerful predictor of bankruptcy emergence than financial and market information. The paper shows that two and three years before bankruptcy employees sense issues within their companies, while one year before bankruptcy financial and market information already reflect what employees knew two and three years prior. From the time the company files for bankruptcy to the time the company either liquidates or restructures, employee satisfaction reflects whether the company would emerge from bankruptcy or not. The results signify that employees hold information on companies' financial health and prospects throughout various years of the bankruptcy process, but that information is expressed in a different way throughout the bankruptcy process.

II. Literature Review and Hypotheses Development

Our paper adds to the literature on bankruptcy prediction models. Finance literature has determined several bankruptcy prediction models, such as Altman's Model (1968), Ohlson's Model (1980), Zmijewski's Model (1984), and Shumway's Model (2001). Since the development of those models, researchers have made efforts to develop models with even greater predictive performance. Prior bankruptcy prediction models have employed financial ratios from financial statements before the bankruptcy filing, while more recent models have used financial market data, such as excess stock returns and stock return volatility, along with the application of the Black-Scholes option-pricing model. The earliest studies on bankruptcy prediction have utilized univariate analyses which have focused on individual ratios and comparison of ratios of failed companies with those of successful firms. Those earliest studies have laid the groundwork for multivariate studies. Among the univariate studies, those to be highlighted include Merwin (1942), Chudson (1945), and Beaver (1966). In his study of small manufacturers, Merwin (1942) found that three ratios are significant indicators of business failure – Net Working Capital to Total Assets, Net Worth to Total Debt, and the Current Ratio – even four or five years before failure. Chudson (1945) has tried to determine whether there is a normal pattern to predict bankruptcy and has reported that there is no such pattern, but there is a clustering of ratios within industry, size, and profitability groups. The most popular univariate study comes from Beaver (1966) in which he compares 30 ratios of 79 failed and 79 non-failed companies in 38 industries and tests their predictive abilities by classifying them under bankrupt and non-bankrupt firms. The author has given future researchers the idea to consider multiple ratios altogether as they might have higher predictive ability than single ratios.

The most popular multivariate study remains Altman (1968). In this paper, the author uses a multivariate discriminant analysis to develop a five-factor model to predict bankruptcy of manufacturing firms. The paper documents that the Z-Score predicts bankruptcy if the firm's score falls within a certain range. The model has high predictive accuracy one year before bankruptcy, but the accuracy falls off two, three, four, and five years before business failure. Since Altman's study on bankruptcy prediction, models' number and complexity have increased. More recent papers have utilized logit and probit models, neural networks, and multivariate discriminant analysis, or some combination of those models. For example, Mensah (1983) has used both multivariate discriminant analysis and logit analysis to predict bankruptcy. In the 1980s, neural networks became the dominant method used. Neural networks analyze inputs to find patterns and develop a model capable of a decision-making process. During the training mode, in which the network learns the decision-making process, several sample cases are run, while during the testing mode the neural network model is validated using hold-out sample data.

The four models tested in the model are Altman (1968), Ohlson (1980), Zmijewski (1984), and Shumway (2001). Altman (1968) uses a multivariate discriminant analysis to develop a five-factor model to predict bankruptcy of manufacturing firms. Altman (2000) adds on his previous paper by showing applications of the Z-score model to private companies, non-manufacturing entities, and to also refer to a new bond-rating equivalent model for emerging markets' corporate bonds and updates the results of the 1968 paper to include results up to 1999. Ohlson (1980) uses a logit model which generates the O-score and shows that four types of variables are predictive of bankruptcy – the company's size, the company's performance, the company's liquidity, and the company's financial structure. Zmijewski (1984) uses a probit model and finds that three variables are predictive of bankruptcy – return on assets, financial leverage, and liquidity. Shumway (2001) uses a hazard model that can capture changes in the company's characteristics over time and shows that market variables are also predictive of bankruptcy. We use key variables from all these various models in addition to an employees' satisfaction proxy in a hazard model and compare the predictive performance of already-established models in their original settings with the predictive performance of our model. We compare the predictive performance of all models both in in-sample and out-of-sample tests. In addition, we compare the predictive performance of the best-performing models – the Altman's model and the employees' model – one, two, and three years before bankruptcy filings. Our approach is described in the data and methodology sections.

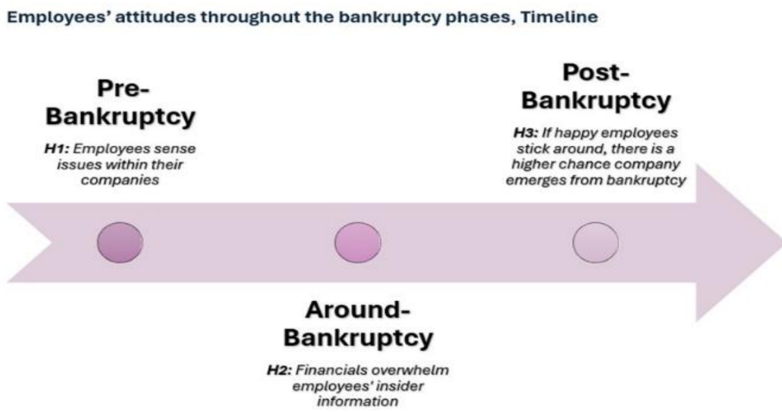
More recent papers on bankruptcy prediction have reviewed the literature on bankruptcy prediction and have compared various models' predictive power utilizing only financial and market variables. Charitou et al. (2004) use an artificial neural network for bankruptcy prediction and credit analysis. As mentioned above, neural networks are designed to find patterns to solve given problems. The authors provide evidence that machine learning methods can provide results as good as established statistical methods. Altman et al. (2014) provide a review of the bankruptcy prediction literature and test the Z-Score model in an international setting to show that the inclusion of country-specific variables could improve the predictive performance of the Z-Score model. Jones et al. (2017) provide a wide range of classifiers for analysis to predict corporate bankruptcies and show that when using financial information, the traditional classifiers perform well, but modern classifiers are recommended because of their performance in cross-sectional and longitudinal tests. In the spirit of those papers, we complement our statistical analysis with the application of a machine learning method with employee textual reviews to show that reviews are also predictive of bankruptcy years before bankruptcy filings and that reviews provide additional predictive power to ratings.

Other recent papers have used other modern machine learning techniques. For instance, Barboza et al. (2017) use data from 1985 to 2013 on U.S. companies analyzing more than 10,000 firm-year observations and compare the predictive performance of financial ratios using machine learning techniques, such as random forest, bagging, and boosting. Their research contributes to the debate regarding the superiority of computational methods over established statistical methods. Our paper is also closely related to papers that use more modern techniques of bankruptcy prediction. For instance, Hillegeist et al. (2004) test market variables in Black-Scholes-Merton option-pricing model; Alfaro et al. (2008) test accounting variables in neural networks and boosted decision trees; Chen et al. (2010) test accounting and market variables in a KVM model; Olson et al. (2012) test accounting and market variables in decision trees, neural networks, and support vector machines; Tobback et al. (2017) test accounting and relational variables in a smoothed wvRN and support vector machines; Zelenkov and Volodorskiy (2021) test accounting and macroeconomic variables in machine learning models.

Another strand of literature is Glassdoor literature, which focuses on various themes. For example, papers have examined companies' corporate climate and its impact on SEC fraud enforcements, its impact on the return effect, its impact on merger and acquisition synergies, and its impact on private equity deals (Ji et al. (2017); Green et al. (2019); Lalova (2023); Lalova (2023)). To be more specific, Lalova (2023) shows that M&A deals with high similarity between acquirer and target employee morale achieve greater short-run and long-run synergies and that high target employee morale is contagious for acquirer employees, while Lalova (2023) shows that low similarity between private equity acquirers and their targets enhances post-merger integration and long-run synergies. Marchetti (2019) measures organizational culture using text reviews employees have posted on Glassdoor and finds that pre-deal acquirer-target culture compatibility is positively associated with the likelihood of a deal announcement and with superior stock returns. Chen et al. (2022) propose an employee sentiment index, complementing investor sentiment and manager sentiment indices, and find that high employee sentiment predicts low monthly (weekly) market returns significantly both in- and out-of-sample. Campbell and Shang (2021) show that information extracted from Glassdoor reviews can be used to develop measures with useful properties for measuring misconduct risk and those measures clearly discriminate between high and low misconduct firms. Liu et al. (2022) use Glassdoor data to show that firms offer higher quality maternity leave benefits in labor markets where female talent is relatively scarce. Welch and Yoon (2021) find that high-ability managers allocate resources to ESG efforts in a way that enhances shareholder value. In the spirit of those papers, I use Glassdoor data to show that employees can predict bankruptcy filings and emergences.

While there is no direct evidence suggesting that employee satisfaction can predict company failures, employee satisfaction is a factor that can impact employees' productivity, creativity, and innovation, which in turn could impact companies' financial health. In this paper, we define employee satisfaction as employees' attitudes toward and perceptions of the tasks employees have in the companies they work for and various firm dynamics. Those perceptions toward various firm dynamics include perceptions toward career opportunities, compensation and benefits, culture and values, work-life balance, senior leadership, and overall organizational performance. All these firm dynamics are determinants of employee satisfaction. To put it in other words, leadership styles (senior leadership), organizational culture (culture and values), work-life balance (work-life balance), compensation and benefits (compensation and benefits), and opportunities for career advancement (career opportunities) are all determinants of employee satisfaction. We take the level of perceptions toward those various firm dynamics to build employee satisfaction. While employee satisfaction can influence bankruptcy risk through its effect on organizational performance, it is not the sole predictor of bankruptcy. As mentioned, researchers have determined that financial and market information is a predictor of bankruptcy in various models and settings. The downside of those various papers is that the financial and market models' predictive power decreases the further we move from bankruptcy filings. Thus, in this paper, we don’t contradict other papers’ findings, but rather improve on other papers by arguing that employee satisfaction shows up as a predictor of bankruptcy prior to financial and market information, that employee satisfaction improves other models’ performance in the year prior to bankruptcy (where their predictive power is the highest), and that employee satisfaction is a more powerful predictor of bankruptcy emergence than financial and market information.

We expect to find that employees possess unique insider knowledge about operational inefficiencies, management challenges, and workplace dynamics that precede formal financial deterioration. Employees often observe early signs of trouble, such as reduced investment in core operations, degradation of processes, or changes in leadership focus, well before these manifest in financial statements. The predictive power likely stems from both explicit knowledge (direct observation of operational changes) and implicit factors (workplace atmosphere, management communication styles). As bankruptcy approaches, financial indicators become more visible and material, naturally increasing their predictive power. However, employee satisfaction measures likely capture complementary dimensions not fully reflected in financial metrics, including organizational resilience, innovative potential, and human capital quality. The complementary nature of these indicators explains why combined models would show improved performance. Employee satisfaction also provides context for interpreting financial indicators - similar financial positions may represent different risk levels depending on employee sentiment. This hypothesis addresses a critical gap in bankruptcy literature, which focuses primarily on predicting bankruptcy occurrence rather than post-filing outcomes. Employee retention and satisfaction during bankruptcy proceedings likely indicates several critical factors for successful reorganization: (1) preservation of essential human capital and institutional knowledge, (2) continued employee belief in the company's core business viability, (3) organizational capacity to execute turnaround strategies, and (4) positive stakeholder relationships that facilitate favorable restructuring terms. Employee satisfaction may be particularly valuable in predicting emergence when combined with financial restructuring metrics. Below is a timeline of employees’ attitudes throughout the bankruptcy process.



i. **HI:** Employee satisfaction shows up as a predictor of bankruptcy prior to financial statement data.

Building on information asymmetry theory and stakeholder perspectives, our first hypothesis proposes that employee satisfaction serves as an early warning indicator for bankruptcy. Edmans (2011) and Green et al. (2019) provide strong empirical support for employee sentiment containing value-relevant information not immediately reflected in financial statements. This information advantage exists because employees directly observe operational inefficiencies, management quality, and organizational capabilities before these factors manifest in financial performance. As Bae et al. (2011) demonstrate, these employee-related factors influence financial risk profiles, suggesting that deteriorating employee satisfaction would precede rising bankruptcy probability.

ii. **HII:** Around bankruptcy announcements, financial information overwhelms employee satisfaction information, but the addition of employee satisfaction into already-established models improves their predictive performance.

Our second hypothesis addresses the dynamic interaction between financial indicators and employee satisfaction as bankruptcy approaches. While traditional bankruptcy prediction models rely heavily on financial ratios, we propose that employee satisfaction provides complementary information even when financial distress becomes apparent. This perspective aligns with Agrawal and Matsa's (2013) findings on the bidirectional relationship between employee concerns and financial decisions. Becker and Stromberg's (2012) work on stakeholder conflicts during financial distress further supports the value of incorporating multiple perspectives. We expect that as bankruptcy approaches, financial indicators gain predictive power, but models incorporating both financial and employee satisfaction measures will demonstrate superior performance due to their capturing of complementary risk dimensions.

iii. **HIII:** Employee satisfaction around the bankruptcy filing predicts whether the company will emerge from bankruptcy.

The third hypothesis extends bankruptcy prediction literature into the post-filing phase, proposing that employee satisfaction predicts successful emergence from bankruptcy proceedings. This builds on Hotchkiss et al.'s (2008) review of bankruptcy resolution factors and addresses gaps in existing prediction frameworks like Campbell et al. (2008). Companies maintaining employee satisfaction through bankruptcy likely preserve critical human capital necessary for successful reorganization. As Graham et al. (2022) document substantial costs to employees during bankruptcy, firms able to sustain employee satisfaction during this period likely possess underlying strengths in leadership, core business viability, and stakeholder management that contribute to successful emergence. This hypothesis offers value to creditors, investors, and policymakers evaluating reorganization potential once bankruptcy proceedings have begun.

In this paper, we show that employees have information on upcoming bankruptcies two and three years before bankruptcy filings by testing various already-established models in the literature against a newly-established one consisting of employees' attitudes and show that its predictive power is greater than that of the established models up to two and three years before bankruptcy filings, and that when a proxy for employee satisfaction is added to the established models, their predictive power increases. Our paper is also the first paper that shows how employees' information predicts bankruptcy across various phases of the bankruptcy prediction process, including bankruptcy emergence.

III. Data and Methodology

In this paper, we utilize UCLA's LoPucki, Glassdoor, Compustat, and CRSP databases. We use UCLA's LoPucki data for bankruptcy filings' information, Glassdoor data for employees' satisfaction metrics, Compustat data for financial statement variables, and CRSP data for return variables. Our sample consists of 327 bankruptcy filings in the period between 2008 and 2020. We employ a random-sampling method to construct the non-bankrupt companies' sample (the results of the paper also hold if we use a matched-sample method). Our final dataset contains 327 bankruptcies (those companies that have filed for either Chapter 7 or Chapter 11 bankruptcy over our sample period) and 7,924 non-bankrupt companies (those that haven't filed for either Chapter 7 or Chapter 11 bankruptcy over our sample period). For the multi-period logit models, we include one firm-year observation for the bankrupt companies and all firm-year observations (going back to three years before bankruptcy filings). In addition to including data on employees' satisfaction, we include profitability variables, liquidity variables, leverage variables, firm-size variables, other firm characteristics, such as standard deviation of the return, excess return, and logarithm of firm age, in accordance with prior bankruptcy prediction studies. The variables we choose to include in our model are based on key variables included already in prior bankruptcy prediction literature. The models we include in our study are Altman (1968), Ohlson (1980), Zmijewski (1984), Shumway (2001), and we build a new model where we use some key variables from previous models and include the employees' satisfaction proxy.

- Altman (1968): Multiple discriminant analysis with financial ratios

$Z = \beta' X$,

where Z is the MDA score, and X represents the variables listed. Cutoff point: $Z \geq 2.675$, classified as non-bankrupt. Under X, we include Net Working Capital/Total Assets, Retained Earnings/Total Assets, EBIT/Total Assets, Market Value of Equity/Book Value of Total Liabilities, and Sales/Total Assets. Altman's model is a linear discriminant analysis model which uses the above-mentioned ratios to predict the likelihood of a company facing financial distress. The model assigns weights to several financial ratios based on their predictive power and combines them to generate a single score, which is known as the Z-Score. The score is then used to classify companies into different bankruptcy risk categories.

- Ohlson (1980): Logit model with financial ratios

$P = (1 + exp\{-\beta' X\})^{-1}$,

where P is the probability of bankruptcy and X represents the variables listed. The logit function maps the value of $\beta' X$ to a probability bounded between 0 and 1. Under X, we include Ohlson's

Size, Total Liabilities/Total Assets, Working Capital/Total Assets, Current Liabilities/Current Assets, OENEG (a dummy variable indicating if Total Liabilities exceed Total Assets), Operating Income/Total Assets, INTWO (a dummy variable indicating if Net Income was negative for the last 2 years, and 0 otherwise), Change in Net Income, and Funds from Operations/Total Liabilities. The Ohlson's O-Score model uses both financial ratios and accounting variables to calculate a bankruptcy prediction score for companies. The model assigns weights to each variable based on their statistical significance in predicting bankruptcy. Based on their score, companies are classified into two categories – those in high risk of distress and those in low risk of distress.

- Zmijewski (1984): Probit model with financial ratios

$P = \Phi(\beta' X)$,

where P is the probability of bankruptcy and X represents the variables listed, and $\Phi(\bullet)$ represents the cumulative normal distribution function. The probit function maps the value of $\beta' X$ to a probability bounded between 0 and 1. Under X, we include Net Income/Total Assets, Total Liabilities/Total Assets, and Current Liabilities/Current Assets. The model is one of the early models of bankruptcy prediction based on financial ratios. The model's coefficients are estimated using maximum likelihood estimation based on financial information for both distressed and non-distressed companies.

- Shumway (2001): Multi-period logit model with both financial ratios and market data

$$P_{i,t} = (1 + \exp\{-y_{i,t}\})^{-1}$$

$$y_{i,t} = \alpha + \beta' X_{i,t-1} = \beta' \begin{bmatrix} X_{1,t-1} \dots X_{1,t-j} \\ \dots \dots \\ X_{n,t-1} \dots X_{n,t-j} \end{bmatrix},$$

where P is the probability of bankruptcy and X represents the variables listed. This is a multi-period logit model, but instead of treating each firm year as an independent observation, all prior values of the independent variables for a particular firm are included in the information set. n represents the number of independent variables, and j represents the number of time periods prior to time t for which data are available. Under X, we include Net Income/Total Assets, Total Liabilities/Total Assets, Relative Size, Cumulative Annual Return in prior year minus the value weighted CRSP index in prior year, and Standard Deviation of Return in prior year. The technique behind Shumway's model involves estimating bankruptcy probability over a specific period based on financial ratios. We refine the model slightly by including one firm-year observation for each healthy company and all firm-year observations for failing companies.

- Employees' Model: Multi-period logit model with employees' data

$$P_{i,t} = (1 + \exp\{-y_{i,t}\})^{-1}$$

$$y_{i,t} = \alpha + \beta' X_{i,t-1} = \beta' \begin{bmatrix} X_{1,t-1} \dots X_{1,t-j} \\ \dots \dots \\ X_{n,t-1} \dots X_{n,t-j} \end{bmatrix},$$

where *P* is the probability of bankruptcy and *X* represents the variables listed. This is a multi-period logit model. *n* represents the number of independent variables, and *j* represents the number of time periods prior to time *t* for which data are available. We keep only one firm-year observation for each bankrupt firm but all firm-year observations for surviving and pseudo firms. We go back three years before bankruptcy filings and track all variables included in our model up to three years of bankruptcy filing. Under X, we include Mean of Employees' Satisfaction, EBIT/Total Assets, Working Capital/Total Assets, Total Liabilities/Total Assets, Change in Net Income, Excess Return, Standard Deviation of Return, Firm Age, Turnover, and Relative Size. We include liquidity, profitability, and leverage variables, as well as a firm size variable, in addition to market variables, such as the company's lagged return and volatility. We are expecting that companies with higher liquidity and profitability are less likely to go bankrupt, while we are expecting that companies with higher leverage are more likely to go bankrupt. We follow Shumway's approach of a multi-period logit model where we include one firm-year observation for bankrupt companies and all firm-year observations for non-bankrupt companies. Because of the inclusion of many serially correlated variables in the same model, we need to adjust standard errors where the Wald-Chi Square needs to be divided by the number of firm-years.

IV. Results

[Insert Table 1 here]

Table 1 presents summary statistics for each variable used in the study over the period 2008-2020. The dataset contains 327 actual bankrupt firms, which we define as non-healthy, and 7,924 non-bankrupt firms, which we define as healthy (those who haven't filed for either a Chapter 7 or a Chapter 11 filing over our sample period). Panel 1.1. of Table 1 groups the variables into various categories going back three years before actual bankruptcy filings. The profitability variables include EBITTA (EBIT to Total Assets), STA (Sales to Total Assets), NITA (Net Income to Total Assets), and CHIN (Change in Net Income), and they measure the ability of the firm to generate sufficient profits or returns to remain a company that is going concern. The liquidity variables include WCTA (Working Capital to Total Assets), CLCA (Current Liabilities to Current Assets), FUTL (Funds from Operations to Total Liabilities), INTWO (a dummy variable signifying if the firm has a negative Net Income over the past two years), and they measure the ability of the firm to meet its short-term obligations. The leverage variables include RETA (Retained Earnings to Total Assets), MVETL (Market Value of Equity to Total Liabilities), TLTA (Total Liabilities to Total Assets), OENEG (a dummy variable indicating if Total Liabilities exceed Total Assets), and they measure the relative amount of debt and other obligations of the firm. The firm-size variables include OhlsonSize (calculated as the natural logarithm of Total Assets to the GNP Price-Level index) and RelativeSize (calculated as the natural logarithm of the Number of Outstanding Shares multiplied by the Year-End Share Price to Total Market Value), and they reflect the ability of larger firms to trade through difficult times and their ability to be less likely to go bankrupt. We also include other firm characteristics, such as the Excess Return, Standard Deviation of Excess Return, and we determine that bankrupt firms tend to have lower and more volatile returns and that they have substantially underperformed in their years prior to bankruptcy. In addition, those firms tend to be younger (as observed by their firm age). We also include two other variables – Turnover (signifying employee turnover, calculated as the change in employment of the firm from year to year) and FirmAge (the age of the firm since its IPO). We take the financial ratio data from Compustat and stock return data from CRSP. We assume that annual financial statements are available by the end of the fourth month of the following year. We take financial information one year prior to, two years prior to, and three years prior to bankruptcy. We also exclude any financial firms from our sample.

Panel 1.2. of Table 1 presents the breakdown of the sum of mean and standard deviation into different categories – *Career Opportunities*, *Compensation Benefits*, *Culture Values*, *Senior Leadership*, *Work-Life Balance*, and *Overall Rating* – up to three years before actual bankruptcy filings. One can observe that the rating category means are relatively low on a possible range between 1 and 5. Figure A1 presents the correlation heat map of correlations between the Z-Score and the mean and standard deviation of sum of rating categories, and the individual employees' satisfaction rating categories. The correlation between the Z-Score and the mean of the sum and the various rating categories is low and negative one and two years before actual bankruptcy filings, while the correlation between the Z-Score and the mean of the sum and the various rating categories is low and positive three years before actual bankruptcy filings. This could be attributed to the fact that the predictive power of the Z-Score decreases the further we move back in time from actual bankruptcy filings. This finding is documented by Altman (1968), but it is also what we find in our sample of bankruptcies between 2008 and 2020. Our main findings are discussed in the following few pages. Table A1 presents the summary statistics of the financial variables for the control sample.

