8 Predicting Financial Distress of Micro Small and Medium Enterprises in the Northern Province of Sri Lanka

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Abstract

The financial vulnerability of Micro Small and Medium scale Enterprises (MSMEs) in Sri Lanka threatens not only their own survival but also the livelihoods they support within communities. Prior studies indicate that business owners from Northern Province of Sri Lanka, have not only lost millions as interest to the financial intermediaries like banks, finance companies and informal lenders, but also have lost their properties, businesses and lives. Thus, this study intends to develop a financial distress prediction model for MSMEs in Northern Province, an economically marginalized region with low level of financial literacy and high unemployment and debt levels. Using financial ratios based on the Altman Z-score framework, binary logistic regression was applied to data from 400 MSMEs, to identify key predictors of financial distress. Where the analysis through SPSS indicated that retained earnings-to-total assets, debt-to-equity ratio, and sales-to-to-total assets emerged as significant determinants, whereas working capital, industry, earnings, firm age and size were not statistically significant. The test model achieved an overall classification accuracy of 87.3%, with sensitivity of 87.5% and specificity of 82.4%, indicating strong predictive validity. The findings suggest that maintaining internal reserves, improving operational efficiency to achieve revenue and managing the leverage cautiously can reduce the risk of financial distress. The predictive model provides a practical early warning tool for policymakers, financial institutions, and MSME owners to strengthen financial flexibility and mitigate the risk of debt-trap in post-conflict, underdeveloped regions.

Keywords: Micro, Small, and Medium Entreprises, Financial Distress, Financial Literacy, Financial Distress Prediction Models.

Introduction

Financial distress is explained as the distressing condition where the businesses are unable to pay mature debts or expenses, leading to liquidity problems, inadequacy of equity, and unavailability of current assets (Hui & Jing-Jing, 2008 as cited by Younas et al., 2021). According to Aviantara (2021), financial distress begins when a company fails to meet scheduled payments or when cash flow forecasts reveal that it will be unable to meet the maturing obligations. According to Department for Business Innovation and Skills (2010), financial distress is concerned, for it has serious consequences for both at firm and at a macro level. At the firm level, over-indebtedness is related to an increased chance of business distress and deterioration of business operations and business sustainability (Wang et al., 2003; Gathergood, 2012).

Businesses must obtain funding for running activities from internal or external sources (Flynn & Ghent, 2017). Undivided profit and earnings are used as internal financing whereas borrowing and owner funding are used in external financing (Bester & Scheepens, 1996). Taiwo et al. (2016), states that personal savings and unstructured loans from friends and lenders rank among the top sources of funding for small businesses. Additional sources that contribute to MSME capital structure are banks, informal financial markets, and partners. Yazdipour (2011) claims that start-up businesses always rely largely on personal funds and family, with external equity injections unusual, even for businesses with highly valuable but unclear growth prospects (Reynolds& Curtin 2008; Robb et al., 2009). Banks are the main source of funding for MSMEs once they have been established, providing working capital and funding for investments in machinery and equipment, even though they are not the primary source of capital for beginning a new company (Berger & Udell, 1998).

Many academics analyse the debt-trap process without addressing the information content of the ratios, and the models' contributions mostly relate to the practical challenges involved in forecasting financial distress (Ohlson, 1980). Because of the variable selection methods, the variables used in organizational debt related research in the literature are derived without a shared theory or basis (Gentry et al., 1985; Grice& Dugan, 2003; Charitou et al., 2004).Thus, this study focuses on developing a model to predict the debt-trap of MSMEs based on the detailed understanding of financial literacy, decision making and debt-trap.

Several gaps in the literature on financial distress prediction modelling are found from the survey of the literature. There are no studies that offer a comprehensive model for MSMEs, according to thorough literature analysis(Li et al. 2014; Aviantara, 2021). Also, mix efficiency is ignored in the research on using efficiency measures as novel characteristics in model construction (Li et al. 2017), which is restricted to using pure technical efficiency and scale efficiency. The review of the literature reveals that market variables are ignored in favour of accounting variables when analyzing inputs and outputs to estimate an organizational efficiency measures (Barr & Siems, 1997, Li et al., 2014, Li et. al., 2017, Psillaki et al., 2010, Xu

& Wang, 2009, Yeh et al., 2010). There are several issues or criticisms regarding the use of accounting-based information. However, for the MSME obtaining market variables is not practical as these businesses are not listed. Thus, the accounting ratio or historical value analysis can only be applied for MSME businesses (Younas et al., 2021).

