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DISTRESS PREDICTION AND STRESS TESTING OF NONFINANCIAL FIRMS: CASE OF MONGOLIA

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DISTRESS PREDICTION AND STRESS TESTING OF NON-FINANCIAL FIRMS: CASE OF MONGOLIA

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Abstract: This paper investigates the resilience of non-financial firms in Mongolia against financial distress. Utilizing firm-level financial data from 2013 to 2022, we employed a LASSO variable selection technique and logistic regression analysis to develop a distress prediction model for these firms. Among the 54 calculated financial ratios and indexes, the key indicators predictive of financial distress were identified as three profitability ratios, one liquidity ratio, one leverage ratio, and two financial indexes. Furthermore, our micro stress tests revealed that reductions in sales revenue significantly increase the likelihood of financial distress, with the probability rising to 32% under scenarios involving a 50% decline in sales. Additionally, sensitivity to income and expenditure shocks varies by firm size and economic sector. Firms in the mining and transportation sectors exhibit a higher probability of distress compared to those in the services sector. Similarly, micro and small firms are more vulnerable to distress than medium and large firms when subjected to stress scenarios.

Keywords: Distress prediction, corporate distress, non-financial firms, stress testing, Mongolia
Jel codes: C50, C52, D22, L25

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Content

1. Introduction

Stress testing emerged as a vital risk management tool for financial institutions following the Global Financial Crisis of 2007-2008. Its importance was underscored by the COVID-19 pandemic, which expanded the scope of stress testing beyond the banking sector to include non-financial firms. This shift reflects a growing recognition among policymakers of the need to ensure the financial stability and resilience of the broader corporate sector. Consequently, stress testing non-financial firms has become a critical framework for policymakers and researchers, providing valuable insights into the vulnerabilities and risk exposures of these entities.

The research aims to construct a distress prediction model and conduct stress testing for non-financial firms at the individual level in Mongolia, estimating the impact of shocks on these firms' probability of distress. Our motivation for conducting this research is twofold. First, prior research on financial distress in Mongolia's non-financial sector has been limited, almost non-existent, due to the unavailability of detailed micro-level data. This study addresses this gap by utilizing a comprehensive dataset from the E-Balance electronic tax system, providing new insights into the financial conditions and resilience of these firms. Second, different economic sectors and firm sizes could exhibit varying degrees of resilience to financial shocks. By highlighting these differences, we aim to enable sector-specific and size-specific risk assessments, which can guide more effective resource allocation and support mechanisms.

With these motivations, we have formulated the following key research questions:

- How resilient or vulnerable are non-financial firms to financial distress? What is the probability of distress?
- What financial indicators are best predictors for financial distress?
- Does the resilience level differ based on the size of the firm and the economic sector it operates in?

This paper aims to contribute to the literature on financial distress prediction by providing a tailored model for non-financial firms in Mongolia, offering practical tools for risk management and decision-making. The insights gained from this study can guide stakeholders in developing strategies to enhance the financial stability and sustainability of firms in the face of economic uncertainties. The following sections of this paper will cover literature review, data descriptives, methodology, empirical analysis on distress prediction and micro stress testing, and the conclusion.

2. Literature review

2.1. Predictive models for financial distress on balance sheet data

The framework for assessing the financial stability and sustainability of firms using balance sheets has been extensively studied since the 1960s. Kumar & Ravi (2006), Sun et al., (2014) and Alaka, et al., (2018) provide comprehensive reviews of bankruptcy prediction methods, focusing on both statistical and intelligent techniques Liang, Lu, Tsai, & Shih (2016). combined financial ratios with corporate governance indicators to predict bankruptcy using data collected from the Taiwan Economic Journal for the years 1999-2009. They compared three filter models and two wrapper-based models to select predictor variables and five supervised machine learning techniques for prediction models. While the abovementioned works cover a broad range of intelligent techniques such as fuzzy set theory, neural networks, genetic algorithms, case-based reasoning, rough sets, support vector machines, decision trees, data envelopment analysis, and soft computing, our focus is specifically on the statistical techniques used in bankruptcy prediction.

In a seminal study, Beaver (1966) conducted a univariate analysis using a paired sample of 79 failed and 79 non-failed industrial, publicly owned firms, matched by industry (using the Standard Industrial Classification system) and asset size. Beaver calculated a total of 30 financial ratios, categorized into six groups, focusing on one representative ratio from each group for the analysis. He evaluated the predictive power of these ratios using a cutoff point derived from a subsample and concluded that the cash-flow to total-debt ratio was the strongest predictor of financial distress. This study is widely regarded as a foundational contribution to the field of financial distress prediction. Later, Altman (1968) criticized the use of univariate analysis for bankruptcy prediction, noting its susceptibility to faulty interpretation and potential confusion. As an advancement to univariate analysis, he employed multiple discriminant analysis (MDA), a more sophisticated statistical technique, to predict bankruptcy using financial ratios. The study's sample comprised of 33 bankrupt and 33 non-bankrupt firms, matched by industry and asset size. Altman initially examined 22 financial ratios, categorized into five groups, and identified working capital/total assets, retained earnings/total assets, EBIT/total assets, market value equity/book of value of total debt and sales/total assets as the most effective predictors when combined. These ratios were then integrated into a single score known as the "Z score", which represents the numerical likelihood of bankruptcy. The Altman's Z-score model then extended into the ZETA model in. Altman, Iwanicz-Drozdowska, Laitinen, & Suvas (2017) subsequently assessed the classification performance of various modifications of the Z-Score model in Altman (1983). Utilizing data extracted from the ORBIS database of Bureau Van Dijk for the years 2002 to 2010, the authors found that while market-based or hazard models have demonstrated superior performance in some contexts, the general Z-Score model performed relatively well for short-term distress prediction across most countries. Cox (1972) provides an alternative approach to investigating the relationship between the time until an event occurs and one or more predictors. Unlike traditional models that focus solely on whether an event occurs, the Cox model emphasizes the duration until the event, which is why it is known as survival analysis. Later, Shumway (2001) employed a modification of the Cox proportional-hazards model in Cox and Oakes (1984) to determine each firm's bankruptcy risk at each point in time. He argued that hazard models are preferred over static models because they adjust for the period at risk, incorporate time-varying covariates, and may produce more efficient out-of-sample forecasts.

Ohlson (1980) employed conditional logit analysis to predict corporate bankruptcy, a method that addressed key limitations associated with MDA. The limitations include strict distributional assumptions, issues with interpretability and challenges related to "matching" procedures. Ohlson analyzed a dataset comprising of 105 bankrupt and 2058 non-bankrupt publicly traded firms, spanning from 1970 to 1976. His model included an intercept and nine commonly cited independent variables. Ohlson concluded that predictive power of any bankruptcy prediction model depends on the timing of the available information, and he emphasized that additional predictors are required for significant improvements in model's accuracy. Zavgren (1985) extended the approach pioneered by Ohlson in a more sophisticated manner to predict financial distress, while Zmijewski (1984) proposed probit regression as an alternative advancement to MDA. Bauer & Agarwal (2014) compared hazard models to traditional accounting-based approach using a database of UK Main listed firms between 1979 to 2009 and concluded that it is superior to the alternative. Tian, Yu & Guo (2015) investigated the relative importance of various bankruptcy predictors using daily and monthly equity data from the CRSP (Center for Research in Security Prices) and annually updated information from COMPUSTAT Global database, covering the period from 1980 to 2009. Their study introduced LASSO (Least Absolute Shrinkage and Selection Operator) in the field of bankruptcy prediction. They found that certain financial ratios, derived solely from accounting data, provide valuable incremental information regarding future default risk. Moreover, the study concluded that variables selected using LASSO demonstrated superior out-of-sample predictive power compared to the models of Campbell et al., (2008) and Merton (1974). Tian & Yu (2017) conducted a study on bankruptcy prediction utilizing COMPUTSTAT Global database, covering the years 1998 to 2012 across international markets. The authors employed adaptive LASSO to select a streamlined set of default predictor variables and subsequently applied discrete hazard models. Their findings indicate that, in the Japanese market, the variables selected through adaptive LASSO demonstrate superior out-of-sample predictive power compared to Altman's Z-Score model. Serrano-Cinca et al., (2019) utilized data extracted from Amadeus database to investigate specific accounting anomalies indicative of business failure. Their analysis employed logistic regression and decision tree methodologies to evaluate the predictive efficacy of these anomalies. The study concluded that while earnings management indicators exhibit statistically significant differences between failed and non-failed firms, their discriminatory power is limited. Notably, the model demonstrated slightly improved accuracy exclusively within the private firm sample. Li et al., (2021) also used LASSO and logistic regression models to explore the significance of various earnings management predictors and to develop an advanced distress prediction model. Their research demonstrates that, after accounting for the costs associated with misclassification, real earnings management (REM) provides incremental information regarding the risk of impending corporate distress. A summary of selected research studies on distress prediction utilizing statistical techniques is presented in Table 4 of the appendix. In various studies, hazard models have been demonstrated to be highly efficient for predicting distress. However, given that this research represents pioneering work in distress prediction within the Mongolian context, we have opted to use static models. The choice of static models is driven by their simplicity and interpretability, their lower data point requirements, and their stability and accuracy.

2.2. Stress testing non-financial firms using financial variables

Stress testing frameworks can be implemented through two primary approaches: top down and bottom-up. The top-down stress test is conducted by a public authority using its own stress test framework, including data, scenarios, assumptions, and models Baudino et al., (2018). This approach offers a comprehensive perspective on industry or economic resilience using standardized scenarios. Siuda (2020) presents a framework for stress testing non-financial firms using national accounting and input-output tables to simulate shock propagation within the sector. The simulation framework captures standard macroeconomic developments and allows for the implementation of one-off measures like government compensation and loan moratoria, producing industry-level performance and profitability variables useful for credit risk, profitability, and liquidity analysis.

Bottom-up stress testing is conducted by a bank using its own stress test framework, either as part of a system-wide exercise or in response to common scenarios and assumptions provided by authorities Baudino et al., (2018). This approach offers detailed insights into how individual entities react to shocks, allowing for a thorough understanding of specific vulnerabilities and impacts. Roulet (2020) conducted an analysis to assess the sensitivity of high-yield corporate and leverage loans to potential macroeconomic and financial shocks. Utilizing data from Refinitiv for the period 2004 to 2019 in United States, Emerging Market Economies (EMEs) and China, the analysis identified the share of corporate debt associated with the riskiest firms in these regions. The findings indicated that under stressed conditions, there would be a significant deterioration in credit quality, increasing the likelihood of defaults across all examined countries, including China. Nehrebecka (2021) examined the impact of COVID-19 scenarios on the probability of default for non-financial firms, focusing both on domestic and foreign-currency debt. The analysis utilized individual data from sources such as Prudential Reporting, the Polish Business Register and Amadeus, covering the period from 2007 to 2020. A statistical model based on logistic regression was employed to estimate the probability of default, while a Merton-type model was used to capture the feedback effects of macroeconomic conditions on the banking sector. The findings revealed that although all industries were affected by the COVID-19 pandemic, the service sector experienced particularly severe impacts. Tressel & Ding (2021) conducted an assessment of firms' resilience to liquidity, viability, and solvency shocks induced by the COVID-19 pandemic. Utilizing annual and monthly data from Datastream, Capital IQ, and IBES for the period 2003-2019, the study employed multi-factor sensitivity analysis to evaluate the immediate liquidity impact on individual firms under various shock scenarios. Additionally, dynamic scenario-based stress testing techniques were used to analyze the evolution of each firm's capacity to service their debt over time. The results indicated that a significant proportion of publicly listed firms became vulnerable due to the pandemic shock, facing substantial additional borrowing requirements to manage cash shortfalls. However, firm behavioral responses and policy interventions were found to be crucial in mitigating the immediate impacts of the shock.

While some stress testing frameworks have been applied to the household sector in Mongolia, there has been limited application of such frameworks to non-financial firms. This is primarily due to methodological complexities and challenges in data accessibility. Recently, Byambatsogt & Enkhbayar (2020) investigated the impact of foreign debt, exchange rates, and industry type on firm failure in Mongolia. Utilizing data from sources such as the E-Balance electronic tax

System, DMFAS, and ITRS, they found that currency depreciation exerts financial pressure on indebted firms, leading to reduced investment. The study also concluded that high financial leverage and increasing foreign debt elevate the likelihood of firm failure, while a larger market share within an industry decreases this risk. Given the absence of a distress prediction model specifically tailored to Mongolia's non-financial sector, our empirical study provides a valuable foundation for future research. A summary of relevant research studies on stress testing non-financial firms is provided in Table 5 in the appendix.

3. The data

3.1. Database and sampling

The research data for this study was obtained from Mongolia's E-Balance electronic tax system. This database includes quarterly financial statements (Statement of Financial Position, Income Statement, Statement of Changes in Ownership Equity, and Statement of Financial Transactions) for all registered firms in Mongolia, starting from 2002. However, the dataset is subject to certain data quality issues and incomplete statements.

We sampled 811 non-financial firms, representing 1.1% of the total operating non-financial firms in Mongolia from 2013 to 2022. We focused exclusively on year-end statements of these firms over the past decade, considering data quality and variations in statement formats and variables. The sample was randomly selected to ensure representation across different locations, economic sectors, and revenue groups. The breakdown of the firm population and sample by these classifications is presented in Figures 9, 10 and 11 in the appendix. The dataset comprises a total of 8,110 observations; however, 6,147 observations were utilized due to some firms having only recently commenced operations. The data was sampled annually and firm-by-firm, processed mechanically, and subsequently combined and cleaned for further analysis.

3.2. Measurement of financial distress

To develop the distress prediction model, first, it is essential first to define what constitutes a distressed firm. The definition of "failure" or "distress" varies across the literature, reflecting different focuses and objectives of the models. According to Beaver (1966), “failure” is defined as the inability of a firm to pay its financial obligations as they mature. In the context of the business registration database of Mongolia, firms are categorized into five operational status groups: active, not yet started, temporarily ceased operations, permanently ceased operations, and other (e.g., not found at the registered address). Within this database, firms that have permanently ceased operations represent approximately 1.1% of the total, while those that have temporarily ceased operations account for about 41.0%. Given the lack of specific data on bankruptcy status, our approach involves classifying firms into distressed and non-distressed[4] categories. Firms are categorized as distressed if they are experiencing significant financial difficulties that may disrupt their operations.

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[4] According to Bankruptcy Law of Mongolia Article 4, the business entity is considered insolvent when it is unable to fulfill its obligations to the amount equal or higher than 10 percent of equity by the deadline specified by law or contract.

We classified a firm as distressed if one recent year of EBIT is negative and the most recent year of equity is negative, as specified by the second criterion in Li et al., (2021). In cases where firms temporarily cease operations and no EBIT data is available, we classify the firm as distressed if its most recent year's equity is negative. The number of firms by distress classification and the proportion of distressed firms in the sample by year are shown in Figures 1 and 2. Distressed firms constitue 14.5 percent of the total firms. The distribution of distressed firms varies significantly across economic sectors. Manufacturing has the lowest share of distressed firms at 7%, indicating relatively higher stability. In contrast, mining shows the highest vulnerability, with 28% of firms in distress. In terms of revenue groups, firms with less than 5 million MNT in revenue show the highest distress at 33%, indicating significant financial vulnerability in this segment. Other revenue groups have a distress share of around 9% to 12%, indicating relative stability.

Figure 1. Share of distressed firms in the sample by economic sectors

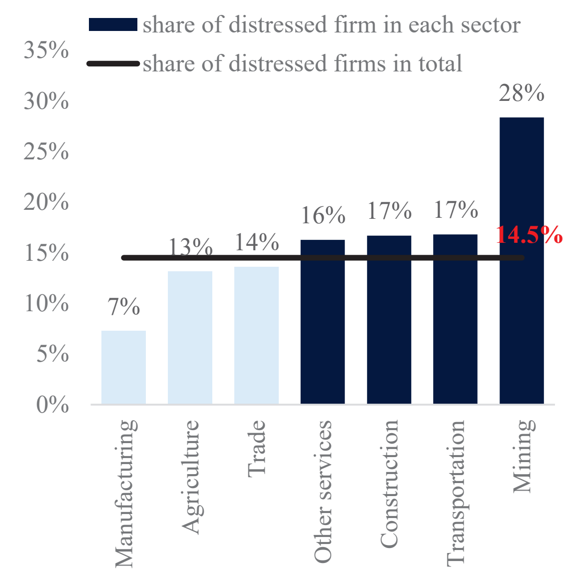
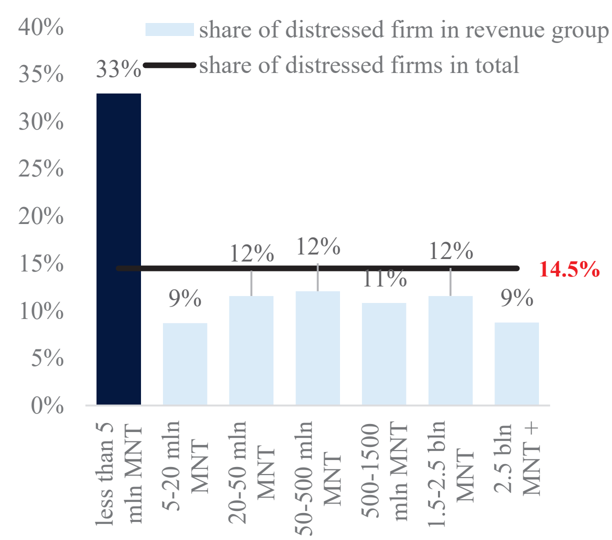


Figure 2. Share of distressed firms in the sample by revenue group



Source: Authors' calculation

3.2. Construction of candidate predictors

We calculated 54 financial ratios and indicators, encompassing liquidity, leverage, profitability, turnover, cash flow, interest, and other relevant metrics, as potential predictors of firm distress. The selection of these variables was guided by three key criteria: 1) their prominence in existing literature, 2) their relevance to our study, and 3) the nature of the balance sheet data available. here are no strict criteria for variable selection; rather, we focused on variables that are well-established, pertinent to our analysis, and compatible with the data at hand.

To develop the candidate predictors, we first calculated a range of financial ratios available in the E-Balance electronic tax system. These ratios include liquidity ratios, financial stability ratios, turnover ratios, productivity ratios, fixed asset utilization ratios, profitability ratios, and cash flow ratios.