[Insert Figure 1 and Figure 2 here]

Figure 1 shows the yearly distribution of our bankruptcy sample from 2008-2020. As expected, 2009 and 2020 are the years with the most bankruptcies (63 and 51, respectively). Figure 2 presents a detailed analysis of how employee satisfaction relates to bankruptcy risk across different time horizons. The plots display both average marginal effects and predictive margins with 95% confidence intervals for employee satisfaction ratings measured one, two, and three years before bankruptcy filings. The Average Marginal Effects plots (Panel 2.1.) show consistently negative relationships across all time periods, indicating that higher employee satisfaction is associated with lower bankruptcy probability regardless of when it's measured. Several interesting patterns emerge across these plots. First, there appears to be a non-linear relationship in some time horizons, with the steepest decline in bankruptcy probability occurring in the middle ranges of employee satisfaction. Second, the confidence intervals widen considerably at both very low and very high satisfaction ratings, indicating greater uncertainty in predictions at these extremes. Third, there seems to be evidence of threshold effects, where bankruptcy probability decreases more dramatically after satisfaction ratings cross certain levels. The Predictive Margins plots (Panel 2.2.) further reinforce that the relationship holds consistently across different temporal distances from bankruptcy events. These findings collectively demonstrate that employee satisfaction serves as an early warning indicator of financial distress, with predictive value extending up to three years before actual bankruptcy filings.

IV.I. Results with Information from One Year Before Bankruptcy

[Insert Table 2 here]

In this Results section, we test established statistical models against our model with information from one year before bankruptcy filings. Table 2 reports the parameter estimates from the various four models and our model discussed above. We use the same variables that have been used by the original authors in the authors' proposed setting except for Altman's model in which we use a multi-period logistic setting. We include one firm-year observation for each company filing for bankruptcy and all firm-year observations for control and surviving companies for all three years prior to bankruptcy filing. The discriminant analysis coefficients from the Altman's model (both standardized and unstandardized) are presented in Table A2 columns (1) and (2) in the Appendix. The estimated coefficients in Table 2 from the models are bolded if there is any statistical significance. We set the dependent variable to be equal to 1 for bankrupt firms and to 0 otherwise. Therefore, if we observe a positive coefficient, it means that a higher value of that variable increases the likelihood of bankruptcy. We can see that companies with lower profitability and liquidity, but higher leverage are more likely to file for bankruptcy, and smaller firms are more likely to file for bankruptcy. Our employee satisfaction model includes employee satisfaction proxy and profitability, liquidity, leverage variables, firm age, and employee turnover additionally. It also includes the lagged return and volatility of the return, and the firm-size variable, such as the relative size of the firm.

Our model shows that higher employee satisfaction reduces bankruptcy probability. We include various statistics for comparison – Pseudo R-Squared, Adjusted R-Squared, Wald Chi-Square, and Log Pseudolikelihood. Pseudo R-Squared indicates how well the model explains variation in the dependent variable (our dummy variable of bankruptcy), while the Adjusted R-Squared is a modified version of Pseudo R-Squared that penalizes predictors that don't significantly improve the model. If we compare the models based on Adjusted R-Squared, which is a more accurate measure of the models' fit than the Pseudo R-Squared, the Ohlson's model has the highest Adjusted R-Squared (0.754), the Employees' model has the second-best Adjusted R-Squared (0.588), and the Altman's model has the third best Adjusted R-Squared (0.505). We further examine whether the models' fit improves with the addition of employee satisfaction to the models in Table 3. We also examine Wald Chi-Square and Log Pseudolikelihood. The Wald Chi-

Square is a statistical test that evaluates the overall significance of the model by testing whether any of the predictor variables have non-zero coefficients with higher values indicating greater model significance. The Ohlson's model has the highest value (411.77), while the Zmijewski's model has the lowest value (62.20). The Log Pseudolikelihood is a measure that calculates how probable the actual observed outcomes (bankruptcy or no bankruptcy) are according to the model's predictions. A higher (less negative) value indicates a better model fit. For example, a value of -259.21 (Ohlson's model) represents a better fit than -840.82 (Altman's model). We further explore how the Wald Chi-Square and Log Pseudolikelihood values change with the addition of the employee satisfaction variable.

[Insert Figure 3 and Figure 4 here]

In Figure 3, we plot the ROC curves of the five models. The ROC curve measures a classification model's performance across all possible classification thresholds. It plots the True Positive Rate (sensitivity) against the False Positive Rate (1-specificity). The curve illustrates the trade-off between correctly classifying bankruptcies (sensitivity) and incorrectly flagging healthy companies as bankrupt (false positives). The area under the curve (AUC) summarizes the model's discriminative ability with an AUC of 1.0 representing perfect prediction and an AUC of 0.5 indicating performance no better than random chance. Higher AUC values signify better model performance. All models perform substantially better than random chance (0.5) with the Ohlson's model demonstrating the strongest discriminative ability for bankruptcy prediction (0.950). The Employees' model ranks second, suggesting that employee satisfaction metrics provide strong predictive power comparable to traditional financial indicators in bankruptcy prediction.

Figure 4 plots the optimal cut-off points for the various bankruptcy prediction models. These cut-off points represent the threshold probability values that optimize the balance between sensitivity (the model's ability to correctly identify companies that will go bankrupt) and specificity (the model's ability to correctly identify companies that will not go bankrupt). The horizontal line on the plots demonstrates the optimal probability cutoff values for classifying a company as likely to go bankrupt, while the vertical line demonstrates the corresponding sensitivity/specificity values at that optimal threshold. The optimal cut-off maximizes the overall correct classification rate while considering the costs of different types of errors. The Ohlson's model shows the most balanced and strong performance across both metrics, while the Employees' model performs well in both dimensions but is slightly weaker in sensitivity compared to ' model.

[Insert Table 3 here]

[Insert Figure 5 and Figure 6 here]

Table 3 presents parameter estimates for the four models with inclusion of the employee satisfaction proxy. We present the parameter estimates of the Ohlson's model in a logit setting, the parameter estimates of the Zmijewski's model in a probit setting, the parameter estimates of the Shumway's model in a multi-period logit setting, and the parameter estimates of the Altman's model in a multi-period logit setting (following the approach in Table 2). We use the same variables that have been used by the original authors in the authors' proposed setting except for Altman's model in which we use a multi-period logistic setting. The discriminant analysis coefficients (both standardized and unstandardized) are presented in Table A2, columns (3) and (4), in the Appendix. The addition of employee satisfaction (Mean_1) improves model fit across all four models based on Pseudo R-Squared and Adjusted R-Squared measures (which adds proof to our second hypothesis). The employee satisfaction variable is statistically significant in all models, with the negative coefficients across all four models confirming that higher employee satisfaction reduces bankruptcy probability. Zmijewski's model shows the most dramatic improvement in Wald Chi- Square (from 62.20 to 167.70), suggesting employee satisfaction adds substantial predictive power to this model. Ohlson's model maintains the highest explanatory power even after incorporating employee satisfaction, with both the highest Pseudo and Adjusted R-Squared values. Still, the relative performance ranking of the models remains consistent after adding employee satisfaction, with Ohlson's model performing best, followed by Altman's, Zmijewski's, and Shumway's models.

Figure 5 shows a plot of the ROC curves for the four models with inclusion of the employee satisfaction proxy. All models show at least a slight improvement in discriminative ability after incorporating employee satisfaction, though some gains are modest. The relative performance ranking of the models remains unchanged, with Ohlson's model demonstrating the strongest discriminative ability, followed by Zmijewski's, Altman's, and Shumway's models. The similar ROC values between base models and employee-enhanced models suggest that the traditional financial indicators remain strong predictors, with employee satisfaction providing incremental improvement (for instance, the Altman's model demonstrates an ROC of 0.907 – an improvement from 0.904 in the base model, while the Ohlson's model has the highest ROC value at 0.950, maintaining its superior performance from the base model). Figure 6 plots the optimal cutoff point between sensitivity and specificity for the models in Table 3. The addition of employee satisfaction generally improves model performance at their optimal threshold, with most models showing increases in both sensitivity and specificity. Ohlson's model still demonstrates the highest specificity (0.9725), making it exceptionally good at correctly identifying non-bankrupt companies.

[Insert Table 4 here]

[Insert Figure 7 here]

Table 4 presents the classification error rates for all five bankruptcy prediction models (Ohlson's, Altman's, Zmijewski's, Employees', and Shumway's models) without the inclusion of employee satisfaction metrics. The table shows Type I errors (misclassifying bankrupt firms as healthy), Type II errors (misclassifying healthy firms as bankrupt), and Total error rates across different model score percentiles. For all models, Type I errors decrease and Type II errors increase as the model score percentile increases. This illustrates the fundamental trade-off in bankruptcy prediction: being more aggressive in predicting bankruptcies reduces missed bankruptcies but increases false alarms. Most models achieve their lowest total errors rates in the 85^{th}-95^{th} percentile range. The Ohlson's model reaches its minimum total error around the 95^{th} percentile (0.012344), while the Employees' model shows particularly strong performance in the 93^{rd}-95^{th} percentile range. The Ohlson's model consistently achieves the lowest total error rates across most percentile thresholds, while the Employees' model performs comparably to the traditional financial models despite using different predictor variables.

Figure 7 provides a visual representation of the classification rates (Total error rates) for the five bankruptcy models as presented in Table 4. All five models show a U-shaped error curve pattern where total error rates initially decrease as the percentile model score increases, reach a minimum point, and then begin to increase again. This U-shaped pattern illustrates the trade-off between Type I and Type II errors at different threshold levels. The lowest points on each curve represent the optimal threshold percentiles for each model. These optimal points appear to fall between approximately the 90th and 95th percentiles for most models, which confirms the numerical findings in Table 4.

[Insert Table 5 here]

[Insert Figure 8 here]

In Table 5, we report the rate of Types I and II errors for the four models with the inclusion of the employee satisfaction proxy. The table shows Type I errors (missing actual bankruptcies), Type II errors (false bankruptcy predictions), and Total error rates across different model score percentiles. All four models show improved classification accuracy after including employee satisfaction, with the improvement being evident in the generally lower total error rates compared to the base models in Table 4. The Ohlson's model reaches the minimum total error of 0.012932 at the 96th percentile (improved from 0.012344), while the Altman's model achieves the lowest error rate around the 96th percentile (0.036738). The addition of employee satisfaction appears to improve the balance between Type I and Type II errors. The most significant improvements occur in the higher percentiles ranges between the 90th and 99th percentiles. This suggests that employee satisfaction metrics are particularly effective at improving discrimination among firms with higher baseline bankruptcy risk.

Figure 8 provides a visual representation of the classification rates (Total error rates) for the four bankruptcy models (Ohlson's, Altman's, Zmijewski's, and Shumway's) after incorporating employee satisfaction metrics, corresponding to the data presented in Table 5. Similar to Figure 7, all models display a U-shaped error curve pattern. This confirms that the fundamental trade-off between Type I and Type II errors remains consistent even after adding employee satisfaction. The Ohlson's model maintains its position as the best performer with the lowest error curve. When visually compared to Figure 7, the error curves in Figure 8 appear slightly lower in certain ranges. This visual difference represents the incremental improvement from incorporating employee satisfaction. The greatest improvements appear in the 85th-95th percentile range for most models. The visualization reinforces that employee satisfaction metrics add incremental predictive value to traditional bankruptcy models, particularly in optimizing the threshold for bankruptcy prediction decisions.

[Insert Table 6 here]

Table 6 presents out-of-sample performance statistics for the five bankruptcy prediction models (Altman's, Ohlson's, Zmijewski's, Shumway's, and Employees' models) using a 20-80 split methodology. We separate companies into two groups – bankrupt and non-bankrupt companies. We randomly select 20% of companies from each group for the test set; we allocate the remaining 80% of companies to the training set; finally, we ensure that a company appears in either the training or test set, but not in both. This approach allows us to preserve the original bankruptcy distribution and simulate real-world bankruptcy prediction scenarios, treating each company as a discrete, indivisible unit.

The table shows Actual bankruptcy counts versus Predicted counts for each decile, along with Chi-Square statistics that measure the deviation between observed and expected values. The Employees' model shows the strongest alignment between actual and predicted bankruptcies, particularly in Decile 1 (49 actual vs. 49.39 predicted) with a minimal Chi-Square statistic (0.003060). The Ohlson's model demonstrates good performance in lower deciles but shows more deviation in higher risk categories, while the Altman's model shows notable deviation between actual and predicted values, particularly in Decile 1 (43 actual vs. 17.76 predicted) with a high Chi-Square statistic (35.86641). All models effectively concentrate most bankruptcies in the lowest deciles. Overall, the results in the table suggest that the Employees' model demonstrates the most consistent calibration across all deciles, while the Ohlson's model shows good alignment in most deciles but is less precise than the Employees' model. The findings add significant credibility to the value of employee satisfaction metrics in bankruptcy prediction models.

[Insert Table 7 here]

Table 7 reports the out-of-sample performance for the four models (Altman's, Ohlson's, Zmijewski's, and Shumway's) with the inclusion of the employee satisfaction proxy. Like Table 6, it organizes observations into deciles based on bankruptcy probabilities and shows actual versus predicted bankruptcies along with Chi-Square statistics. The inclusion of employee satisfaction generally improves the alignment between actual and predicted bankruptcies across models. Most models show reduced Chi-Square statistics compared to their base versions in Table 6, which indicates a better model due to the addition of employee satisfaction into all four models. Ohlson's model with employee satisfaction shows the best overall calibration, with consistently low Chi-Square statistics across deciles. For example, the Ohlson's model maintains strong performance with slight improvement in alignment (59 actual vs. 56.69 predicted with a Chi-Square of 0.094320). The consistent improvement from the base models provides additional evidence that employee satisfaction contains valuable predictive information for bankruptcy risk that complements traditional financial indicators.

Table A4 and Table A5 present out-of-sample forecast accuracy for the models (Table A4 is for the five models and Table A5 is for the four models) using a cross-validation methodology. The cross-validation methodology is a resampling technique that divides the dataset into multiple subsets, using each subset as a test while training on the remaining data to provide a comprehensive performance assessment. We divide our dataset into equal subsets, ensuring that each subset maintains the proportional representation of bankrupt and non-bankrupt companies, and we iteratively use each subset as a test set while using the other subsets for training. This allows us to compute performance metric for each iteration and aggregate the results across all iterations. The results in Tables 6 and 7 are robust to other out-of-sample tests, such as those using a cross-validation methodology. Both methodologies demonstrate that the Employees' model shows good alignment between actual and predicted bankruptcies, particularly in the highest risk deciles. Even in Table A4, the Employees' model shows good calibration in Deciles 1 (275 actual vs. 260.37 predicted) with a relatively low Chi-Square statistic (0.821506). In addition, both methodologies consistently show that incorporating employee satisfaction improves prediction accuracy across all models. The reduction in Chi-Square statistics from Table A4 to Table A5 mirrors the improvements seen between Tables 6 and 7. The results in Tables A4 and A5 add additional robustness to the finding that employee satisfaction, when added to traditional financial bankruptcy prediction models, improves out-of-sample forecast accuracy.

Table A6 provides insights into the relative information content of the bankruptcy prediction models through Vuong tests, both with and without employee satisfaction. From Panel A6.1. (the five bankruptcy prediction models), we can see that the Ohlson's model demonstrates the strongest information content with the lowest Log Likelihood (-90.6089), while the Employees' model ranks third. If we look at the pairwise comparisons, the Vuong test statistics confirm statistically significant differences in information content between all model pairs (all p-values = 0). Ohlson's model significantly outperforms all other models (positive statistics against all models), while Employees' model outperforms Altman's (-88.3283) and Shumway's (-206.421) models. From

Panel A6.2., we can see that all models show slight improvements in Log Likelihood after incorporating employee satisfaction, with the Ohlson's model maintaining superior performance (-89.6373, improved from -90.6089). The enhanced models maintain statistically significant differences in information content (all p-values = 0), with the magnitude of most Vuong statistics increasing slightly, suggesting employee satisfaction enhances the discriminative power between models. These information content tests provide robust statistical evidence that employee satisfaction contains valuable predictive information for bankruptcy risk, both aa a standalone predictor and as a complement to traditional financial indicators.

To provide additional robustness to employee satisfaction being a predictor of bankruptcy filings, we quantify employee satisfaction's predictive value in a likelihood ratio test and in an incremental predictive power test. Table A8 provides the results of a likelihood ratio test. The likelihood ratio test formally evaluates whether adding employee satisfaction to the Employees' model provides statistically significant improvement in model fit. This test quantifies the marginal contribution of employee satisfaction by comparing the nested model (with and without employee satisfaction) across different time horizons. Employee satisfaction delivers highly significant predictive power across all three time horizons (p-value<0.01). The predictive contribution strengthens at longer time horizons, with likelihood ratio statistics increasing from 7.67 (one year before) to 16.05 (two years before) to 28.06 (three years before). The strongest effect appears three years before bankruptcy, suggesting employee satisfaction serves as an early warning indicator that captures deteriorating conditions well before they manifest in financial statements (which we further discuss in Section IV.II.).

Table A9 decomposes the individual predictive contribution of each variable in the Employees' model to identify which indicators provide the strongest signals at different time horizons. We exclude FirmAge and Turnover in this test to make sure that we are able to compare the incremental performance of the employee satisfaction variable to other financial variables only. By examining ROC statistics and incremental contributions, the table reveals both the absolute and relative predictive power of employee satisfaction compared to traditional financial metrics. Employee satisfaction demonstrates substantial and consistent predictive power across all time horizons (ROC areas – 0.573, 0.611, and 0.606 for one, two, and three years, respectively). At the one-year horizon, WCTA (0.835) and RelativeSize (0.826) show the strongest discriminative ability, followed by ExcessReturn (0.753). Employee satisfaction's predictive power remains stable across the three time horizons, unlike some financial indicators that lose effectiveness at longer horizons. These two tables show that employee satisfaction contributes unique and valuable information to bankruptcy prediction models, with particularly strong performance as an early warning indicator up to three years before bankruptcy occurs.

IV.II. Results with Information from Two and Three Years Before Bankruptcy

[Insert Table 8 and Table 9 here]

In this Results section, we compare the Employees' model with the other four models. For all five models, we use information for the variables from two and three years before bankruptcy filings. Table 8 compares the predictive accuracy of the Employees' model and the Altman's model (given that it's the most established bankruptcy prediction model in the literature). These tests evaluate how effectively each model identifies bankrupt and non-bankrupt firms using threshold-based classification measures. The Employees' model correctly classifies 97.21%, 96.38%, and 95.31% of bankruptcies one, two, and three years before bankruptcy, respectively. The model identifies 67.45% of bankruptcies one year prior, with this declining to 63.14% two years prior and 50.98% three years prior, while the model maintains high specificity across all time horizons (99.65%, 99.10%, and 98.94%, respectively), indicating minimal false positives. The Employees' model exhibits a very low false positive rate across all three time horizons (0.35%, 0.90%, and 1.06%, respectively), which makes the model particularly valuable for practical applications where misclassifying healthy firms is costly. Altman's model shows strong performance one year before bankruptcy (correctly classifying 96.65% of firms) but drops for longer horizons (two and three years before) to 92.41%. In Table A3, we present error rates but in a discriminant analysis setting for both models, and in this setting, we also find more balanced and lower stratified and unstratified total error rates for the Employees' model persisting three years before the bankruptcy filing.

In Table 9, we report the sensitivity analyses and provide the accuracy of the employee satisfaction's model based on the various rating categories, at a given threshold level, in predicting in-sample defaults along with sensitivity and specificity. The rating categories present in our dataset are Career Opportunities, Compensation Benefits, Culture Values, Senior Leadership, Work-Life Balance, and Overall Rating. This breakdown allows us to determine which aspects of employee satisfaction most effectively predicts bankruptcy at different time horizons. The results show that all rating categories show similar classification accuracy when used one before bankruptcy. The models exhibit low false positive rates across all categories. All rating categories show identical classification performance two years before bankruptcy (96.32% correctly classified). The models exhibit consistently low false positive rates across all categories even two years before bankruptcy. The results stay consistent across the various rating categories three years before bankruptcy as well despite small fluctuations across the various models.

[Insert Figure 9 here]

Figure 9 visually represents the discrimination ability of the Employees' model and the Altman's model. The Employees' model shows great discriminative ability with an AUC of 0.9640 two years before bankruptcy, while the model maintains strong predictive power with an AUC of 0.9308, demonstrating stability in performance at a longer time horizon. The Altman's model shows good, but notably weaker performance with an AUC of 0.7726 two years before bankruptcy and an AUC of 0.6935 three years before bankruptcy. The Employees' model outperforms the Altman's model at both time horizons, with the performance gap widening at the longer three-year horizon. The results are an example of the Employees' model stable discriminative ability across time horizons, which underscores employee satisfaction's values as a reliable early warning system for financial distress.

Table A7 presents the classification rates for the Ohlson's, Zmijewski's, and Shumway's models. One year before bankruptcy, the Employees' model (97.21% correctly classified) performs comparably to Ohlson's (98.46%) and Zmijewski's (96.71%). Two years before bankruptcy, the Employees' model maintains the strongest overall performance (96.38%), followed by Shumway's (95.94%), Ohlson's (93.68%), and Zmijewski's (92.70%). Three years before bankruptcy, the Employees' model (95.31%) and Shumway's (94.96%) perform similarly, outperforming the other two models. The results in the table show that the Employees' model demonstrates the most consistent performance across all time horizons, with the smallest decay in predictive power from one to three years before bankruptcy. While Ohlson's model excels at identifying bankruptcies one year before occurrence, it struggles at longer horizons. The Employees' model maintains a more balanced trade-off between sensitivity and specificity across all time periods. Two and three years before bankruptcy, the Employees’ model substantially outperforms traditional financial models in sensitivity, making it the most effective early warning system. Even though all models maintain very low false positive rates, the Employees’ model achieves this while maintaining higher sensitivity at longer horizons compared to the other models.

When comparing the Employees' model to other traditional bankruptcy prediction models beyond Altman's, the results further validate its exceptional predictive power (results are presented in Figure A2). At the two-year horizon, the Employees' model (AUC of 0.9640) outperforms all other models, including Shumway's (AUC of 0.9530), Ohlson's (AUC of 0.8181), and especially Zmijewski's (AUC of 0.5190), which shows barely better discrimination than random chance. Similarly, at the three-year horizon, the Employees' model (AUC of 0.9368) maintains superior performance compared to Shumway's (AUC of 0.9118), Ohlson's (AUC of 0.8199), and Zmijewski's (AUC of 0.5453). The comparison reveals that only Shumway's model approaches the discriminative ability of the Employees' model, while both substantially outperform Ohlson's and Zmijewski's models at longer time horizons. Notably, while most models show some performance degradation between two and three years before bankruptcy, the Employees' model demonstrates remarkable stability with minimal decline in predictive accuracy. Taken together, the results in this section show that employee satisfaction serves as an early warning sign for bankruptcy filings.

IV.III. Results from Survival Analyses

[Insert Table 10 and Table 11 here]

In this Results section, we provide survival analyses examining whether employee satisfaction impacts bankruptcy emergence. Tables 10 and 11 present additional survival analyses to investigate predictions of companies' emergence from bankruptcies. Our sample includes 327 company bankruptcy filings. In our sample, we have 219 company reorganizations (Chapter 11 filings) and 108 company failures (Chapter 7 filings). We use a Cox proportional hazards model to test whether employee satisfaction, financial and market data increase the hazard of bankruptcy emergence. We test whether the company would emerge from bankruptcy given their time of filing to their time of liquidation/restructuring.

In the Cox proportional hazards model, coefficient estimates represent the log hazard ratio, indicating the change in the hazard of bankruptcy emergence associated with a one-unit change in the predictor variable, holding all else constant. Our findings are documented in Tables 10 and 11. Contrary to our initial expectations, our results show mixed and often statistically insignificant relationships between employee satisfaction measures and bankruptcy emergence. For Mean_1 (one year before bankruptcy), we find a negative coefficient (-0.016) that is not statistically significant (t-statistic of -1.45). However, for Mean_2 (two years before bankruptcy), we observe a positive and statistically significant coefficient (0.029) at the 1% level (t-statistic of 3.37). Mean_3 (three years before bankruptcy) shows a positive but insignificant coefficient (0.012, t-statistic of 1.41).

When examining specific rating categories, we find some interesting patterns. One year before bankruptcy filing, career opportunities (careropps_mean_1), compensation and benefits (compensation_mean_1), culture and values (culture_mean_1), and senior leadership (seniorleadership_mean_1) all show negative and statistically significant coefficients at the 5% or 10% level, with t-statistics ranging from -1.80 to -3.33. This suggests that higher satisfaction in these areas is associated with a lower likelihood of immediate emergence from bankruptcy. Interestingly, two years before bankruptcy filing, these same categories show positive and statistically significant coefficients (ranging from 0.133 to 0.157), with t-statistics between 3.09 and 3.29. This indicates that higher employee satisfaction two years prior to filing may enhance the likelihood of eventual bankruptcy emergence.