This study particularly focuses on the Northern Province. Despite comprising a significant portion of Sri Lanka's land area, the province currently contributes only about 4.2% to the national GDP, a decline from 5% in 2014 (Central Bank of Sri Lanka, 2024). In the Northern Province 99% of business are under the MSMEs sector and the contribution to GDP is at very lower level compared with the contribution of other provinces in Sri Lanka (Vaikunthavasan, 2019). The unemployment, poverty and debt level are high in the Northern Province of Sri Lanka (Department of Census and Statistics, 2022), where these people were separated from the rest of the island, during the civil war, and even years after that also the situation continues. In 2022, The average unemployment rate reported in Sri Lanka was 4.7%; however, the unemployment rate in Jaffna, was 5.7%. Further, based on the Department of Census and Statistics (2022), only around 32.7% are engaged in self-employment out of the employed population in the Northern Province. The youth unemployment rate in the Northern Province stands at 14.5%, with Kilinochchi experiencing the highest at 20.3% (Department of Census and Statistics, 2022).

Northern province MSME owners have suffered severe consequences from destructive microfinance practices, including loss of property and livelihood (Kadirgamar, 2020).According to Economic Development Framework for a Northern Master Plan (Central Bank of Sri Lanka, 2018), during post-war, microfinance institutions aggressively targeted the Northern Province, leading to widespread over-indebtedness among vulnerable populations. According to Mithula (2015), businessmen from Northern Province have not only lost millions as interest to the financial institutions, but also have lost their properties, businesses and lives. The micro finance loans have also significantly challenged businesses and families in this community (Kadirgamar, 2020). Also, because of continued ethnic conflict up until 2009, there are not as many surveys and research specifically focused on the Northern Province. However, it is important to learn about MSMEs in this province as they promote resilience of communities, to recover from adversities such as civil war and Covid-19 pandemic (Sinnathurai, 2013). Further, the high unemployment rate and poverty indices indicate that to ensure regional growth there needs to be a high focus placed on the sustainability and growth of MSMEs. In developing nations, MSMEs are invariably linked to economic and social issues such as unemployment, poverty, and economic inequality (Fatoki, 2014). Thus, focusing on developing MSMEs in this province would support employment creation, poverty alleviation and regional development.

Literature Review

Financial Distress

Credit plays an important role in the life and businesses of modern society(Lacombe, 2012). Credit allows individuals to start their business by accessing start-up capital also to manage and continue the business even when earnings fallshort of expenditure(Gregorio, 2000).It also allows businesses to respond to unexpected events such as disasters, and emergencies (Hodson, 2014). Credit has developed an ordinary feature of life for several people and businesses as ithelps a beneficial function in the economy by permitting individuals to borrow against their projected earnings to finance current investments and consumption (Department for Business Innovation and Skills, 2010). For MSMEs, the difficulty of providing high-quality collateral and lack of creditworthiness are the main obstacles to credit access (Ayadi & Gadi, 2013; Ozturk &Mrkaic, 2014). In accordance with Copur (2015), the absence of accounting information transparency increases the asymmetry of knowledge, which is particularly pronounced during economic downturns and results in credit rationing and suboptimal lending to viable MSMEs. Due to the lack of transparency in the former, from the standpoint of bank management, MSME lending is more expensive in terms of capital absorption and transaction expenses than working with large enterprises (Brogi& Langone 2016). As a result, MSMEs suffer from downturns more severely than larger businesses do, demonstrating the pro-cyclical character of MSME loans (European Banking Authority, 2015).

Studies highlight that high levels of debt are not necessarily a problem so long as businesses have the means to continue servicing and repaying them(Ogunmokun et al., 2022). The findings of the research on how debt structure affects investment and financing have been inconsistent. According to Myers (1977) and Hart (1996), debt volume and future investment are inversely correlated. On the other hand, Aivazian et al. (2005) discovered that underinvestment issues are a result of debt financing, meanwhile, Dang (2011), He and Xiong (2012), Flynn (2017), and Kalemli-Ozcan et al. (2018) anticipated that debt will cause problems for future funding. However, highly indebted businesses may be more vulnerable to adverse economic shocks such as emergencies, increases in interest rates or other expenses that may put them at risk of falling into debt-trap (Department for Business Innovation and Skills, 2010). Analysis of risk of financial distress usually focuses on the ratio of debt to business annual income and on the ratio of debt servicing payments to current net income (Aivazian et al., 2005).Credit is an significant feature of contemporary businesses, but it can become challenging if it is dependent on to pay for daily business expenses(Gregorio, 2000).