We then incorporated earnings management predictors such as SGI, LEVI, GMI, AQI, SGAI, DSRI, and TATA from Li et al., (2021) to achieve a more comprehensive and accurate assessment of the company's financial stability. Additionally, we calculated a range of financial ratios, including EBIT/SALE, NI/TA, NI/SALE, RE/TA, CL/TA, (CL-CH)/TA, ln(SALE), CH/TA, CH/CL, WC/TA, CL/TL, I/SALE, SALE/TA, ln(TA), EQ/TL, CL/SALE, RE/CL, CFO/TL, PROFIT, INT/SALE, and SGR. Many of these ratios are also stated in the E-Balance electronic tax system and are widely utilized in distress prediction research, as demonstrated in studies by Altman (1968), Serrano-Cinca et al. (2019) and Tian & Yu (2017).

Table 6 in the appendix provides a detailed list of the 54 ratios and indexes used in the analysis, along with their descriptions and the number of observations. Summary statistics and results of the Mann-Whitney U test for all 54 financial ratios and indicators, both for the full sample and split sample, are presented in Tables 7 and 8 in the appendix.

4. Methodology

4.1. Mann Whitney U & Median test, Lasso variable selection methodology

We commenced our analysis by employing the Mann Whitney U test and median test on the lagged values (1 to 5 years) of the 54 variables. While Mann-Whitney U test determine whether there is a significant difference exists between distressed and non-distressed firms for the variables as outlined by Li et al., (2021), median test determine whether there is a significant difference between the medians of distressed and non-distressed firm groups. The Mann-Whitney U test offers several advantages, including its non-reliance on normality assumptions, suitability for small sample sizes, applicability to both ordinal and continuous data, and reduced sensitivity to outliers. The results of these tests are detailed in Section 5.

In the next part, we utilized the LASSO variable selection technique to identify the strongest predictors from the 54 candidate variables, which encompass various categories of financial ratios and indexes. This method, initially employed by Tian, Yu & Guo (2015) for predicting financial distress, default, and bankruptcy, has demonstrated its effectiveness in selecting predictors compared to discretionary selection methods.

LASSO is an optimization objective that estimates the coefficients of $\hat{\beta}$ by minimizing the following function, which includes an l_1 penalty applied to the independent variables, excluding the intercept James et al., (2013). We utilized a modification of the LASSO method as described by Li et al., (2021).

$$\hat{\beta} = argmin\left\{\sum_{i}^{n}\left[\left(y_{i,t+1} - \sum_{j}^{p}\beta_{i,j}\,x_{i,j,t}\right)^2 + \lambda\sum_{j}|\beta_j|\right]\right\} \quad (1)$$

Here, $i = 1,2,3,\dots,n$ represents the n firms in the sample
$j = 1,2,3 \dots p$ denotes the p variables collected
$x_{i,j,t}$ represents the j_{th} explanatory variable of i_{th} company at time t
$y_{i,t+1}$ represents the financial status of the i_{th} company 1 year from time t, here $y_{i,t+1}$ equals 1 if a firm is distressed, equals 0 if a firm is non-distressed.

In the above LASSO model, the first term represents the goodness of the fit, while the second constitutes the penalty function to mitigate overfitting. When tuning parameter λ is sufficiently large, the l_1 penalty will shrink some of the coefficient estimates to exactly zero, thereby facilitating variable selection.

We estimated the LASSO model through 100 iterations for both full sample and randomly split sample (training sample and testing sample) to assess the model performance, in line with practices observed in the literature on financial distress by Li et al., (2021), Serrano-Cinca et al., (2019) and Tian, Yu & Guo, (2015). The training sample for our analysis includes 140 distressed firms (approximately 60% of all distressed firms in the sample) and 140 randomly selected non-distressed firms. The testing sample comprises the remaining 94 distressed firms and 437 non-distressed firms. For all empirical analyses, we removed outliers from the full sample and training sample using the interquartile range (IQR) methodology by setting upper and lower boundaries. For the testing sample, we applied winsorization at the 1st and 99th percentiles to manage extreme values.

4.2. Lasso logit estimation and goodness of it

Based on the key predictors selected by LASSO, we developed the following logistic regression model for predicting firm distress:

$$
\begin{aligned}
&Logit(distressed_t) \\
&\quad = \beta_0 + \beta_1 \frac{EBIT_{t-1}}{TA_{t-1}} + \beta_2 \frac{EBIT_{t-1}}{SALE_{t-1}} + \beta_3 \frac{CL_{t-1} - CH_{t-1}}{TA_{t-1}} \\
&\quad + \beta_4 \frac{CL_{t-1}}{SALE_{t-1}} + \beta_5 PROFIT_{t-1} + \beta_6 AQI_{t-1} + \beta_7 SGAI_{t-1}
\end{aligned} \tag{2}
$$

Where $distressed_{\mathrm{t}}$ equals 1 if firm is distressed, 0 otherwise (see distress definition in data section)

$\frac{EBIT}{TA}$:	Earnings before interest and tax/Total assets
$\frac{EBIT}{SALE}$:	Earnings before interest and tax/Sales revenue
$\frac{CL-CH}{TA}$:	(Current liabilities-Cash)/Total assets
$\frac{CL}{SALE}$:	Current liabilities/Sales revenue
$PROFIT$:	Equals 1 if profit is positive, 0 if not
AQI :	Assets Quality Index: $\frac{1-(\text{Current Assets}_t+\text{Property, plant and machine}_t)/Sales_t}{1-(\text{Current Assets}_{t-1}+\text{Property, plant and machine}_{t-1})/Sales_{t-1}}$
SGAI :	Operational Expenses Index: $\frac{\text{Operational expenses}_t}{\text{Operational expenses}_{t-1}} / \frac{\text{Sales}_t}{\text{Sales}_{t-1}}$
t :	Annual data from 2013 to 2022

We evaluated the model's goodness of fit using several metrics, including McFadden's pseudo R^2, AUC, accuracy rate and F_β-score, as outlined by Li et al., (2021). Higher pseudo R^2 indicates a better fit of the model to the data. The formula for pseudo R^2 is given by:

$$R^2_{McF} = 1 - \frac{\ln(L_M)}{\ln(L_0)} \tag{3}$$

L_M : log-likelihood value obtained from the fitted model

L_0: log-likelihood value of a model with no predictors

AUC represents the area under receiver operating characteristic (ROC) curve where x-axis denotes the false positive rate (FPR), and y-axis represents the true positive rate (TPR). A higher AUC value signifies a better performing model with greater accuracy. Accuracy rate refers to the proportion of correctly classified cases relative to the total number of cases. In this context, three specific rates are used:

1. **Overall Accuracy Rate**: This is the ratio of the total number of correctly classified firms to the total number of firms.
2. **True Positive Rate (Sensitivity)**: This rate represents the percentage of firms that are correctly identified as distressed.
3. **True Negative Rate (Specificity)**: This rate indicates the percentage of firms correctly classified as non-distressed.

F_β-score is a measure of model performance taking the cost of misclassifications into consideration Li et al., (2021). The F_β-score is calculated using the formula:

$$F_\beta = \frac{(1+\beta^2) \times true\ positive}{(1+\beta^2) \times true\ positive + \beta^2 \times type\ \mathrm{II}\ error + type\ \mathrm{I}\ error} \tag{4}$$

$$\beta = \frac{Importance\ of\ type\ \mathrm{II}\ error}{Importance\ of\ type\ \mathrm{I}\ error} \tag{5}$$

$True\ positive$: correctly classify non-distressed firms as non-distressed

$Type$ I : number of distressed firms misclassified as non-distressed firms

$Type$ II : number of non-distressed firms misclassified as distressed firms

β : misclassifying non-distressed firm will cause β times as great loss as misclassifying a distressed film, here β is set as 1/35 according to Altman, Haldeman & Narayanan (1977) and Serrano-Cinca et al., (2019)

Additionally, we applied the same model to split samples categorized by four economic sectors (agriculture + industry, mining + transport, trade, and services) and three different firm sizes (micro + small firms, medium firms, and large firms) to analyze and compare sectoral and size-based differences.

4.3. Micro stress testing methodology

The micro stress testing methodology involves assessing the financial resilience of non-financial firms by simulating adverse scenarios and evaluating their impact on firms' financial health. This process begins with the development of a distress prediction model using a LASSO logit estimate, as explained in the previous section, which forecasts the probability of distress based on various financial indicators. Firms' balance sheets are then reconstructed to accurately transmit revenue and expense shocks through financial statements. We considered two micro shocks in different ranges: A decrease in sales revenues of 10-50% and a decrease in firm expenses of 10-50% in 2022. The magnitude of the shocks is derived from our sample results, findings from Chen & Bolormaa (2023), and revenue data from the NSO (National Statistics Office of Mongolia) database. These sources indicate that firms typically experienced a 10% to 50% decline in revenue, varying by industry classification.

The shock transmissions are as follows:

Transmission of Revenue shock

1. **Sales Revenue Drop**
   ↓ Gross Profit
   ↓ Operating Profit (EBIT)
   ↓ Net Income
   ↓ Retained Earnings
   ↓ Equity
2. **Sales Revenue Drop**
   ↓ Cash Inflows
   ↑ Accounts Payable
   ↑ Short-term Debt
   ↑ Long-term Debt
3. **Financial Ratios**
   ↓ Profitability Ratios
   ↓ Liquidity Ratios
   ↑ Leverage Ratios
   ↓ Efficiency Ratios

Transmission of Expense shock

1. **Increase in Cost of Sales**
   ↓ Gross Profit
   ↓ Operating Profit (EBIT)
   ↓ Net Income
   ↓ Retained Earnings
   ↓ Equity
2. **Increase in Cost of Sales**
   ↓ Cash Inflows
   ↑ Inventories
   ↑ Accounts Payable
   ↑ Short-term Debt
   ↑ Long-term Debt
3. **Financial Ratios**
   ↓ Profitability Ratios
   ↓ Liquidity Ratios
   ↑ Leverage Ratios
   ↓ Efficiency Ratios

After applying these shocks, financial ratios such as profitability, liquidity, leverage, and efficiency are recalculated. Finally, the distress prediction model compares the baseline scenario with the shock scenarios to determine the impact on the probability of distress, providing insights into the firms' financial stability under adverse conditions.

5. Results

5.1. Mann Whitney *U* & Median test, Lasso variable and model selection

Table 7 presents the summary statistics for the 54 variables, along with the results of the Mann-Whitney *U* and Median tests for the full sample, considering 1-5 years prior to distress. Table 8 displays the results of these tests for the training and testing samples to ensure robustness and validity. Figure 20 illustrates the dynamic of median values for the aforementioned variables, segmented by distressed and non-distressed groups. Each panel of the figure represents this analysis across different categories of financial ratios and indexes.

Our analysis reveals substantial difference between distressed and non-distressed groups for liquidity ratios based on both Mann Whitney *U* & Median tests. Ratios such as CH/CL, LA/CL, QA/CL, CA/CL, RE/CL, WC/TA, WC/CA how significantly higher mean values in the years leading up to distress (1-5 years) for non-distressed firms, indicating a stronger financial position and a better ability to meet short-term obligations compared to distressed firms. Conversely, ratios such as CA/TA and CH/TA exhibit less significant differences 2-5 years prior to distress. While the median line for non-distressed firms remains nearly flat, indicating minimal variation, we observe noticeable trends in the median line for distressed firms for certain ratios. The median values of ratios such as CH/CL, LA/CL, QA/CL, CA/CL, RE/CL, and WC/TA are typically higher for non-distressed firms. However, as we look further back in time, the difference in median values diminishes, suggesting that the discriminating power of these variables decreases with time. For leverage ratios, substantial differences are also observed between distressed and non-distressed groups for both tests. Ratios such as (CL-CH)/TA, CL/TA and TL/TA, reveal that distressed firms have significantly higher mean and median values compared to non-distressed firms. This suggests that distressed firms carry a greater proportion of debt relative to their equity or assets, thereby increasing their financial risk. Conversely, for ratios like EQ/TA, EQ/TL, and RE/TA, non-distressed firms exhibit higher mean and median values, indicating a larger proportion of assets financed by equity or retained earnings rather than debt, which reflects greater financial stability. However, as we look further back in time, the differences in median values between distressed and non-distressed firms for these ratios decrease, confirming that the discriminating power of these variables diminishes over time. For profitability ratios, significant differences are observed between distressed and non-distressed firms in both tests. For all four ratios, on-distressed firms consistently exhibit higher mean and median values compared to distressed firms, indicating superior income generation relative to their assets or sales revenue. This suggests better overall profitability for non-distressed firms. Like liquidity and leverage ratios, the discriminating power of these profitability ratios diminishes as we look further back in time. For turnover ratios, significant differences are evident between distressed and non-distressed groups in both tests. For ratios such as RT, CAST, PT, IT, OC, NOC, SALE/TA, and I/SALE, non-distressed firms consistently show higher mean and median values compared to distressed firms. This indicates that non-distressed firms exhibit superior efficiency in managing receivables, current assets, purchases, and inventories. For the indexes, substantial differences are also observed between distressed and non-distressed groups in both tests.

We employed LASSO variable selection to identify the most significant predictors for the distress prediction model. The LASSO model was estimated over 100 iterations using three distinct samples: the full sample (234 distressed firms and 577 non-distressed firms), the training sample (140 distressed firms and 140 non-distressed firms), and the test sample (94 distressed firms and 437 non-distressed firms).

The most significant predictors identified across these samples are summarized in Table 1. Key variables consistently selected with high frequency (****) include EBIT/TA, EBIT/SALE, TL/TA, and PROFIT, underscoring their critical role in distress prediction across all samples. Variables such as INT/SALE, CI/TA, and SQR were significant only in the full sample, while WC/SALE and WC/CA were important in both the full and training samples. SGAI was frequently selected in the full and test samples, highlighting its relevance in assessing the impact of operational expenses. Other variables like ln (TA), INV/SALE, and 360/CAST were selected with lower frequency, indicating a less consistent but still pertinent role in the prediction model.

Table 1. Variable selection results

	Full sample (234:577)	Training sample (140:140)	Testing sample (94:437)
EBIT/TA	****	****	****
EBIT/SALE	****	****	****
TL/TA	****	****	****
PROFIT	****	****	****
INT/SALE	****		
CI/TA	****		
WC/SALE	****	****	****
SQR	****		
AQI	****	****	
SGAI	****		****
(CL-CH)/TA	*	*	
WC/TA	*	****	****
INV/SALE	*		*
ln (TA)	*	*	*
CL/SALE	*		*
WC/CA	*	****	****
CI/SALE	*		
GMI	*		*
CAST	*		*
360/CAST	*	*	*

*Note: **** frequency of being selected out* $\geq$

*** *frequency of being selected out 30* $\leq$ *the frequency* $\leq$ *50*

** *frequency of being selected out 20* $\leq$ *the frequency* $\leq$ *30*

* *frequency of being selected out 10* $\leq$ *the frequency* < 20

Source: Author's calculations

5.2. Distress prediction estimation

The estimated logit model for predicting firms' distress, based on full sample[5] is specified as follows (see Table 2 for detail):

[5] Due to missing values, the model was estimated for 3423 observations.

$$
\begin{aligned}
&Logit(distressed_t) \\
&\quad = -2.832 - 0.512 * \frac{EBIT_{t-1}}{TA_{t-1}} - 0.378 * \frac{EBIT_{t-1}}{SALE_{t-1}} + 0.651 \\
&\quad * \frac{CL_{t-1} \text{ - } CH_{t-1}}{\mathrm{TA}_{t-1}} + 0.024 * \frac{CL_{t-1}}{SALE_{t-1}} - 0.985 * PROFIT_{t-1} - 0.017 \\
&\quad * AQI_{t-1} + 0.166 * SGAI_{t-1}
\end{aligned}
\tag{6}
$$

The distribution of the variables used in the models is illustrated in Figures 14 to 19 in the appendix through hex plots. These plots reveal notable differences in the distribution of variables between distressed and non-distressed firms.

The estimated coefficients of the distress prediction model provide insights into the factors influencing firm distress, and all coefficients are statistically significant except for EBIT/SALE. The negative coefficient for EBIT/TA (-0.512) indicates that higher profitability relative to total assets reduces the likelihood of distress, signifying the importance of asset efficiency. Similarly, the negative coefficient for EBIT/SALE (-0.378) suggests that efficient conversion of sales into profits lowers distress risk. Conversely, the positive coefficient for (CL - CH)/TA (0.651) implies that higher current liabilities relative to available cash and total assets increase the likelihood of distress, highlighting the risk associated with high short-term obligations. The coefficient for CL/SALE (0.024), though small, indicates that an increase in current liabilities relative to sales revenue slightly raises the probability of distress, emphasizing the potential danger of short-term financial pressures. A significantly negative coefficient for PROFIT (-0.985) shows that positive profitability substantially reduces distress risk, underscoring the critical role of maintaining profits. The negative but small coefficient for AQI (-0.017) suggests that higher asset quality, represented by a lower proportion of current and fixed assets relative to sales, marginally decreases distress risk. Lastly, the positive coefficient for SGAI (0.166) indicates that an increase in operational expenses relative to sales heightens the probability of distress, pointing to the detrimental impact of rising costs without corresponding sales growth.

The model's goodness of fit metrics indicates strong predictive performance. With an pseudo R^2 of 0.20, AUC of 0.8265, the model effectively distinguishes between distressed and non-distressed firms. The average accuracy of 70.68% shows that the model correctly classifies firms' distress status over 70% of the time. The true negative rate of 61.18% reflects the model's ability to avoid false positives, while the true positive rate of 72.28% demonstrates its strength in correctly identifying distressed firms. An F_β score of 0.723 indicates a good balance between precision and recall, underscoring the model's overall effectiveness in predicting firm distress (see Table 9).

The distress prediction model reveals varying influences of financial ratios across different economic sectors. In Agriculture and Industry, high profitability relative to total assets (EBIT/TA) significantly reduces the probability of distress, while a higher ratio of current liabilities minus cash to total assets (CL−CH)/TA substantially increases it, indicating the critical impact of short-term obligations. In Mining and Transport, both EBIT/TA and EBIT/SALE ratios significantly lower the probability of distress, emphasizing the importance of asset and sales efficiency, while the same short-term liabilities ratio (CL−CH)/TA increases distress risk. In the Trade sector, profitability relative to sales (EBIT/SALE) is crucial for reducing distress, but high short-term obligations still pose a significant risk. The Services sector follows a similar pattern, where higher profitability relative to total assets reduces distress, but the risk from short-term liabilities remains significant. These sectoral differences highlight the varying importance of profitability and short-term financial management across industries.