Among control variables, Change in Net Income (CHIN_1) shows marginal significance ($p<0.10$) in some models, with a negative coefficient one year before bankruptcy filing, suggesting that higher cash flow might be associated with a lower likelihood of immediate emergence. Excess returns (ExcessReturn_3) show a consistent negative and significant relationship three years before filing. Turnover also appears significant in several models, particularly for years 2 and 3 before filing. In summary, our results suggest a complex temporal relationship between employee satisfaction and bankruptcy emergence. While higher employee satisfaction one year before filing may delay emergence, possibly due to reorganization efforts prioritizing employee concerns, higher satisfaction two years before filing appears to facilitate eventual emergence. This pattern suggests that the timing of employee satisfaction measurements relative to bankruptcy filing is crucial in understanding its impact on corporate restructuring outcomes.

IV.IV. Results from Machine Learning Analyses

[Insert Figure 10 here]

In this Results section, we provide machine learning analyses. Figure 10 provides results from CatBoost, Random Forest, Support Vector Machine (SVM), and Logistic Regression model, and an Autoencoder Anomaly Detection model (GenAI model) for predicting bankruptcy by leveraging employee reviews one year before bankruptcy to uncover patterns that signal financial distress in companies. The purpose of this section is to show whether employee satisfaction reviews have predictive power above employee satisfaction ratings, financials, and market information.

The CatBoost model is a gradient boosting algorithm designed to handle categorical features and sparse data, making it particularly well-suited for textual data like employee reviews. It builds an ensemble of decision trees sequentially, where each tree corrects the errors of its predecessors by minimizing a loss function. CatBoost is robust against overfitting due to its advanced regularization techniques and incorporates a unique algorithm to process categorical data efficiently, which is crucial for features, such as employee reviews. In this context, CatBoost leverages the TF-IDF-transformed text data to capture complex, non-linear relationships, allowing it to identify subtle patterns in employee feedback that are predictive of bankruptcy.

The Random Forest model, on the other hand, is an ensemble learning algorithm that constructs multiple decision trees during training and aggregates their predictions to improve robustness and accuracy. Each tree is trained on a random subset of the data, with the final prediction determined by majority voting, ensuring reduced overfitting compared to single decision trees. Random Forest is highly effective with high-dimensional data and provides interpretability through feature importance scores. While it may not handle non-linear relationships as intricately as CatBoost, it excels in producing stable and reliable results, making it a strong benchmark for bankruptcy prediction.

The Support Vector Machine (SVM) model is a powerful algorithm designed to find the optimal hyperplane that separates data into different classes. For regression or classification, SVM uses kernels like the Radial Basis Function to map data into higher-dimensional spaces, enabling the model to capture complex, non-linear relationships. The model is particularly effective at handling high-dimensional data, as it identifies the decision boundary with the maximum margin between classes. With the addition of probability estimates, SVM further enhances its predictive capabilities by providing insights into the confidence of its predictions. Unlike other ensemble methods, SVM focuses on a subset of the training data (support vectors) to determine the hyperplane, making it robust to overfitting in sparse datasets like textual data. Its ability to effectively separate overlapping classes while minimizing misclassifications makes it highly suitable for nuanced prediction, such as bankruptcy.

The logistic regression model is designed to predict continuous outcomes by identifying relationships between input features and the target variable. Using textual data from employee reviews, the regression model attempts to capture patterns in employee reviews that correlate with bankruptcy risk. By minimizing error metrics, such as Mean Squared Error, during training, the model learns to provide a continuous score reflecting the likelihood or severity of bankruptcy. While effective at handling high-dimensional data, the regression model assumes a linear or near-linear relationship between features and bankruptcy risk, which may limit its ability to fully capture complex, non-linear patterns in the data. This approach provides valuable insights into the relative impact of employee reviews on bankruptcy risk, offering a probabilistic framework for understanding company financial health.

The Autoencoder Anomaly Detection model, which is a type of Generative AI model, is designed to identify anomalies, such as bankruptcy, by reconstructing input data and measuring the reconstruction error. Using textual data from employee reviews, the autoencoder learns to encode and decode the input into a compressed latent representation. During training, the model minimizes reconstruction error metrics, such as Mean Squared Error, on non-bankrupt companies, learning to represent patterns in normal employee feedback effectively. When applied to bankrupt companies, the model often fails to reconstruct their data accurately, resulting in higher reconstruction errors, which serve as a signal for potential anomalies. While effective at capturing high-dimensional and complex relationships, this approach relies on the assumption that bankrupt companies exhibit fundamentally different patterns in their employee reviews compared to non-bankrupt companies. By setting a reconstruction error threshold, the autoencoder provides a probabilistic framework for detecting anomalies, offering valuable insights into bankruptcy risk based on deviations in employee feedback patterns.

We take the following steps to clean and process employee reviews one year before bankruptcy for all models. First, any missing values of employee reviews are filled with an empty string. Thereafter, the text is cleaned by converting the text to lowercase, removing special characters and numbers, removing common stop words, such as “the”, “and”, and “is”, and applying lemmatization to reduce words to their root form. The pros, cons, and feedback sections are merged into the same column for analysis. The processed text is transformed into numerical features using TF-IDF which turns text into numerical values based upon its importance in the text. The number of features is reduced to 5,000 to reduce dimensionality and computational cost. We use the Synthetic Minority Oversampling Technique to oversample the minority class. Since the dataset contains many reviews for non-bankrupt companies, we apply under-sampling to the majority class and limit the number of non-bankrupt company reviews is limited to 22,009 reviews. We then use the SMOTE technique to the training data to create synthetic samples for the minority class which ensures that the model doesn’t become biased toward the majority class. This procedure was first introduced by Chawla et al. (2002) and has been used in machine learning research thereafter. It allows us to use random under-sampling to trim the number of examples in the majority class and to oversample the minority class to balance the class distribution. We use the same approach for all models, except for the Autoencoder Anomaly Detection model in which case we train the model on non-bankrupt reviews only. Employee pros, cons, and feedback sections on Glassdoor represent the parameters in our models and we utilize 6,334 failed company reviews (pros, cons, and feedback) and 22,009 non-failed company reviews (pros, cons, and feedback).

The CatBoost model demonstrated exceptional predictive performance in identifying bankruptcy risk using employee review data. The ROC curve (AUC = 0.9249) indicates that the model performs well in distinguishing between bankrupt and non-bankrupt firms. This high AUC suggests that the CatBoost model is adept at capturing patterns in employee textual feedback, pros, and cons. These results of low false positive and false negative rate translate to high accuracy and robust classification performance, with the CatBoost model effectively utilizing the textual features to predict bankruptcy. The Random Forest model also showed strong performance but slightly lagged the CatBoost model in terms of predictive power. The ROC curve (AUC = 0.9365) suggests slightly better separation between classes compared to CatBoost, indicating that Random Forest is highly competitive. The Random Forest model achieves excellent classification and achieves lower false negatives (842), and lower false positives (302) compared to the CatBoost model (899 and 488, respectively).

The ROC curve of the support vector machine model shows an impressive AUC of 0.9567, indicating the model's ability to differentiate between bankrupt and non-bankrupt firms. This demonstrates that the SVM effectively captures patterns in the employee review data, enabling high predictive accuracy. These results indicate that the SVM model excels in minimizing false positives (93) while maintaining a strong recall for bankrupt firms. However, the false negatives (874) suggest that some bankrupt companies are being misclassified, which could be a point for further refinement in feature engineering. The logistic regression achieves an AUC of 0.8491. This still indicates a good, but lower, discriminative ability between bankrupt and non-bankrupt firms than the other three models. The model shows a slight tendency toward over-predicting bankruptcy (1,057 false positives vs. 984 false negatives). This bias could potentially result from certain language patterns in employee reviews that appear negative but don't necessarily indicate financial distress. The confusion matrix reveals that while the logistic regression model performs reasonably well, its linear nature struggles to perfectly separate bankruptcy cases based on the complex linguistic patterns in employee reviews. This explains its lower AUC compared to more sophisticated models.

The Autoencoder Anomaly Detection model demonstrates promising results for identifying bankruptcy risk. The training and validation loss curves indicate effective learning, with both losses decreasing steadily and stabilizing after 10-15 epochs, showing that the model generalizes well to unseen data and avoids overfitting. The reconstruction error distribution further highlights the model's capability to distinguish between bankrupt and non-bankrupt companies. Non-bankrupt companies exhibit lower reconstruction errors, while bankrupt companies generally have higher errors, reflecting their deviation from the patterns learned during training. The red dashed line represents the threshold for classification, separating anomalies (bankrupt companies) from normal data. While the two distributions show a clear separation, some overlap exists, potentially leading to false positives (non-bankrupt companies classified as bankrupt) or false negatives (bankrupt companies classified as non-bankrupt). Overall, the Autoencoder effectively identifies bankruptcy as an anomaly, and the threshold can be adjusted to balance precision and recall based on the business context and tolerance for classification errors.

We can conclude from our findings that the machine learning models with employee reviews one year before bankruptcy perform as well as the financial models without any employee satisfaction information. Overall, these machine learning models demonstrate that textual data from employee reviews contains strong signals for predicting company bankruptcy, with each model offering complementary insights into how employee feedback patterns relate to financial distress.

V. Conclusion

Our paper demonstrates that employee satisfaction is a powerful predictor of bankruptcy across different phases of the bankruptcy process – years before filing, immediately before filing, and during the restructuring or liquidation phase. We find that two to three years before bankruptcy, employee sentiment provides an early warning signal, outperforming traditional financial models in predictive accuracy. Employees possess unique insider knowledge about operational inefficiencies and declining workplace conditions that financial statements fail to capture at such an early stage. However, in the year leading up to bankruptcy, financial indicators become dominant, reflecting distress that was previously only visible to employees.

When we incorporate employee satisfaction into established bankruptcy prediction models, we observe significant improvements in their predictive performance. Employees' attitudes enhance the models' ability to detect financial distress earlier, strengthens their in-sample fit, and improves out-of-sample forecasting accuracy. This suggests that employee satisfaction complements financial metrics rather than merely duplicating their predictive power. Furthermore, during the bankruptcy process itself, employees' attitudes play a critical role in predicting whether a firm will successfully emerge from bankruptcy or face liquidation. Higher employee satisfaction is strongly associated with successful reorganizations, highlighting the importance of human capital in corporate recovery.

We further extend our analysis by leveraging advanced machine learning techniques to assess employees' attitudes from textual reviews. Our results show that qualitative feedback from employees contains rich predictive signals beyond numerical satisfaction ratings, underscoring the depth of employee insight into corporate distress. This finding contributes to the growing literature on alternative data sources for financial risk assessment.

We use a Cox proportional hazards model to test whether employee satisfaction, financial and market data increase the hazard of bankruptcy emergence. We test whether the company would emerge from bankruptcy given their time of filing to their time of liquidation/restructuring. Our results suggest a complex temporal relationship between employee satisfaction and bankruptcy emergence. While higher employee satisfaction one year before filing may delay emergence, possibly due to reorganization efforts prioritizing employee concerns, higher satisfaction two years before filing appears to facilitate eventual emergence. This pattern suggests that the timing of employee satisfaction measurements relative to bankruptcy filing is crucial in understanding its impact on corporate restructuring outcomes.

Overall, our findings suggest that employees' perspectives offer valuable, forward-looking information that traditional financial models overlook. The results highlight the need for bankruptcy prediction models that incorporate workforce sentiment to improve risk assessment and credit analysis. Future research should explore the causal mechanisms underlying the relationship between employee satisfaction and financial distress, as well as the broader implications of workforce morale for corporate stability and long-term performance.

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Table 1: Summary Statistics

Table 1 presents summary statistics for the bankruptcy sample from 2008 through 2020 (those companies that have filed for either a Chapter 7 or a Chapter 11 over the sample period). The final dataset contains 327 bankruptcies. EBITTA = earnings before interest and taxes to total assets; STA = sales to total assets; NITA = net income divided by total assets; CHIN = change in net income from year of to year before bankruptcy filing; WCTA = working capital to total assets; CLCA = current liabilities to current assets; FUTL = income from operations after depreciation divided by total liabilities; INTWO = 1 if net income was negative for the previous two years, 0 otherwise; RETA = retained earnings to total assets; MVETL = market equity to total liabilities; TLTA = total liabilities to total assets; OENEG = 1 if total liabilities exceed total assets, 0 otherwise; OhlsonSize = log(total assets/GNP price-level index), the index assumes a base value of 100 for 1968; RelativeSize = log(the number of outstanding shares multiplied by year-end share price then divided by total market value); ExcessReturn = cumulative annual return in year t-1 minus the value-weighted CRSP index return in year t-1; SDReturn = standard deviation of the residual derived from regressing monthly stock return on market return in year t-1; FirmAge = number of years since the company's IPO; Turnover = employment changes from year to year. Panel 1.1. presents the above-mentioned bankruptcy models' characteristics one, two, and three years before, while Panel 1.2. presents mean and breakdown of various rating categories one, two, and three years before bankruptcy filings.

1.1. Bankruptcy Models' Characteristics One, Two, and Three Years Before

Stats	N	Mean	SD	p25	p50	p75
Mean_1	327	15.90133	6.360336	13.5	16.85000	19.70000
OhlsonSIze_1	327	1.520219	0.521722	1.348977	1.541645	1.741637
NITA_1	327	-69.74220	1052.186	-0.521190	-0.246190	-0.127790
CHIN_1	327	-0.146190	10.02666	0	0.373332	1
WCTA_1	327	-0.462370	0.980659	-0.873660	-0.334860	0.124719
CLCA_1	327	-0.373080	3.139038	-0.381390	-0.137360	0.128379
FUTL_1	327	0.831060	3.029125	0	0.326352	0.812321
INTWO_1	327	0.204013	0.403654	0	0	0
TLTA_1	327	75.94961	821.2321	0.127996	0.878320	1.287294
OENEG_1	327	0.377926	0.485682	0	0	1
RETA_1	327	-2.248200	17.08637	-0.753930	-0.143670	0
EBITTA_1	327	-40.15580	702.6309	-0.392340	-0.133240	0.353433
MVETL_1	327	0.462721	3.011979	0	0	0.345942
STA_1	327	0.783285	0.755391	0.239111	0.549838	1.157318
RelativeSize_1	327	0.847088	4.172617	0	0.118486	0.418184
ExcessReturn_1	327	-0.530090	0.720094	-0.884320	-0.666860	-0.211410
SDReturn_1	327	0.084347	1.082473	-0.171970	0.458446	0.771954
FirmAge_1	327	34.06355	43.89141	7	16	26
Turnover_1	327	-0.077500	0.396188	-0.228680	0	0

Stats	N	Mean	SD	p25	p50	p75
Mean_2	327	7.873960	8.246870	0	3.714286	15.91667
OhlsonSize_2	327	1.318103	0.753909	1.245299	1.488463	1.756648
NITA_2	327	-30.73450	447.9100	-0.355230	-0.115360	0
CHIN_2	327	0.109336	2.539441	-0.453320	0	0.556692
WCTA_2	327	0.117183	0.409991	0	0	0.294117
CLCA_2	327	1.551554	3.544277	0	0.328355	1.249264
FUTL_2	327	0.086819	0.532161	-0.136930	0	0.296954
INTWO_2	327	0.374582	0.484826	0	0	1
TLTA_2	327	43.65008	333.8130	0.382940	0.769543	0.971825
OENEG_2	327	0.334448	0.472588	0	0	1
RETA_2	327	-1.213240	5.903359	-0.747470	-0.226570	0
EBITTA_2	327	5.130330	94.73547	-0.134230	0	0.335768
MVETL_2	327	0.740037	5.501951	0	0.163454	0.423649
STA_2	327	0.625667	0.759807	0	0.388732	0.933700
RelativeSize_2	327	-0.434750	0.718060	-0.848290	-0.279120	0
ExcessReturn_2	327	0.679902	15.15156	-0.651750	-0.396400	0.171825
SDReturn_2	327	-0.007480	1.017575	-0.357640	0.199294	0.525348
FirmAge_2	327	30.89632	42.26458	5	15	21
Turnover_2	327	1.553336	27.53364	-0.232560	0	0.125000

Stats	N	Mean	SD	p25	p50	p75
Mean_3	327	5.638668	8.017498	0	0	13.88889
OhlsonSize_3	327	0.850289	0.685313	0	1.143928	1.356837
NITA_3	327	-1.555340	13.81232	-0.295860	0	0
CHIN_3	327	-0.818440	13.62658	-0.462120	0	0.589739
WCTA_3	327	0.135703	0.411156	0	0.116322	0.378920
CLCA_3	327	0.662515	0.763221	0	0.515185	0.876245
FUTL_3	327	0.159783	0.996467	0	0	0.344521
INTWO_3	327	0.371238	0.483946	0	0	1
TLTA_3	327	210.0360	3169.091	0.418315	0.735499	0.976717
OENEG_3	327	0.324415	0.468941	0	0	1
RETA_3	327	-0.809050	3.286916	-0.671680	-0.158930	0.147392
EBITTA_3	327	8.268136	150.0175	0	0	0.236484
MVETL_3	327	1.032988	4.525308	0	0.227768	0.662898
STA_3	327	0.646710	0.746072	0	0.437780	0.945264
RelativeSize_3	327	-0.274640	0.583986	-0.542380	0	0
ExcessReturn_3	327	-0.149700	1.993082	-0.734830	-0.437340	-0.111850
SDReturn_3	327	0.029233	1.051986	-0.177370	0.263539	0.494527
FirmAge_3	327	28.51171	40.87207	5	14	19
Turnover_3	327	0.045130	1.048733	-0.247760	0	0.137566

1.2. Rating Categories' Statistics

Stats	N	Mean	SD	p25	p50	p75
careeropps_mean_1	327	2.786930	0.835572	2.333333	2.8	3.2
compensation_mean_1	327	3.352397	0.883726	2.833333	3.4	4
culture_mean_1	327	2.481346	1.552748	1.5	2.9	3.564126
seniorleadership_mean_1	327	2.833700	0.942733	2.25	2.833333	3.4
worklife_mean_1	327	3.343012	0.898521	2.833333	3.4	4
overall_mean_1	327	3.224273	0.857432	2.666667	3.128251	3.8
careeropps_mean_2	327	1.369011	1.506156	0	0	2.758627
compensation_mean_2	327	1.542305	1.671700	0	0	3
culture_mean_2	327	1.151759	1.529649	0	0	2.7
seniorleadership_mean_2	327	1.292651	1.452401	0	0	2.677833
worklife_mean_2	327	1.745325	1.704238	0	2	3.25
cverall_mean_2	327	1.497341	1.629037	0	0	3
careeropps_mean_3	327	1.033251	1.382341	0	0	2.5
compensation_mean_3	327	1.164214	1.568353	0	0	2.634483
culture_mean_3	327	0.868754	1.395432	0	0	2
seniorleadership_mean_3	327	0.947489	1.303114	0	0	2.231773
worklife_mean_3	327	1.160605	1.554511	0	0	2.723391
overall_mean_3	327	1.126300	1.507303	0	0	2.711539

Figure 1: Number of Bankruptcies per Year

Figure 1 presents the number of bankruptcies per year from UCLA's LoPucki data over the paper sample from 2008 through 2020.

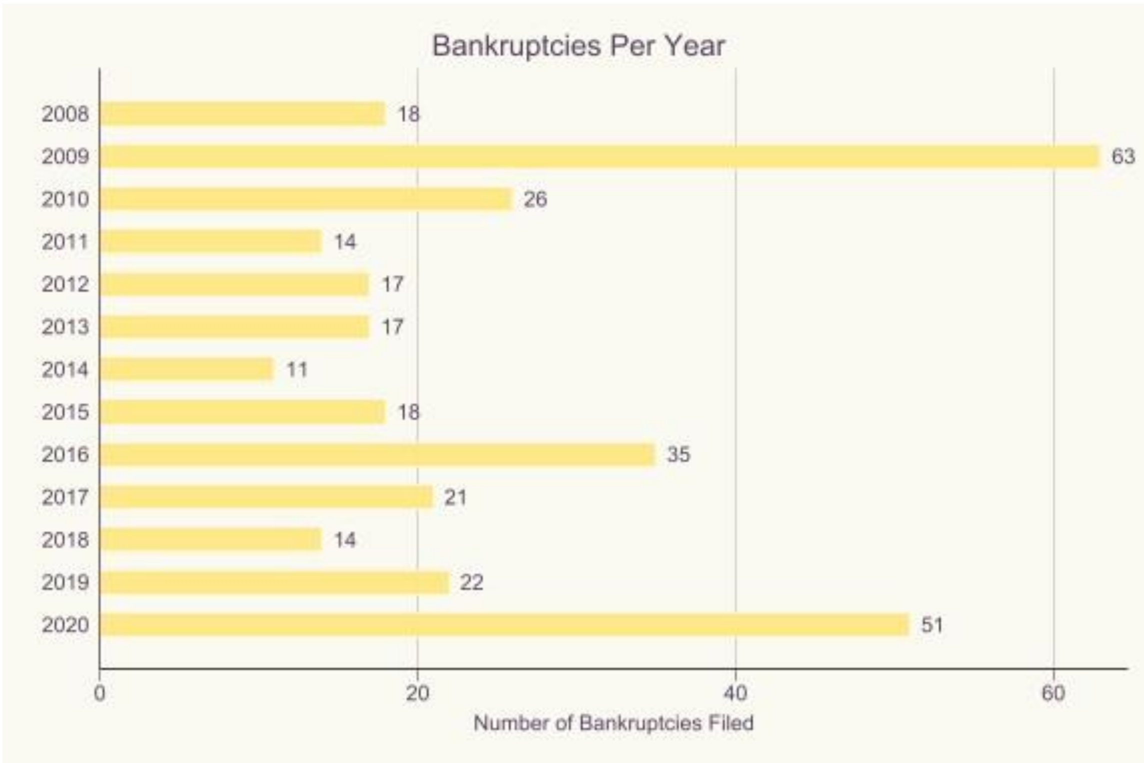
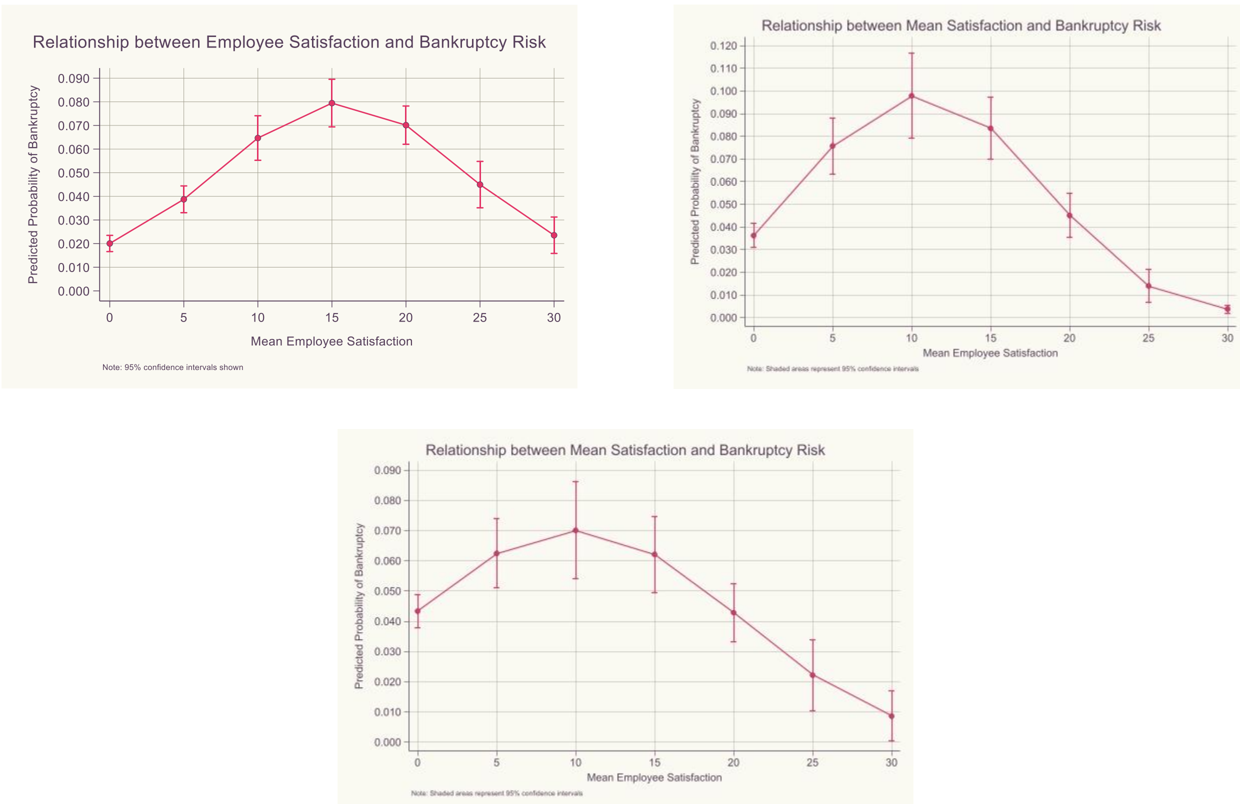


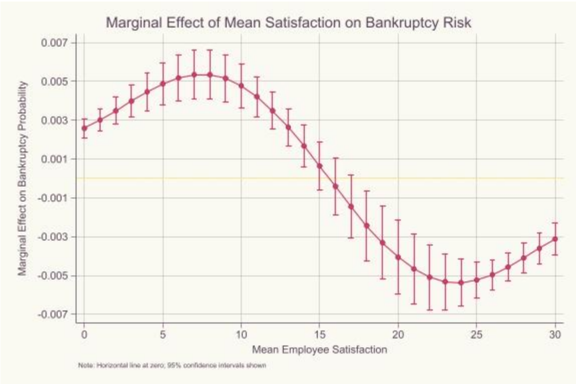
Figure 2: Marginal Effects and Predictive Margins of Mean Ratings

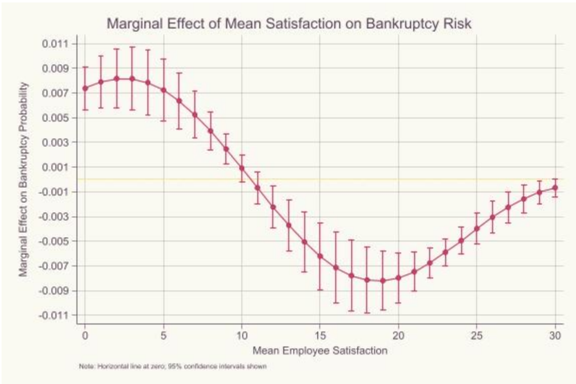
Figure 2 shows a plot of the average marginal effects and the predictive margins with 95% confidence intervals of employee satisfaction ratings one, two, and three years before bankruptcy filings. The average marginal effects demonstrate the incremental impact of changing employee satisfaction on bankruptcy probability, revealing a consistent negative relationship across all time horizons. The predictive margins illustrate the estimated bankruptcy probability across the full spectrum of satisfaction ratings, showing that companies with higher employee satisfaction consistently maintain lower bankruptcy risk.