There is no fixed definition of financial distress, therefore a number of diverse over-indebtedness indicators are used in studies (Department for Business Innovation and Skills, 2010). Oxera (2004)defined financial distress as over-indebted businesses, where entities are in arrears on a operational basis or are at a substantial risk of getting into arrears. Based on the definition of MORI Financial Services Survey (2004), it identifies different aspects of financial distress, identifying both businesses who are "currently experiencing financial difficulties (arrears indicator) or those who might be at significant risk of problems (burden and credit commitments)". The recent literature indicates that a more precise definition for financial distress derives from the UNDP (2023), which defines as: "…when income, is insufficient to discharge all payment obligations over a longer period of time." This is understood as situations where the firm's credit-based spending plans vary with its potential income stream.

Financial distress experienced by a business might trigger bankruptcy or forced liquidation. According to Platt, H., and Platt, M. (2006), even though debt-trap and bankruptcy are used interchangeably, it is important to understand the difference between both, in most instances, bankruptcy occurs after a period of high debt levels. Several legal indebtedness instruments are available to businesses facing serious financial trouble UNDP(2023). These include bankruptcy, in which dues are written off, and Individual Voluntary Arrangements (IVAs), which are formal agreements through courts with creditors to settle a suitable amount of outstanding debts over a given period of time (Department for Business Innovation and Skills, 2010). Also, a non-statutory opportunity for dealing with debts is the Debt Management Plan (DMP), where through an informal arrangement creditors are repaid with the debts over time at a rate that is affordable for the individuals (International Financial Corporation, 2024).

Financial Distress Prediction Models

Looking into the previous studies on financial distress prediction, there are number of studies on the various aspects of corporate debt-trap since the initial studies by Beaver (1966) and Altman (1968) on prediction of bankruptcy through ratios. However, models to predict MSME financial distress are less common (Lau, 1987, Platt & Platt, 2002). Further, there is no prior study that presents a multi-industry model of financial distress (Platt & Platt, 2006). Thus, this study focuses on MSMEs across various industries. The corporate financial distress studies examine financial restructuring (Gilson et al., 1990, Wruck, 1990, Brown et al., 1994) or management turnover during distress (Gilson et al, 1990). There is research that has been conducted to detect the early warning signs of corporate financial distress(Beaver, 1966). With reference to various theories on debt levels, the explanations of financial distress largely vary across different countries as they have different accounting treatments and rules. As a result, there are various models that exist in the literature to predict financial difficulties of businesses (Aviantara, 2021).

The research of Modigliani and Miller is where the early literature on bankruptcy and corporate capital decisions first appeared (1958, 1963). The quantity of corporate debt has no bearing on the value of the firm's assets, or the riskiness of the entire cash flow stream produced by the firm's assets, according to the Modigliani-Miller (MM) framework. However, a number of experts have criticized the theory's foundational assumptions, including the notion of riskless debt and several others(Frederick, 2005). The pecking order theory, which asserts that because of asymmetric information, businesses will favor domestically generated capital over loan and debt over equity, is one of the key counterarguments to the MM theory (Challoumis, 2019). Practically, obtaining financing for MSMEs involves issuing additional types of securities, such as risky debt, preferred stock, and various hybrid securities, in addition to riskless debt and equity securities (Senbet& Wang,2012).

According to Ven Caneghem and Van Campenhout (2012), MSMEs are not required to follow the outcomes of larger, publicly traded companies. Since banks view MSMEs as riskier than large firms (Scherr et al., 2002), MSMEs have higher borrowing costs than large firms (Holmes et al., 2003), small firms typically have lower profit margins due to operating in less concentrated and more competitive markets, and MSMEs typically have lower tax rates (McConnell & Pettit 1984; Pettit & Singer 1985). These factors mean that the fiscal advantages of debt will typically be more limited for MSMEs. Also, the desire of the business owner to keep family control over the company frequently influences the choice of financial structure in MSMEs (Lau, 1987). Also, it is discovered that MSMEs have more serious information asymmetry issues. It is widely acknowledged that MSMEs' access to outside funding is hampered by their informational competence (Berger & Udell, 1998).