Table 2. Logit regression results

Dependent Variable: Probability of Firm Distress								
		by economic sector				by firm size *j*		
	(1) Full sample	(2) Agriculture, Industry	(3) Mining, Transport	(4) Trade	(5) Services	(6) Micro, small	(7) Medium	(8) Large
EBIT/TA	-0.512***	-0.652**	-0.790***	-0.092	-0.422*	-0.595***	-0.239	-1.245***
	(0.114)	(0.290)	(0.243)	(0.191)	(0.226)	(0.136)	(0.215)	(1.698)
EBIT/SALE	-0.378***	-0.097	-0.609**	-0.417***	-0.818**	-0.104	-0.548***	-0.378*
	(0.073)	(0.182)	(0.241)	(0.106)	(0.365)	(0.106)	(0.185)	(0.199)
(CL-CH)/TA	0.651***	1.307***	0.308***	0.575***	1.202***	0.360***	0.782***	1.838***
	(0.081)	(0.279)	(0.075)	(0.130)	(0.253)	(0.068)	(0.141)	(0.314)
CL/SALE	0.024***	0.029	0.179***	0.013	0.034	0.038***	0.032**	0.008
	(0.008)	(0.018)	(0.058)	(0.011)	(0.027)	(0.013)	(0.016)	(0.018)
PROFIT	-0.985***	-0.578	-0.436	-1.407***	-0.670	0.241	-0.835	-0.294
	(0.258)	(0.729)	(0.556)	(0.421)	(0.597)	(0.598)	(0.619)	(0.436)
AQI	-0.017**	-0.005	-0.003	-0.028**	-0.023	-0.013	-0.029**	-0.003
	(0.008)	(0.017)	(0.020)	(0.012)	(0.020)	(0.011)	(0.014)	(0.020)
SGAI	0.166***	0.030	-0.110	-0.116	-0.600**	-0.086	-0.292**	-0.079
	(0.106)	(0.100)	(0.143)	(0.075)	(0.236)	(0.063)	(0.122)	(0.113)
Constant	-2.832***	-2.869***	-1.634***	-1.191***	-1.406**	-2.451***	-1.575**	-2.975***
	(0.748)	(0.748)	(0.601)	(0.422)	(0.619)	(0.601)	(0.621)	(0.471)
Observations	3423	930	537	1384	571	940	1110	1372

**** - indicates 99% significance, ** - 95% significance, * - 90% significance*
j - micro, small firms: revenue less than 50 mln MNT, medium firms: 50-1500 mln MNT, large firms: more than 1.5 bln MNT

Source: Author's calculations

The distress prediction model's results vary significantly across firm sizes. For micro and small firms, higher profitability relative to total assets (EBIT/TA) reduces distress probability, while high short-term liabilities ((CL-CH)/TA and CL/SALE) increase it, emphasizing the importance of asset efficiency and short-term financial management. Medium-sized firms also benefit from higher profitability relative to sales (EBIT/SALE) and asset quality (AQI), which reduce distress probability, but face increased risk from short-term liabilities ((CL-CH)/TA and CL/SALE) and operational expenses (SGAI). In contrast, large firms show the strongest effect from profitability ratios (both EBIT/TA and EBIT/SALE), with high profitability significantly lowering distress probability, while high short-term liabilities ((CL-CH)/TA) substantially increase distress risk. These findings indicate that while profitability is crucial across all firm sizes, short-term financial pressures are particularly impactful for smaller firms, and operational efficiency becomes more critical for medium-sized firms.

There is a potential concern of endogeneity, as our definition of firm's financial distress is based on EBIT and the explanatory variables include EBIT/TA and EBIT/SALE. As a robustness test to address the issue, we estimated an alternative model by modifying the distress criteria. In this revised approach, firms are classified as distressed if they have negative working capital in at least one recent year and negative equity in the most recent year.

Table 3. Logit regression results (alternate model)

Variable	**Coefficient**	**Standard Error**
EBIT/TA	-0.784^{***}	(0.094)
EBIT/SALE	-0.238^{***}	(0.069)
CL/SALE	0.043^{***}	(0.076)
PROFIT	-0.907^{***}	(0.251)
AQI	-0.013^{***}	(0.007)
SGAI	-0.195^{***}	(0.052)
Constant	-1.198^{***}	(0.251)
Observations	3423	

Source: Author's estimation

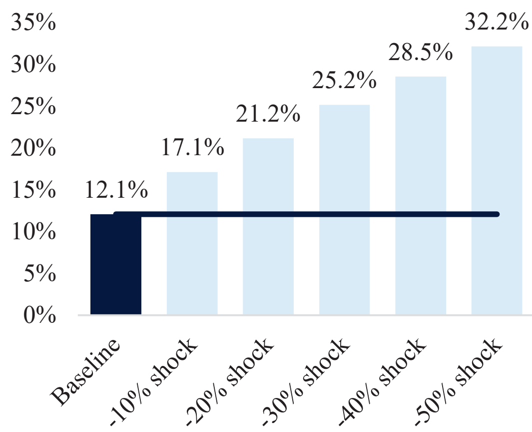
In the alternative model, both EBIT/TA and EBIT/SALE remained statistically significant, with signs consistent with the results of the original model. This consistency suggests that these variables are robust predictors of financial distress, regardless of the specific criteria used to define distress.

5.3. Micro stress testing results

5.3.1. Firms' sales revenue shock

We applied sales revenue shocks of 10%, 20%, 30%, 40%, and 50% declines for the year 2022, subsequently recalculated the financial statements, ratios, and indexes, and then input these adjusted figures into the distress prediction model (estimated on the full sample) to forecast the likelihood of firms' distress in 2023. The resulting proportion of distressed firms under these shock scenarios is as follows:

Figure 3. Sales revenue shock on firms' distress



Source: Author's calculation

The firms' distress outcomes under various shock scenarios to sales revenue for 2022 indicate a significant increase in the share of distressed firms in 2023 as the severity of the shock escalates. Starting from a baseline distress share of 12.1%, a 10% decline in sales revenue raises the distress share to 17.1%. As the shock intensity increases, the distress share rises progressively to 21.2% (-20% shock), 25.2% (-30% shock), 28.5% (-40% shock), and peaks at 32.2% with a 50% decline in sales revenue. This pattern suggests that the declines in sales revenue have a pronounced effect on firm distress.

Figure 4. Sales revenue shock on firms' distress, by industry

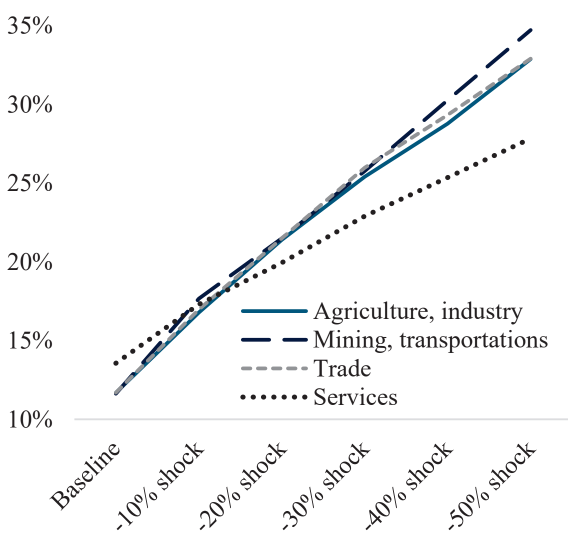
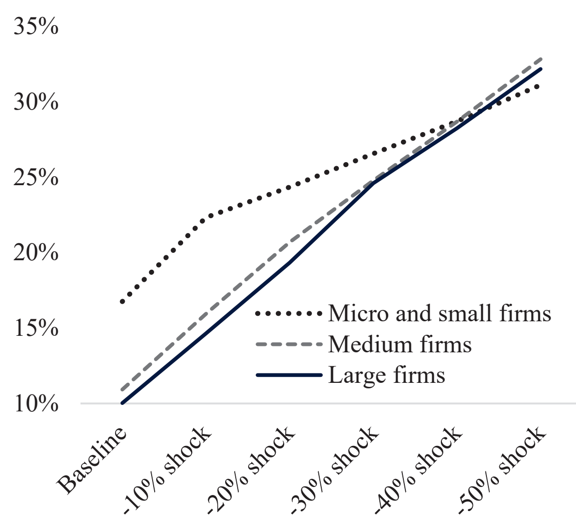


Figure 5. Sales revenue shock on firms' distress, by firm size[6]



Source: Author's calculation

The impact of sales revenue shocks on firm distress exhibits a consistent pattern across industries, with distress levels rising as revenue declines. At baseline, distress shares are similar, but a 10% revenue drop increases distress in all sectors. As declines reach 20% and 30%, the Mining and Transportation, and Trade sectors show the highest increases in distress. At a 40% decline, distress peaks across all industries, with the Mining and Transportation, and Trade sectors most affected. A 50% decline further increases distress, particularly in these sectors.

[6] Micro and small firms: revenue less than 50 mln MNT, medium firms: 50-1500 mln MNT, large firms: more than 1.5 bln MNT

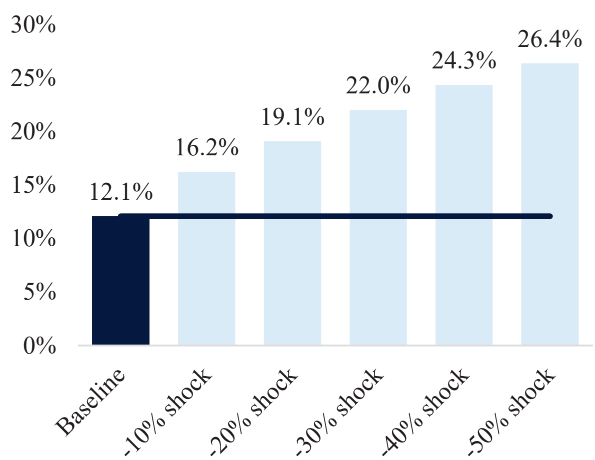
Overall, all industries are highly sensitive to revenue shocks, with the Mining and Transportation, and Trade sectors being the most impacted.

The stress test results indicate that small firms are the most vulnerable to sales revenue shocks, with their distress share rising from 16.8% at baseline to 31.1% at a 50% revenue decline. Medium-sized firms show a similar pattern, with distress increasing from 10.9% to 32.8% under the same shock. Large firms, while also affected, have the lowest baseline distress share at 10.0% and see their distress share increase to 32.2% at a 50% decline. Overall, while all firms are impacted by revenue shocks, small firms are the most sensitive, followed by medium and then large firms.

5.3.2. Firm's expense shock

Like the sales revenue shock analysis, we applied expense shocks of 10%, 20%, 30%, 40%, and 50% increases for 2022. Following these adjustments, we recalculated the financial statements, financial ratios, and indexes. These revised metrics were then input into the distress prediction model to forecast the likelihood of firm distress in 2023. The resulting share of distressed firms under these expense shock scenarios is presented as follows:

Figure 6. Expense shock on firms' distress



Source: Author's calculation

The firm expense stress test results show a clear pattern of increasing distress in 2023 as the shock severity intensifies. At the baseline level, the share of distressed firms stands at 12.1%. When firm expenses rise by 10%, the distress share increases to 16.2%. This upward trend continues with a 20% increase in expenses, pushing the distress share to 19.1%. A 30% expense shock results in 22.0% of firms becoming distressed. The distress share further rises to 24.3% with a 40% increase in expenses. At a 50% increase, the share of distressed firms peaks at 26.4%. Overall, these results highlight a strong correlation between rising expenses and increased firm distress, indicating that firms are increasingly likely to become distressed as their expenses grow significantly.

The expense shock scenario reveals sectoral differences in firm distress as expenses increase. At the baseline, distress levels are similar across sectors. As expenses rise by 10%, distress shares increase uniformly across all sectors. With a 20% expense shock, Agriculture, Industry, Mining, and Transportation sectors see distress levels surpassing the overall average, while Trade and Other Services remain slightly lower. The trend continues with a 30% shock, where Agriculture and Industry, and Trade sectors show higher distress compared to Mining and Transportation, and Other Services. At 40% and 50% shocks, distress levels in Agriculture, Industry, and Trade are notably higher, where Trade experiences the highest distress, followed by Agriculture and Industry, and Mining and Transportation. Services sector consistently show a more moderate increase in distress throughout the shock scenarios. This pattern indicates that Trade and

Agriculture, and Industry sectors are more sensitive to expense shocks, while Services sector exhibit greater resilience.

Figure 7. Expense shock on firms' distress, by industry

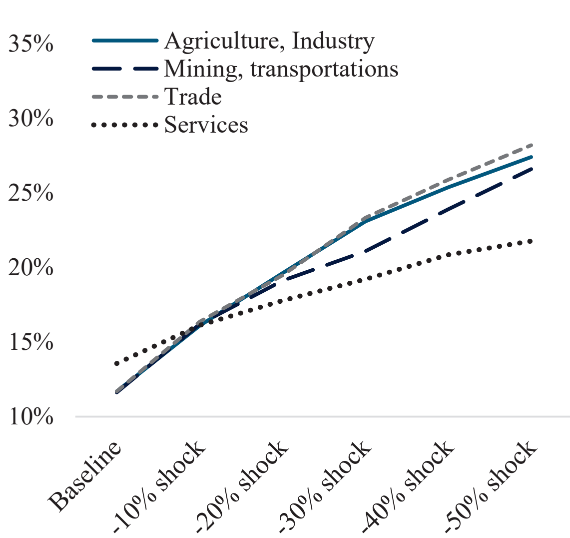
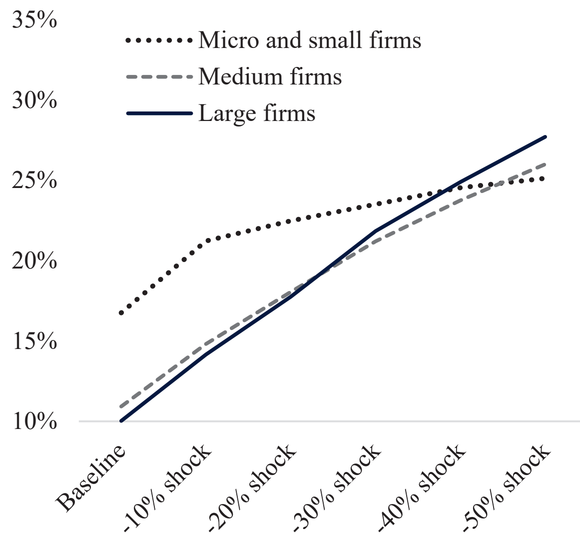


Figure 8. Expense shock on firms' distress, by firm size



Source: Author's calculation

The expense stress test results show that small firms are the most vulnerable to rising expenses, starting with the highest baseline distress level. As expenses increase, small firms consistently exhibit higher distress rates compared to medium and large firms. Medium firms show a gradual rise in distress, with a notable increase in higher expense shocks, but they remain less distressed than small firms. Large firms demonstrate the greatest resilience, starting with the lowest baseline distress and experiencing the least increase in distress as expenses rise. At the 50% shock level, small firms' distress peaks but remains lower than that of medium and large firms, whose distress continues to increase significantly. This pattern highlights that while all firms are affected by expense shocks, small firms are the most sensitive, followed by medium and then large firms.

6. Conclusion

This research paper aimed to develop a distress prediction model for non-financial firms in Mongolia and examine the resilience of the firms against financial distress through micro stress tests. Using a sample of 811 firms from Mongolia's E-Balance electronic tax system, representing 1.1% of the total operating non-financial firms from 2013 to 2022, we identified key financial indicators predictive of financial distress and assessed firms' vulnerability to such distress in stress testing.

We employed a Lasso logit model for distress prediction, which selected the most significant variables across different samples. The estimated coefficients for the full sample showed that one period lagged values of EBIT/TA, EBIT/SALE, (CL-CH)/TA, CL/SALE, Profit, AQI index, SGAI index were significant predictors of firm distress in the next year, with statistical significance. Goodness-of-fit measures indicated a robust model, with an AUC of 0.8265 and an average accuracy of 70.68%.

Stress testing was applied to assess the impact of shocks to sales revenue and expenses. Sales revenue and expense shocks showed that as declines intensified from 10% to 50%, the share of distressed firms increased, the impact of revenue shock being stronger than expense shock. Sectoral analysis revealed that the trade, agriculture, and industry sectors were most sensitive to both revenue and expense shocks, while services sector showed more resilience. Firm size analysis under revenue and expense shocks demonstrated that small firms were the most vulnerable, exhibiting the highest distress levels throughout, while large firms showed the greatest resilience. Medium firms experienced a gradual increase in distress, positioning them between small and large firms in terms of sensitivity.

The research faced limitations due to the nature of the dataset, which is accessible only on a firm-by-firm and year-by-year basis. Consequently, we were able to collect and clean only a sample of firms within the given time constraints. Future research could be further validated with a larger sample if full access to the dataset is granted. Additionally, we were unable to analyze exchange rate stress testing because foreign currency debt data was available for only a small fraction of firms, and the model lacks the intricate mechanisms needed to fully explain exchange rate transmissions.

Overall, the findings underscore the varying impacts of financial shocks on different sectors and firm sizes, highlighting the importance of tailored financial management strategies to mitigate distress risks. The developed distress prediction model and the insights from stress testing provide valuable tools for policymakers and business leaders to anticipate and address potential financial vulnerabilities in the non-financial sector.