<u>2.1. Average Marginal Effects</u>



2.2. Predictive Margins





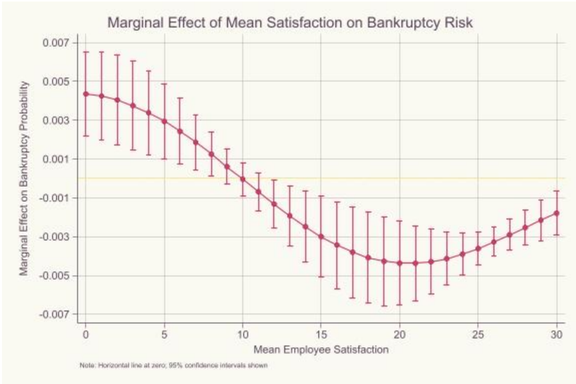


Table 2: Estimation Results for Bankruptcy Models

Table 2 presents the parameter estimates from the bankruptcy prediction models discussed in the paper. The sample is from 2008 to 2020 and contains 327 bankruptcies and 7,924 non-bankrupt companies. Column (1) represents estimation results for the Ohlson's model in a logit setting with the original variables presented in the author's paper; Column (2) represents estimation results for the Zmijewski's model in a probit setting with the original variables presented in author's paper; Column (3) represents estimation results for the Shumway's model in a multi-period logit setting with the original variables presented in the author's paper; Column (4) represents estimation results for the Employees' model in a multi-period logit setting using the variables presented in this paper; Column (5) represents estimation results for the Altman's model in a multi-period logit setting using the variables presented in the author's paper. Bold font signifies an estimate that is statistically significant. All models' estimates include the Wald Chi-Square, Log Pseudolikelihood, Pseudo R-Squared, and Adjusted R-Squared. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	<u>**Ohlson's (1)**</u>	<u>**Zmijewski's (2)**</u>	<u>**Shumway's (3)**</u>	<u>**Employees' (4)**</u>	<u>**Altman's (5)**</u>
Intercept	**-4.647*** (0.0925)**	**-1.674*** (0.0271)**	**-10.81*** (0.388)**	**-5.286*** (0.787)**	**-7.345*** (0.515)**
Mean_1				**-0.0638*** (0.0210)**	
EBITTA_1				**-0.112* (0.0610)**	**-0.0109* (0.0583)**
STA_1					**1.175*** (0.133)**
NITA_1	**-0.0881*** (0.00748)**	**-0.0206*** (0.00426)**	-0.00473 (0.00881)		
CHIN_1	**-0.0198** (0.00883)**			-0.0173 (0.0122)	
WCTA_1	**-6.418*** (0.493)**			**-6.175*** (0.634)**	**-8.293*** (0.683)**
CLCA_1	**-0.216*** (0.0491)**	**-1.606*** (0.226)**			
FUTL_1	0.142 (0.101)				
INTWO_1	**2.535*** (0.244)**				
RETA_1					**0.0266*** (0.00986)**
MVETL_1					**-0.131*** (0.0485)**
TLTA_1	0.172 (0.116)	0.000149 (0.000211)	0.00276 (0.00360)	**0.318*** (0.0934)**	
OENEG_1	**-1.290*** (0.354)**				
OhlsonSize_1	**0.467*** (0.0480)**				
RelativeSize_1			**-0.0266*** (0.0791)**	-0.0843 (0.0642)	
ExcessReturn_1			**-2.686*** (0.319)**	**-1.232*** (0.251)**	
SDReturn_1			**-0.286* (0.149)**	**-0.387*** (0.113)**	
FirmAge_1				**0.152*** (0.0231)**	
Turnover_1				**-1.295*** (0.397)**	
Log Pseudolikelihood	-259.21092	-469.93116	-597.43163	-268.18561	-840.81994
Pseudo R-Squared	0.764	0.468	0.260	0.598	0.512
Adjusted R-Squared	0.754	0.463	0.253	0.588	0.505
Wald Chi-Square	411.77	62.20	85.88	140.10	157.55
N (Observations)	8,251	8,251	24,099	24,057	24,099

T-statistics in parentheses
* p<0.10, ** p<0.05, *** p<0.01

Figure 3: ROC Curves for Bankruptcy Models

Figure 3 plots the Receiver Operating Characteristic (ROC) generated from the various models: Altman's, Ohlson's, Zmijewski's, Shumway's, and Employees' models. The ROC curve measures a classification model's performance across all possible classification thresholds. It plots the True Positive Rate (sensitivity) against the False Positive Rate (1-specificity). The ROC for Altman's model is 0.904, the ROC for Ohlson's model is 0.950, the ROC for Zmijewski's model is 0.914, the ROC for Shumway's model is 0.832, and the ROC for Employees' model is 0.927.

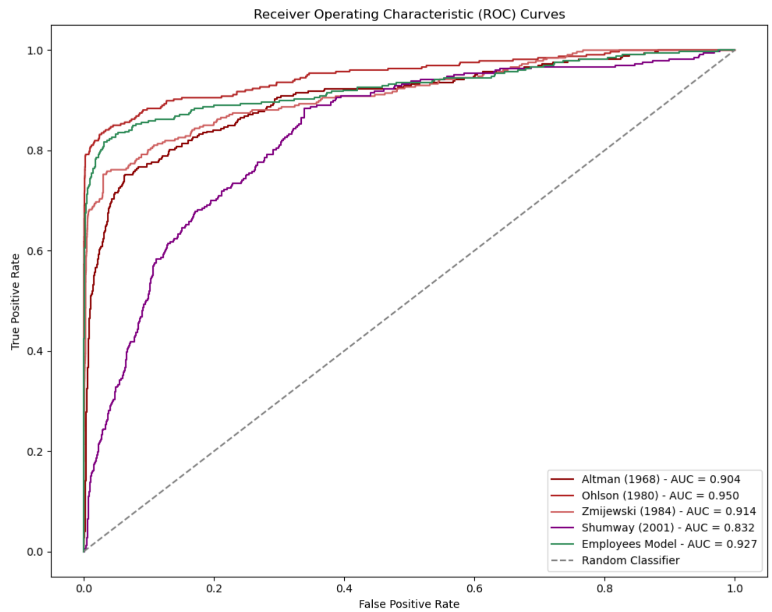


Figure 4: Optimal Cut-Off Points for Bankruptcy Models

Figure 4 plots the optimal cut-off points generated from the various models: Ohlson's, Altman's, Zmijewski's, Shumway's, and Employees' models. These cutoff points represent the threshold probability values that optimize the balance between sensitivity and specificity.

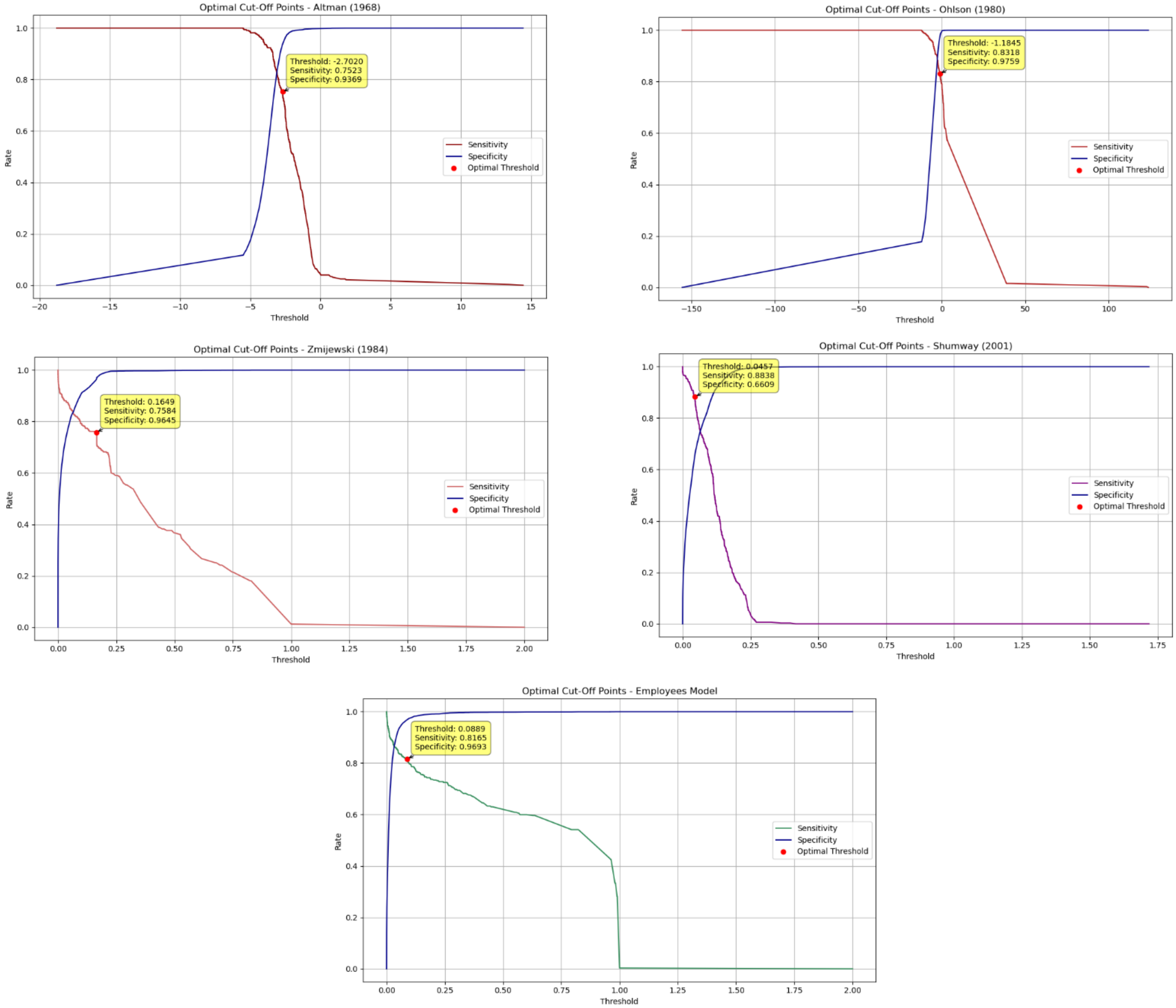


Table 3: Estimation Results for Bankruptcy Models with Employee Satisfaction

Table 3 presents the parameter estimates from the bankruptcy prediction models discussed in the paper, including employee satisfaction into all models. The sample is from 2008 to 2020 and contains 327 bankruptcies and 7,924 non-bankrupt companies. Column (1) represents estimation results for the Ohlson's model in a logit setting; Column (2) represents estimation results for the Zmijewski's model in a probit setting; Column (3) represents estimation results for the Shumway's model in a multi-period logit setting; Column (4) represents estimation results for the Altman's model in a multi-period logit setting. Bold font signifies an estimate that is statistically significant. All models' estimates include the Wald Chi-Square, Log Pseudolikelihood, Pseudo R-Squared, and Adjusted R-Squared. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	Ohlson's (1)	Zmijewski's (2)	Shumway's (3)	Altman's (4)
Intercept	**2.286*** (0.438)**	**-0.255* (0.134)**	**-3.599*** (0.857)**	**-6.001*** (0.547)**
Mean_1	**-0.0675*** (0.0180)**	**-0.0312*** (0.00741)**	**-0.0804*** (0.0286)**	**-0.107*** (0.0237)**
EBITTA_1				**-0.0127** (0.00595)**
STA_1				**1.246*** (0.141)**
NITA_1	**-0.0848*** (0.00781)**	-0.00414 (0.00701)	-0.00273 (0.00695)	
CHIN_1	**-0.0229*** (0.00751)**			
WCTA_1	**-3.431*** (0.401)**			**-8.647*** (0.725)**
CLCA_1	**-3.848*** (0.439)**	**-2.514*** (0.210)**		
FUTL_1	0.00339 (0.00394)			
INTWO_1	-0.237 (0.345)			
RETA_1				**0.0294*** (0.0105)**
MVETL_1				**-0.140*** (0.0507)**
TLTA_1	0.164 (0.237)	**0.000155* (0.0000936)**	0.00268 (0.00176)	
OENEG_1	**-3.517*** (0.294)**			
OhlsonSize_1	**0.116*** (0.0377)**			
RelativeSize_1			**-0.284*** (0.0819)**	
ExcessReturn_1			**-2.822*** (0.333)**	
SDReturn_1			**-0.303* (0.156)**	
FirmAge_1				
Turnover_1				
Log Pseudolikelihood	-254.20083	-461.57395	-591.49977	-828.34850
Pseudo R-Squared	0.769	0.479	0.277	0.517
Adjusted R-Squared	0.758	0.473	0.268	0.508
Wald Chi-Square	230.60	167.70	36.71	153.95
N (Observations)	8,251	8,251	24,099	24,099

T-statistics in parentheses
* p<0.10, ** p<0.05, *** p<0.01

Figure 5: ROC Curves for Bankruptcy Models with Employee Satisfaction

Figure 5 plots the Receiver Operating Characteristic (ROC) generated from the various models: Altman's, Ohlson's, Zmijewski's, and Shumway's, but including the mean employee satisfaction in those models. The ROC curve measures a classification model's performance across all possible classification thresholds. It plots the True Positive Rate (sensitivity) against the False Positive Rate (1-specificity). The ROC for Altman's model is 0.907, the ROC for Ohlson's model is 0.950, the ROC for Zmijewski's model is 0.915, and the ROC for Shumway's model is 0.834.

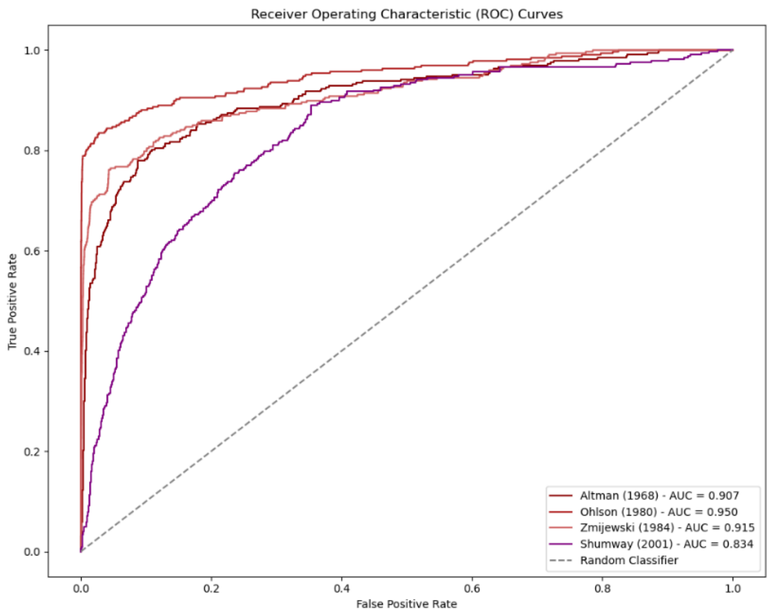


Figure 6: Optimal Cut-Off Points for Bankruptcy Models with Employee Satisfaction

Figure 6 plots the optimal cut-off points generated from the various models: Ohlson's, Altman's, Zmijewski's, and Shumway's, but including the mean employee satisfaction in each model. These cut-off points represent the threshold probability values that optimize the balance between sensitivity and specificity.

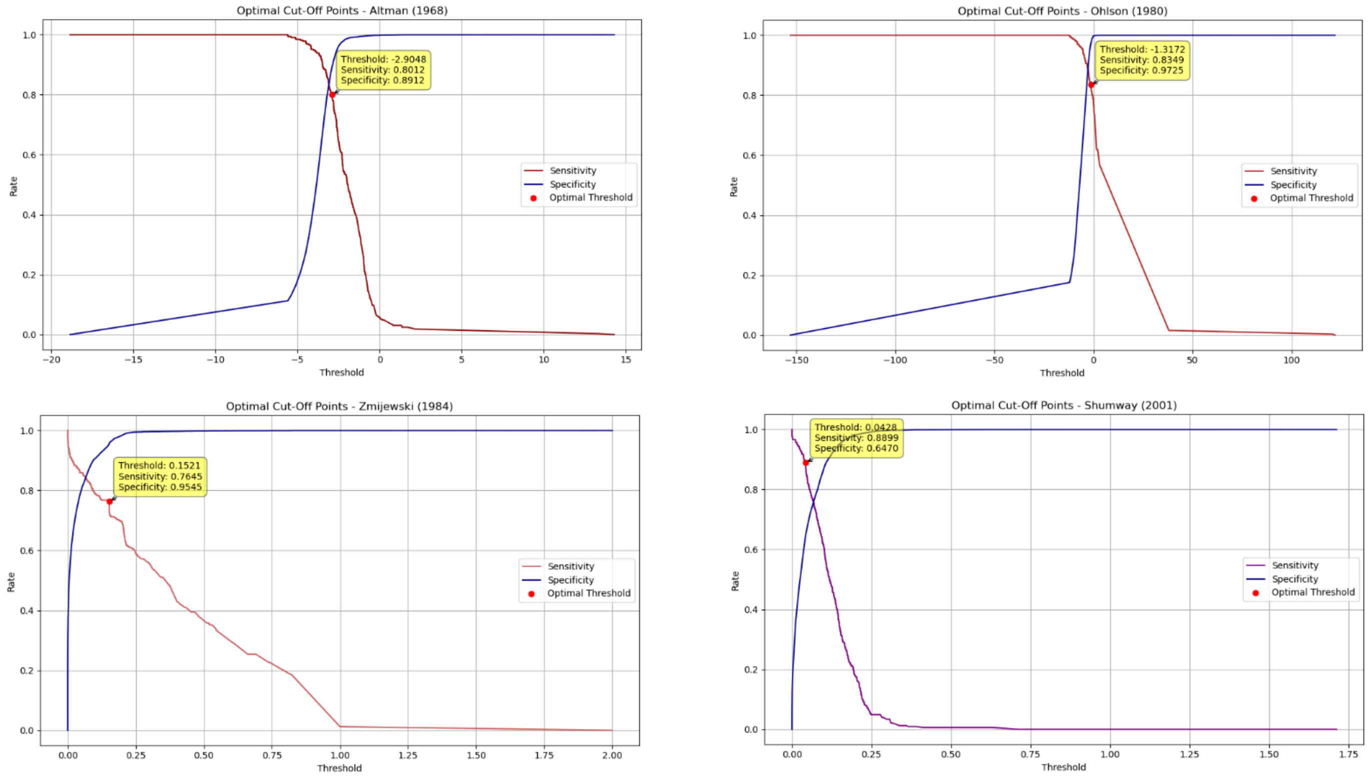


Table 4: Classification Rates for Bankruptcy Models

Table 4 presents the incidence of Type I errors (classifying a bankrupt firm as healthy) and Type II errors (classifying a healthy firm as bankrupt) and Total error (both Type I and Type II errors), according to model scores for Ohlson's, Altman's, Zmijewski's, Employees', and Shumway's models. Type I errors represent misclassifying bankrupt firms as healthy; Type II errors represent misclassifying healthy firms as bankrupt, and Total errors represent the sum of Type I and Type II errors.