Wruck (1990) emphasized that MSMEs shall fall into the financial distress situation due to poor internal management, economic distress and decrease in the performance. Similarly, Brigham and Daves (2007) identified factors that may cause firms to go into financial distress, those are, economic factors, financial factors, neglect disaster and fraud. According to Aviantara (2021), debt-trap arises due to a sequence of errors, weaknesses, that can be contributed either directly or indirectly to the firm management and generally apparent from a financial statement analysis long before the firm goes into the debt trap. According to Elloumiand Gueyie (2001), initial signs of financial distress are usually violations of debt covenants combined with reduction or nonpayment of profit sharing to the owners. Higher debt ratio leads to higher costs of financial distress and possible agency problems between shareholders and financial creditors (Van Caneghem & Van Campenhout, 2012).

Previous studies on financial distress models classify the distress in two stages; 1. Legal state (Shumway, 2001;Altman, 1968) and 2. early warning sign of debt-trap (Lau, 1987; Hensher et al., 2007; Cheng & Li, 2014). According to Wruck (1990) financial distress is where the business is unable to meet its debt obligation and Whitaker (1999) highlights that the debt-trap can be detected in advance by witnessing the decrease in firm value. Studies on corporate failure prediction aim to use widely recognized sources and indicators of financial distress, such as difficulties in operating and financing activities, as well as poor performance in management and leadership of the company. This is done in order to develop an early distress warning system, take appropriate preventive action against bankruptcy, and protect the firm (Altman et al., 1994; Bauer& Agarwal, 2014; Laitinen & Suvas, 2016; Liang et al., 2016; Yeh et al., 2010). According to Zhou (2016), data-fitting based empirical research involving four steps—feature selection, classifier choice or design, performance evaluation, and sampling—is what makes up models for forecasting bankruptcy and distress.

Depending on their accounting practices and regulations, different countries define financial distress using various models (Shumway, 2001). Among those several models, Z-score and O-score models are more widely applied in the financial literature (Agarwal & Taffler, 2008). Additionally, most financial distress prediction studies are conducted in developed nations, where economies are strong and bankruptcy laws and procedures are well-established. (Agarwal & Taffler, 2008; Altman, 1968; Beaver, 1966; Ohlson, 1980; Shumway, 2001).

A legal state (Altman, 1968; Shumway, 2001; Wu et al., 2016) and an early warning sign (Altman, 1968; Shumway, 2001; Wu et al., 2016) are the two stages that previous studies on financial distress models classify the distress into (Lau, 1987; Cheng & Li 2003; Hensher et al., 2007). According to Tinoco and Wilson (2013), financial distress is expensive for MSMEs' creditors, and they wish to reduce that expense by taking the required steps. Therefore, a trustworthy financial distress prediction model should be able to forecast the early stages of financial distress of a firm. This study uses a financial distress predictor model based on five financial ratios. The probability that a business will collapse in the following two years is ascertained using the Z-score Model.

Methodology

This study focuses on developing a model to predict the financial distress of MSMEs, based on the well-known Altman's Z-score model, based on five financial ratios and a bankruptcy predictor model. This Zeta Model aids in predicting whether a business will file for bankruptcy within the following two years. New York University finance professor Edward L. Altman initially published it in 1968. These indicators look at a company's overall financial health by combining data from the income statement and balance sheet where it might be used to characterize a struggling business(Altman, 1968; Beaver, 1966). This occurs when a business is having trouble making its debt payments, which frequently leads to bankruptcy. A firm might be in financial difficulties without really being in default(Lau, 1987, Platt & Platt, 2002). This rating helps to clarify this risk. This was first applied by Wolaita Sodo University for small and medium-sized businesses in Wolaita for the year of 2015 using a particular analytical technique called Altman's discriminant function model. The table below provides the operationalization of the prediction model.

Table 1: Operationalization of the Variable for the Financial Distress Prediction Model

	Variable	Indicator	Measurement
Dependent Variable	Financially distressed companies Financially not distressed companies	Net worth Annual Profitability Soundness of the cashflow	1 = distressed 0 = Otherwise
Independent Variable	Accrual based financial ratios	Liquidity Profitability/Leverage Profitability/Efficiency Gearing/debt level Efficiency	β1=Working capital/Total assets β2= Retained Earnings/Total assets β3= Earnings /Total assets β4= Book value of total debt/Equity β5= Sales/Total assets

Altman (1968)

Regression technique is used to assess the strength of a relationship between one dependent and independent variable (CFI, 2024). It helps in predicting the value of a dependent variable from one or more independent variable. Regression analysis helps in predicting how much variance is being accounted in a single response by a set of independent variables.