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Appendix

Table 4. Summary of the research papers predicting bankruptcy, default or distress using balance sheet

Author	Research objective	Sample	Distress definition	Methodology	Candidate predictors	Selected predictors
Bauer & Agarwal. (2014)	UK	2,748 unique firms, 28,804 firm years	Liquidation, administration/receivership or valueless company	Hazard models	Accounting and market variables	NITA, NIMTA, CASHMTA, TLTA, TLMTA, BM, RSIZE, SIZE, PRICE, EXRET, SIGMA
Tian et al., (2015)	USA	17,570 firms 1,571,115 firm-months	A company is in default if it files for bankruptcy	Discrete hazard model and LASSO	39 financial and market variables	LTMTA, NIMTA, CASHMTA, RSIZE, PRICE, MB SIGMA, EXCESS RETURN
Altman et al., (2017)	31 European and 3 non-European countries	Estimation sample includes 2,602,503 non-failed and 38,215 failed firms, test sample includes 3,148,079 non-failed and 43,664 failed firms	Based on ORBIS status	Z-Score model	22 financial ratios	WCTA, RETA, EBITTA, BVETD
Tian & Yu. (2017)	Japan and selected set of European countries including UK, France and Germany	4,722 firms and 62,837 firm-year observations for Japan, 52,581 firm-year observations for Europe	classified as "bankruptcy" if it files either Chapter 7 (liquidation) or Chapter 11(reorganization) under the Bankruptcy Protection Codes	adaptive LASSO discrete hazard model	29 accounting-based variables	Japan – Retained Earning/Total Asset, Total Debt/Total Asset and Current Liability/Sales UK, Germany and France – equity ratio variable, Equity/Total Liability
Serrano-Cinca et al., (2019)	Europe	51, 337 public and private European companies	Bankruptcy status on Amadeus database	Logistic regression, decision tree	9 traditional financial ratios and 11 indicators	Classical financial ratios perform better for public companies than private companies while indexes perform well for private companies
Li et al. (2021)	China	3,555 firms and 15,413 firm-years	Any of the 4 types of criteria based on earnings, equity, financial statement and stock exchange	LASSO	43 candidate predictors combining traditional financial ratios and REM indicators	REM is selected out as the key distress predictor

Source: Authors compilation

Table 5. Summary of the research papers on stress testing firms using individual firm data

Author	Research objective	Sample	Distress definition	Methodology
Roulet, 2020	Global sample	8361 firms	Based on company rating information on Infinitive and ICR	Stress testing
Nehrebecka, 2021	Poland	15,375 enterprises	Based on default rate DR	Logistic regression Merton-type model
Tressel & Ding, 2021	Sample of 24 countries	17,000 publicly listed firms	Based on external borrowing needs, ICR and solvency position	Multi-factor sensitivity analysis Dynamic scenario-based stress test
Byambatsogt & Enkhbayar, 2020	Mongolia	175 major firms	Based on equity and cease of operation	Logit regression

Source: Authors compilation

Figure 9. Breakdown by economic activities

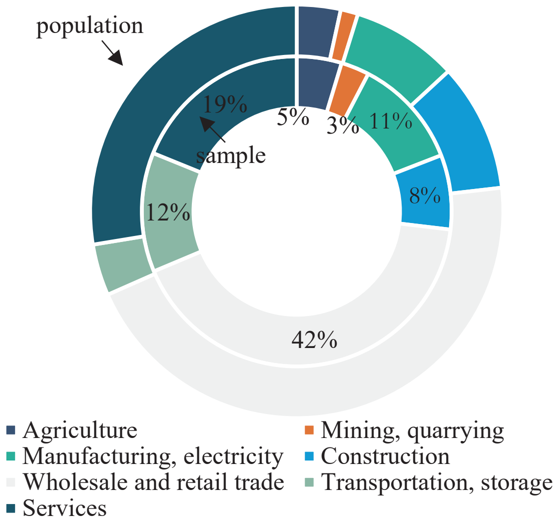


Figure 10. Breakdown by region

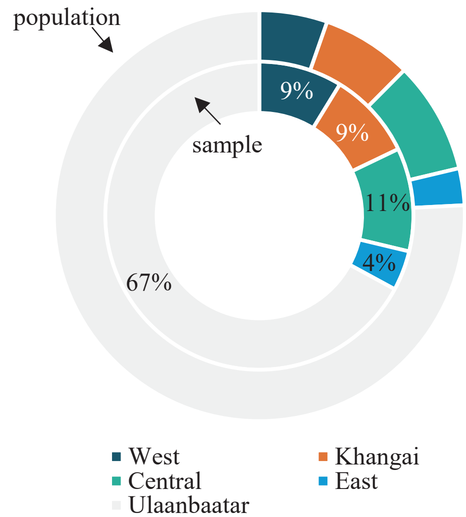
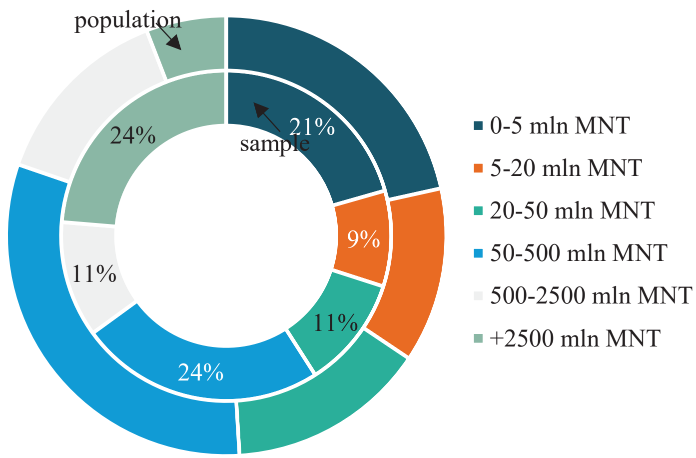


Figure 11. Breakdown by income group



Source: "Business registration" database, NSO, Author's calculation

Figure 12. Number of firms by distressed classification each year

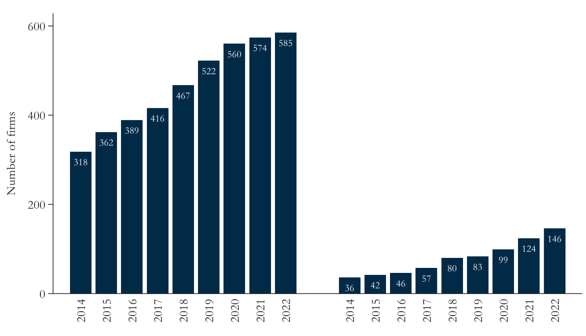
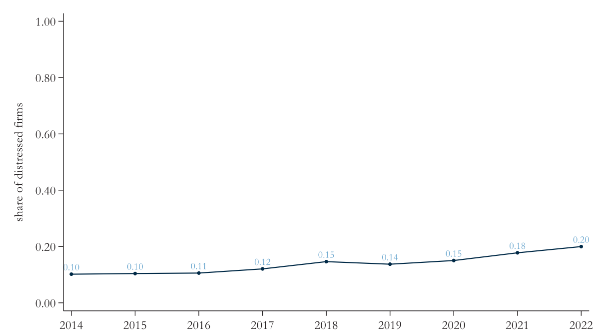


Figure 13. Share of distressed firms in the sample by each year



Source: "Business registration" database, NSO, Author's calculation

Table 6. Description of financial ratios and indexes

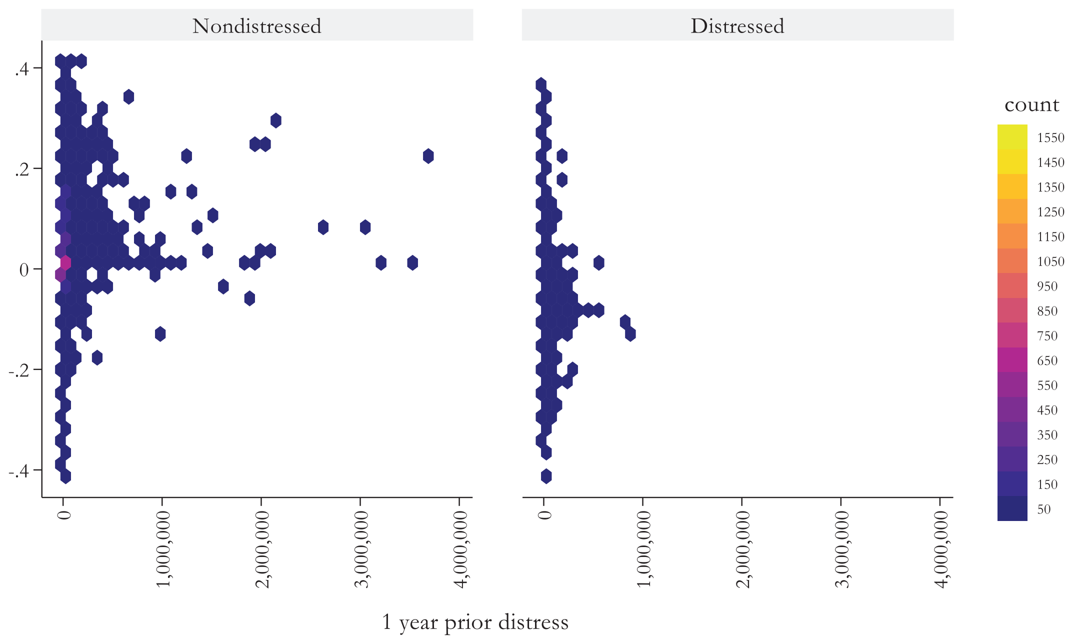
Variables	Description	Number of observations
Liquidity ratios (11)		
CH/CL	Cash / Current liabilities	784 firms, 5028 firm-year observations
LA/CL	(Cash + Other financial assets) / Current liabilities	
QA/CL	(Cash + Receivables + Other financial assets) / Current liabilities	
CA/CL	Current assets / Current liabilities	
RE/CL	Retained earnings / Current liabilities	
CA/TA	Current assets / Total assets	811 firms, 5995 firm-year observations
CH/TA	Cash / Total assets	
WC/TA	Working capital / Total assets	810 firms, 5928 firm-year observations
WC/CA	Working capital / Current assets	811 firms, 5921 firm-year observations
CL/TL	Current liabilities / Total liabilities	784 firms, 5053 firm-year observations
CL/SALE	Current liabilities / Sales revenue	794 firms, 4985 firm-year observations
Leverage ratios (6)		
(CL-CH)/TA	(Current liabilities – Cash) / Total assets	811 firms, 5995 firm-year observations
CL/TA	Current liabilities / Total assets	
TL/TA	Total liabilities / Total assets	811 firms, 6093 firm-year observations
EQ/TA	Equities / Total assets	811 firms, 5995 firm-year observations
EQ/TL	Equities / Total liabilities	811 firms, 5053 firm-year observations
RE/TA	Retained earnings / Total assets	811 firms, 5995 firm-year observations
Profitability ratios (4)		
EBIT/TA	EBIT / Total assets	811 firms, 5995 firm-year observations
EBIT/SALE	EBIT / Sales revenue	794 firms, 4985 firm-year observations
NI/TA	Profit after tax / Total assets	811 firms, 5995 firm-year observations
NI/SALE	Profit after tax / Sales revenue	794 firms, 4985 firm-year observations
Turnover ratios (13)		
RT	Sales revenue / Average receivables	636 firms, 4046 firm-year observations
360/RT	360 × Average receivables / Sales revenue	
CAST	Sales revenue / Average current assets	810 firms, 6007 firm-year observations
360/CAST	360 × Average current assets / Sales revenue	793 firms, 4979 firm-year observations
PT	Purchases / Average accounts payable	549 firms, 3327 firm-year observations
360/PT	360 × Average accounts payable / Purchases	
IT	Cost of goods sold / Average inventory	575 firms, 3895 firm-year observations
360/IT	360 × Average inventory / Cost of goods sold	
OC	360 × (Average receivables / Sales revenue + Cost of goods sold / Average inventory)	690 firms, 4252 firm-year observations
NOC	360 × (Average receivables / Sales revenue + Cost of goods sold / Average inventory – Average accounts payable / Purchases)	710 firms, 4432 firm-year observations
WC/SALE	Working capital / Sales revenue	792 firms, 4976 firm-year observations
SALE/TA	Sales revenue / Total assets	811 firms, 5995 firm-year observations
I/SALE	Inventories / Sales revenue	794 firms, 4985 firm-year observations

Table 6. Description of financial ratios and indexes, continued

Variables	Description	
Cash flow ratios (4)		
CI/SALE	Cash inflow from operating activities / Sales revenue	794 firms, 4985 firm-year observations
CI/TA	Cash inflow from operating activities / Total assets	811 firms, 5995 firm-year observations
CO/COGS	Cash outflow from operating activities / Cost of goods sold	660 firms, 3769 firm-year observations
CFO/TL	Cash flow from operation / Total liabilities	784 firms, 5053 firm-year observations
Interest ratios (2)		
ICR	EBIT / Interest payment	321 firms, 1626 firm-year observations
INT/SALE	Interest expense / Sales revenue	794 firms, 4985 firm-year observations
Productivity ratios (2)		
SALE/FA	Sales revenue / Average fixed assets	591 firms, 4469 firm-year observations
SALE/I	Sales revenue / Average inventory	575 firms, 3895 firm-year observations
Indexes (7)		
SGI	Sales Growth Index: $\frac{\text{Sales}_t}{\text{Sales}_{t-1}}$	794 firms, 4984 firm-year observations
LEVI	Leverage Index: $\frac{\text{Total Debts}_t}{\text{Total Assets}_t} / \frac{\text{Total Debts}_{t-1}}{\text{Total Assets}_{t-1}}$	786 firms, 5045 firm-year observations
GMI	Gross Margin Index: $\frac{\text{Gross Profits}_{t-1}}{\text{Sales}_{t-1}} / \frac{\text{Total Debts}_{t-1}}{\text{Total Assets}_{t-1}}$	786 firms, 4969 firm-year observations
AQI	Assets Quality Index: $\frac{1-(\text{Current Assets}_t+\text{property,plant and machine}_t)/Sales_t}{1-(\text{Current Assets}_{t-1}+\text{property,plant and machine}_{t-1})/Sales_{t-1}}$	689 firms, 4336 firm-year observations
SGAI	Operational Expenses Index: $\frac{\text{Operational expenses}_t}{\text{Operational expenses}_{t-1}} / \frac{\text{Sales}_t}{\text{Sales}_{t-1}}$	791 firms, 4952 firm-year observations
DSRI	Days' Sales in Receivable Index: $\frac{\text{Receivables}_t}{\text{Sales}_t} / \frac{\text{Receivables}_{t-1}}{\text{Sales}_{t-1}}$	549 firms, 2875 firm-year observations
TATA	Total Accruals / Total Asset	811 firms, 5995 firm-year observations
Other (5)		
FA/TA	Fixed assets / Total Assets	811 firms, 5995 firm-year observations
ln(SALE)	ln(Sales revenue)	794 firms, 4984 firm-year observations
ln(TA)	ln(Total assets)	811 firms, 5995 firm-year observations
PROFIT	Equals 1 if profit is positive, 0 if not	811 firms, 6093 firm-year observations
SGR	Sales growth rate	713 firms, 4612 firm-year observations