	Altman's (1)			Ohlson's (2)			Zmijewski's (3)		
Model Score (Percentile)	Type I	Type II	Total	Type I	Type II	Total	Type I	Type II	Total
50	0.478697	0.076453	0.459368	0.476690	0.036697	0.455547	0.479006	0.082569	0.459956
70	0.260574	0.125382	0.254078	0.258259	0.079511	0.249669	0.260266	0.119266	0.253490
71	0.250386	0.131498	0.244673	0.247916	0.082569	0.239971	0.250077	0.125382	0.244085
72	0.240198	0.137615	0.235268	0.237419	0.082569	0.229978	0.239580	0.125382	0.234093
73	0.230318	0.149847	0.226451	0.227385	0.091743	0.220867	0.229083	0.125382	0.224100
74	0.219975	0.152905	0.216752	0.216888	0.091743	0.210874	0.219049	0.134557	0.214989
75	0.209633	0.159021	0.207201	0.206391	0.094801	0.201029	0.208552	0.137615	0.205143
76	0.199136	0.159021	0.197208	0.195894	0.094801	0.191036	0.198672	0.149847	0.196326
77	0.188793	0.162080	0.187509	0.185397	0.094801	0.181043	0.188175	0.149847	0.186334
78	0.178605	0.168196	0.178104	0.174900	0.094801	0.171051	0.177987	0.155963	0.176929
79	0.168416	0.174312	0.168699	0.164403	0.094801	0.161058	0.167644	0.159021	0.167230
80	0.158537	0.186544	0.159882	0.153906	0.094801	0.151065	0.157765	0.171254	0.158413
81	0.148348	0.192661	0.150478	0.143563	0.097859	0.141367	0.147422	0.174312	0.148714
82	0.138160	0.198777	0.141073	0.133220	0.100917	0.131668	0.137234	0.180428	0.139309
83	0.128280	0.211009	0.132256	0.123186	0.110092	0.122557	0.126737	0.180428	0.129317
84	0.118092	0.217125	0.122851	0.112998	0.116208	0.113152	0.116548	0.186544	0.119912
85	0.107904	0.223242	0.113446	0.102501	0.116208	0.103159	0.106360	0.192661	0.110507
86	0.097561	0.226300	0.103747	0.092158	0.119266	0.093461	0.096635	0.207951	0.101984
87	0.087373	0.232416	0.094342	0.082278	0.131498	0.084644	0.086446	0.214067	0.092579
88	0.077339	0.241590	0.085231	0.072245	0.140673	0.075533	0.076567	0.226300	0.083762
89	0.067150	0.247706	0.075827	0.062056	0.146789	0.066128	0.066533	0.235474	0.074651
90	0.057888	0.272171	0.068185	0.051713	0.149847	0.056429	0.056190	0.238532	0.064952
91	0.048009	0.284404	0.059368	0.041371	0.152905	0.046730	0.045693	0.238532	0.054960
92	0.039055	0.314985	0.052314	0.031337	0.162080	0.037619	0.035505	0.244648	0.045555
93	0.031182	0.366972	0.047318	0.021766	0.180428	0.029390	0.027632	0.296636	0.040558
94	0.022847	0.409786	0.041440	0.011732	0.189602	0.020279	0.017598	0.305810	0.031447
95	0.015128	0.464832	0.036738	**0.002316**	**0.211009**	**0.012344**	**0.007873**	**0.321101**	**0.022924**
96	**0.008490**	**0.541284**	**0.034093**	0.000463	0.382263	0.018810	0.003396	0.440367	0.024394
97	0.004940	0.678899	0.037325	0.000154	0.584098	0.028215	0.002007	0.620795	0.031741
98	0.003087	0.850153	0.043791	0.000154	0.792049	0.038207	0.000463	0.798165	0.038795
99	0.478697	0.076453	0.459368	0.476690	0.036697	0.455547	0.479006	0.082569	0.459956

	Shumway's (4)			**Employees' (5)**		
Model Score (Percentile)	Type I	Type II	Total	Type I	Type II	Total
50	0.478388	0.070336	0.458780	0.478234	0.067278	0.458486
70	0.265823	0.229358	0.264071	0.259648	0.107034	0.252314
71	0.256098	0.244648	0.255547	0.249151	0.107034	0.242322
72	0.246218	0.256881	0.246730	0.238808	0.110092	0.232623
73	0.236184	0.266055	0.237619	0.228311	0.110092	0.222630
74	0.225996	0.272171	0.228215	0.217814	0.110092	0.212638
75	0.215653	0.278287	0.218663	0.207163	0.110092	0.202498
76	0.205928	0.293578	0.210140	0.196820	0.113150	0.192799
77	0.195739	0.299694	0.200735	0.186323	0.113150	0.182807
78	0.185860	0.311927	0.191918	0.175980	0.116208	0.173108
79	0.175672	0.318043	0.182513	0.165638	0.119266	0.163409
80	0.166255	0.339450	0.174578	0.155604	0.128440	0.154298
81	0.156375	0.351682	0.165760	0.145261	0.131498	0.144600
82	0.146650	0.366972	0.157237	0.135073	0.137615	0.135195
83	0.136925	0.382263	0.148714	0.124575	0.137615	0.125202
84	0.127045	0.394495	0.139897	0.114078	0.137615	0.115209
85	0.117629	0.415902	0.131962	0.103736	0.140673	0.105511
86	0.107749	0.428135	0.123145	0.093393	0.143731	0.095812
87	0.100185	0.486239	0.118736	0.083050	0.146789	0.086113
88	0.091077	0.513761	0.111389	0.073171	0.159021	0.077296
89	0.082742	0.556575	0.105511	0.062982	0.165138	0.067891
90	0.073479	0.581040	0.097869	0.052640	0.168196	0.058193
91	0.064835	0.617737	0.091403	0.042606	0.177370	0.049082
92	0.056345	0.657492	0.085231	0.032417	0.183486	0.039677
93	0.047700	0.694190	0.078766	0.023155	0.207951	0.032035
94	0.038438	0.718654	0.071124	0.014202	0.238532	0.024982
95	0.029793	0.755352	0.064658	**0.005712**	**0.278287**	**0.018810**
96	0.021612	0.801223	0.059074	0.001389	0.400612	0.020573
97	0.013121	0.840979	0.052902	0.000309	0.587156	0.028508
98	**0.006792**	**0.923547**	**0.050845**	0	0.788991	0.037913
99	0.478388	0.070336	0.458780	0.478234	0.067278	0.458486

Figure 7: Classification Rates for Bankruptcy Models

Figure 7 presents classification rates for the various bankruptcy models – Ohlson's, Altman's, Zmijewski's, Shumway's, and Employees' models – from the tests in Table 4. The horizontal axis plots the percentile model score, while the vertical axis plots the Total error (Type I and Type II errors) for each respective model.

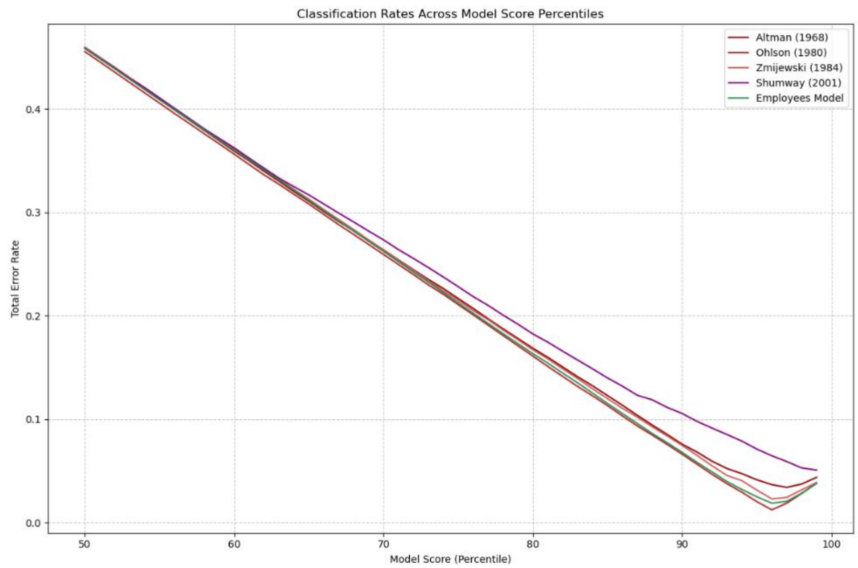


Table 5: Classification Rates for Bankruptcy Models with Employee Satisfaction

Table 5 presents the incidence of Type I errors (classifying a bankrupt firm as healthy) and Type II errors (classifying a healthy firm as bankrupt) and Total error (both Type I and Type II errors), according to model scores for Ohlson's, Altman's, Zmijewski's, and Shumway's models with inclusion of mean of employee satisfaction.

	Altman's (1)			Ohlson's (2)		
Model Score (Percentile)	Type I	Type II	Total	Type I	Type II	Total
50	0.477925	0.061162	0.457899	0.476690	0.036697	0.455547
70	0.270608	0.116208	0.263189	0.268601	0.076453	0.259368
71	0.260111	0.116208	0.253196	0.258104	0.076453	0.249375
72	0.249614	0.116208	0.243204	0.247916	0.082569	0.239971
73	0.239117	0.116208	0.233211	0.237573	0.085627	0.230272
74	0.229083	0.125382	0.224100	0.227076	0.085627	0.220279
75	0.218740	0.128440	0.214401	0.216888	0.091743	0.210874
76	0.208552	0.137615	0.205143	0.206236	0.091743	0.200735
77	0.198364	0.143731	0.195738	0.195894	0.094801	0.191036
78	0.188021	0.146789	0.186040	0.185397	0.094801	0.181043
79	0.177833	0.152905	0.176635	0.174900	0.094801	0.171051
80	0.167953	0.165138	0.167818	0.164403	0.094801	0.161058
81	0.157919	0.174312	0.158707	0.153906	0.094801	0.151065
82	0.147885	0.183486	0.149596	0.143717	0.100917	0.141661
83	0.137388	0.183486	0.139603	0.133683	0.110092	0.132550
84	0.127354	0.192661	0.130492	0.123186	0.110092	0.122557
85	0.117011	0.195719	0.120794	0.112843	0.113150	0.112858
86	0.106823	0.201835	0.111389	0.102501	0.116208	0.103159
87	0.097252	0.220183	0.103159	0.092312	0.122324	0.093755
88	0.087218	0.229358	0.094048	0.082278	0.131498	0.084644
89	0.077956	0.253823	0.086407	0.072245	0.140673	0.075533
90	0.067922	0.262997	0.077296	0.061902	0.143731	0.065834
91	0.058197	0.278287	0.068773	0.051868	0.152905	0.056723
92	0.049398	0.311927	0.062013	0.041525	0.155963	0.047024
93	0.040753	0.348624	0.055547	0.031491	0.165138	0.037913
94	0.031954	0.382263	0.048788	0.021612	0.177370	0.029096
95	0.023310	0.418960	0.042322	0.011886	0.192661	0.020573
96	0.015128	0.464832	0.036738	**0.002624**	**0.217125**	**0.012932**
97	**0.008799**	**0.547401**	**0.034680**	0.000463	0.382263	0.018810
98	0.005403	0.688073	0.038207	0.000154	0.584098	0.028215
99	0.003242	0.853211	0.044085	0.000154	0.792049	0.038207

	<u>Zmijewski's (3)</u>			**<u>Shumway's (4)</u>**		
Model Score (Percentile)	Type I	Type II	Total	Type I	Type II	Total
50	0.478543	0.073394	0.459074	0.478543	0.073394	0.459074
70	0.270763	0.119266	0.263483	0.275394	0.211009	0.272300
71	0.260420	0.122324	0.253784	0.265514	0.223242	0.263483
72	0.250077	0.125382	0.244085	0.255326	0.229358	0.254078
73	0.239734	0.128440	0.234386	0.245292	0.238532	0.244967
74	0.229392	0.131498	0.224688	0.235258	0.247706	0.235856
75	0.218895	0.131498	0.214695	0.225533	0.262997	0.227333
76	0.208706	0.140673	0.205437	0.215499	0.275229	0.218369
77	0.198209	0.140673	0.195445	0.205928	0.293578	0.210140
78	0.187712	0.140673	0.185452	0.196048	0.305810	0.201323
79	0.177678	0.149847	0.176341	0.186323	0.321101	0.192799
80	0.167336	0.152905	0.166642	0.176135	0.327217	0.183395
81	0.157147	0.159021	0.157237	0.166255	0.339450	0.174578
82	0.146805	0.162080	0.147539	0.156530	0.354740	0.166054
83	0.136771	0.171254	0.138428	0.146805	0.370031	0.157531
84	0.126428	0.174312	0.128729	0.136925	0.382263	0.148714
85	0.116240	0.180428	0.119324	0.127200	0.397554	0.140191
86	0.106360	0.192661	0.110507	0.118092	0.425076	0.132843
87	0.096635	0.207951	0.101984	0.108984	0.452599	0.125496
88	0.086601	0.217125	0.092873	0.099877	0.480122	0.118148
89	0.076412	0.223242	0.083468	0.090614	0.504587	0.110507
90	0.066379	0.232416	0.074357	0.081044	0.522936	0.102278
91	0.055881	0.232416	0.064364	0.071936	0.550459	0.094930
92	0.045539	0.235474	0.054666	0.062982	0.581040	0.087877
93	0.037512	0.284404	0.049375	0.054801	0.626911	0.082292
94	0.027323	0.290520	0.039971	0.046619	0.672783	0.076708
95	0.017444	0.302752	0.031154	0.037975	0.709480	0.070242
96	0.010343	0.370031	0.027627	0.029639	0.752294	0.064364
97	**0.003705**	**0.446483**	**0.024982**	0.020994	0.788991	0.057899
98	0.001698	0.614679	0.031154	0.014511	0.868502	0.055547
99	0.000463	0.798165	0.038795	**0.008027**	**0.948012**	**0.053196**

Figure 8: Classification Rates for Bankruptcy Models with Employee Satisfaction

Figure 8 presents classification rates for the various bankruptcy models – Ohlson's, Altman's, Zmijewski's, and Shumway's models – from the tests in Table 5. The horizontal axis plots the percentile model score, while the vertical axis plots the Total error (Type I and Type II errors) for each respective model.

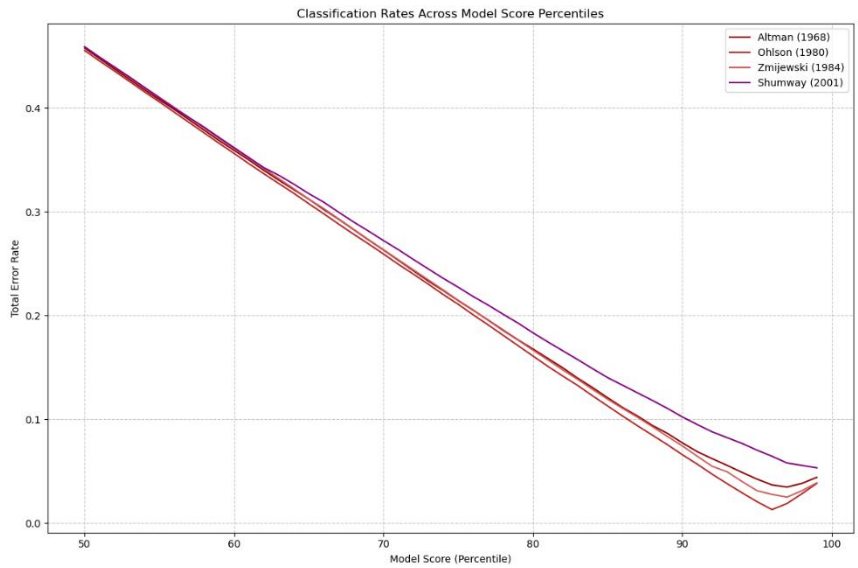


Table 6: Out-of-Sample Forecast Accuracy for Bankruptcy Models

Table 6 reports statistics relating to out-of-sample performance based on a 20-80 split methodology. We randomly select 20% of companies from each group for the test set and allocate the remaining 80% of companies to the training set. The methodology ensures that a company appears in either the training or test set, but not in both. Observations are classified into deciles based on these bankruptcy probabilities (Decile 1 being the lowest). Actual and predicted probabilities are presented together with Chi-Square statistic. The results for the following models are presented – Ohlson's, Altman's, Zmijewski's, Employees', and Shumway's models.

		Altman's (1)			**Ohlson's (2)**	
Decile	Actual	Predicted	Chi-Square Stats	Actual	Predicted	Chi-Square Stats
1	43	17.76081	35.86641	61	56.74173	0.319568
2	5	6.382948	0.299634	2	3.308634	0.517592
3	5	5.011764	2.76E-05	2	1.518753	0.152493
4	6	4.002651	0.996691	0	0.806180	0.80618
5	1	3.211602	1.522973	0	0.467701	0.467701
6	1	2.490019	0.891623	0	0.262329	0.262329
7	2	1.881920	0.007409	0	0.129504	0.129504
8	1	1.290526	0.065404	0	0.046674	0.046674
9	1	0.726933	0.102576	0	0.008413	0.008413
10	0	0.175846	0.175846	0	0.000137	0.000137

		Zmijewski's (3)			**Shumway's (4)**	
Decile	Actual	Predicted	Chi-Square Stats	Actual	Predicted	Chi-Square Stats
1	54	44.01800	2.263626	25	26.21396	0.056218
2	3	11.58704	6.363767	14	14.76980	0.040122
3	2	6.209970	2.854095	8	9.874403	0.355807
4	2	3.235947	0.472061	7	6.182451	0.108110
5	1	1.640529	0.250088	5	4.244029	0.134658
6	0	0.696134	0.696134	0	2.498314	2.498314
7	1	0.223238	2.702770	1	1.239542	0.046292
8	2	0.040335	95.20969	1	0.496180	0.511577
9	0	0.007801	0.007801	1	0.121781	6.333226
10	0	0.000282	0.000282	3	0.007868	1137.926

		Employees' (5)	
Decile	Actual	Predicted	Chi-Square Stats
1	**49**	**49.38876**	**0.003060**
2	1	4.816184	3.023817
3	3	2.706007	0.031941
4	3	1.647006	1.111466
5	2	1.052312	0.853467
6	3	0.641825	8.664334
7	1	0.375591	1.038063
8	1	0.146700	4.963330
9	1	0.033103	28.24144
10	1	0.003552	279.5412

Table 7: Out-of-Sample Forecast Accuracy for Bankruptcy Models with Employee Satisfaction

Table 7 reports statistics relating to out-of-sample performance of the models including employee satisfaction into all models based on a 20-80 split methodology. We randomly select 20% of companies from each group for the test set and allocate the remaining 80% of companies to the training set. The methodology ensures that a company appears in either the training or test set, but not in both. Observations are classified into deciles based on these bankruptcy probabilities (Decile 1 being the lowest). Actual and predicted probabilities are presented together with Chi-Square statistic. The results for the following models are presented – Ohlson's, Altman's, Zmijewski's, and Shumway's models with the inclusion of mean of employee satisfaction.

	Altman's (1)			Ohlson's (2)		
Decile	Actual	Predicted	Chi-Square Stats	Actual	Predicted	Chi-Square Stats
1	44	18.03201	37.39662	59	56.68769	0.094320
2	6	6.362826	0.020689	4	3.259593	0.168181
3	4	4.853717	0.150160	2	1.470977	0.190258
4	5	3.837858	0.351908	0	0.745804	0.745804
5	2	3.138249	0.412845	0	0.442746	0.442746
6	0	2.432790	2.432790	0	0.243171	0.243171
7	3	1.827750	0.751837	0	0.122215	0.122215
8	0	1.260727	1.260727	0	0.044676	0.044676
9	1	0.702121	0.126377	0	0.007917	0.007917
10	0	0.165999	0.165999	0	0.000128	0.000128

	Zmijewski's (3)			Shumway's (4)		
Decile	Actual	Predicted	Chi-Square Stats	Actual	Predicted	Chi-Square Stats
1	53	44.28705	1.714171	25	26.28721	0.063031
2	4	11.44709	4.844822	15	14.16840	0.048810
3	3	6.029194	1.521931	7	9.934790	0.866953
4	2	3.137780	0.412566	7	6.076285	0.140423
5	0	1.557400	1.557400	5	4.120803	0.187582
6	0	0.652461	0.652461	0	2.503421	2.503421
7	1	0.206140	3.057212	2	1.246481	0.455515
8	2	0.038051	101.1615	0	0.499992	0.499992
9	0	0.006537	0.006537	1	0.117034	6.661550
10	0	0.000233	0.000233	3	0.007775	1151.626

Table 8: Classification Rates Using Altman's Model and Employees' Model One, Two, and Three Years Before

Table 8 presents a comprehensive comparison of classification performance between the Employees' model and Altman's Z-score model across multiple time horizons before bankruptcy – one, two, and three years before. For each time horizon, the table reports a full spectrum of classification metrics: sensitivity (ability to correctly identify actual bankruptcies), specificity (ability to correctly identify non-bankruptcies), positive predictive value (reliability of bankruptcy predictions), negative predictive value (reliability of non-bankruptcy predictions), false positive rates (healthy firms incorrectly flagged), false negative rates (missed bankruptcies), and overall correct classification percentages.

8.1. Classification Rates for Employees' Model

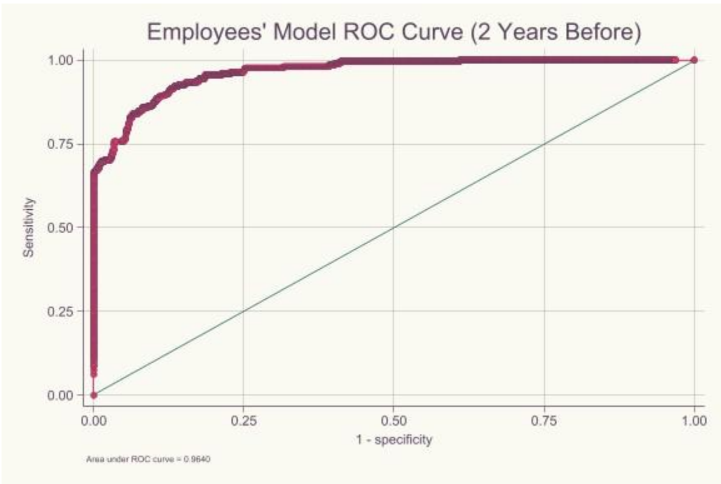
Classified + if predicted Pr(D)	>= .5			
True D defined as bankruptcy !=	0	One Year Before	Two Years Before	Three Years Before
Sensitivity	Pr(+ D)	67.45%	63.14%	50.98%
Specificity	Pr(-~D)	99.65%	99.10%	98.94%
Positive predictive value	Pr(D +)	93.99%	85.19%	79.75%
Negative predictive value	Pr(~D -)	97.40%	97.05%	96.10%
False positive rate	Pr(+~D)	0.35%	0.90%	1.06%
False negative rate	Pr(- D)	32.55%	36.86%	49.02%
Correctly classified		97.21%	96.38%	95.31%

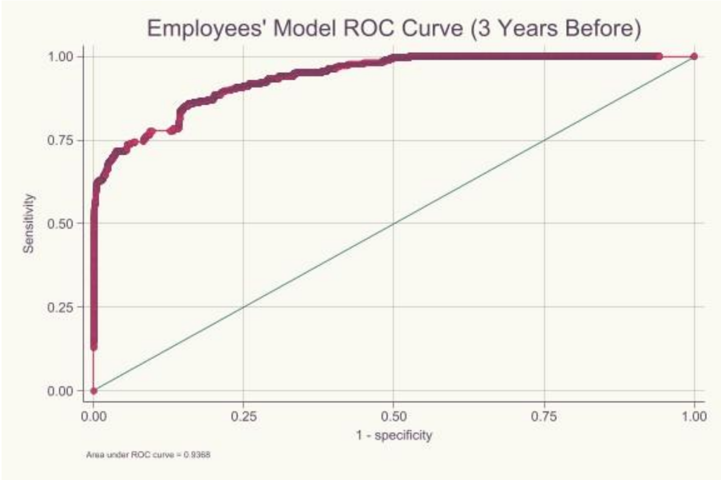
8.2. Classification Rates for Altman's Model

Classified + if predicted Pr(D)	>= .5			
True D defined as bankruptcy !=	0	One Year Before	Two Years Before	Three Years Before
Sensitivity	Pr(+ D)	60.00%	0.00%	0.00%
Specificity	Pr(-~D)	99.65%	99.97%	99.97%
Positive predictive value	Pr(D +)	93.29%	0.00%	0.00%
Negative predictive value	Pr(~D -)	96.82%	92.43%	92.43%
False positive rate	Pr(+~D)	0.35%	0.03%	0.03%
False negative rate	Pr(- D)	40.00%	100.00%	100.00%
Correctly classified		96.65%	92.41%	92.41%

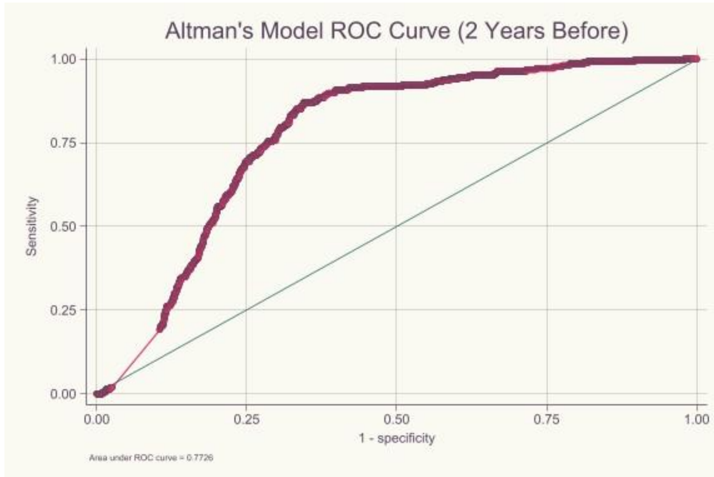
Figure 9: ROC Curves for Employees' Model and Altman's Model Two and Three Years Before
Figure 9 plots the Receiver Operating Characteristic (ROC) generated from Employees' and Altman's models. The ROC curve measures a classification model's performance across all possible classification thresholds. It plots the True Positive Rate (sensitivity) against the False Positive Rate (1-specificity). The ROC for Employees' model two years before is 0.9640 and the ROC for Employees' model three years before is 0.9368, while the ROC for Altman's model two years before bankruptcy filing is 0.7726 and the ROC for Altman's model three years before is 0.6935.