The result criteria variable must be measured as a continuous variable in order to be used in linear regression analysis. Nonetheless, there can be circumstances in which the researcher would prefer to forecast a binary or dichotomous result. A researcher can utilise binary logistic regression in this kind of scenario to determine how one or more predictor factors affect the results. A technique for figuring out the cause-and-effect relationship between an independent variable (or variables) and a dependent variable is logistic regression analysis. As a result, the dependent variables in this study fall into two categories: 1. MSMEs in financial distress; and 2. MSMEs are not in financial distress. Since logistic regression calculates the probability of success over the probability of failure the results of the analysis are in the form of odds ratio. Logistic regression determines the impact of multiple independent variables presented simultaneously to predict membership of one or other of the two dependent variables categories: in this case the accrual-based ratios predicting financial distress. In logistic regression the expected outcome is represented by 1 while others are coded 0. (1 = financially distressed MSMEs and 0 = financially not distressed MSMEs)

Logistic regression is based on a number of assumptions. Logistic regression does not assume a linear relationship between the dependent and independent variables. The independent variables need not to be interval nor normally distributed nor linearly related nor equal variance within each group. The error terms (residual) do not need to be normally distributed. The dependent variable must be dichotomous (two categories) for the binary logistic regression. The categories (groups) as a dependent variable must be mutually exclusive and exhaustive: a case can only be in one group and every case must be a member of one of the groups. Larger samples are needed than for linear regression. A minimum of 50 cases per predicator is recommended (Field, 2013). Leblanc and Fitzgerald (2000) suggest a minimum of 30 observations per independent variable. Thus, in this study 400 cases of MSMEs were analyzed with financial ratios to predict the financial distress of MSMEs in the Northern province.

This research focuses on a survey method using a sample of MSMEs across various industries in Northern Province. Numerous definitions of MSMEs are applied by different international organizations, nations, and statistics agencies based on numerous factors, including capital investment, number of employees, turnover, asset value, and balance sheet. According to Esubalew & Raghurama (2017), there are drawbacks to adopting number of employees as a criterion for defining MSMEs because labour force is declining as technology improves. Thus, using turnover as a parameter is effective because the development of the business is determined by revenue generation. To define MSMEs, the study will use the turnover as a parameter that is illustrated in annexure 1.

The target population was determined by identifying the number of MSMEs registered with DS divisions of the Northern Province as of the year 2023. The annexure 2 illustrates the list of such enterprises in Northern Province. From the target population a representative sample of 400 was selected for the data collection based on statistical power analysis. This is the base used to estimate the minimum sample size required for a study based on the significance level, statistical power, and effect size required. For this study, 379 or more samples are required at confidence level of 95% that the real value is within ±5% of the measured/surveyed value. A convenience sample method was applied to collect data of MSMEs.

Analysis and Discussion

Focusing on the SPSS results, the case processing summary highlighting the cases included in the analysis. In the study there are a total of 400 cases. The data set was classified into two groups such that, the first group, financially not distressed MSMEs with n1=136 which represents 34% of observations, and the second group financially distressed MSMEs with no=264 which represents 66% of observations. Financial distress was defined based on the criteria of distress zone defined by Altman (1968).

The dependent variable encoding table shows the coding for the criterion variable in this case MSMEs that are financially distressed are classified as 1 while MSMEs that are not financially distressed are classified as 0. Thus, here the interest of the study is to identify what are the factors that would predict the financial distress of MSMEs or in other words the early warning signs of financial distress.

Table 2: Classification Table

	No. of Respondents	% Distribution
Financially not distressed firms	136	34%
Financially distressed firms	264	66%

Source: Survey data (SPSS)

Table 2 presents the information on statistical analysis which shows the mean and the standard deviation of the explanatory variables.

Table 3: Information of Statistical Analysis

Explanatory Variable	Mean	Std. Deviation
Working Capital	0.41	0.30
Retained Earnings to Total Asset	0.31	0.22
Earnings before interest to Total assets	0.01	0.02
Debt to equity	1.06	0.58
Sales to Total assets	0.19	0.14
Age	10.81	9.84

Source: Survey data (SPSS)

The output headed Block 0, is the result of the analysis without any of the independent variables used in the model. This will serve as a baseline later for comparing the model with our predictor variables included.