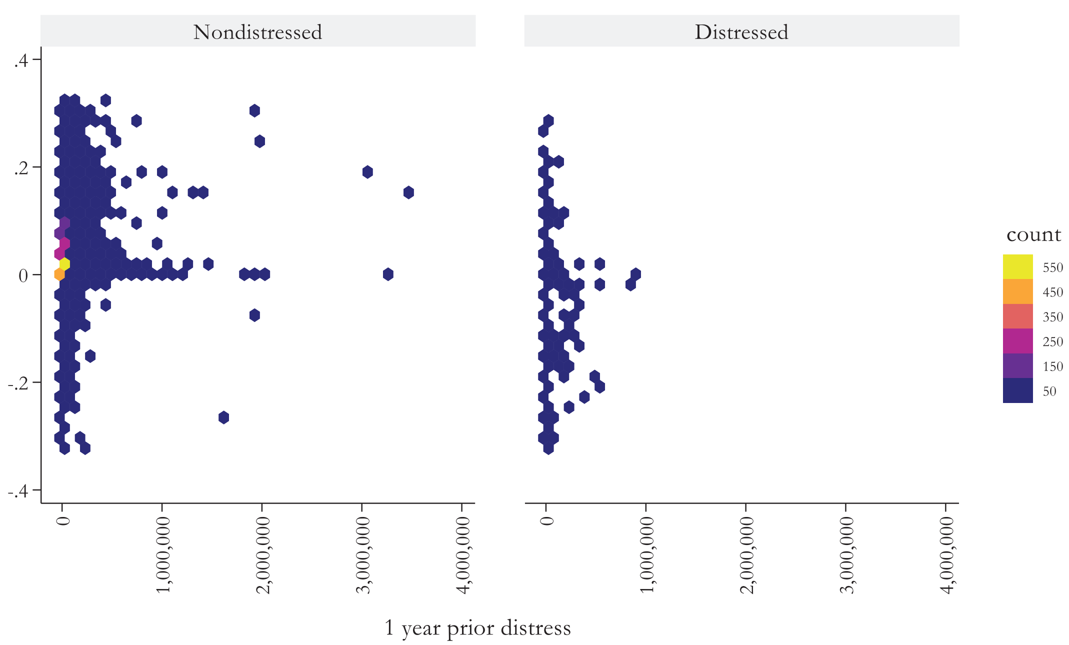
Source: Author's calculation

Figure 14. Distribution of EBIT/TA, by distressed and non-distressed firms



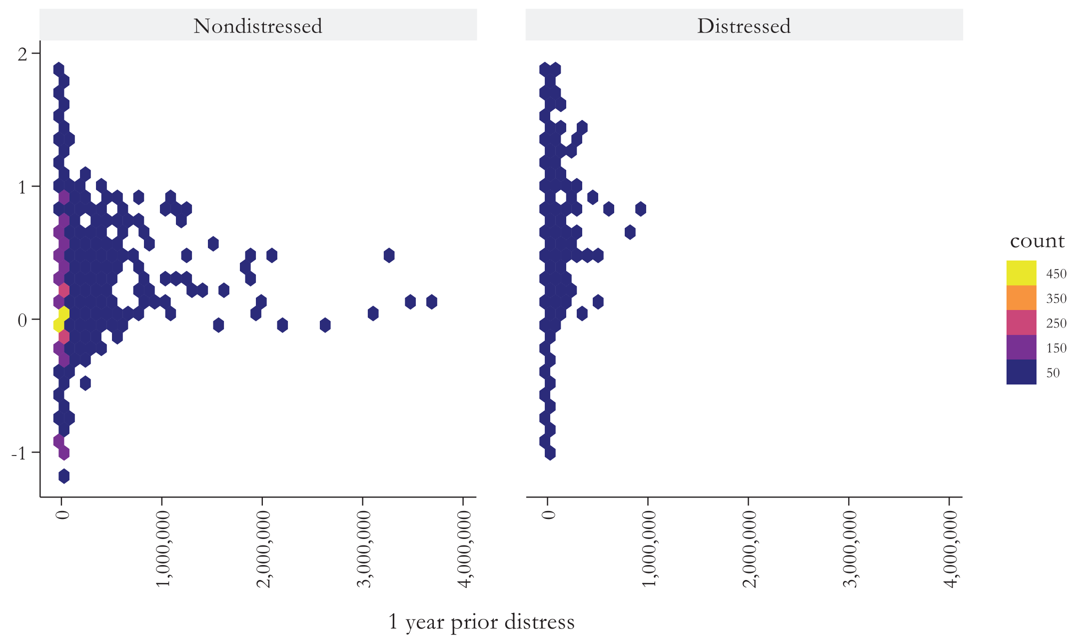
Source: Author's calculation

Figure 15. Distribution of EBIT/SALE, by distressed and non-distressed firms



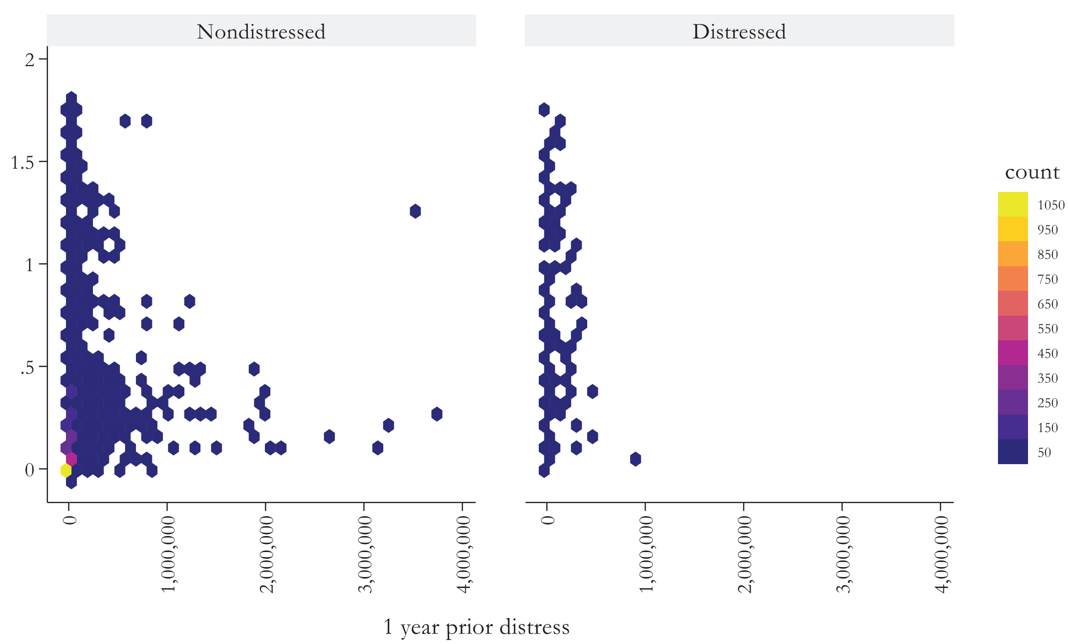
Source: Author's calculation

Figure 16. Distribution of (CL-CH)/TA, by distressed and non-distressed firms



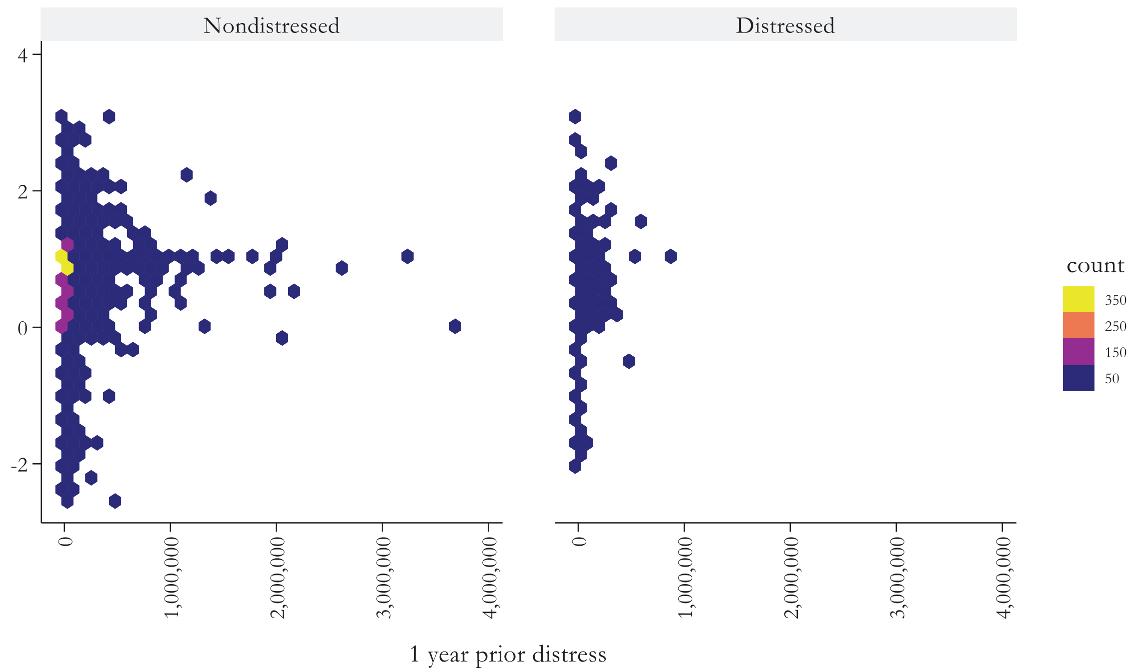
Source: Author's calculation

Figure 17. Distribution of CL/SALE, by distressed and non-distressed firms



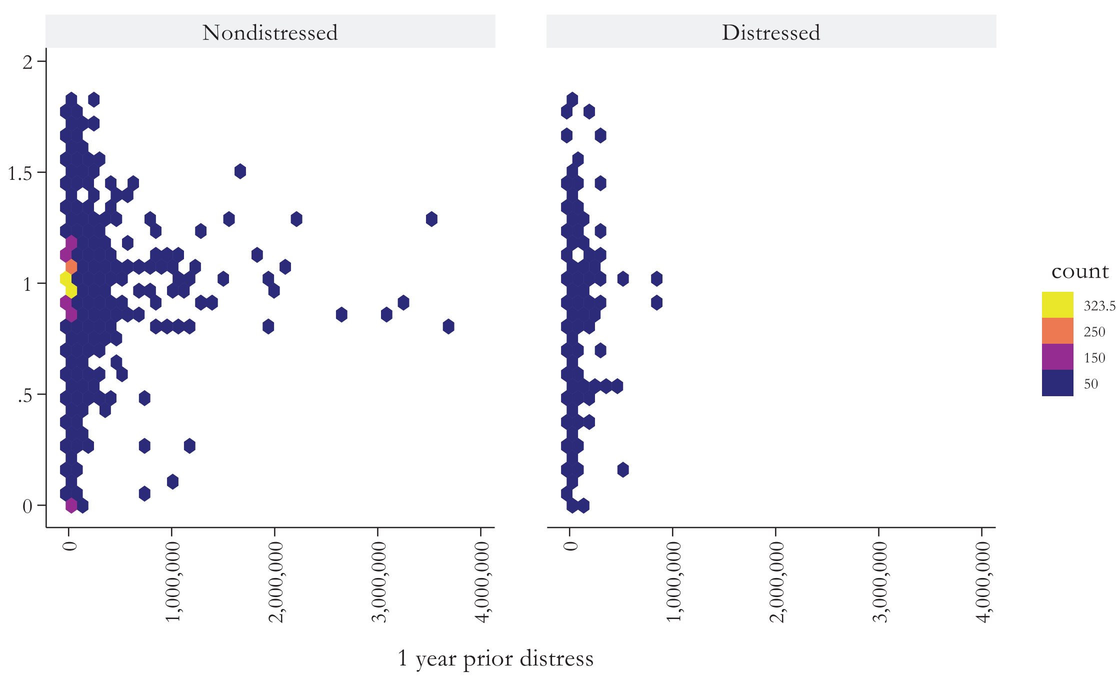
Source: Author's calculation

Figure 18. Distribution of AQI, by distressed and non-distressed firms



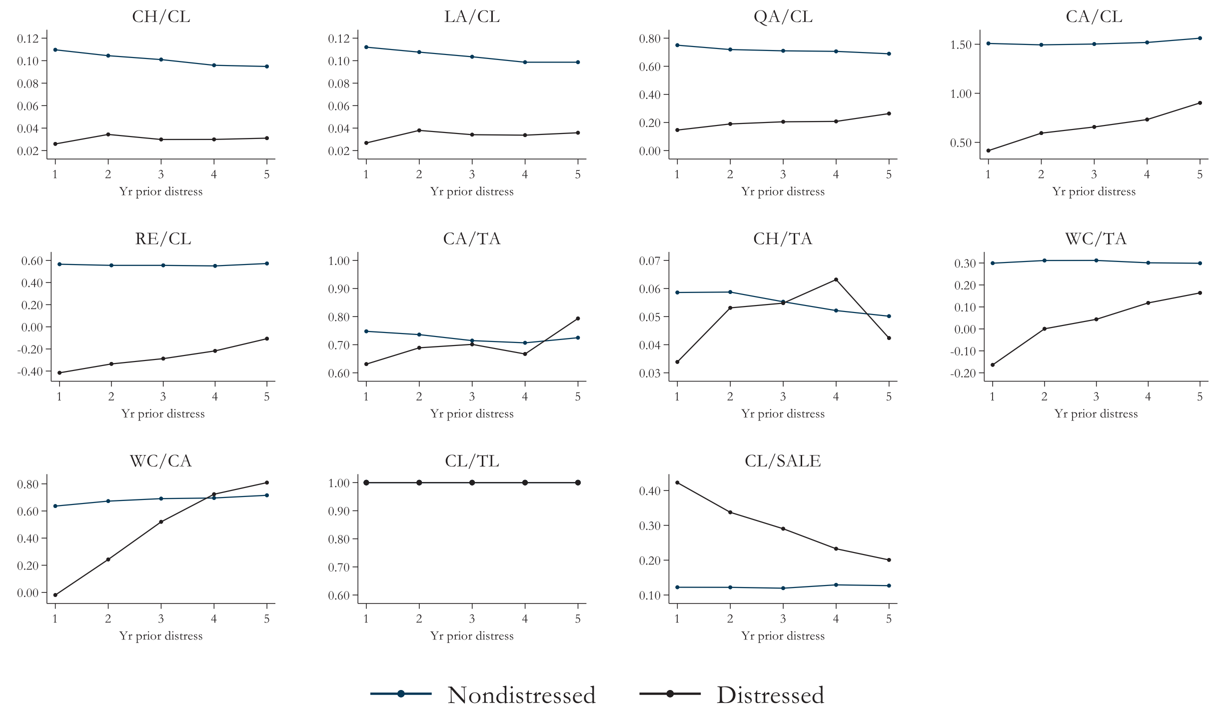
Source: Author's calculation

Figure 19. Distribution of SGAI, by distressed and non-distressed firms



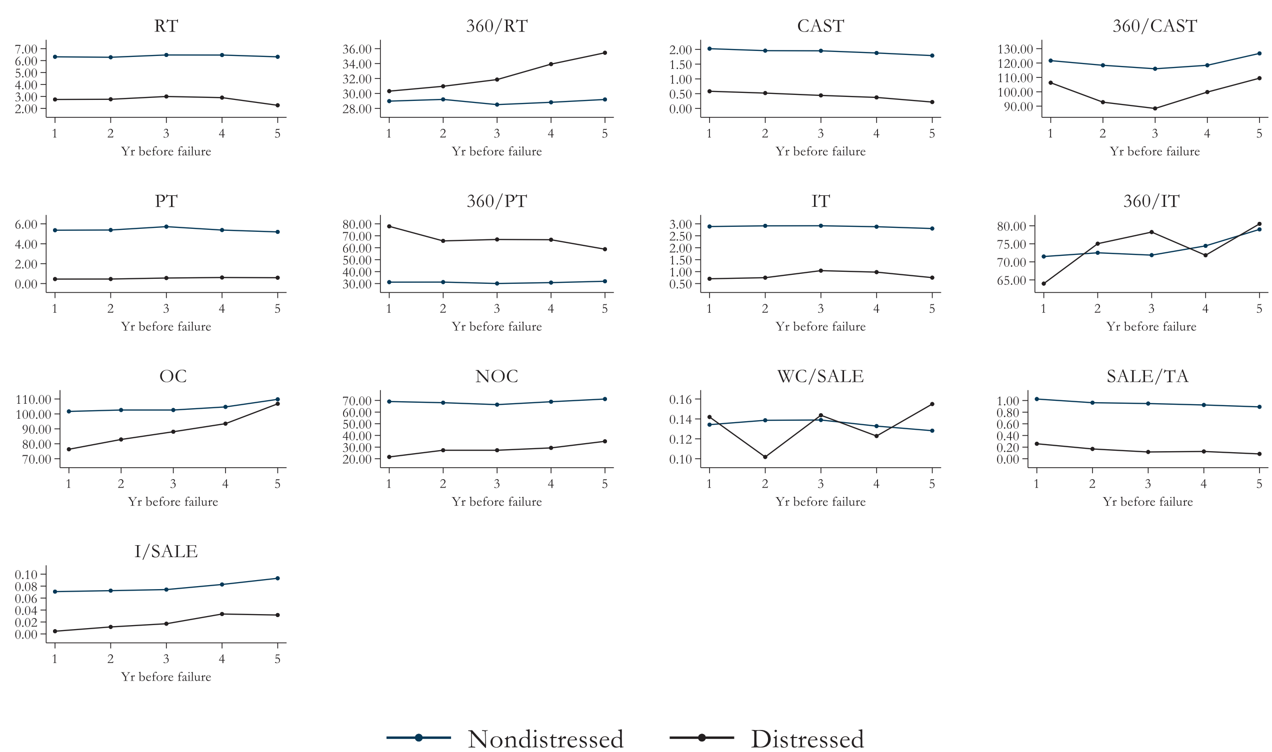
Source: Author's calculation

Figure 20.a. Comparison of median values for distressed and non-distressed firms using liquidity ratios



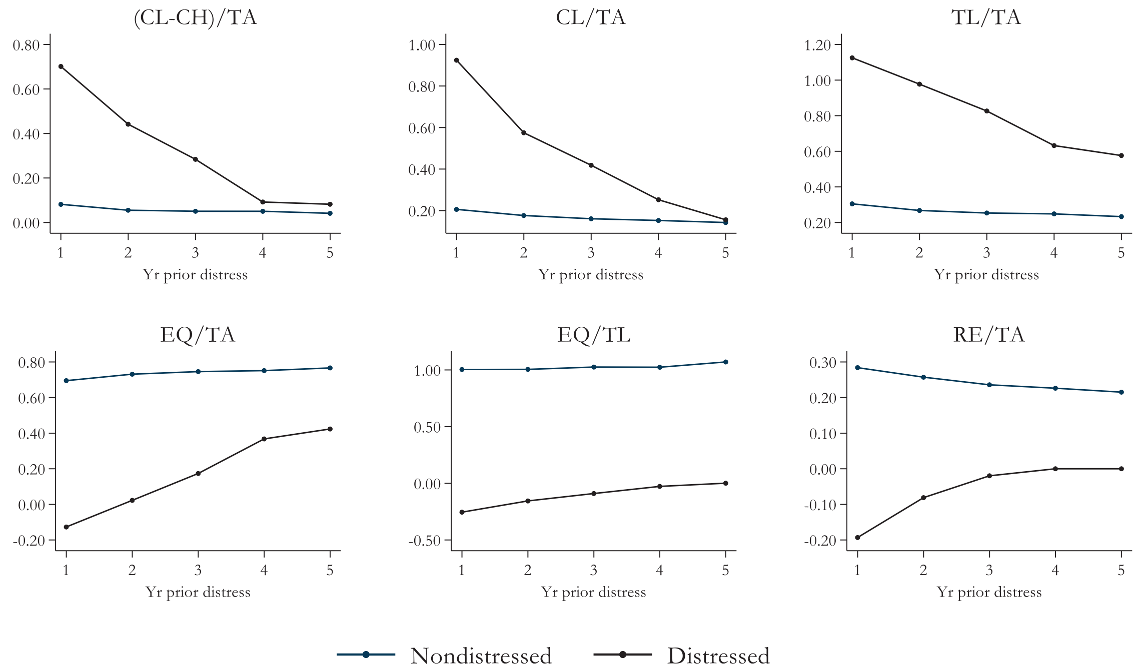
Source: Author's calculation

Figure 20.b. Comparison of median values for distressed and non-distressed firms using turnover ratios



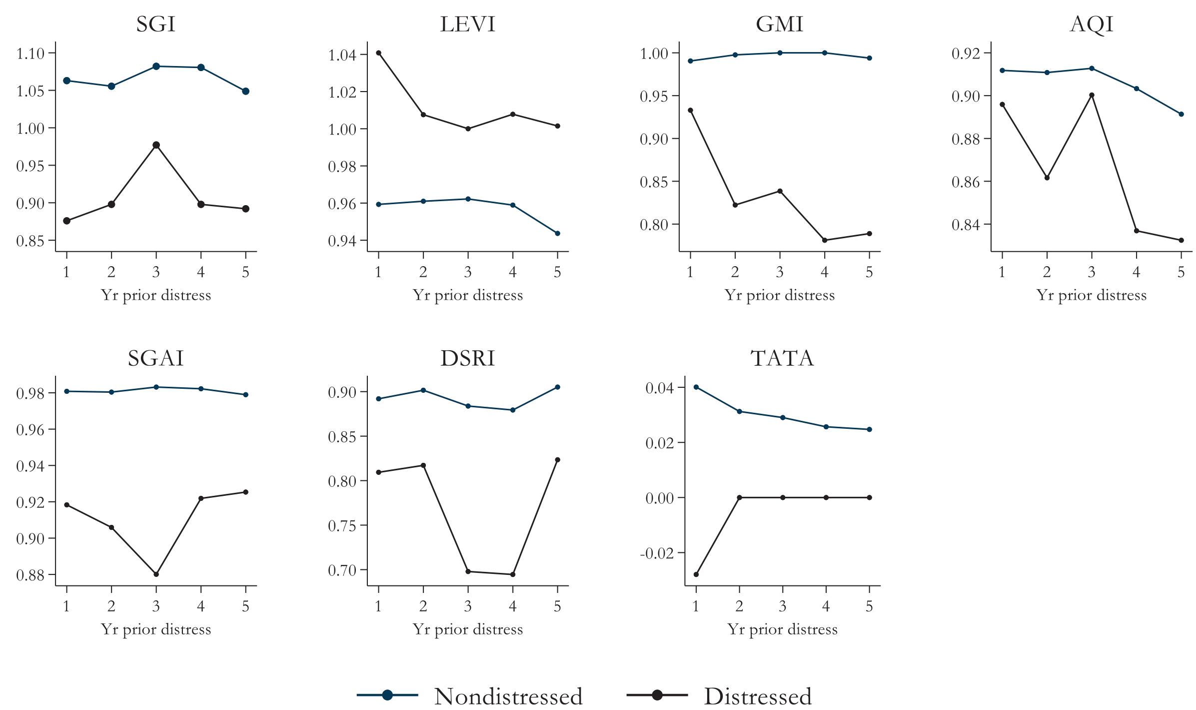
Source: Author's calculation

Figure 20.c. Comparison of median values for distressed and non-distressed firms using leverage ratios