9.1. Employees' Model





9.2. Altman's Model



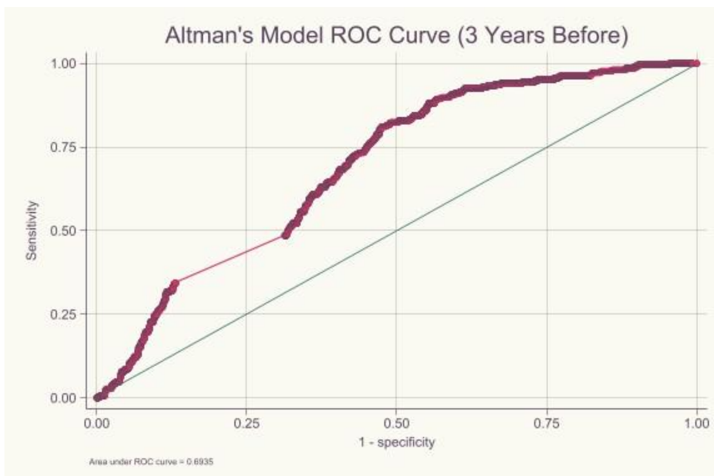


Table 9: Classification Rates Using Rating Categories' Model One, Two, and Three Years Before

Table 9 reports classification rates for breakdown of ratings' which shows sensitivity, specificity, positive predictive value, negative predictive value, false positives, and false negatives. The results are reported for the Employees' model one, two, and three years before bankruptcy filings using breakdown of rating categories. For each time horizon, the table reports a full spectrum of classification metrics: sensitivity (ability to correctly identify actual bankruptcies), specificity (ability to correctly identify non-bankruptcies), positive predictive value (reliability of bankruptcy predictions), negative predictive value (reliability of non-bankruptcy predictions), false positive rates (healthy firms incorrectly flagged), false negative rates (missed bankruptcies), and overall correct classification percentages.

Classified + if predicted Pr(D)	>= .5	Career_ Opps_1	Comp_ Benefits_1	Culture_ Values_1	Senior_ Lead_1	Worklife_ Balance_1	Overall_ Rating_1
True D defined as dealnodeal !=	0						
Sensitivity	Pr(+ D)	68.63%	69.02%	68.63%	68.63%	69.02%	69.02%
Specificity	Pr(-~D)	99.61%	99.61%	99.58%	99.61%	99.65%	99.61%
Positive predictive value	Pr(D +)	93.58%	93.62%	93.09%	93.58%	94.12%	93.62%
Negative predictive value	Pr(~D -)	97.49%	97.52%	97.49%	97.49%	97.52%	97.52%
False positive rate	Pr(+~D)	0.39%	0.39%	0.42%	0.39%	0.35%	0.39%
False negative rate	Pr(- D)	31.37%	30.98%	31.37%	31.37%	30.98%	30.98%
Correctly classified		97.27%	97.30%	97.24%	97.27%	97.33%	97.30%

Classified + if predicted Pr(D)	>= .5	Career_ Opps_2	Comp_ Benefits_2	Culture_ Values_2	Senior_ Lead_2	Worklife_ Balance_2	Overall_ Rating_2
True D defined as dealnodeal !=	0						
Sensitivity	Pr(+ D)	62.35%	62.35%	62.35%	62.35%	62.35%	62.35%
Specificity	Pr(-~D)	99.10%	99.10%	99.10%	99.10%	99.10%	99.10%
Positive predictive value	Pr(D +)	85.03%	85.03%	85.03%	85.03%	85.03%	85.03%
Negative predictive value	Pr(~D -)	96.98%	96.98%	96.98%	96.98%	96.98%	96.98%
False positive rate	Pr(+~D)	0.90%	0.90%	0.90%	0.90%	0.90%	0.90%
False negative rate	Pr(- D)	37.65%	37.65%	37.65%	37.65%	37.65%	37.65%
Correctly classified		96.32%	96.32%	96.32%	96.32%	96.32%	96.32%

Classified + if predicted Pr(D)	>= .5	Career_ Opps_3	Comp_ Benefits_3	Culture_ Values_3	Senior_ Lead_3	Worklife_ Balance_3	Overall_ Rating_3
True D defined as dealnodeal !=	0						
Sensitivity	Pr(+ D)	49.80%	49.80%	49.80%	49.41%	49.80%	49.80%
Specificity	Pr(-~D)	99.04%	99.04%	99.04%	98.91%	99.10%	98.91%
Positive predictive value	Pr(D +)	80.89%	80.89%	80.89%	78.75%	81.94%	78.88%
Negative predictive value	Pr(~D -)	96.02%	96.02%	96.02%	95.98%	96.02%	96.01%
False positive rate	Pr(+~D)	0.96%	0.96%	0.96%	1.09%	0.90%	1.09%
False negative rate	Pr(- D)	50.20%	50.20%	50.20%	50.59%	50.20%	50.20%
Correctly classified		95.31%	95.31%	95.31%	95.16%	95.37%	95.19%

Table 10: Survival Analyses for Employees' Model (using Mean and Standard Deviation of Employee Satisfaction)

Table 10 presents survival analyses with Cox regression for bankruptcy emergence with mean of employee satisfaction one, two, and three years before bankruptcy filings. Firm controls (EBITTA, WCTA, TLTA, CHIN, ExcessReturn, SDReturn, FirmAge, and Turnover) are also included in the model, as per in the employee satisfaction hazard model. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	Cox Regression for Bankruptcy Emergence with Mean					
Main Effects						
Mean_1	-0.016	(-1.45)				
Mean_2			**0.029*** **	**(3.37)**		
Mean_3					0.012	(1.41)
Controls						
EBITTA_1/2/3	-0.000	(-1.23)	0.000	(0.50)	0.000	(0.31)
WCTA_1/2/3	-0.058	(-0.70)	0.099	(0.57)	-0.121	(-0.70)
TLTA_1/2/3	0.000	(0.68)	-0.000	(-0.18)	-0.000	(-0.32)
CHIN_1/2/3	**-0.009***	**(-1.65)**	**0.042****	**(1.99)**	-0.001	(-0.16)
ExcessReturn_1/2/3	-0.043	(-1.60)	-0.123	(-1.29)	**-0.231****	**(-2.04)**
SDReturn_1/2/3	0.073	(0.73)	0.004	(0.96)	-0.018	(-0.45)
FirmAge_1/2/3	0.043	(0.64)	-0.087	(-1.38)	0.098	(1.37)
Turnover_1/2/3	0.003	(1.61)	0.002	(1.48)	**0.004****	**(2.37)**
Observations	327		327		327	

T-Statistics in Parentheses
="* p<0.05
** p<0.01
*** p<0.001"

Table 11: Survival Analyses for Employees' Model (using Rating Categories)

Table 11 presents survival analyses with Cox regression for bankruptcy emergence with mean of employee satisfaction rating categories (Career Opportunities, Compensation Benefits, Culture Values, Senior Leadership, Work-Life Balance, and Overall Rating) one, two, and three years before bankruptcy filings. Firm controls (EBITTA, WCTA, TLTA, CHIN, ExcessReturn, SDReturn, FirmAge, and Turnover) are also included in the model, as per in the employee satisfaction hazard model. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	Cox Regression for Bankruptcy Emergence with Mean Rating Categories							
Main Effects								
careeropps_mean_1	**-0.141***	**(-1.80)**						
compensation_mean_1			**-0.276*****	**(-3.33)**				
culture_mean_1					**-0.193****	**(-2.56)**		
seniorleadership_mean_1							**-0.193****	**(-2.56)**
Controls								
EBITTA_1	-0.000	(-1.53)	**-0.000***	**(-1.78)**	-0.000	(-1.58)	-0.000	(-1.58)
WCTA_1	-0.046	(-0.56)	-0.032	(-0.37)	-0.051	(-0.62)	-0.051	(-0.62)
TLTA_1	0.000	(0.69)	0.000	(0.56)	0.000	(0.64)	0.000	(0.64)
CHIN_1	-0.009	(-1.59)	-0.008	(-1.48)	-0.009	(-1.56)	-0.009	(-1.56)
ExcessReturn_1	-0.042	(-1.59)	**-0.045***	**(-1.70)**	-0.042	(-1.56)	-0.042	(-1.56)
SDReturn_1	0.059	(0.60)	0.064	(0.65)	0.037	(0.37)	0.037	(0.37)
FirmAge_1	0.033	(0.49)	0.023	(0.35)	0.042	(0.62)	0.042	(0.62)
Turnover_1	0.003	(1.55)	**0.003***	**(1.92)**	0.002	(1.40)	0.002	(1.40)
Observations	327		327		327		327	

T-Statistics in Parentheses
="* p<0.05
** p<0.01
*** p<0.001"

	Cox Regression for Bankruptcy Emergence with Mean Rating Categories			
Main Effects				
worklife_mean_1	-0.106	(-1.38)		
overall_mean_1			-0.099	(-1.27)
Controls				
EBITTA_1	-0.000	(-1.41)	-0.000	(-1.48)
WCTA_1	-0.061	(-0.74)	-0.051	(-0.62)
TLTA_1	0.000	(0.61)	0.000	(0.67)
CHIN_1	-0.009	(-1.63)	-0.009	(-1.62)
ExcessReturn_1	-0.042	(-1.61)	-0.043	(-1.64)
SDReturn_1	0.062	(0.63)	0.063	(0.63)
FirmAge_1	0.034	(0.51)	0.039	(0.58)
Turnover_1	0.003	(1.55)	0.003	(1.64)
Observations	327		327	

T-Statistics in Parentheses
="* p<0.05
** p<0.01
*** p<0.001"

	Cox Regression for Bankruptcy Emergence with Mean Rating Categories							
Main Effects								
careeropps_mean_2	**0.145*** **	**(3.09)**						
compensation_mean_2			**0.137*** **	**(3.28)**				
culture_mean_2					**0.155*** **	**(3.29)**		
seniorleadership_mean_2							**0.157*** **	**(3.21)**
Controls								
EBITTA_2	0.000	(0.49)	0.000	(0.50)	0.000	(0.43)	0.000	(0.48)
WCTA_2	0.121	(0.69)	0.121	(0.69)	0.072	(0.41)	0.115	(0.65)
TLTA_2	-0.000	(-0.13)	-0.000	(-0.10)	-0.000	(-0.17)	-0.000	(-0.10)
CHIN_2	**0.041***	**(1.96)**	**0.044** **	**(2.07)**	**0.039***	**(1.86)**	**0.042***	**(1.94)**
ExcessReturn_2	-0.128	(-1.35)	-0.128	(-1.34)	-0.151	(-1.59)	-0.124	(-1.31)
SDReturn_2	0.004	(1.04)	0.004	(1.05)	0.004	(0.99)	0.004	(1.04)
FirmAge_2	-0.064	(-1.01)	-0.078	(-1.24)	-0.101	(-1.56)	-0.073	(-1.15)
Turnover_2	**0.003***	**(1.67)**	**0.003***	**(1.72)**	0.002	(1.32)	**0.003***	**(1.68)**
Observations	327		327		327		327	

T-Statistics in Parentheses
="* p<0.05
** p<0.01
*** p<0.001"

	Cox Regression for Bankruptcy Emergence with Mean Rating Categories			
Main Effects				
worklife_mean_2	**0.133*** **	**(3.15)**		
overall_mean_2			**0.141*** **	**(3.22)**
Controls				
EBITTA_2	0.000	(0.57)	0.000	(0.47)
WCTA_2	0.155	(0.88)	0.107	(0.61)
TLTA_2	-0.000	(-0.13)	-0.000	(-0.10)
CHIN_2	**0.045** **	**(2.01)**	**0.042** **	**(1.98)**
ExcessReturn_2	-0.096	(-0.98)	-0.127	(-1.33)
SDReturn_2	0.002	(0.57)	0.004	(1.05)
FirmAge_2	**-0.112***	**(-1.71)**	-0.075	(-1.19)
Turnover_2	**0.003***	**(1.69)**	**0.003***	**(1.67)**
Observations	327		327	

T-Statistics in Parentheses
="* p<0.05
** p<0.01
*** p<0.001"

	Cox Regression for Bankruptcy Emergency with Mean Rating Categories							
Main Effects								
careeropps_mean_3	**0.126****	**(2.48)**						
compensation_mean_3			**0.108****	**(2.47)**				
culture_mean_3					**0.115****	**(2.33)**		
seniorleadership_mean_3							0.080	(1.52)
Controls								
EBITTA_3	0.000	(0.17)	0.000	(0.28)	0.000	(0.21)	0.000	(0.34)
WCTA_3	-0.129	(-0.74)	-0.095	(-0.54)	-0.148	(-0.85)	-0.111	(-0.64)
TLTA_3	-0.000	(-0.18)	-0.000	(-0.27)	-0.000	(-0.23)	-0.000	(-0.34)
CHIN_3	-0.000	(-0.09)	-0.000	(-0.09)	-0.000	(-0.05)	-0.001	(-0.16)
ExcessReturn_3	**-0.224****	**(-1.97)**	**-0.222***	**(-1.95)**	**-0.231****	**(-2.03)**	**-0.227****	**(-2.00)**
SDReturn_3	-0.021	(-0.50)	-0.020	(-0.48)	-0.019	(-0.46)	-0.020	(-0.48)
FirmAge_3	0.098	(1.37)	0.105	(1.46)	0.086	(1.18)	0.097	(1.36)
Turnover_3	**0.004****	**(2.21)**	**0.004****	**(2.26)**	**0.004****	**(2.25)**	**0.004****	**(2.41)**
Observations	327		327		327		327	

T-Statistics in Parentheses
="* p<0.05
** p<0.01
*** p<0.001"

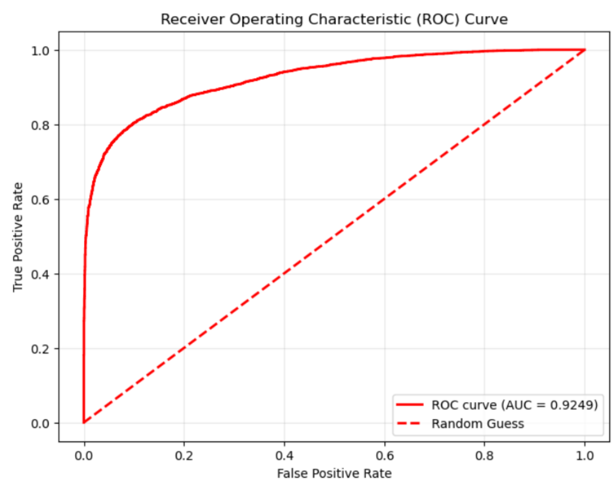
	Cox Regression for Bankruptcy Emergence with Mean Rating Categories			
Main Effects				
worklife_mean_3	**0.093****	**(2.14)**		
overall_mean_3			**0.096****	**(2.09)**
Controls				
EBITTA_3	0.000	(0.30)	0.000	(0.31)
WCTA_3	-0.113	(-0.65)	-0.101	(-0.58)
TLTA_3	-0.000	(-0.30)	-0.000	(-0.30)
CHIN_3	-0.001	(-0.21)	-0.001	(-0.12)
ExcessReturn_3	**-0.225****	**(-1.98)**	**-0.227****	**(-2.00)**
SDReturn_3	-0.019	(-0.46)	-0.020	(-0.48)
FirmAge_3	0.101	(1.41)	0.099	(1.38)
Turnover_3	**0.004****	**(2.26)**	**0.004****	**(2.25)**
Observations	327		327	

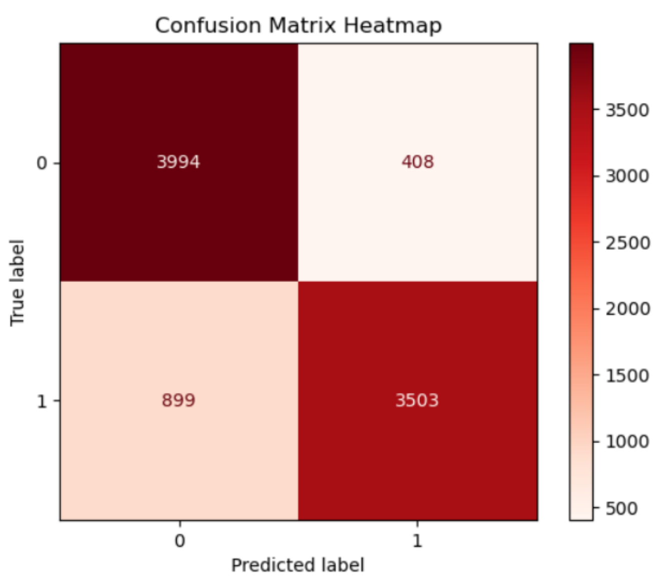
T-Statistics in Parentheses
="* p<0.05
** p<0.01
*** p<0.001"

Figure 10: Results from Machine Learning Models with Textual Reviews' Data

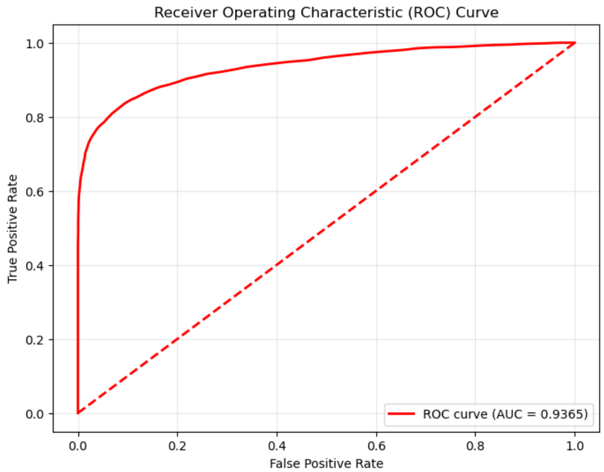
Figure 10 provides results of CatBoost model (10.1.), Random Forest model (10.2), Support Vector Machine model (10.3.), Regression model (10.4.), and Autoencoder Anomaly Detection model (10.5.) with employee satisfaction reviews one year before bankruptcy. For the models, we use 6,344 actual failed company reviews and 22,009 pseudo company reviews (randomly chosen from our healthy firm employee reviews). We use the pros, cons, and feedback sections in Glassdoor to make our bankruptcy filing predictions. Our test set contains 5,671 observations and our training set contains 22,682 observations. We use several models to test bankruptcy predictions – CatBoost model, Random Forest model, Support Vector Machine model, Logistic Regression model, and Autoencoder Anomaly Detection model. We compute the AUC and the confusion matrix for each model and compute the models' accuracy. The confusion matrix presents the true negatives (non-bankrupt companies correctly identified), false positives (non-bankrupt companies incorrectly classified as bankrupt), false negatives (bankrupt companies incorrectly classified as non-bankrupt), and true positives (bankrupt companies correctly identified). We provide the results in the following figures.

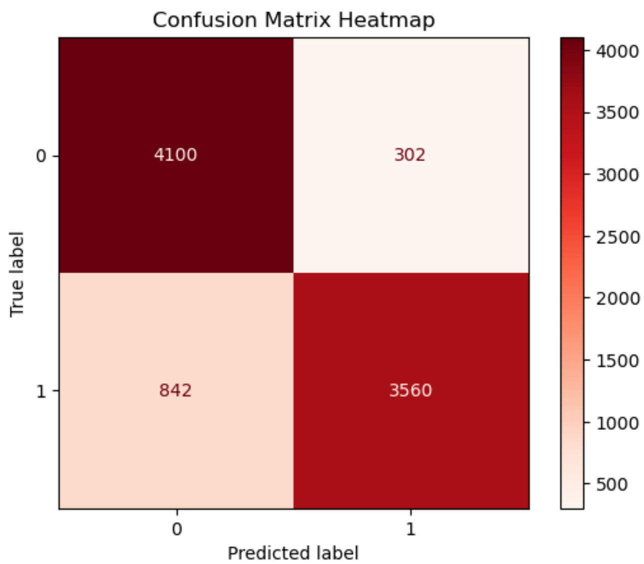
10.1. Catboost Model – ROC Curve and Error Rate Heat Map using Textual Reviews 1 Year Prior



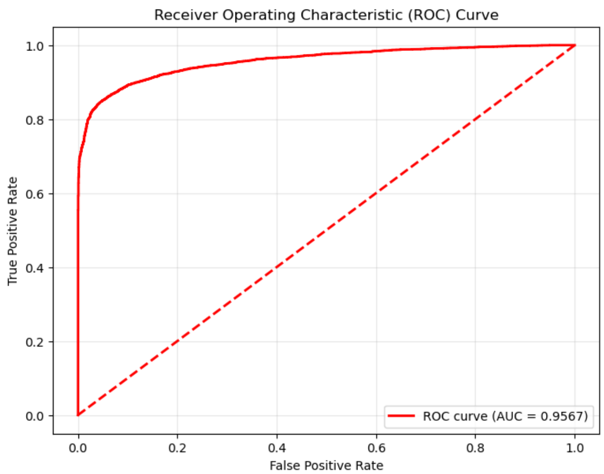


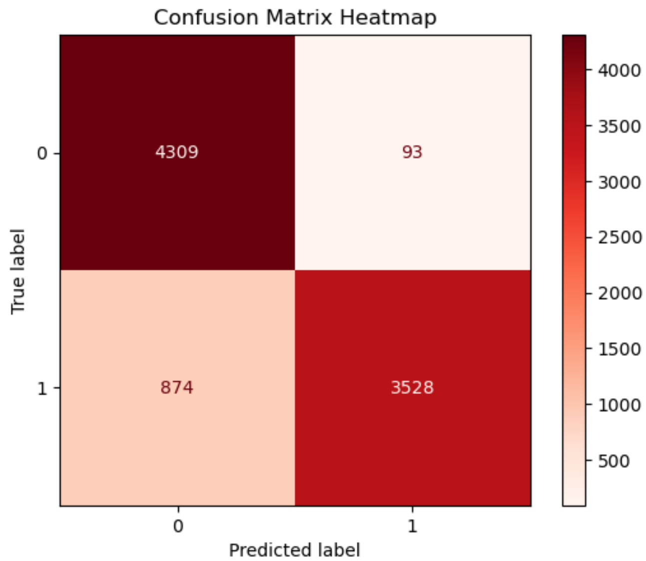
10.2. Random Forest Model – ROC Curve and Error Rate Heat Map using Textual Reviews 1 Year Prior



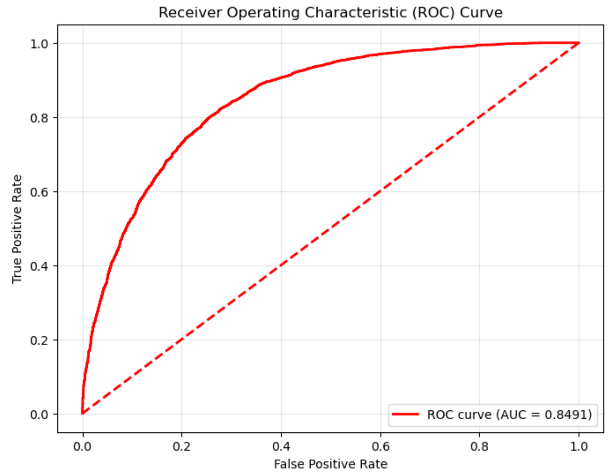


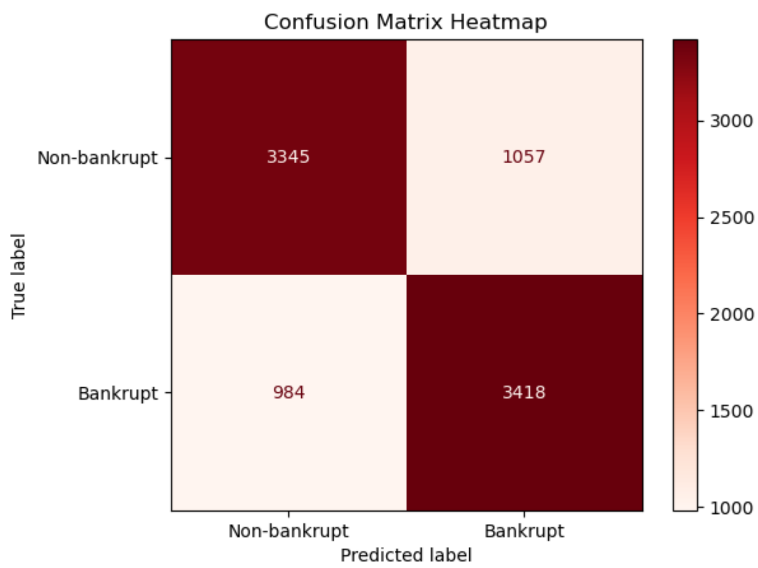
10.3. Support Vector Machine Model – ROC Curve and Error Rate Heat Map using Textual Reviews 1 Year Prior



