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Financial Distress Prediction Model in Indonesian State-Owned Enterprises (SOEs)

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Abstract

This paper aims to test the capacity of financial distress model using financial variables (liquidity, cash flow operation, leverage, gross profit margin, return on asset), and non-financial variables (going concern opinion, audit report lag, opinion shopping, additional paid-in capital, subsidies). This study uses 7 years of panel data with a total of 350 observations. The model developed, namely Model 1 (financial variables), Model 2 (non-financial variables), and Model 3 (financial and non-financial variables). Finally, Model 4 (financial and non-financial variables in listed SOEs; and Model 5 (financial and non-financial variables in non-listed SOEs). Data analysis used ordinal logistic regression, where the dependent variable used Altman Z-score. The model's results prove that the predictive ability of Model 1 is better than Model 2. Likewise, the predictive ability of Model 3 is better than Model 1, and Model 2 predictive ability of Model 4 is better than Model 5. Empirical evidence shows that the variables that are consistently significant across Models (1,2,3,4,5) are Leverage, Gross Profit Margin, and ROA. Meanwhile, the model with the highest prediction accuracy value is Model 4. Financial distress prediction could indeed supervise which businesses have the strongest capital adequacy and which are giving up their ability to compete and are consequently in danger.

Keywords: Financial Distress, Altman Z-score, State-Owned Enterprises, Indonesia

1 Introduction

Being one of the nation adversely infected with the COVID-19 disease that has been spreading. Indonesia has experienced economic weakness in various sectors, including those experienced by State-Owned Enterprises (SOEs). Various economic policy innovations carried out by the government during 2020-2021 include, among others, the Ministry of Finance allocating an economic recovery budget expected to maintain the momentum of national economic recovery, especially encouraging economic growth. At the beginning of 2022, the Indonesian government prepared a budget of Rp451 trillion for the 2022 National Economic Recovery Program (https://covid19.go.id) and the Ministry of SOEs changing its big strategy in 2021, namely the BUMN plan to survive the pandemic. According to the Ministry of SOEs, the COVID-19 outbreak has impacted the decline in the performance of most Indonesian SOEs. As stated by Jencova et al. (2016) in Stefko et al. (2019), Company's performance is a distinctive feature of entrepreneurial success. In the short term, the risk faced by the company is a decrease in income which causes a reduction in cash flow, so the company will experience liquidity risk. However, in the long run, it can increase the risk of default in fulfilling maturing obligations, causing financial distress, bankruptcy (insolvency), or having negative working capital. In addition, the risk of financial losses experienced by SOEs in Indonesia in recent years can increase the company's inability to conduct business (going concerned) in the future. Therefore, the competitiveness issue is highly relevant for SOEs, especially during the current COVID-19 pandemic, when even surviving in the market is difficult.

As one of the actors in economic activities, SOEs have an essential role in implementing the national economy to realize the community's welfare. However, based on law number 19 of 2003, the duties of SOEs are not only commercial in nature but also carry out some of the tasks of the government whose purpose is to serve the public interest or public service obligation (PSO) (Law No.19 of 2003, 2004). Thus, SOEs are required to carry out two different tasks simultaneously: seeking profit on the one hand and serving the public interest on the other. Assagaf (2017) states that the policy of public service obligations by providing subsidies to SOEs hurts the tier of financial distress, causing a drop significantly in the level of financial distress. However, Assagaf (2017) also emphasizes that routine government subsidies can result in higher dependence. Sayidah et al. (2019) confirm that SOE’s financial health decreases when funding maintains subsidies yearly. Still, on the other hand, financial health will improve if the authority gradually reduces subsidies and grants broad discretion over price frameworks and strategic planning to promote cost-effectiveness. Cost efficiency is one of the main factors that drive the motivation of companies to implement the innovation process to be better (Suwignjo et al., 2022). In another study, Sayidah et al. (2020) revealed that earnings management and subsidies do not affect financial distress.

The problem of predicting financial distress and failure is considered the far more crucial component investigated by scholars and researchers to determine the potential influence that may arise on shareholders, creditors, and society (Arkan, 2015; Awwad & Razia, 2021). Due to its damaging consequences on businesses, investments, and the economic system. Indicators of creditworthiness and bankruptcy are used to more accurately predict the future status of companies in terms of their ability to keep going or cease operations by reviewing historical circumstances and linking them to the coming years, and by evaluating the company's ability to develop its resources (Awwad & Razia, 2021).