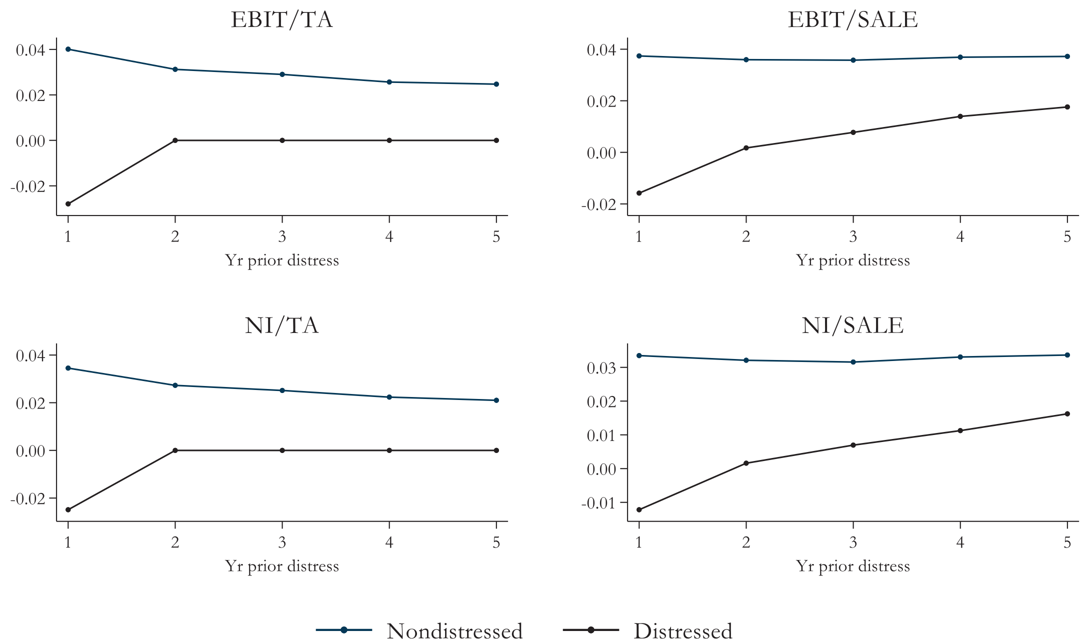
Source: Author's calculation

Figure 20.d. Comparison of median values for distressed and non-distressed firms using indexes



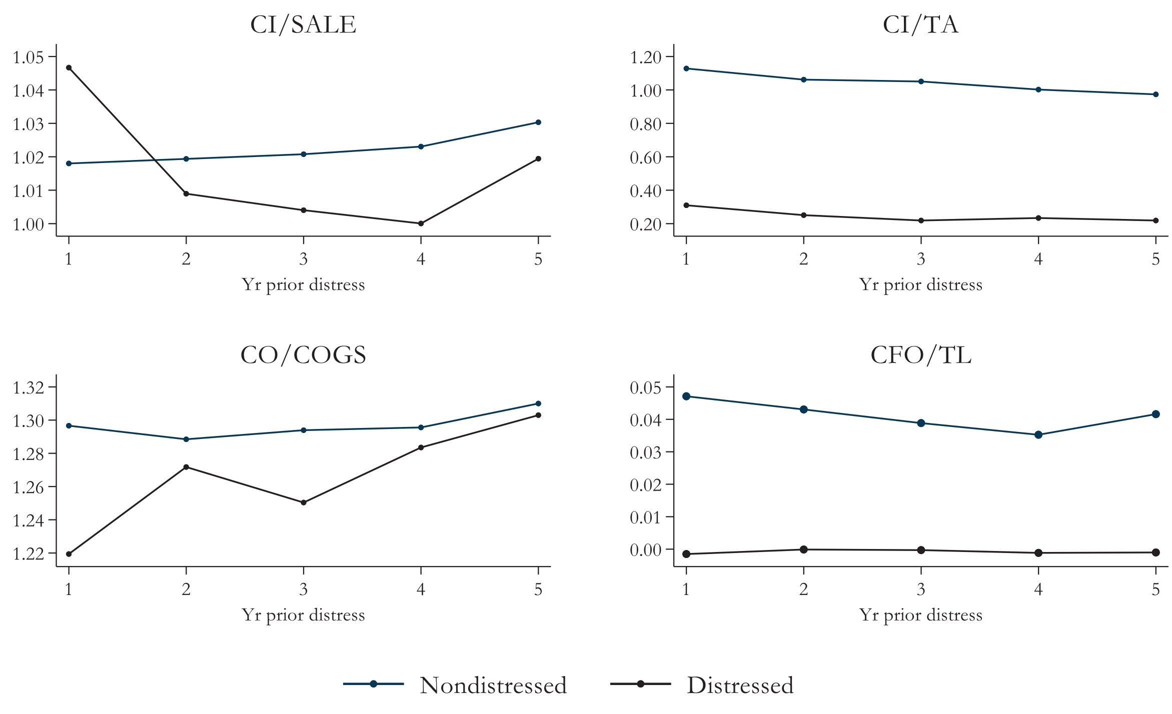
Source: Author's calculation

Figure 21.d. Comparison of median values for distressed and non-distressed firms using profitability ratios



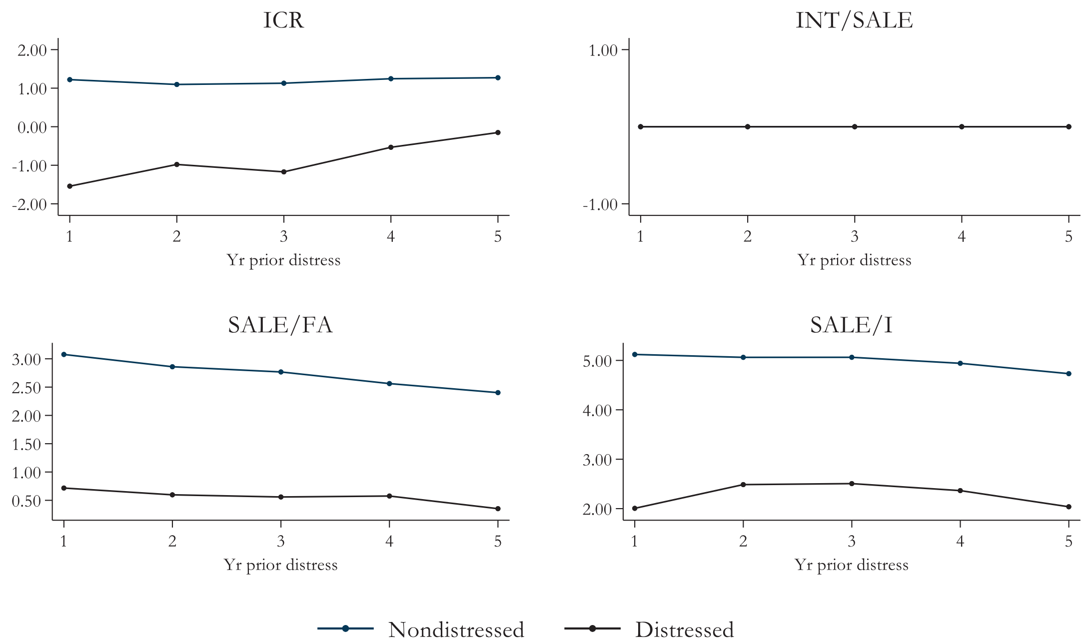
Source: Author's calculation

Figure 22.d. Comparison of median values for distressed and non-distressed firms using cash flow ratios



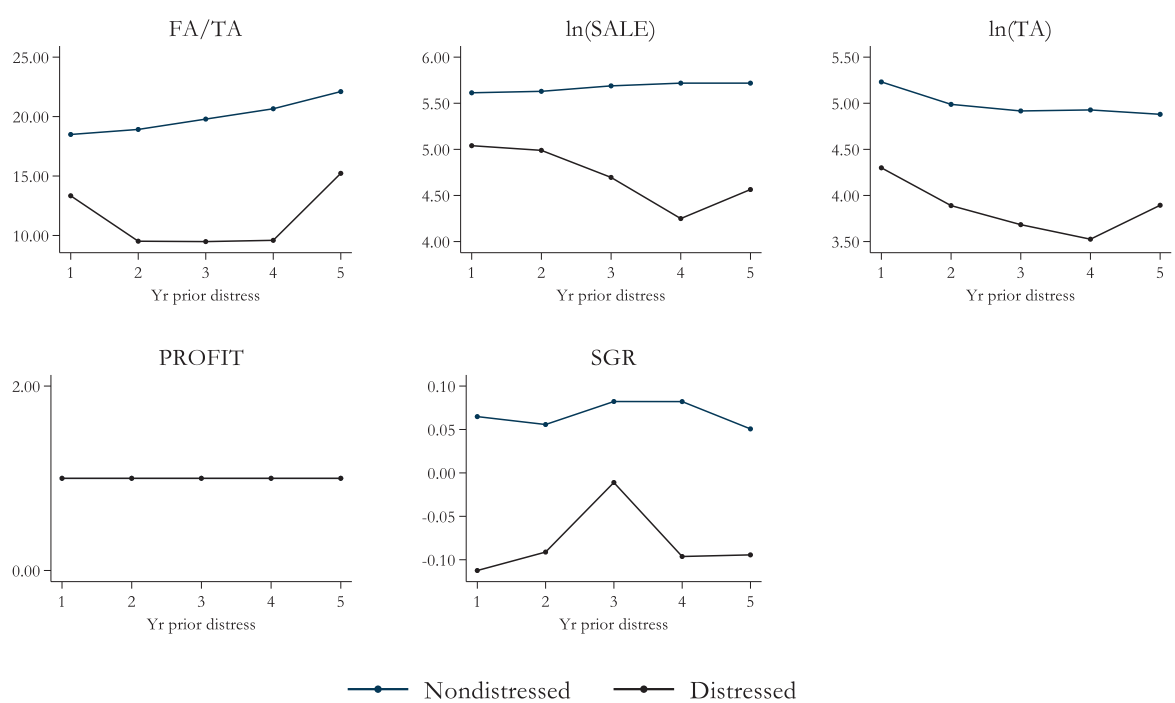
Source: Author's calculation

Figure 22.e. Comparison of median values for distressed and non-distressed firms using interest and productivity ratios



Source: Author's calculation

Figure 22.f. Comparison of median values for distressed and non-distressed firms using other variables



Source: Author's calculation

Table 7.a. Wilcoxon ***Z*** and Median χ^2 of liquidity ratios under full sample

		1 year prior		2 years prior		3 years prior		4 years prior		5 years prior	
		Non	**Dist**	**Non**	**Dist**	**Non**	**Dist**	**Non**	**Dist**	**Non**	**Dist**
	N										
Liquidity ratios											
CH/CL	Mean	0.62	0.27	0.59	0.35	0.57	0.38	0.57	0.42	0.63	0.46
	Median	0.11	0.03	0.10	0.03	0.10	0.03	0.09	0.03	0.09	0.03
	Wilcoxon *Z*	11.20***		8.03***		6.88***		5.56***		4.56***	
	Median χ^2	74.81***		38.95***		30.75***		18.86***		17.22***	
LA/CL	Mean	0.63	0.28	0.59	0.36	0.57	0.40	0.58	0.43	0.63	0.48
	Median	0.11	0.03	0.11	0.04	0.10	0.03	0.10	0.03	0.10	0.04
	Wilcoxon *Z*	10.96***		7.58***		6.23***		5.27***		4.19***	
	Median χ^2	74.81***		36.54***		22.67***		15.84***		12.78***	
QA/CL	Mean	1.82	0.71	1.74	0.86	1.75	1.07	1.82	1.12	1.93	1.32
	Median	0.75	0.15	0.72	0.19	0.71	0.21	0.70	0.21	0.69	0.26
	Wilcoxon *Z*	17.26***		13.10***		10.45***		8.81***		5.91***	
	Median χ^2	200.43***		117.50***		77.96***		47.87***		20.21***	
CA/CL	Mean	3.56	1.26	3.54	1.64	3.70	2.31	3.88	2.52	4.05	2.54
	Median	1.51	0.42	1.49	0.59	1.50	0.66	1.52	0.73	1.56	0.90
	Wilcoxon *Z*	23.25***		17.76***		13.54***		10.55***		8.07***	
	Median χ^2	341.02***		209.52***		121.23**		62.48***		34.25***	
RE/CL	Mean	2.02	-0.45	2.00	-0.03	2.05	0.30	2.01	0.64	2.23	0.85
	Median	0.57	-0.42	0.56	-0.34	0.56	-0.29	0.55	-0.22	0.57	-0.11
	Wilcoxon *Z*	27.65***		22.44***		18.51***		13.98***		11.19***	
	Median χ^2	502.86***		354.42***		244.69***		133.06***		80.66***	
CA/TA	Mean	0.65	0.58	0.64	0.60	0.63	0.60	0.62	0.60	0.64	0.63
	Median	0.75	0.63	0.74	0.69	0.71	0.70	0.71	0.67	0.72	0.79
	Wilcoxon *Z*	3.21***		1.07		0.18		-0.30		-1.32	
	Median χ^2	6.43**		1.09		0.03		0.58		1.40	
CH/TA	Mean	0.23	0.23	0.24	0.29	0.24	0.30	0.24	0.31	0.24	0.29
	Median	0.06	0.03	0.06	0.05	0.06	0.05	0.05	0.06	0.05	0.04
	Wilcoxon *Z*	2.52***		0.00		-0.73		-1.67		-0.05	
	Median χ^2	5.21**		0.48		0.00		1.41		0.17	
WC/TA	Mean	0.33	-0.30	0.33	-0.09	0.33	0.00	0.32	0.08	0.31	0.14
	Median	0.30	-0.16	0.31	0.00	0.32	0.04	0.30	0.12	0.30	0.16
	Wilcoxon *Z*	19.87***		12.39***		8.23***		5.15***		3.32***	
	Median χ^2	209.83***		90.97***		46.34***		16.48***		7.60***	
WC/CA	Mean	0.47	-0.17	0.49	0.09	0.49	0.24	0.49	0.35	0.50	0.45
	Median	0.64	-0.02	0.67	0.24	0.69	0.52	0.70	0.72	0.72	0.81
	Wilcoxon *Z*	13.44***		6.81***		2.77***		0.20		-0.55	
	Median χ^2	92.92***		20.31***		4.13***		0.13		0.64	
CL/TL	Mean	0.90	0.83	0.89	0.84	0.89	0.84	0.89	0.84	0.88	0.84
	Median	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
	Wilcoxon *Z*	3.23***		2.24***		1.73*		1.26		1.37	
CL/SALE	Mean	0.30	0.63	0.29	0.54	0.28	0.49	0.29	0.44	0.30	0.40
	Median	0.12	0.42	0.12	0.34	0.12	0.29	0.13	0.23	0.13	0.20
	Wilcoxon *Z*	-10.72***		-7.70***		-5.22***		-2.68***		-1.68*	
	Median χ^2	76.35***		35.37***		18.98***		5.04**		1.16	

Source: Author's calculation

Table 7.b. Wilcoxon $\boldsymbol{Z}$ and Median $\boldsymbol{\chi^2}$ of leverage ratios under full sample

		1 year prior		2 years prior		3 years prior		4 years prior		5 years prior	
		Non	**Dist**	**Non**	**Dist**	**Non**	**Dist**	**Non**	**Dist**	**Non**	**Dist**
	N										
		Leverage ratios									
(CL-CH)/TA	Mean	0.10	0.69	0.08	0.43	0.07	0.30	0.07	0.22	0.06	0.20
	Median	0.08	0.70	0.06	0.44	0.06	0.28	0.05	0.09	0.04	0.08
	Wilcoxon Z	-17.37***		-10.11***		-6.13***		-3.05***		-2.52**	
	Median χ^2	113.71***		38.92***		7.87***		0.48		0.91	
CL/TA	Mean	0.10	0.69	0.08	0.43	0.07	0.30	0.07	0.22	0.06	0.20
	Median	0.08	0.70	0.06	0.44	0.06	0.28	0.05	0.09	0.04	0.08
	Wilcoxon Z	-17.37***		-10.11***		-6.13***		-3.05***		-2.52**	
	Median χ^2	113.71***		38.92***		7.87***		0.48		0.91	
TL/TA	Mean	0.38	1.16	0.37	0.90	0.37	0.77	0.37	0.67	0.36	0.63
	Median	0.30	1.13	0.27	0.98	0.25	0.83	0.25	0.63	0.23	0.58
	Wilcoxon Z	-26.03***		-16.25***		-10.87***		-6.96		-5.73	
	Median χ^2	293.82***		102.63***		44.16***		16.37		7.89	
EQ/TA	Mean	0.62	-0.16	0.63	0.10	0.63	0.23	0.63	0.33	0.64	0.37
	Median	0.70	-0.13	0.73	0.02	0.75	0.17	0.75	0.37	0.77	0.42
	Wilcoxon Z	26.07***		16.24***		10.87***		6.96***		5.73***	
	Median χ^2	295.73***		102.52***		44.07***		16.37***		7.89***	
EQ/TL	Mean	3.42	0.23	3.69	0.71	3.78	1.36	3.84	1.84	4.21	2.02
	Median	1.00	-0.25	1.01	-0.16	1.03	-0.09	1.03	-0.03	1.07	0.00
	Wilcoxon Z	31.62***		24.46***		19.43***		14.68***		11.46***	
	Median χ^2	532.78***		329.95***		207.07***		119.21***		73.01***	
RE/TA	Mean	0.33	-0.26	0.30	-0.13	0.29	-0.08	0.28	-0.03	0.27	-0.01
	Median	0.28	-0.19	0.26	-0.08	0.24	-0.02	0.23	0.0	0.22	0.0
	Wilcoxon Z	24.43***		20.37***		17.78***		14.63***		12.45***	
	Median χ^2	312.01***		251.96***		196.63***		119.75***		78.17***	