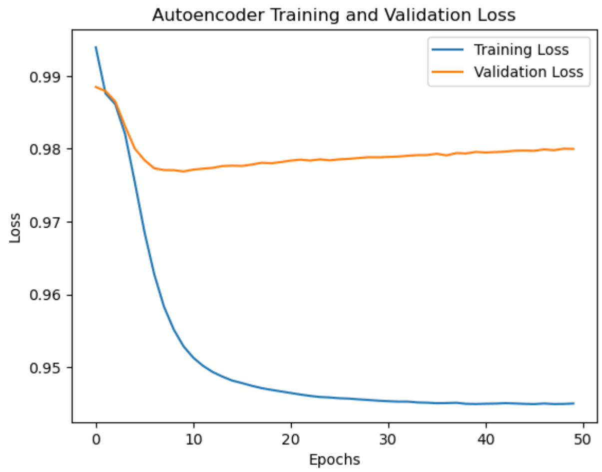


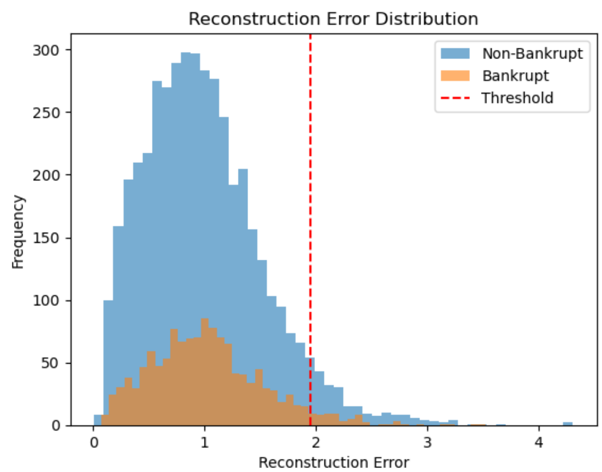
__10.4. Logistic Regression Model – Residual Plot and Actual vs. Predicted Plot using Textual Reviews 1 Year Prior__





10.5. Autoencoder Anomaly Detection – Training and Validation Loss and Reconstruction Error Distribution using Textual Reviews 1 Year Prior





Online Appendix

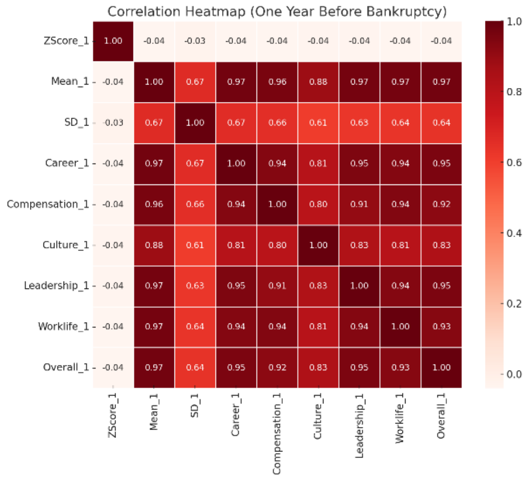
for

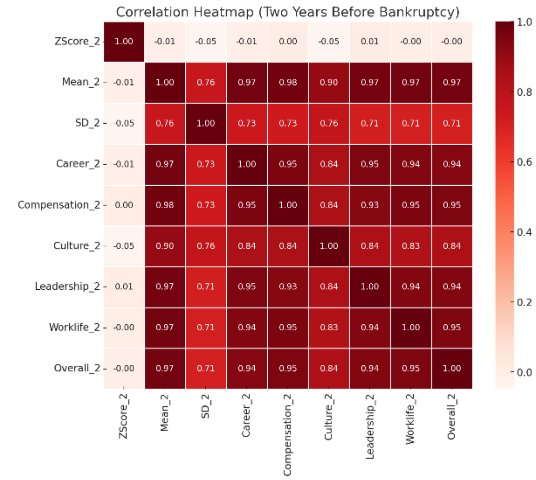
Predicting Bankruptcy: Ask the Employees

By John Knopf and Kristina Lalova

Figure A1: Heat Map of Correlation Matrix

Figure A1 presents correlation matrices between Z-Score and the mean of various rating categories for one, two, and three years before bankruptcy filings (from left to right, respectively). The figures display heatmaps of these correlations using a red scale, where darker shades represent stronger correlations. The matrices include correlations between Z-Score and aggregated sum of rating categories and between Z-Score and categories, such as Career Opportunities, Compensation and Benefits, Culture Values, Senior Leadership, Work-Life Balance, and Overall Rating.





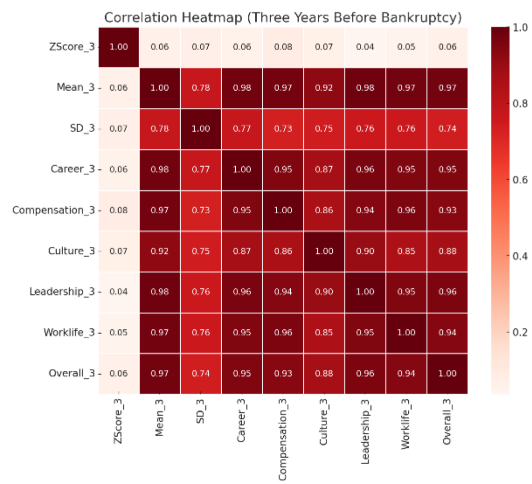


Table A1: Summary Statistics (Control Sample)

Table A1 presents summary statistics for the control bankruptcy sample from 2008 through 2020. The final dataset contains 7,924 non-bankrupt firms. EBITTA = earnings before interest and taxes to total assets; STA = sales to total assets; NITA = net income divided by total assets; CHIN = change in net income from year of to year before bankruptcy filing; WCTA = working capital to total assets; CLCA = current liabilities to current assets; FUTL = income from operations after depreciation divided by total liabilities; INTWO = 1 if net income was negative for the previous two years, 0 otherwise; RETA = retained earnings to total assets; MVETL = market equity to total liabilities; TLTA = total liabilities to total assets; OENEG = 1 if total liabilities exceed total assets, 0 otherwise; OhlsonSize = log(total assets/GNP price-level index), the index assumes a base value of 100 for 1968; RelativeSize = log(the number of outstanding shares multiplied by year-end share price then divided by total market value); ExcessReturn = cumulative annual return in year t-1 minus the value-weighted CRSP index return in year t-1; SDReturn = standard deviation of the residual derived from regressing monthly stock return on market return in year t-1; FirmAge = number of years since the company's IPO; Turnover = employment changes from year to year. Panel 1.1. presents the above-mentioned bankruptcy models' characteristics one, two, and three years before, while Panel 1.2. presents mean and breakdown of various rating categories one, two, and three years before bankruptcy filings.

Stats	N	Mean	SD	p25	p50	p75
Mean_1	7924	18.03390	5.679715	14.77676	18.23315	21.5
OhlsonSize_1	7924	0.673567	2.280230	0	0	1.540779
NITA_1	7924	-0.511420	11.67272	0	0	0
CHIN_1	7924	0.116930	11.64775	0	0	0
WCTA_1	7924	1.265165	31.74657	0	0	0.233537
CLCA_1	7924	2.877874	79.23601	0	0	0.466860
FUTL_1	7924	-0.301250	9.463892	0	0	0
INTWO_1	7924	0.138079	0.345004	0	0	0
TLTA_1	7924	1.428023	31.80762	0	0	0.572229
OENEG_1	7924	0.423919	0.494209	0	0	1
RETA_1	7924	-14.88410	392.8452	0	0	0
EBITTA_1	7924	-0.322590	7.603071	0	0	0
MVETL_1	7924	4.741143	63.55379	0	0	1.212547
STA_1	7924	0.378404	1.648009	0	0	0.469762
RelativeSize_1	7924	4.741143	63.55379	0	0	1.212547
ExcessReturn_1	7924	0.194652	19.59895	-0.526320	-0.185350	0.239582
SDReturn_1	7924	0.065277	0.924424	-0.442280	0.218990	0.518873
FirmAge_1	7924	2.462013	6.646209	0	0	0
Turnover_1	7910	0.052604	0.559017	0	0	0

Stats	N	Mean	SD	p25	p50	p75
Mean_2	7924	12.39282	9.229913	0	15.33333	19.50590
OhlsonSize_2	7924	0.668184	2.227647	0	0	1.465204
NITA_2	7924	-1.409270	99.95890	0	0	0
CHIN_2	7924	0.075239	6.563425	0	0	0
WCTA_2	7924	-0.539250	25.50311	0	0	0.173452
CLCA_2	7924	1.650601	30.64793	0	0	0.458873
FUTL_2	7924	-0.227240	6.364657	0	0	0
INTWO_2	7924	0.126132	0.332019	0	0	0
TLTA_2	7924	1.010266	25.86227	0	0	0.564439
OENEG_2	7924	0.423290	0.494112	0	0	1
RETA_2	7924	-15.26050	553.9754	0	0	0
EBITTA_2	7924	-0.227240	6.364657	0	0	0
MVETL_2	7924	4.633601	66.40143	0	0	1.254793
STA_2	7924	0.370939	0.831229	0	0	0.486689
RelativeSize_2	7924	3.319104	109.1413	0	0	0.637487
ExcessReturn_2	7924	0.227202	22.31009	-0.542390	-0.223210	0.239582
SDReturn_2	7924	0.078118	0.969086	-0.392590	0.272620	0.574112
FirmAge_2	7924	36.92630	50.15169	0	8	112
Turnover_2	7912	0.112510	2.806963	0	0	0

Stats	N	Mean	SD	p25	p50	p75
Mean_3	7924	10.59638	9.524307	0	13.73500	18.79206
OhlsonSize_3	7924	0.621265	2.191419	0	0	1.321797
NITA_3	7924	-0.654860	49.76844	0	0	0
CHIN_3	7924	-0.039310	13.33350	0	0	0
WCTA_3	7924	-0.503530	15.11662	0	0	0.149523
CLCA_3	7924	1.575277	22.69997	0	0	0.436968
FUTL_3	7924	-0.381880	15.02435	0	0	0
INTWO_3	7924	0.119970	0.324947	0	0	0
TLTA_3	7924	1.076518	22.23042	0	0	0.542756
OENEG_3	7924	0.404930	0.490909	0	0	1
RETA_3	7924	-16.30810	295.3733	0	0	0
EBITTA_3	7924	-0.519690	20.65148	0	0	0
MVETL_3	7924	5.090798	80.03523	0	0	1.177844
STA_3	7924	0.446097	6.250444	0	0	0.452267
RelativeSize_3	7924	3.552640	95.08916	0	0	0.615572
ExcessReturn_3	7924	0.544012	49.46777	-0.605640	-0.316360	0.198730
SDReturn_3	7924	0.086910	0.930187	-0.196790	0.232158	0.542531
FirmAge_3	7924	34.88934	48.85895	0	7	111
Turnover_3	7910	0.218468	10.86837	0	0	0

Table A2: Linear Discriminant Analysis with Unstandardized and Standardized Coefficients for Altman's Model (equivalent to Tables 2 and 3)

Table A2 presents Altman's model results equivalent to the results for Altman's model in a multi-period logistic setting. The discriminant analysis coefficients (both standardized and unstandardized) with the original Altman's model variables are presented in columns (1) and (2), while the discriminant analysis coefficients (both standardized and unstandardized) with the original Altman's model variables along with the employee satisfaction variable are presented in columns (3) and (4).

Predictors	Unstandardized Coefficients (1)	Standardized Coefficients (2)	Unstandardized Coefficients (3)	Standardized Coefficients (4)
Mean_1	-	-	0.55508641	0.49149319
WCTA_1	0.00031325	-0.00218370	-0.00043338	-0.00284479
RETA_1	-0.00005668	-0.00002086	0.00004225	0.00006674
EBITTA_1	-0.00002366	-0.00222954	-0.00056365	-0.00272652
MVETL_1	0.00119966	0.00008521	0.00144767	0.00030481
STA_1	0.14205588	0.29923529	0.17153637	0.32533836
_cons	-0.03034147	-0.16250570	-5.04057610	-4.09050930

Table A3: Error Rates for Employees' and Altman's Models in a Discriminant Analysis Setting with Variable Information One, Two, and Three Years Before Bankruptcy Filing

Table A3 presents error rates one, two, and three years before bankruptcy filings for Employees' and Altman's models, but in a discriminant analysis setting instead of a multi-period logit setting. We present stratified and unstratified error rates for both models one, two, and three years before bankruptcy filings with a prior of 0.5.

Employees' Model	**Bankruptcy?**								
	One Year Before			Two Years Before			Three Years Before		
Error rate	0	1	Total	0	1	Total	0	1	Total
Stratified	-0.4560600	0.6195580	0.0817510	0.2310300	0.5339720	0.3825010	0.4202850	0.3519620	0.3861240
Unstratified	-0.8420405	0.9124625	0.0352110	0.0776749	0.6552421	0.3664585	0.2626343	0.4938063	0.3782203
Priors	0.5	0.5		0.5	0.5		0.5	0.5	

Altman's Model	**Bankruptcy?**								
	One Year Before			Two Years Before			Three Years Before		
Error rate	0	1	Total	0	1	Total	0	1	Total
Stratified	0.2188589	0.7290574	0.4739582	0.2417236	0.6524575	0.4470905	-0.0070347	0.9944809	0.4937231
Unstratified	0.1048155	0.8359342	0.4703749	0.1478010	0.7426489	0.4452249	-0.0128896	0.9988866	0.4929985
Priors	0.5	0.5		0.5	0.5		0.5	0.5	

Table A4: Out-of-Sample Forecast Accuracy for Bankruptcy Models

Table A4 reports statistics relating to out-of-sample performance of the five bankruptcy prediction models based on a cross-validation (stratified K-Fold) methodology. Cross-validation is a resampling technique that divides the dataset into multiple subsets, using each subset as a test set while training on the remaining data to provide a comprehensive performance assessment. Observations are classified into deciles based on these bankruptcy probabilities (Decile 1 being the lowest). Actual and predicted probabilities are presented together with Chi-Square statistic. The results for the following models are presented – Ohlson's, Altman's, Zmijewski's, Employees', and Shumway's models.

	Altman's (1)			Ohlson's (2)		
Decile	Actual	Predicted	Chi-Square Stats	Actual	Predicted	Chi-Square Stats
1	246	107.0295	180.4438	302	296.4979	0.102103
2	23	34.76150	3.979486	6	16.10994	6.344587
3	21	26.21396	1.037057	4	7.376910	1.545840
4	11	21.03343	4.786174	3	3.820783	0.176321
5	1	17.14210	15.20043	3	2.004516	0.494377
6	6	13.63539	4.275580	4	1.016206	8.761039
7	8	10.42777	0.565228	1	0.469130	0.600736
8	5	7.231761	0.688733	1	0.171956	3.987398
9	4	3.997801	1.21E-06	3	0.035975	244.2128
10	2	1.044418	0.874303	0	0.000555	0.000555

	Zmijewski's (3)			Shumway's (4)		
Decile	Actual	Predicted	Chi-Square Stats	Actual	Predicted	Chi-Square Stats
1	251	213.7665	6.485255	147	120.6110	5.773747
2	23	60.62957	23.35469	73	71.87534	0.017598
3	14	30.92975	9.266690	34	49.66420	4.940523
4	8	15.59116	3.696051	38	33.12017	0.718979
5	4	7.264041	1.466672	10	23.35131	7.633722
6	9	2.839189	13.36846	7	15.16306	4.394594
7	9	0.828108	80.64139	6	8.415434	0.693288
8	9	0.140890	557.0557	2	3.664813	0.756274
9	0	0.025271	0.025271	2	0.955479	1.141859
10	0	0.000950	0.000950	8	0.076987	815.3904

	Employees' (5)		
Decile	Actual	Predicted	Chi-Square Stats
1	275	260.3747	0.821506
2	12	26.14073	7.649378
3	5	15.15540	6.804974
4	7	9.865026	0.832068
5	3	6.736954	2.072869
6	4	4.414035	0.038836
7	7	2.571044	7.629452
8	7	1.110862	31.22077
9	5	0.309176	71.16929
10	2	0.042133	90.98035

Table A5: Out-of-Sample Forecast Accuracy for Bankruptcy Models with Employee Satisfaction

Table A5 reports statistics relating to out-of-sample performance for the bankruptcy models with the inclusion of employee satisfaction based on a cross-validation (stratified K-Fold) methodology. Cross-validation is a resampling technique that divides the dataset into multiple subsets, using each subset as a test set while training on the remaining data to provide a comprehensive performance assessment. Observations are classified into deciles based on these bankruptcy probabilities (Decile 1 being the lowest). Actual and predicted probabilities are presented together with Chi-Square statistic. The results for the following models are presented – Ohlson's, Altman's, Zmijewski's, Employees', and Shumway's models.

	Altman's (1)			Ohlson's (2)		
Decile	Actual	Predicted	Chi-Square Stats	Actual	Predicted	Chi-Square Stats
1	241	110.8755	152.7155	301	296.8184	0.058911
2	34	35.08145	0.033338	7	15.97740	5.044230
3	15	25.89938	4.586848	5	7.117095	0.629764
4	10	20.63044	5.477645	4	3.660384	0.031510
5	7	16.76575	5.688375	1	1.906530	0.431043
6	3	13.22664	7.907082	3	0.968987	4.257037
7	6	10.11688	1.675292	1	0.446966	0.684274
8	5	7.044366	0.593302	2	0.164050	20.54680
9	4	3.842630	0.006445	3	0.033914	259.4142
10	2	0.992581	1.022480	0	0.000544	0.000544

	Zmijewski's (3)			Shumway's (4)		
Decile	Actual	Predicted	Chi-Square Stats	Actual	Predicted	Chi-Square Stats
1	251	216.0512	5.653371	155	124.7816	7.318000
2	27	60.04228	18.18372	65	69.72202	0.319805
3	10	30.24331	13.54983	36	49.09444	3.492542
4	7	15.14463	4.380097	34	32.75722	0.047150
5	8	6.981524	0.148577	14	22.98339	3.511289
6	6	2.727877	3.924954	5	14.93685	6.610564
7	9	0.787339	85.66552	7	8.378794	0.226891
8	8	0.132398	467.5245	1	3.589441	1.868035
9	1	0.023106	41.30253	2	0.928476	1.236612
10	0	0.000784	0.000784	8	0.074161	847.0615

Table A6: Information Content Tests

Table A6 reports relative information content tests. Panel A6.1. reports relative information content tests for the five models (Altman's, Ohlson's, Zmijewski's, Shumway's, and Employees'), while Panel A6.2. reports relative information content tests for the four models with the inclusion of employee satisfaction (Altman's, Ohlson's, Zmijewski's, and Shumway's). In each case, we estimate a logit regression with an intercept – this represents the lagged bankruptcy rate and the score from one of bankruptcy prediction models. The models are estimated based on the full sample from 2008 to 2020. We also report the Log Likelihood for each. In the table below, we report Vuong test statistics. All the Vuong test statistics are significant at the 1% level. ***, *, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

A6.1. Results without Employee Satisfaction

Model	Lagged Bankruptcy Rate	Score Coefficient	Log Likelihood
Altman's	8.974333	2.156726	-185.381
Ohlson's	11.22917	2.182026	-90.6089
Zmijewski's	9.825132	1.371240	-148.955
Shumway's	9.440683	0.346498	-244.428
Employees'	9.727826	1.664768	-141.217

Model	Model	Statistic	p-value
Altman's	**Ohlson's**	-189.545	0
Altman's	**Zmijewski's**	-72.8532	0
Altman's	**Shumway's**	118.0926	0
Altman's	**Employees'**	-88.3283	0
Ohlson's	**Zmijewski's**	116.6918	0
Ohlson's	**Shumway's**	307.6376	0
Ohlson's	**Employees'**	101.2167	0
Zmijewski's	**Shumway's**	190.9458	0
Zmijewski's	**Employees'**	-15.4751	0
Shumway's	**Employees'**	-206.421	0

A6.2. Results with Employee Satisfaction

Model	Lagged Bankruptcy Rate	Score Coefficient	Log Likelihood
Altman’s	8.895815	2.111197	-186.408
Ohlson’s	11.31255	2.187410	-89.6373
Zmijewski’s	9.770227	1.372864	-150.424
Shumway’s	9.404801	0.365853	-244.172

Model	Model	Statistic	p-value
Altman’s	**Ohlson’s**	-193.541	0
Altman’s	**Zmijewski’s**	-71.9691	0
Altman’s	**Shumway’s**	115.5282	0
Ohlson’s	**Zmijewski’s**	121.5723	0
Ohlson’s	**Shumway’s**	309.0696	0
Zmijewski’s	**Shumway’s**	187.4973	0

Table A7: Classification Error Rates for Ohlson's, Zmijewski's, and Shumway's Models One, Two, and Three Years Before

Table A7 presents a comprehensive comparison of classification performance for Ohlson's, Zmijewski's, and Shumway's models across multiple time horizons before bankruptcy – one, two, and three years before. For each time horizon, the table reports a full spectrum of classification metrics: sensitivity (ability to correctly identify actual bankruptcies), specificity (ability to correctly identify non-bankruptcies), positive predictive value (reliability of bankruptcy predictions), negative predictive value (reliability of non-bankruptcy predictions), false positive rates (healthy firms incorrectly flagged), false negative rates (missed bankruptcies), and overall correct classification percentages.