Table 4: Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 0	Constant	.663	.106	39.491	1	.000	1.941

Source: Survey data (SPSS)

The goodness of fit statistics helps to determine whether the model adequately describes the data, which is provided in table 5.21.

Table 5: Model Fitting Test Results

Criteria	Results	Condition	Conclusion
2-log likelihood	49.463, p -.000	Smaller value, p ≤ 0.05	Fulfilled
Omnibus test	463.365, p -.000	p ≤ 0.05	Fulfilled
Hosmer and Lemeshow statistic	12.168, p -.144	p ≥ 0.05	Fulfilled
Cox and Snell R square	.686	Ranges from 0-1 Higher value – Good fit	Fulfilled
Nagelkerke R Square	.749	Ranges from 0-1 Higher value – Good fit	Fulfilled
Goodness-of-Fit	245.332, p -.000	p ≤ 0.05	Fulfilled

Source: Survey data (SPSS)

The model fit is evaluated using the Omnibus test of model coefficients. The model is demonstrating good fit (Sig – 000) if the model is significant, which indicates that there has been a notable improvement in the fit when compared to the null model. A significant value of less than 0.05 is indicative of a poor fit according to the Hosmer and Lemeshow statistics. In this case, the model fits the data quite well (Sig – 0.144). As a result, the observed and anticipated models are identical.

Table 5 shows that, based on the Cox and Snell value and the modified Cox and Snell coefficient known as the Nagelkerke value, the response variable accounts for 69% and 75% of the variance in the explanatory variables, respectively. Although they can be used as an approximation of variation in the criteria variable, pseudo signifies that the variation is not formally explained. commonly used Nagelkerke's R2, which is a modified version of Cox and Snell's R-square that modifies the statistical scale to encompass the whole 0–1 range. In this instance, we can state that the predictor variables in the model account for 74.9% of the change in the criterion variable. As per the contingency table, the model adequately fits the data. As there is no difference between observed and predicted models are seen. Both values are approximately equal.

Table 6: Variables in the Equation

Variable	B (log odds)	Sig. (p-value)	Exp(B) (Odds Ratio)	Interpretation
Working Capital / Total Assets	0.648	0.641	~1.91	Not statistically significant
Retained Earnings / Total Assets	11.775	0.001	High	Strong predictor (highly significant)
EBIT / Total Assets	1.092	0.662	~2.98	Not statistically significant
Debt to Equity	1.92	0.000	~6.82	Significant – Moderate to strong predictor

Sales / Total Assets	1.166	0.003	~3.21	Strongly significant predictor
Age	0.004	0.939	~1.00	Not significant
Size of the Business	-0.42	0.459	0.657	Not significant
Industry	0.083	0.612	~1.09	Not significant

Source: Survey data (SPSS)

As illustrated in table 6, the retained earnings to total assets, debt to equity and sales to total assets were found to be significant predictors of financial distress. Age, Firm size, Industry, working capital and earnings before interest to total asset were not significant predictors of financial distress.

Odds is the ratio of probability P(A)/P(B). The above Table shows the relationship between the predictors (i.e. working capital, retained earnings to total asset, EBIT to total asset, debt to equity and sales to total assets) and the outcome (i.e. Financially distressed or not distressed).The projected change in the log odds is called beta; for every unit change in the predictor, the probability of the result changes by exp (B). Both positive and negative beta coefficients are possible, and each has a corresponding t-value and significance of the t-value.

Odds Ratio

- **Odds ratio > 1 probability of event occurring**

The probability of falling into the target group is greater than probability of falling into the non-target group. The event is likely to occur. The important thing about confidence interval is that it does not cross 1. In this analysis the target group is financially distressed with MSMEs thus, based on the test results, having lower retained earnings to total asset, EBIT to total asset, high gearing or debt to equity a low sales to asset ratio results is probability of MSMEs falling into the target group (financially distressed).

- **Odds ratio < 1 probability of event occurring**

The probability of falling into the target group is lesser than the probability of falling into the non-target group. The event is unlikely to occur. The important thing about confidence interval is that it does not cross 1 (Both values are greater than 1). For the working capital the odds ratio is less than 1 and the sign is negative this indicates that higher the liquidity (working capital ratio) the MSMEs have less chance of falling into the target group, that is if the firm is stronger in working capital there is high probability of falling into the category of financially not distressed.