Source: Author's calculation

Table 7.c. Wilcoxon Z and Median χ^2 of profitability ratios under full sample

		1 year prior		2 years prior		3 years prior		4 years prior		5 years prior	
		Non	**Dist**	**Non**	**Dist**	**Non**	**Non**	**Dist**	**Non**	**Dist**	**Non**
	N										
		Profitability ratios									
EBIT/TA	Mean	7.74	-4.59	6.84	-2.27	6.36	-1.43	6.01	-0.91	5.94	-0.20
	Median	4.01	-2.79	3.12	0.00	2.90	0.00	2.57	0.00	2.47	0.00
	Wilcoxon Z	19.75***		16.31***		13.84***		10.97***		9.22***	
	Median χ^2	231.64***		171.96***		134.27***		96.42***		68.95***	
EBIT/SALE	Mean	0.06	-0.03	0.06	-0.01	0.06	0.00	0.06	0.01	0.06	0.02
	Median	0.04	-0.02	0.04	0.00	0.04	0.01	0.04	0.01	0.04	0.02
	Wilcoxon Z	14.71***		10.72***		8.62***		5.11***		4.35***	
	Median χ^2	115.24***		55.24***		42.31***		17.64***		13.53***	
NI/TA	Mean	0.07	-0.04	0.06	-0.02	0.05	-0.01	0.05	-0.01	0.05	0.00
	Median	0.03	-0.02	0.02	0.00	0.03	0.00	0.02	0.00	0.02	0.00
	Wilcoxon Z	19.28***		15.70***		13.38***		10.39***		8.50***	
	Median χ^2	225.34***		151.52***		124.31***		87.41***		62.67***	
NI/SALE	Mean	0.06	-0.03	0.05	-0.01	0.05	-0.01	0.05	0.01	0.05	0.02
	Median	0.03	-0.01	0.03	0.00	0.03	0.01	0.03	0.01	0.03	0.02
	Wilcoxon Z	14.53***		10.69***		8.67***		5.69***		3.94***	
	Median χ^2	106.86***		56.25***		40.53***		17.72***		11.07***	

Source: Author's calculation

Table 7.d. Wilcoxon Z and Median χ^2 of turnover ratios under full sample

		1 year prior		2 years prior		3 years prior		4 years prior		5 years prior	
		Non	**Dist**	**Non**	**Dist**	**Non**	**Dist**	**Non**	**Dist**	**Non**	**Dist**
	N										
		Turnover ratios									
RT	Mean	16.38	13.94	16.53	15.25	16.83	14.19	16.24	14.73	16.05	14.20
	Median	6.32	2.75	6.28	2.77	6.48	3.00	6.47	2.91	6.32	2.27
	Wilcoxon Z	7.25***		6.48***		6.08***		5.23***		5.56***	
	Median χ^2	36.46***		26.98***		25.98***		26.84***		28.15***	
360/RT	Mean	57.15	64.85	56.39	62.49	54.90	60.41	55.10	63.33	57.63	75.13
	Median	28.98	30.32	29.21	30.97	28.51	31.86	28.82	33.93	29.20	35.45
	Wilcoxon Z	-0.60		-0.12		-0.41		-0.77		-1.25	
	Median χ^2	0.03		0.02		0.01		0.07		0.33	
CAST	Mean	3.21	2.24	3.13	2.40	3.13	2.41	2.98	2.17	2.85	1.80
	Median	2.02	0.58	1.96	0.52	1.95	0.44	1.88	0.37	1.79	0.22
	Wilcoxon Z	11.62***		10.06***		9.18***		8.70***		8.43***	
	Median χ^2	96.07***		79.69***		69.85***		73.50***		59.77***	
360/CAST	Mean	184.57	201.7	177.63	177.5	174.01	164.1	175.60	177.38	182.17	200.4
	Median	121.69	106.3	118.47	92.79	116.04	88.42	118.45	99.81	126.72	109.5
	Wilcoxon Z	1.19		2.37**		2.64***		1.29		0.71	
	Median χ^2	1.81		6.71**		4.63**		1.46		0.34	
PTR	Mean	11.13	3.98	11.32	4.04	11.91	4.04	11.27	4.29	11.10	5.01
	Median	5.36	0.46	5.38	0.46	5.72	0.56	5.38	0.61	5.19	0.59
	Wilcoxon Z	14.13***		12.43***		11.23***		9.22***		7.58***	
	Median χ^2	161.96***		104.53***		81.78***		63.49***		38.04***	
360/PTR	Mean	69.71	123.4	69.00	111.2	67.04	116.6	71.40	113.37	70.94	103.4
	Median	31.24	77.91	31.27	65.74	30.11	66.94	30.85	66.72	31.96	58.80
	Wilcoxon Z	-7.95***		-6.09***		-6.13***		-4.96***		-3.38***	
	Median χ^2	44.28***		32.88***		33.68***		28.86***		11.86***	
IT	Mean	5.00	3.86	5.08	3.94	5.21	3.88	5.02	3.57	4.75	3.18
	Median	2.89	0.70	2.92	0.75	2.92	1.04	2.88	0.98	2.81	0.75
	Wilcoxon Z	7.73***		7.13***		5.84***		5.68***		5.75***	
	Median χ^2	54.79***		43.70***		25.69***		31.58***		32.88***	
360/IT	Mean	108.44	131.9	108.11	135.5	108.25	125.1	112.45	139.36	120.16	154.0
	Median	71.49	63.98	72.52	75.04	71.87	78.25	74.44	71.83	79.00	80.53
	Wilcoxon Z	-0.34		-0.48		-0.57		-0.70		-0.92	
	Median χ^2	0.01		0.01		0.03		0.03		0.01	
OC	Mean	159.98	159.0	158.14	159.2	156.60	159.0	161.14	164.02	167.60	187.2
	Median	101.71	76.37	102.64	82.92	102.64	88.11	104.72	93.51	109.81	106.8
	Wilcoxon Z	2.47**		1.92*		1.24		0.82		0.11	
	Median χ^2	4.83**		4.03*		2.06		0.83		0.01	
NOC	Mean	103.36	48.18	101.22	63.85	100.37	60.32	103.38	68.05	111.73	85.03
	Median	69.06	21.59	68.07	27.30	66.40	27.30	68.87	29.35	71.20	34.97
	Wilcoxon Z	7.09***		5.21***		4.33***		3.37***		2.51**	
	Median χ^2	34.54***		22.45***		14.50***		10.70***		4.89**	
WC/SALE	Mean	0.21	-0.09	0.20	-0.03	0.19	0.02	0.19	0.07	0.20	0.12
	Median	0.15	-0.08	0.14	0.00	0.14	0.02	0.15	0.05	0.15	0.06
	Wilcoxon Z	13.89***		10.31***		7.55***		5.15***		3.14***	
	Median χ^2	107.47***		64.25***		37.84***		17.98***		10.94***	
SALE/TA	Mean	1.53	1.02	1.47	0.96	1.47	0.99	1.43	0.92	1.35	0.82
	Median	1.03	0.26	0.91	0.17	0.95	0.12	0.92	0.13	0.89	0.08
	Wilcoxon Z	9.02***		10.74***		10.54***		9.47***		8.79***	
	Median χ^2	91.24***		98.53***		90.37***		79.72***		63.40***	
I/SALE	Mean	0.15	0.12	0.16	0.12	0.16	0.14	0.17	0.16	0.18	0.17
	Median	0.07	0.00	0.07	0.01	0.07	0.02	0.08	0.03	0.09	0.03
	Wilcoxon Z	6.36***		5.40***		4.29***		2.93***		2.52**	
	Median χ^2	49.15***		42.27***		21.90***		9.77***		9.31***	

Source: Author's calculation

Table 7.e. Wilcoxon Z and Median χ^2 of indexes under full sample

		1 year prior		2 years prior		3 years prior		4 years prior		5 years prior	
		Non	**Dist**	**Non**	**Dist**	**Non**	**Dist**	**Non**	**Dist**	**Non**	**Dist**
	N										
						Indexes					
SGI	Mean	1.18	0.98	1.17	1.03	1.22	1.07	1.23	1.10	1.20	1.06
	Median	1.06	0.88	1.06	0.90	1.08	0.98	1.08	0.90	1.05	0.89
	Wilcoxon Z	6.03***		4.12***		3.31***		3.64***		2.98***	
	Median χ^2	18.44***		10.48***		3.49*		10.48***		7.75***	
LEVI	Mean	0.91	1.03	0.91	1.01	0.91	0.97	0.91	0.99	0.90	0.96
	Median	0.96	1.04	0.96	1.01	0.96	1.00	0.96	1.01	0.94	1.00
	Wilcoxon Z	-8.49***		-6.29***		-4.00***		-4.32***		-3.19***	
	Median χ^2	109.28***		75.18***		39.93***		40.05***		23.36***	
GMI	Mean	0.87	0.69	0.87	0.67	0.88	0.65	0.88	0.62	0.88	0.63
	Median	0.99	0.93	1.00	0.82	1.00	0.84	1.00	0.78	0.99	0.79
	Wilcoxon Z	5.58***		6.39***		5.86***		5.83***		4.41***	
	Median χ^2	4.38**		15.19***		11.64***		13.90***		7.70***	
AQI	Mean	0.80	0.79	0.78	0.75	0.79	0.75	0.77	0.74	0.76	0.74
	Median	0.91	0.90	0.91	0.86	0.91	0.90	0.90	0.84	0.89	0.83
	Wilcoxon Z	0.22		0.74		0.48		1.08		0.59	
	Median χ^2	0.22		1.53		0.04		1.67		1.54	
SGAI	Mean	0.93	0.79	0.93	0.76	0.94	0.73	0.93	0.78	0.92	0.79
	Median	0.98	0.92	0.98	0.91	0.98	0.88	0.98	0.92	0.98	0.93
	Wilcoxon Z	5.03***		6.11***		6.53***		4.06***		2.88***	
	Median χ^2	10.94***		17.35***		15.61***		8.57***		5.15**	
DSRI	Mean	1.15	1.20	1.15	1.13	1.13	1.00	1.14	1.06	1.17	1.28
	Median	0.89	0.81	0.90	0.82	0.89	0.70	0.88	0.69	0.91	0.82
	Wilcoxon Z	1.05		1.07		2.02**		1.74*		0.43	
	Median χ^2	0.81		2.12		2.91*		1.49		0.04	
TATA	Mean	0.07	-0.05	0.07	-0.02	0.06	-0.01	0.06	-0.01	0.06	0.00
	Median	0.03	-0.03	0.02	0.00	0.03	0.00	0.02	0.00	0.02	0.00
	Wilcoxon Z	19.21***		15.93***		13.54***		10.72***		9.05***	
	Median χ^2	205.97***		155.93***		124.44***		89.46***		64.57***	

Source: Author's calculation

Table 7.f. Wilcoxon Z and Median χ^2 of other ratios under full sample

		1 year prior		2 years prior		3 years prior		4 years prior		5 years prior	
		Non	**Dist**	**Non**	**Dist**	**Non**	**Dist**	**Non**	**Dist**	**Non**	**Dist**
	N										
Cash flow ratios											
CI/SALE	Mean	1.06	1.06	1.06	1.06	1.06	1.06	1.06	1.06	1.06	1.06
	Median	1.02	1.05	1.02	1.01	1.02	1.00	1.02	1.00	1.03	1.02
	Wilcoxon Z	-0.31		0.80		0.32		0.53		0.06	
	Median χ^2	1.77		0.03		0.25		0.82		0.05	
CI/TA	Mean	1.70	1.13	1.63	1.14	1.62	1.15	1.54	1.05	1.46	0.93
	Median	1.13	0.31	1.06	0.25	1.05	0.22	1.00	0.23	0.97	0.22
	Wilcoxon Z	11.97***		11.11***		10.67***		9.15***		8.35***	
	Median χ^2	103.42***		89.66***		84.48***		68.20***		56.00***	
CO/ COGS	Mean	1.45	1.41	1.43	1.42	1.44	1.41	1.43	1.47	1.45	1.49
	Median	1.30	1.22	1.29	1.27	1.29	1.25	1.30	1.28	1.31	1.30
	Wilcoxon Z	2.76***		1.52		1.78*		-0.04		-0.21	
	Median χ^2	3.86**		0.30		1.69		0.11		0.01	
CFO/TL	Mean	0.19	-0.05	0.18	-0.03	0.18	-0.03	0.17	-0.05	0.16	-0.02
	Median	0.05	0.00	0.04	0.00	0.04	0.00	0.03	0.00	0.04	0.00
	Wilcoxon Z	11.49***		9.24***		7.90***		7.27***		6.22***	
	Median χ^2	154.11***		95.52***		77.99***		61.03***		41.07***	
Interest ratios											
ICR	Mean	3.20	-1.78	3.00	-1.33	3.01	-1.35	2.86	-0.78	2.92	-0.37
	Median	1.22	-1.54	1.10	-0.98	1.13	-1.17	1.25	0.53	1.27	-0.15
	Wilcoxon Z	11.06***		9.21***		8.77***		7.25***		5.62***	
	Median χ^2	60.12***		52.32***		41.41***		45.72***		34.37***	
INT/ SALE	Mean	0.00	0.00	0.00	0.00	0.00	0.00	0.00		0.00	0.00
	Median	0.00	0.00	0.00	0.00	0.00	0.00	0.00		0.00	0.00
	Wilcoxon Z	5.06***		4.88***		4.97***		5.54***		3.94***	
	Median χ^2	22.40***		21.47***		22.69***		29.07***		14.97***	
Productivity ratios											
SALE/FA	Mean	8.18	5.79	7.79	5.55	7.70	5.67	7.20	5.40	6.52	3.90
	Median	3.08	0.72	2.86	0.60	2.77	0.56	2.56	0.58	2.40	0.35
	Wilcoxon Z	10.91***		9.58***		9.23***		7.96***		7.41***	
	Median χ^2	83.52***		68.65***		56.27***		40.06***		36.89***	
SALE/I	Mean	9.11	7.31	9.16	8.21	9.33	7.99	8.51	7.74	8.16	6.72
	Median	5.12	2.01	5.06	2.49	5.06	2.51	4.94	2.37	4.73	2.04
	Wilcoxon Z	7.57***		5.70***		4.99***		4.40***		5.26***	
	Median χ^2	35.47***		20.22***		14.99***		12.94***		19.54***	
Fixed asset utilization											
FA/TA	Mean	30.01	30.95	30.66	29.9	31.48	29.99	32.24	30.01	33.10	32.40
	Median	18.50	13.33	18.92	9.52	19.79	9.49	20.66	9.59	22.10	15.23
	Wilcoxon Z	0.93		2.62***		3.11***		3.12***		1.89*	
	Median χ^2	1.40		8.23***		7.80***		4.40**		0.98	
Other											
ln (SALE)	Mean	6.33	5.82	6.33	5.89	6.37	5.63	6.42	5.24	6.38	5.21
	Median	5.61	5.04	5.63	4.99	5.69	4.70	5.72	4.25	5.72	4.56
	Wilcoxon Z	2.66***		2.07**		3.46***		5.06***		4.16***	
	Median χ^2	5.23**		3.96**		13.55***		21.09***		11.51***	
ln (TA)	Mean	5.86	5.32	5.57	4.76	5.51	4.48	5.53	4.35	5.49	4.62
	Median	5.23	4.30	4.99	3.89	4.92	3.68	4.93	3.53	4.88	3.89
	Wilcoxon Z	3.42***		4.59***		5.18***		5.30***		3.54***	
	Median χ^2	7.78***		16.00***		13.86***		10.42***		3.69***	
PROFIT	Mean	0.98	0.92	0.98	0.95	0.98	0.96	0.98	0.96	0.98	0.97
	Median	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
	Wilcoxon Z	9.65***		4.43***		1.85*		2.64***		0.97	

Source: Author's calculation

Table 8.a. Wilcoxon Z and Median χ^2 test results for liquidity ratios under training and test sample

			Liquidity ratios				
CH/CL	Training	Wilcoxon Z	7.35***	5.24***	4.45***	3.08***	1.56
		Median χ^2	30.52***	14.67***	13.82***	5.51***	1.97
	Test	Wilcoxon Z	9.04***	6.79***	4.85***	3.46***	3.34***
		Median χ^2	47.06***	25.69***	11.27***	4.58***	6.54***
LA/CL	Training	Wilcoxon Z	7.19***	4.91***	3.95***	2.84***	1.29
		Median χ^2	29.56***	12.82***	9.36***	4.05**	1.06
	Test	Wilcoxon Z	8.86***	6.51***	4.64***	3.32***	3.18***
		Median χ^2	45.16***	24.16***	10.17***	3.12*	5.50**
QA/CL	Training	Wilcoxon Z	11.58***	8.35***	7.38***	5.90***	3.06***
		Median χ^2	94.38***	62.46***	47.30***	34.50***	7.73***
	Test	Wilcoxon Z	11.48***	8.91***	6.04***	4.35***	3.28***
		Median χ^2	85.41***	43.65***	16.24***	8.33***	3.68*
CA/CL	Training	Wilcoxon Z	16.78***	12.52***	10.03***	8.00***	5.22***
		Median χ^2	219.80***	128.57***	78.20***	35.30***	17.39***
	Test	Wilcoxon Z	14.45***	11.66***	8.31***	5.67***	4.54***
		Median χ^2	98.85***	74.06***	32.62***	11.89***	8.90***
RE/CL	Training	Wilcoxon Z	18.66***	15.59***	13.11***	9.83***	7.17***
		Median χ^2	315.10***	212.99***	159.85***	96.61***	55.85***
	Test	Wilcoxon Z	18.44***	14.67***	11.22***	7.83***	6.23***
		Median χ^2	169.65***	112.47***	62.38***	28.26***	21.98***
CA/TA	Training	Wilcoxon Z	2.77***	1.25	0.22	-0.15	-0.73
		Median χ^2	3.79*	0.69	0.10	0.47	0.10
	Test	Wilcoxon Z	1.88*	0.40	0.31	-0.02	-0.87
		Median χ^2	2.80*	0.57	0.08	0.23	0.91
CH/TA	Training	Wilcoxon Z	-2.14**	0.19	-0.32	-1.42	-0.53
		Median χ^2	2.95*	0.06	0.07	0.75	0.05
	Test	Wilcoxon Z	1.52	-0.16	-0.56	-0.68	0.85
		Median χ^2	2.37	0.38	0.02	0.41	0.41
WC/TA	Training	Wilcoxon Z	15.83***	9.64***	6.18***	4.23***	2.83***
		Median χ^2	157.91***	67.21***	31.56***	14.02***	4.58***
	Test	Wilcoxon Z	14.76***	8.95***	5.94***	3.02***	1.91*
		Median χ^2	99.31***	46.76***	21.79***	4.10***	2.48
WC/CA	Training	Wilcoxon Z	11.79***	5.79***	1.41	1.38	0.44
		Median χ^2	81.98***	15.32***	0.77	0.59	0.28
	Test	Wilcoxon Z	12.59***	7.39***	4.41***	2.33**	2.70***
		Median χ^2	76.77***	31.30***	9.22***	1.12	3.26*
CL/TL	Training	Wilcoxon Z	3.57	2.50	2.25	2.29**	2.72***
	Test	Wilcoxon Z	0.86	0.70	0.09	-0.74	-1.17
CL/SALE	Training	Wilcoxon Z	-8.91***	-6.22***	-5.09***	-3.10***	-1.27
		Median χ^2	58.96***	31.40***	20.91***	6.06**	0.59
	Test	Wilcoxon Z	-10.91***	-7.69***	-4.46***	-2.47***	-3.00***
		Median χ^2	63.96***	27.17***	9.52***	3.02***	3.74*