A7.1. Classification Rates for Ohlson's Model

Classified + if predicted Pr(D)	>= .5			
True D defined as bankruptcy !=	0	One Year Before	Two Years Before	Three Years Before
Sensitivity	Pr(+ D)	83.92%	25.88%	25.49%
Specificity	Pr(-~D)	99.65%	99.23%	99.26%
Positive predictive value	Pr(D +)	95.11%	73.33%	73.86%
Negative predictive value	Pr(~D -)	98.70%	94.24%	94.21%
False positive rate	Pr(+~D)	0.35%	0.77%	0.74%
False negative rate	Pr(- D)	16.08%	74.12%	74.51%
Correctly classified		98.46%	93.68%	93.68%

A7.2. Classification Rates for Zmijewski's Model

Classified + if predicted Pr(D)	>= .5			
True D defined as bankruptcy !=	0	One Year Before	Two Years Before	Three Years Before
Sensitivity	Pr(+ D)	56.47%	3.53%	5.10%
Specificity	Pr(-~D)	100.00%	100.00%	99.94%
Positive predictive value	Pr(D +)	100.00%	100.00%	86.67%
Negative predictive value	Pr(~D -)	96.56%	92.68%	92.79%
False positive rate	Pr(+~D)	0.00%	0.00%	0.06%
False negative rate	Pr(- D)	43.53%	96.47%	94.90%
Correctly classified		96.71%	92.70%	92.76%

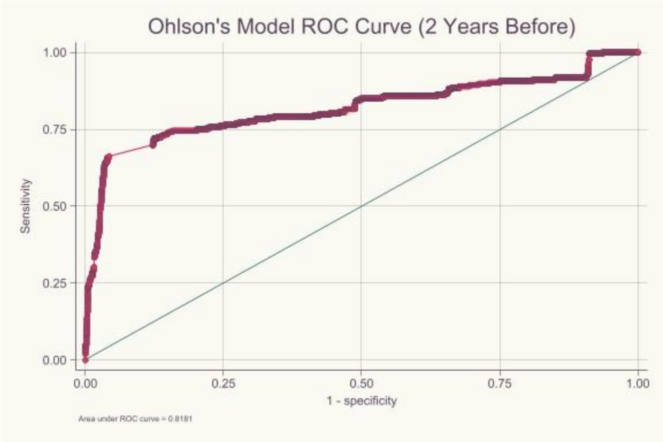
A7.3. Classification Rates for Shumway's Model

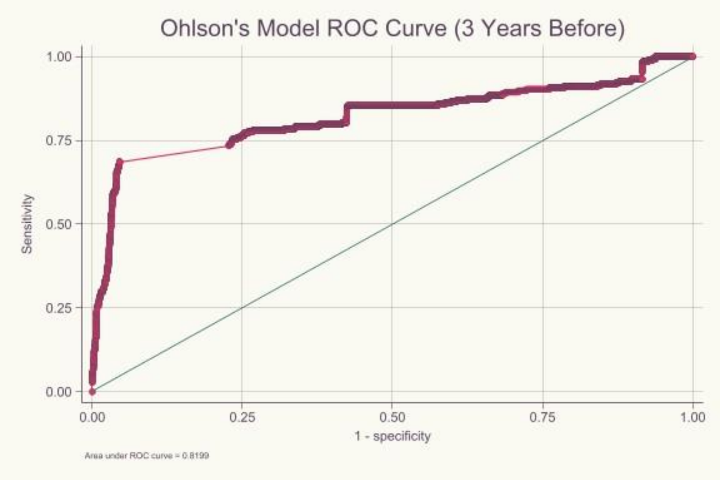
Classified + if predicted Pr(D)	>= .5			
		One Year Before	Two Years Before	Three Years Before
True D defined as bankruptcy !=	0			
Sensitivity	Pr(+ D)	1.18%	58.82%	45.10%
Specificity	Pr(-~D)	99.87%	98.97%	99.04%
Positive predictive value	Pr(D +)	42.86%	82.42%	79.31%
Negative predictive value	Pr(~D -)	92.51%	96.71%	95.66%
False positive rate	Pr(+~D)	0.13%	1.03%	0.96%
False negative rate	Pr(- D)	98.82%	41.18%	54.90%
Correctly classified		92.41%	95.94%	94.96%

Figure A2: ROC Curves for Ohlson's, Zmijewski's, and Shumway's Models Two and Three Years Before

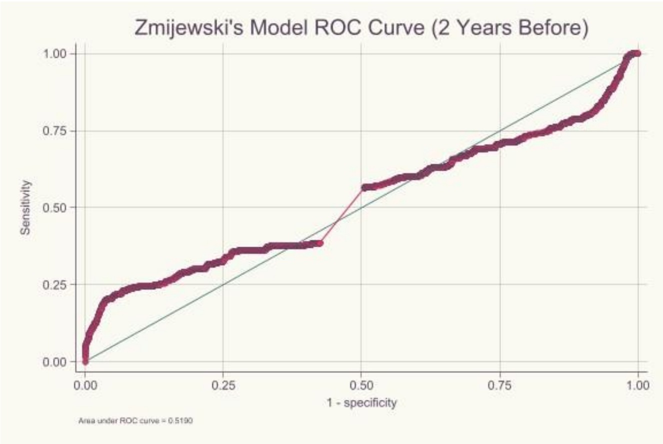
Figure A2 plots the Receiver Operating Characteristic (ROC) generated Ohlson's, Zmijewski's, and Shumway's models. The ROC curve measures a classification model's performance across all possible classification thresholds. It plots the True Positive Rate (sensitivity) against the False Positive Rate (1-specificity). The ROC for Ohlson's model two years before is 0.8181 and the one three years before is 0.8199. The ROC for Zmijewski's model two years before is 0.5190 and the one three years before is 0.5453. The ROC for Shumway's model two years before is 0.9530 and the one three years before is 0.9118.

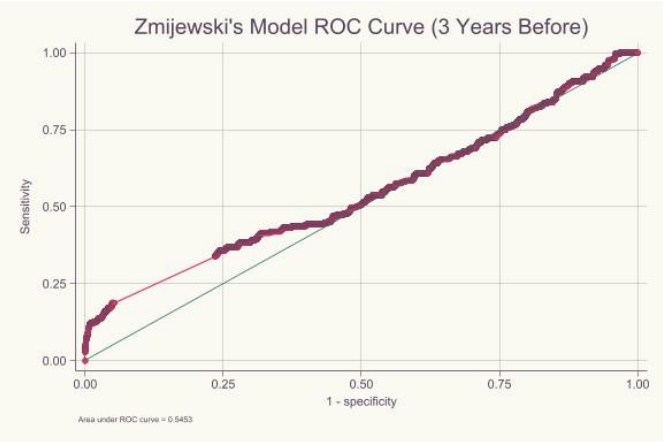
A2.1. Ohlson's Model



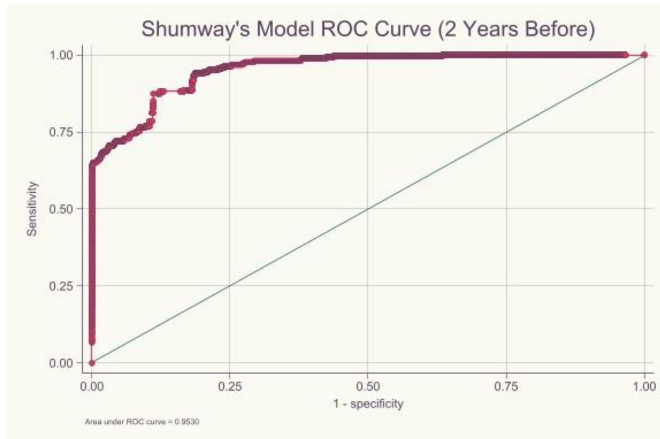


A2.2. Zmijewski's Model





A2.3. Shumway's Model



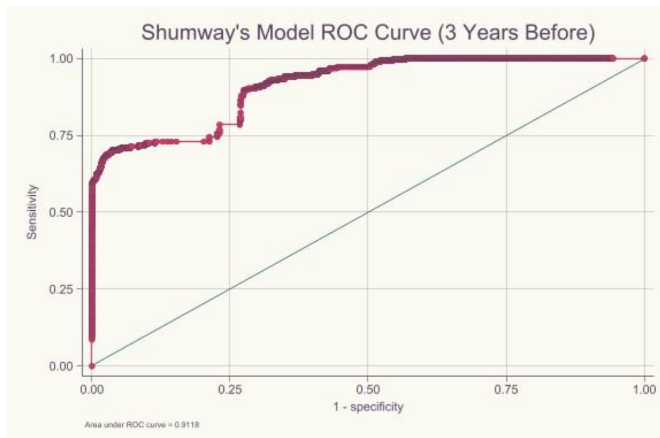


Table A8: Likelihood Ratio Test

Table A8 presents the results of likelihood ratio tests examining the incremental predictive power of employee satisfaction in bankruptcy prediction models across different time horizons. The tests evaluate whether adding employee satisfaction significantly improves model fit compared to models based solely on traditional financial indicators. These statistical tests provide a formal assessment of employee satisfaction's contribution to bankruptcy prediction by comparing nested models with and without this variable, offering rigorous evidence regarding its marginal explanatory value.

Time Horizon	LR Chi-square	Degrees of Freedom	p-value	Significance
1 Year Before	7.67	1	0.0056	***
2 Years Before	16.05	1	0.0001	***
3 Years Before	28.06	1	0	***

Table A9: Incremental Predictive Power in Employees' Model

Table A9 decomposes the predictive contribution of individual variables in the Employees' model across three time horizons before bankruptcy – one year before, two years before, and three years before. The analysis quantifies each variable's discriminative ability through ROC Area statistics and incremental contributions beyond the base model. By examining each predictor's individual performance across different time periods, the table provides insight into which indicators serve as leading versus contemporaneous signals of financial distress, while also revealing the temporal stability of each variable's predictive power.

A9.1. 1 Year Before

Variable	ROC Area	Incremental Contribution	Standard Error	95% CI
Base model (no variables)	0.500	NA	0	[0.500, 0.500]
Mean_1	0.573	0.073	0.0185	[0.537, 0.610]
EBITTA_1	0.538	0.038	0.0188	[0.501, 0.575]
WCTA_1	0.835	0.335	0.0186	[0.798, 0.871]
TLTA_1	0.609	0.109	0.0245	[0.561, 0.657]
CHIN_1	0.428	-0.072	0.0184	[0.392, 0.464]
RelativeSize_1	0.826	0.326	0.0119	[0.803, 0.850]
ExcessReturn_1	0.753	0.253	0.0181	[0.718, 0.789]
SDReturn_1	0.565	0.065	0.0197	[0.527, 0.604]

A9.2. 2 Years Before

Variable	ROC Area	Incremental Contribution	Standard Error	95% CI
Base model (no variables)	0.500	NA	0	[0.500, 0.500]
Mean_2	0.611	0.111	0.0158	[0.580, 0.642]
EBITTA_2	0.497	-0.003	0.0176	[0.463, 0.532]
WCTA_2	0.439	-0.061	0.0183	[0.403, 0.475]
TLTA_2	0.618	0.118	0.0223	[0.574, 0.662]
CHIN_2	0.539	0.039	0.0201	[0.499, 0.579]
RelativeSize_2	0.934	0.434	0.0083	[0.917, 0.949]
ExcessReturn_2	0.618	0.118	0.0193	[0.581, 0.656]
SDReturn_2	0.528	0.028	0.0185	[0.491, 0.564]

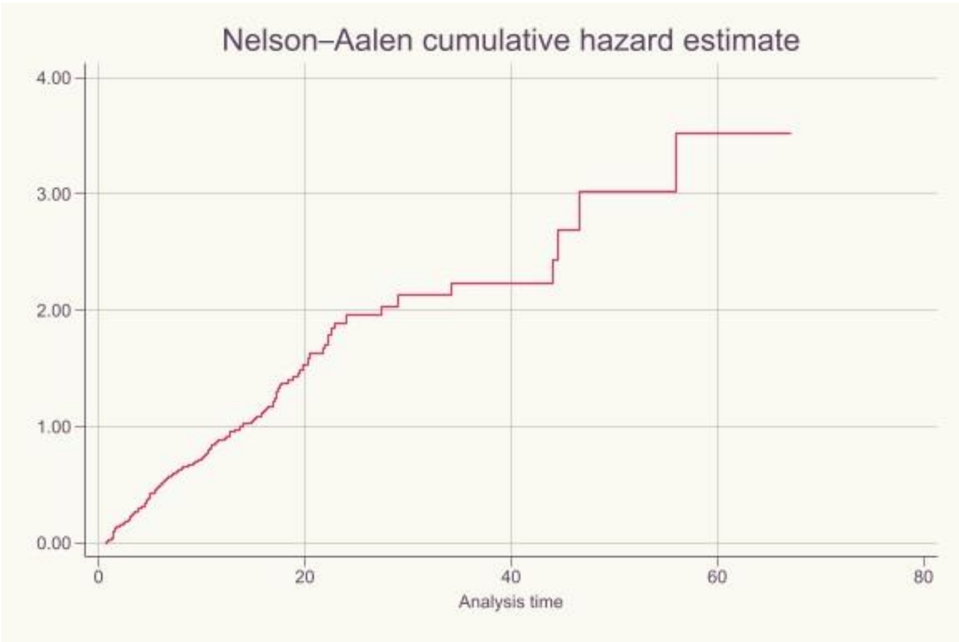
A9.3. 3 Years Before

Variable	ROC Area	Incremental Contribution	Standard Error	95% CI
Base model (no variables)	0.500	NA	0	[0.500, 0.500]
Mean_3	0.606	0.106	0.0157	[0.575, 0.636]
EBITTA_3	0.488	-0.012	0.0177	[0.453, 0.522]
WCTA_3	0.483	-0.017	0.0189	[0.446, 0.520]
TLTA_3	0.649	0.118	0.0205	[0.609, 0.689]
CHIN_3	0.527	0.027	0.0213	[0.486, 0.569]
RelativeSize_3	0.897	0.397	0.01	[0.878, 0.917]
ExcessReturn_3	0.631	0.131	0.0204	[0.591, 0.671]
SDReturn_3	0.515	0.015	0.0185	[0.479, 0.552]

Figure A3: Cumulative Hazard Curve

Figure A3 presents Nelson-Aalen cumulative hazard estimate (A3.1.) and Kaplan-Meier survival estimates (A3.2.). Nelson-Aalen cumulative hazard estimate figure plots the analysis time (time from bankruptcy filing to time of emergence) on the horizontal axis, while the Kaplan-Meier survival estimates figure plots the analysis time (time from bankruptcy filing to time of emergence) on the horizontal axis. The Nelson-Aalen cumulative hazard estimate (A3.1) demonstrates a steady increase in hazard over the first 20 months, followed by a more gradual rise with several step-like increases at later time points. The Kaplan-Meier survival curve (A3.2) shows a rapid decline in survival probability during the first 20 months, with approximately 80% of emergence events occurring within this timeframe.

A3.1. Nelson-Aalen Cumulative Hazard Estimate



A3.2. Kaplan-Meier Survival Estimates

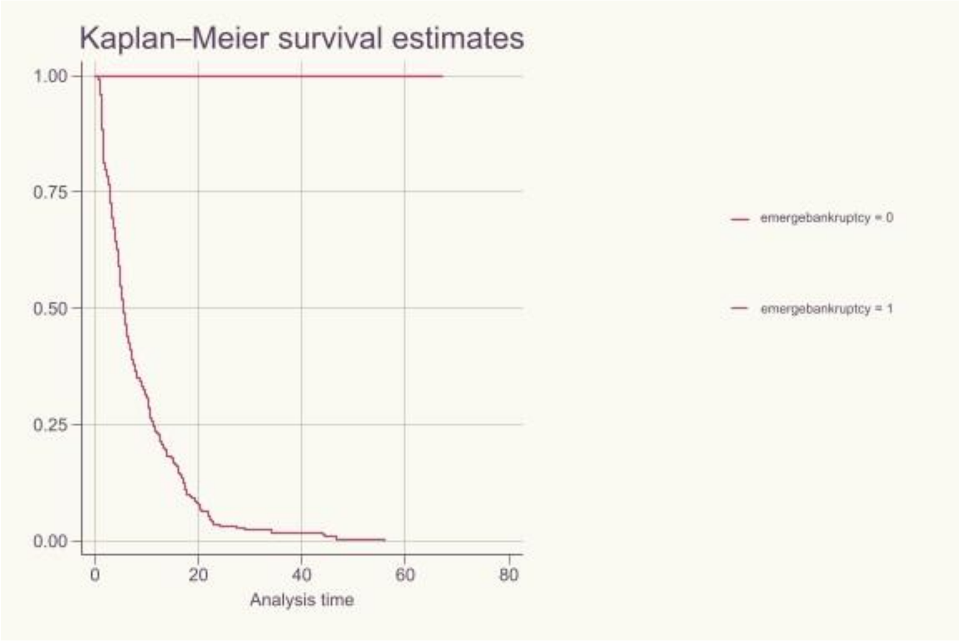
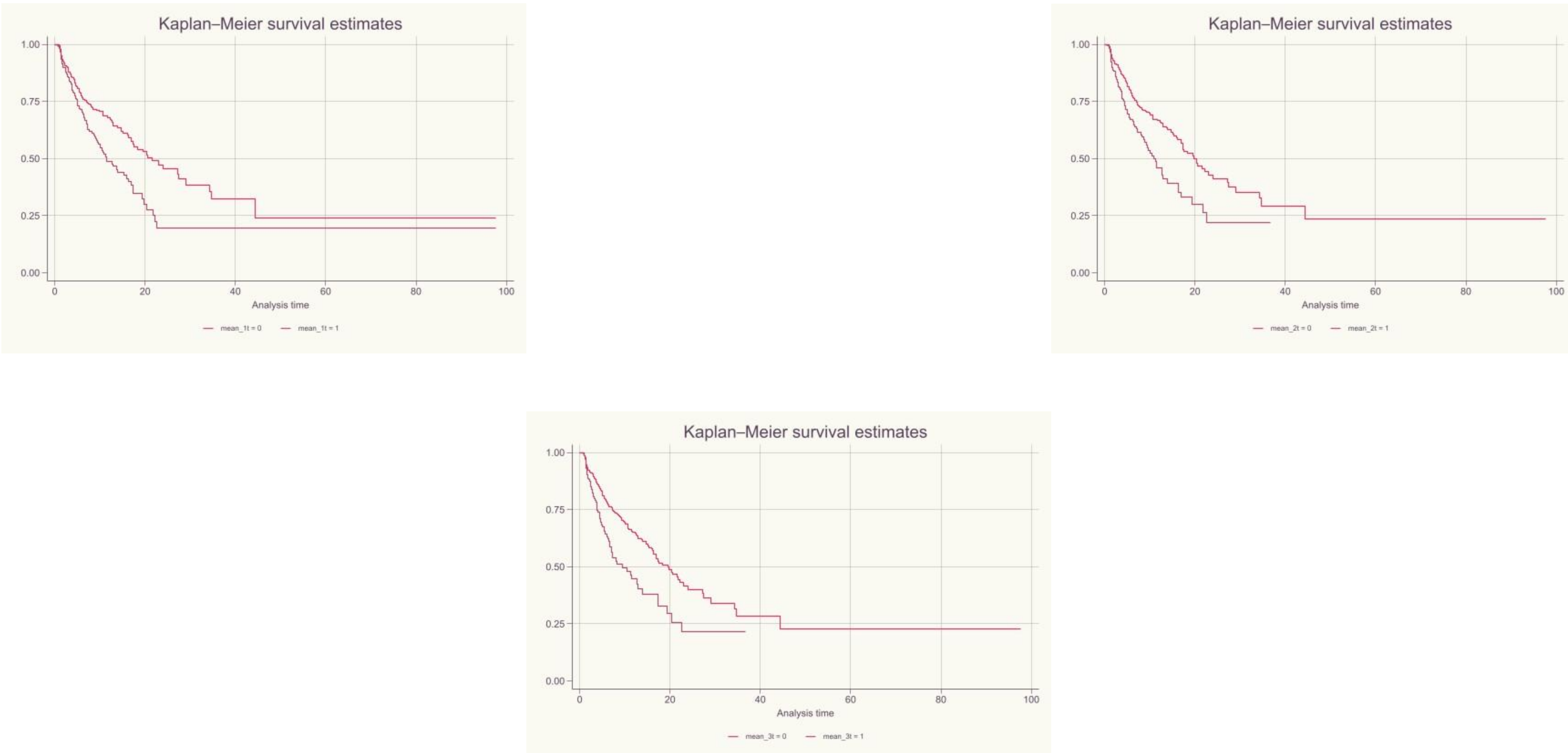


Figure A4: Univariate Analyses

Figure A4 presents Kaplan-Meier survival estimates from univariate analyses with mean employee satisfaction one, two, and three years before bankruptcy filing. In all three panels, companies that successfully emerge from bankruptcy consistently show higher survival probabilities throughout the analysis period. The divergence between the curves is most evident during months 10-30 after filing, indicating this is a critical period when emergence versus liquidation outcomes become apparent.



Variable	Definition
EBITTA	(EBIT to Total Assets): Measures the firm’s profitability relative to its assets. A negative value indicates that the firm is not generating enough profit to cover its operational costs.
STA	Represents the total sales relative to total assets. Higher sales indicate greater efficiency in using assets to generate revenue.
NITA	(Net Income to Total Assets): Indicates profitability by comparing net income with total assets. Negative values indicate losses.
CHIN	(Change in Net Income): Measures the change in net income from the previous period, helping capture recent improvements or deteriorations in financial health.
WCTA	(Working Capital to Total Assets): Measures liquidity, indicating how well the firm can cover its short-term liabilities with its current assets.
CLCA	(Current Liabilities to Current Assets): Provides insight into liquidity, where higher ratios may indicate potential liquidity issues.
FUTL	(Funds from Operations to Total Liabilities): Reflects a firm's ability to meet its liabilities from operating cash flows.
INTWO	A binary variable that flags firms with negative income over the past two years.
RETA	(Retained Earnings to Total Assets): Measures how much profit the firm reinvests in its operations relative to its total assets.
MVETL	(Market Value of Equity to Total Liabilities): Represents the firm's leverage by comparing the market value of equity with total liabilities.
TLTA	(Total Liabilities to Total Assets): A common leverage ratio that indicates the proportion of a company’s assets financed by liabilities.
OENEG	A binary variable indicating when a firm's liabilities exceed its assets, which could signal insolvency.
OhlsonSize	The logarithm of total assets adjusted for inflation, often used in Ohlson’s bankruptcy prediction model.
RelativeSize	Logarithm of the firm's outstanding shares multiplied by share price, reflecting firm size in market terms.
FirmAge	The age of the firm since its IPO date.

Turnover	The rate at which employees leave and are replaced within the firm. We calculate it as the change in employment from year to year.
Price	The log of the closing price at the end of the previous fiscal year, used as a market-based variable.
ExcessReturn	The firm's stock return in the previous year minus the market return (CRSP Index), used to gauge market sentiment.
SDReturn	The standard deviation of the residuals produced by regressing firm return on market return over the time period (usually 12 months). This value represents the SDReturn and captures the firm-specific risk or volatility in returns that is not explained by the overall market.
FirmAge	Age of each company relative to the time of incorporation.
Mean	The average of the sum of aggregated rating subcategories, or the average of individual rating subcategories one, two, and three years before a bankruptcy filing, which is used as a proxy for a company's employee satisfaction average.
SD	The variation or dispersion of aggregated rating subcategories, or the variation or dispersion of individual rating subcategories one, two, and three years before a bankruptcy filing, which is used as a proxy for a company's employee satisfaction variability.
careeropps_mean	Average of a company's career opportunities ratings as provided in Glassdoor in the one, two, and three years before a bankruptcy filing (based on the test conducted).
careerops_sd	Variability of a company's career opportunities ratings as provided in Glassdoor in the one, two, and three years before a bankruptcy filing (based on the test conducted).
compensation_mean	Average of a company's compensation benefits ratings as provided in Glassdoor in the one, two, and three years before a bankruptcy filing (based on the test conducted).
compensation_sd	Variability of a company's compensation benefits ratings as provided in Glassdoor in the one, two, and three years

	before a bankruptcy filing (based on the test conducted).
culture_mean	Average of a company's culture values ratings as provided in Glassdoor in the one, two, and three years before a bankruptcy filing (based on the test conducted).
culture_sd	Variability of a company's culture values ratings as provided in Glassdoor in the one, two, and three years before a bankruptcy filing (based on the test conducted).
seniorleadership_mean	Average of a company's senior leadership ratings as provided in Glassdoor in the one, two, and three years before a bankruptcy filing (based on the test conducted).
seniorleadership_sd	Variability of a company's senior leadership ratings as provided in Glassdoor in the one, two, and three years before a bankruptcy filing (based on the test conducted).
worklife_mean	Average of a company's work-life balance ratings as provided in Glassdoor in the one, two, and three years before a bankruptcy filing (based on the test conducted).
worklife_sd	Variability of a company's work-life balance ratings as provided in Glassdoor in the one, two, and three years before a bankruptcy filing (based on the test conducted).
overall_mean	Average of a company's overall rating ratings as provided in Glassdoor in the one, two, and three years before a bankruptcy filing (based on the test conducted).
overall_sd	Variability of a company's overall rating ratings as provided in Glassdoor in the one, two, and three years before a bankruptcy filing (based on the test conducted).
Z-Score	A bankruptcy prediction score that uses a weighted sum of five financial ratios (working capital/total assets, retained earnings/total assets, EBIT/total assets, market value of equity/book value of liabilities, and sales/total assets) to assess a firm's financial health, where a lower score indicates a higher risk of bankruptcy.