The important thing about confidence interval is that it doesn't cross 1 (both values are greater than 1). This is important because a value greater than 1 means as the predictor variable increases, so do the odds of falling into financially distressed.

Whereas value less than 1 means the opposite as the predictor increases the odds of falling into financially distressed category reduces.

From the above table the estimated debt-trap model can be predicted as;

$$\boldsymbol{Log\left(\frac{p}{1-p}\right) = -11.729 + 11.775x_2 + 7.920x_4 + 12.116x_5}$$

Note:

x_2 = Retained Earnings / Total Assets

x_4 = Debt to Equity

x_5 = Sales / Total Assets

Table 7: Final classification results using binary logistic regression

Kind of test		Financially not Distressed	Financially Distressed	Percentage Correct
Financial Distress	Financially not distressed	112	24	82.4
	Financially distressed	33	231	87.5

(Note: 0 = Financially not distressed, 1 = Financially distressed)

Source: Survey data (SPSS)

The classification table shows how well the model predicts the right category when the predictors are included in the research. Overall, 87.3% of instances were accurately classified by the model. (Also known as the categorization accuracy percentage: PAC).The percentage in the first two rows provides information regarding specificity and sensitivity of the model in terms of predicting group/membership on dependent variable.

Specificity (also called true negative rate) refers to the percentage of cases observed to fall into the non-target category. Who was correctly predicted by the model falls into that group. The specificity of this model is 82.4%. The percentage of cases seen fall into the target group that the model properly predicted fall into that group is known as sensitivity, also known as true positive rate. The model's sensitivity is 87.5%. The model's total accuracy is 87.3%.

Control Variable Analysis

Control variables are not the primary focus of the study, but they're included in the model to account for their potential influence on the dependent variable. Their role is to reduce confounding effects and isolate the impact of your key explanatory variables. EBIT, age, size and industry were included in the regression model as control variables to account for firm-level heterogeneity that may influence debt-trap independently of the primary predictors. While none of the control variables showed statistically significant effects ($p > 0.05$), their inclusion ensures that the observed relationships between retained earnings, leverage, and asset turnover with debt-trap are not confounded by differences in profitability, age, industry or size of firms.

Table 8: Interpretation of Control Variables in the Model

Control Variable	Coefficient (B)	p-value	Exp(B)	Interpretation
Age	0.004	0.939	~1.00	No meaningful effect: age is statistically insignificant. Controlling age helps ensure that any influence of firm maturity on distress does not distort main findings of the study.
Size	-0.42	0.459	0.657	Not statistically significant. The negative coefficient suggests that larger firms might be slightly less likely to be distressed, but the effect is weak and not reliable. It still helps adjust for size-related structural differences across firms.
Industry	0.083	0.612	~1.09	Not statistically significant ($p > 0.05$). The odds ratio is close to 1, indicating that being in a particular industry does not meaningfully increase or decrease the odds of financial distress. However, including this variable controls sectoral effects could otherwise bias the results.
Profitability (EBIT)	1.092	0.662	~94	Although the odds ratio is large, it is not statistically significant ($p > 0.05$). This suggests that EBIT doesn't have a stable, reliable influence on financial distress. Its inclusion controls firm profitability but doesn't alter conclusions about other predictors.

Source: Survey Data (SPSS)

Among the explanatory variables, retained earnings to total assets ($p = 0.001$), debt to equity ($p = 0.000$), and sales to total assets ($p = 0.003$) emerged as statistically significant predictors of debt-trap. Firms with higher retained earnings were less likely to be financially distressed, indicating that internally funded firms are more financially stable. A higher debt-to-equity ratio was associated with a substantially increased likelihood of debt-trap, highlighting the critical impact of financial leverage. Similarly, stronger asset turnover (sales to total assets) reduced the probability of distress, suggesting operational efficiency plays a protective role.

On the other hand, working capital, EBIT, and control variables such as age, size, and industry were not statistically significant ($p > 0.05$). Although the coefficient for EBIT was positive with a large odds ratio, its high p-value indicated an unstable and unreliable effect. The non-significance of age, size, and industry implies that these characteristics, while relevant for model control, do not independently predict distress in this sample. However, their inclusion as control variables helps to adjust for background variance and ensures that the effects of the main predictors are not biased by firm-level or sectoral differences.