Source: Author's calculation

Table 8.b. Wilcoxon Z and Median χ^2 test results for leverage ratios under training and test sample

Leverage ratios							
(CL-CH)/TA	Training	Wilcoxon Z	-13.94***	-8.00***	-5.02***	-2.55**	-1.95*
		Median χ^2	82.26***	27.98***	8.53***	0.89	0.34
	Test	Wilcoxon Z	-13.11***	-7.28***	-4.17***	-2.09***	-2.55**
		Median χ^2	65.48***	19.82***	3.12*	0.10***	1.47
CL/TA	Training	Wilcoxon Z	-13.75***	-8.17***	-5.41***	-3.36***	-2.29**
		Median χ^2	93.94***	29.42***	12.84***	3.41***	0.31
	Test	Wilcoxon Z	-13.60***	-7.70***	-4.46***	-2.09**	-2.11**
		Median χ^2	74.42***	23.65***	4.24***	0.00	0.01
TL/TA	Training	Wilcoxon Z	-20.38***	-12.95***	-8.72***	-6.06***	-4.94***
		Median χ^2	238.75***	93.12***	37.61***	19.81***	9.42***
	Test	Wilcoxon Z	-18.20***	-10.78***	-6.92***	-3.82***	-3.06***
		Median χ^2	127.74***	42.35***	13.48***	2.58	1.47
EQ/TA	Training	Wilcoxon Z	20.38***	12.95***	8.72***	6.06***	4.94***
		Median χ^2	237.92***	93.12***	37.61***	19.48***	9.42***
	Test	Wilcoxon Z	18.12***	10.79***	6.93***	3.82***	3.06***
		Median χ^2	127.74***	42.35***	133.39***	2.58	1.44
EQ/TL	Training	Wilcoxon Z	22.29***	16.19***	12.87***	9.59***	7.17***
		Median χ^2	351.74***	192.52***	134.46***	63.82***	35.82***
	Test	Wilcoxon Z	19.97***	15.92***	11.77***	7.97***	5.88***
		Median χ^2	165.44***	103.90***	54.89***	24.13***	13.71***
RE/TA	Training	Wilcoxon Z	16.85***	13.50***	12.22***	9.78***	8.57***
		Median χ^2	190.14***	145.83***	128.22***	81.38***	62.87***
	Test	Wilcoxon Z	18.98***	15.28***	12.48***	10.18***	7.88***
		Median χ^2	149.78***	118.62***	82.53***	45.59***	25.99***

Source: Author's calculation

Table 8.c. Wilcoxon Z and Median χ^2 test results for leverage ratios under training and test sample

Profitability ratios							
EBIT/TA	Training	Wilcoxon Z	14.15***	9.89***	8.42***	6.10***	5.17***
		Median χ^2	135.12***	71.09***	55.69***	36.10***	26.28***
	Test	Wilcoxon Z	17.18***	13.65***	11.19***	8.47***	6.82***
		Median χ^2	149.78***	104.17***	74.73***	39.31***	27.92***
EBIT/SALE	Training	Wilcoxon Z	11.93***	7.17***	6.09***	4.23***	3.23***
		Median χ^2	89.69***	30.81***	19.79***	13.32***	5.14**
	Test	Wilcoxon Z	14.00***	11.00***	7.54***	5.17***	4.09***
		Median χ^2	79.89***	49.69***	26.29***	14.29***	9.76***
NI/TA	Training	Wilcoxon Z	13.88***	11.22***	7.99***	5.70***	4.88***
		Median χ^2	129.68***	92.45***	50.07***	33.13***	23.78***
	Test	Wilcoxon Z	17.35***	13.61***	11.41***	8.67***	6.75***
		Median χ^2	146.52***	104.17***	77.29***	41.35***	27.92***
NI/SALE	Training	Wilcoxon Z	11.61***	7.07***	6.02***	4.04***	3.14***
		Median χ^2	76.51***	27.64***	19.39***	11.04***	4.79***
	Test	Wilcoxon Z	14.17***	10.93***	7.75***	5.38***	4.01***
		Median χ^2	85.60***	49.69***	28.24***	12.79***	9.76***

Source: Author's calculation

Table 8.d. Wilcoxon Z and Median χ^2 test results for turnover ratios under training and test sample

			Turnover ratios				
RT	Training	Wilcoxon Z	2.83^{***}	2.38^{**}	2.00^{**}	1.03	1.80^{*}
		Median χ^2	5.10^{**}	1.73	1.36	1.78	3.17^{*}
	Test	Wilcoxon Z	5.72^{***}	4.44^{***}	4.93^{***}	4.55^{***}	4.55^{***}
		Median χ^2	19.05^{***}	11.06^{***}	12.35^{***}	8.76^{***}	10.01^{***}
360/RT	Training	Wilcoxon Z	-0.08	0.19	0.25	0.12	-0.29
		Median χ^2	0.18	0.22	0.01	0.05	0.02
	Test	Wilcoxon Z	-2.18	-1.05	-1.02	-1.28	-1.44
		Median χ^2	1.84	0.81	1.33	1.65	1.66
CAST	Training	Wilcoxon Z	11.39^{***}	9.95^{***}	9.14^{***}	8.77^{***}	8.37^{***}
		Median χ^2	76.98^{***}	63.50^{***}	54.90^{***}	65.02^{***}	65.41^{***}
	Test	Wilcoxon Z	8.67^{***}	7.14^{***}	6.35^{***}	5.35^{***}	5.30^{***}
		Median χ^2	36.98^{***}	28.27^{***}	22.84^{***}	21.09^{***}	23.73^{***}
360/CAST	Training	Wilcoxon Z	0.70	1.59	1.29	0.86	1.17
		Median χ^2	0.97	3.93	1.56	0.22	1.25
	Test	Wilcoxon Z	-2.91^{****}	-1.11	0.20	-0.26	-0.94
		Median χ^2	3.45^{*}	0.12	0.15	0.01	0.59
PT	Training	Wilcoxon Z	16.08^{***}	14.09^{***}	12.55^{***}	10.60^{***}	9.01^{***}
		Median χ^2	200.96^{***}	124.30^{***}	103.21^{***}	74.12^{***}	46.74^{***}
	Test	Wilcoxon Z	11.00^{***}	9.48^{***}	8.11^{***}	7.22^{***}	5.93^{***}
		Median χ^2	73.69^{***}	53.18^{***}	38.21^{***}	33.95^{***}	24.39^{***}
360/PT	Training	Wilcoxon Z	-5.60^{***}	-3.94^{***}	-4.01^{***}	-2.45^{**}	-1.66^{*}
		Median χ^2	36.39^{***}	19.75^{***}	27.84^{***}	9.71^{***}	4.10^{**}
	Test	Wilcoxon Z	-8.19^{***}	-7.00^{***}	-6.29^{***}	-6.14^{***}	-4.69^{***}
		Median χ^2	31.00^{***}	25.51^{***}	18.71^{***}	23.07^{***}	12.33^{***}
IT	Training	Wilcoxon Z	2.96^{***}	2.65^{***}	1.75^{*}	2.03^{**}	11.60
		Median χ^2	9.69^{***}	9.09^{***}	2.46	3.05^{*}	1.76
	Test	Wilcoxon Z	8.80^{***}	7.41^{***}	6.51^{***}	5.20^{***}	5.77^{***}
		Median χ^2	56.42^{***}	39.54^{***}	28.87^{***}	22.68^{***}	26.94^{***}
360/IT	Training	Wilcoxon Z	3.14^{***}	2.59^{***}	2.08^{**}	1.78*	1.34
		Median χ^2	4.84^{**}	1.69	0.92	2.27	1.51
	Test	Wilcoxon Z	-5.45^{***}	-4.31^{***}	-3.42^{***}	-2.51^{**}	-2.75^{***}
		Median χ^2	15.36^{***}	10.60^{***}	6.75^{***}	4.56^{**}	6.30^{**}
OC	Training	Wilcoxon Z	2.86^{***}	2.34^{***}	2.15^{***}	1.72*	0.99
		Median χ^2	7.52^{***}	7.86^{***}	3.54^{***}	2.21	0.88
	Test	Wilcoxon Z	-1.78^{*}	-1.23	-1.04	-0.56	-0.69
		Median χ^2	0.37	0.23	0.05	0.23	0.31
NOC	Training	Wilcoxon Z	7.87^{***}	6.11^{***}	5.34^{***}	4.31^{***}	2.80^{***}
		Median χ^2	31.90^{***}	24.11^{***}	13.54^{***}	12.66^{***}	4.47^{**}
	Test	Wilcoxon Z	1.75^{*}	1.63	1.50	1.17	1.64
		Median χ^2	3.32^{*}	2.68	1.46	1.05	1.74
WC/SALE	Training	Wilcoxon Z	-1.48	1.77^{*}	0.97	0.42	-0.48
		Median χ^2	0.59	1.30	0.02	0.00	0.01
	Test	Wilcoxon Z	-0.11	1.17	-0.57	0.54	1.27
		Median χ^2	0.47	1.87	0.07	0.29	0.01
SALE/TA	Training	Wilcoxon Z	5.72^{***}	5.68^{***}	5.38^{***}	5.31^{***}	4.85^{***}
		Median χ^2	39.38^{***}	42.71^{***}	31.22^{***}	31.16^{***}	29.65^{***}
	Test	Wilcoxon Z	9.06^{***}	8.05^{***}	7.30^{***}	6.31^{***}	6.21^{***}
		Median χ^2	45.62^{***}	51.73^{***}	37.85^{***}	26.47^{***}	24.13^{***}
I/SALE	Training	Wilcoxon Z	3.99^{***}	3.77^{***}	2.85^{***}	1.91^{*}	1.85^{*}
		Median χ^2	25.92^{***}	25.38^{***}	12.63^{***}	4.05^{**}	5.75^{**}
	Test	Wilcoxon Z	2.18^{**}	1.45	1.32	0.57	0.57
		Median χ^2	9.84^{***}	5.51^{**}	3.12^{*}	1.76	2.07

Source: Author's calculation

Table 8.e. Wilcoxon Z and Median χ^2 test results for indexes under training and test sample

		Indexes					
SGI	Training	Wilcoxon Z	3.43^{***}	2.54^{**}	2.12^{**}	2.71^{***}	1.13
		Median χ^2	8.59^{***}	5.26^{**}	1.30	6.83^{***}	1.08
	Test	Wilcoxon Z	3.29^{***}	1.65^{*}	1.07	0.44	0.92
		Median χ^2	5.51^{**}	1.46	0.26	0.23	0.90
LEVI	Training	Wilcoxon Z	-7.50^{***}	-5.47^{***}	-3.07^{***}	-3.25^{***}	-3.65^{***}
		Median χ^2	60.97^{***}	36.26^{***}	10.56^{***}	12.25^{***}	13.29^{***}
	Test	Wilcoxon Z	-4.19^{***}	-2.63^{***}	-1.88^{*}	-2.15^{**}	0.03
		Median χ^2	38.20^{***}	19.50^{***}	13.06^{***}	12.30^{***}	4.68^{**}
GMI	Training	Wilcoxon Z	4.61^{***}	4.54^{***}	4.60^{***}	3.81^{***}	2.42^{**}
		Median χ^2	4.69^{**}	8.24^{***}	8.84^{***}	8.19^{***}	4.24^{**}
	Test	Wilcoxon Z	2.65^{***}	3.85^{***}	1.72^{*}	2.89^{***}	1.91^{*}
		Median χ^2	9.39^{***}	14.3^{***}	2.91^{*}	7.71^{***}	3.38^{*}
AQI	Training	Wilcoxon Z	-0.43	-0.52	-0.45	-0.09	-0.10
		Median χ^2	0.02	0.19	0.01	0.10	0.36
	Test	Wilcoxon Z	1.29	1.38	-0.51	0.91	0.45
		Median χ^2	0.51	1.65	0.44	1.29	0.77
SGAI	Training	Wilcoxon Z	1.95^{*}	3.76^{***}	3.89^{***}	1.60	0.96
		Median χ^2	0.76	6.36^{**}	5.49^{**}	0.75	0.48
	Test	Wilcoxon Z	1.71^{*}	3.00^{***}	3.41^{***}	2.73^{***}	1.97^{**}
		Median χ^2	3.42^{*}	5.42^{**}	3.77^{*}	4.70^{**}	1.48
DSRI	Training	Wilcoxon Z	-1.90^{*}	0.58	0.93	-0.06	-1.00
		Median χ^2	1.95	0.38	1.48	0.14	0.28
	Test	Wilcoxon Z	1.55	0.26	0.68	1.98^{**}	1.38
		Median χ^2	2.35	0.05	0.28	1.38	1.65
TATA	Training	Wilcoxon Z	14.15^{***}	9.89^{***}	8.42^{***}	6.10^{***}	5.17^{***}
		Median χ^2	135.12^{***}	71.09^{***}	55.69^{***}	36.10^{***}	26.28^{***}
	Test	Wilcoxon Z	17.18^{***}	13.65^{***}	11.19^{***}	8.47^{***}	6.82^{***}
		Median χ^2	149.78^{***}	104.17^{***}	74.74^{***}	39.31^{***}	27.92^{***}

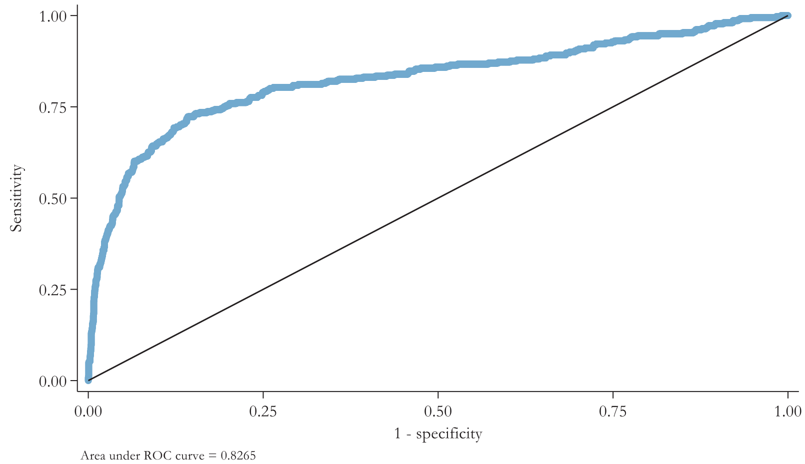
Source: Author's calculation

Table 8.f. Wilcoxon Z and Median χ^2 test results for other ratios under training and test sample

Cash flow ratios							
CI/SALE	Training	Wilcoxon Z	-1.90*	-0.38	-0.84	-1.07	-0.74
		Median χ^2	5.82**	1.01	0.34	0.69	0.27
	Test	Wilcoxon Z	-0.21	1.23	1.42	1.26	0.24
		Median χ^2	0.02	1.01	1.46	2.35	0.05
CI/TA	Training	Wilcoxon Z	5.39***	5.24***	4.83***	4.67***	4.33***
		Median χ^2	29.30***	29.42***	25.57***	20.94***	22.82***
	Test	Wilcoxon Z	7.95***	7.13***	6.68***	5.46***	5.05***
		Median χ^2	38.68***	38.85***	34.33***	20.26***	20.62***
CO/COGS	Training	Wilcoxon Z	2.01**	0.54	0.26	-0.71	-0.37
		Median χ^2	1.96	0.14	0.00	0.00	0.00
	Test	Wilcoxon Z	-1.36	-0.41	-0.42	-0.65	-1.11
		Median χ^2	0.50	0.00	0.00	0.27	0.57
CFO/TL	Training	Wilcoxon Z	7.25***	6.01***	4.85***	4.16***	4.28***
		Median χ^2	36.49***	24.67***	12.14***	6.94***	9.27***
	Test	Wilcoxon Z	18.44***	14.67***	11.22***	7.83***	6.23***
		Median χ^2	169.65***	112.47***	62.38***	28.26***	21.98***
Interest ratios							
ICR	Training	Wilcoxon Z	9.64***	6.41***	6.25***	5.14***	3.71***
		Median χ^2	60.03***	27.25***	22.91***	18.83***	9.18***
	Test	Wilcoxon Z	6.74***	6.73***	6.71***	5.53***	4.95***
		Median χ^2	16.27***	20.20***	19.96***	13.55***	12.64***
INT/SALE	Training	Wilcoxon Z	1.53	0.92	1.13	2.16**	1.39
		Median χ^2	1.84	0.48	0.75	3.63*	1.75
	Test	Wilcoxon Z	3.71***	3.81***	3.95***	3.72***	2.57**
		Median χ^2	15.50***	18.50***	20.38***	18.36***	7.81***
Productivity ratios							
SALE/FA	Training	Wilcoxon Z	4.98***	4.13***	4.12***	3.58***	3.22***
		Median χ^2	20.07***	18.15***	20.55***	19.95***	12.94***
	Test	Wilcoxon Z	7.17***	5.95***	6.41***	5.31***	5.16***
		Median χ^2	28.21***	21.20***	22.95***	18.14***	16.89***
SALE/I	Training	Wilcoxon Z	1.96**	1.82*	0.74	0.49	2.05**
		Median χ^2	2.62	3.10*	0.72	0.92	3.99**
	Test	Wilcoxon Z	6.81***	4.17***	4.61***	4.38***	3.72***
		Median χ^2	23.01***	10.19***	10.65***	11.10***	10.41***
Fixed asset utilization							
FA/TA	Training	Wilcoxon Z	-0.49	0.77	1.44	1.53	1.14
		Median χ^2	0.21	2.03	2.09	0.93	0.14
	Test	Wilcoxon Z	1.73*	2.75***	2.60***	2.53**	1.08
		Median χ^2	1.97	5.75**	4.19**	3.13*	0.21
Other							
PROFIT	Training	Wilcoxon Z	6.90***	3.66***	1.18	1.76	0.27
	Test	Wilcoxon Z	3.02***	-1.05	-1.19	-0.55	-0.33
SGR	Training	Wilcoxon Z	3.09***	2.26**	1.87*	2.51**	0.92
		Median χ^2	6.68***	4.04**	0.81	5.54**	1.11
	Test	Wilcoxon Z	2.96***	1.38	0.77	0.46	0.73
		Median χ^2	4.47**	1.06	0.09	0.23	0.67

Source: Author's calculation

Figure 23. ROC curve



Source: Author's calculation

Table 9. Goodness of fit summary

Pseudo R^2	0.20
AUC	0.8265
Average accuracy	70.68%
True negative rate	61.18%
True positive rate	72.28%
F_β score	0.723

Source: Author's calculation