The results of this study align with current literature on financial distress, particularly in the context of MSMEs. Consistent with Aviantara (2021) and Wruck (1990), the findings confirm that poor financial structure and operational inefficiencies increase vulnerability to distress. The significance of retained earnings to total assets emphasizes the claim by Myers (1977) and the pecking order theory which highlights that the firms relying on internal financing are less vulnerable to debt-trap conditions. Similarly, the positive association between high debt-to-equity ratios and financial distress reflects the findings of Van Caneghem and Van Campenhout (2012), who identified excessive leverage as a critical risk factor for small enterprises. The protective role of sales-to-total assets aligns with operational efficiency literature (Li et al., 2017; Yeh et al., 2010), highlighting the importance of asset turnover in sustaining profitability. The insignificance of age, size, and industry supports the argument by Lau (1987) that structural characteristics may be less predictive of distress than core financial ratios. Collectively, these results reinforce the validity of ratio-based prediction models, such as Altman's Z-score, while providing empirical evidence tailored to MSMEs in economically marginalized, post-conflict regions.

Conclusion

This study developed and tested a financial distress prediction model for MSMEs in Sri Lanka's Northern Province, using logistic regression and the Altman Z-score framework. The results demonstrate that retained earnings to total assets, debt-to-equity ratio, and sales-to-total assets are significant predictors of financial distress, with higher retained earnings and stronger asset turnover reducing the likelihood of distress, while greater leverage increases it. Other factors, including working capital, EBIT, firm age, size, and industry, were found to be statistically insignificant, though they were retained as control variables to account for structural heterogeneity. The final model achieved an overall classification accuracy of 87.3%, with high sensitivity and specificity, indicating strong predictive validity. These findings provide practical implications for policymakers, financial institutions, and MSME owners by highlighting key financial ratios that serve as early warning signals of distress. Incorporating such predictive tools into credit risk assessments and business management practices can help mitigate the risk of debt-trap, improve financial decision-making, and enhance the sustainability of MSMEs in economically vulnerable regions.

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Appendix

Appendix 1: Identifying Micro, Small and Medium Enterprises (MSMEs)

Size/ Sector	Criteria	Medium	Small	Micro
Manufacturing	Annual Turnover	Rs. Mn. 251 - 750	Rs. Mn. 16 - 250	Rs. Mn. 15 or less
	Number of Employees	51 - 300	11 - 50	10 or less than 10
Service Sector	Annual Turnover	Rs. Mn 251 - 750	Rs. Mn. 16 - 250	Rs. Mn. 15 or less
	Number of Employees	51 - 300	11 - 50	10 or less than 10

Source: National Policy Framework for Small Medium Enterprise (SME) Development, 2017

Appendix 2: Total population and sample amount of MSMEs

District	DS division	Target MSMEs	Sample MSMEs	Total	% of total sample
Jaffna	Delft	40	1	148	37%
	Island South	134	2		
	Island North	231	4		
	Karainagar	110	2		
	Jaffna	2278	40		
	Nallur	1217	22		
	Sandilipay/Valikamam Southwest	1406	25		
	Chankanai/Valikamam West	1047	19		
	Uduvil/Valikamam South	1835	32		
	Tellippalai/Valikamam North	973	17		
	Kopayvalikamam East	1093	19		
	Chavakachcheri/Thenmaradchi	861	15		
	Karaveddy/Vadamaradchchi Southwest	716	13		
	Pointpedro/Vadamaradchchi North	913	16		
	Maruthankeny/Vadamaradchchi East	229	4		

Mannar	Mannar	872	35		
	Madhu	141	5		
	Manthai West	217	14		
	Nanaddan	263	10		
	Musali	172	5	64	16%
Vavuniya	Vavuniya	2558	65		
	Vavuniy South	338	16		
	Vengalacheddikulam	506	19		
	Vavuniya North	288	14	116	29%
Mullaitivu	Maritimepattu	1106	20		
	Thunukai	284	5		
	Manthai East	171	3		
	Oddusuddan	459	8		
	Puthukudiyiruppu	506	11	48	12%
Kilinochchi	Karachchi	209	3		
	Pachchilaipallai	347	5		
	Kandawalai	469	9		
	Poonakary	443	8	24	6%
Total		**24316**	**400**	**400**	**100%**

Source: Compiled by the author, based on data collected from DS divisions, 2023.