Predicting financial distress is very necessary for making a business decision. The existence of the potential for bankruptcy in each company also has implications for the concerns of internal parties (managers, employees) and external companies (investors, creditors) (Yuliastry & Wirakusuma, 2014). One of the innovations of the financial distress prediction model is financial ratio analysis. Financial ratio analysis is widely used as a model to predict company failure. Beaver (1966a) discovered that financial percentages are useful to anticipate the inability of a company helped to help firms firmware. In addition, Beaver (1968b) also uses ratios and stock market prices to predict company failure. Furthermore, Altman (1968b) improved Beaver's financial ratios by conducting rigorous testing through multiple discriminant analysis (MDA) and suggested using five main financial ratios. Finally, financial analysts should use several predictive methods to assess and clarify the financial health of companies (Stefko et al., 2019).

Given the importance of bankruptcy prediction models for a company, various kinds of model development innovations have been carried out and tested empirically. For example, Keasey & Watson (1987) predict firm failure using non-financial and financial indicators (ratio) and try them into three models. Likewise, Aziz & Dar (2006) constructed a bankruptcy forecasting model that could be placed into one of three categories: data analysis models, artificially intelligent expert system (AIES) models, and theoretical frameworks. Furthermore, Hu & Sathye (2015); Li et al. (2021); and Karas (2022) confirmed that the financial distress prediction model that includes non-financial and macroeconomic variables has better predictive power than the model that only considers financial performance. The results of this study support the previous opinion, which shows that prediction models combining both financial and non-monetary factors can produce superior predictive values (Ooghe & Balcaen, 2007). Wilkins's (1997) study shows that the auditor's opinion is a significant predictor of future financial difficulties for companies experiencing technical problems. Furthermore, Dimitras et al. (1999) put more emphasis on qualitative attributes than economic attributes by testing a set of rules that can distinguish between healthy and failing companies to predict business failure. Likewise, Chen (2008) and Li et al. (2021), in their study, found that incorporating corporate governance measures into the binary logistic analysis can increase the validity of predicting financial distress compared to using financial ratios alone.

This study aimed to test the ability of the financial distress prediction model using three five models. First, Model 1 uses financial variables, Model 2 uses non-financial variables, and Model 3 uses financial and non-financial variables. Model 4 uses financial and non-financial variables to sample listed SOEs, and Model 5 for non-listed SOEs. The difference with previous research lies in using three five testing models at once and using research samples in all SOEs companies. Previous research, especially in Indonesia, has never conducted specific tests on all SOEs but only on some sectors. This study develops the previous financial distress prediction model by Tinoco & Wilson (2013); Hu & Sathye (2015); Vo et al. (2019); Li et al. (2021); Elbannan (2021), and Emuron et al. (2021) used a dummy measure, while this study used the Altman model score rating (1=distress, 2=grey area, 3=safe). This study can provide a new perspective on the use of financial distress prediction models, provide empirical evidence for the development of literature on financial distress prediction models, and give consideration to the government in determining future SOE management policies. Therefore, the question in this study is whether using financial distress prediction models that use financial and non-financial variables provides more accurate results. This investigation is broken up into four distinct parts. The first section is the introduction, which explains why this research is important and what findings have been obtained from previous studies. In the second step of our process, we review the relevant literature to investigate the factors involved. In the third section, we talk about the research sample and the model analysis methods. In the fourth step, we will present the findings of the research and the outcomes of the discussion. Section five is where the researchers offer some succinct conclusions to wrap things up.

2 Literature Review

2.1 Financial Distress

Relationship lending, the most common techniques for lending to small firms, is based on the "soft" information which is accessible by keeping a close relationship with the client. Alternatively, there exist transaction-based lending techniques, those are mainly based on the "hard" information about the businesses. For example, financial statements based lending, asset-based lending and credit scoring (Petersen & Rajan, 2002). Researches dealing with the soft information generation and bank lending efficiency argue that the soft information collection and careful examination of the information can increase the lending efficiency of the bank that can positively affect the small business access to credit (D'Aurizio et al., 2015). On the other hand, empirical results show that commercial banks can improve the credit rating model by including the relationship lending qualitative (soft) information of the borrower in the rating process, and that focus only on the hard-financial information can be misleading (Dolezal et al., 2015).

Companies experience financial distress when they cannot meet their financial obligations, so they are forced to take drastic measures to meet their obligations. For example, they are filing for bankruptcy, going through a troubled debt restructuring, selling assets at a "discounted" price, or being acquired by a company that is more financially strong than themselves are all options (Chang et al., 2015). Meanwhile, Platt & Platt (2002) describe financial distress as the concluding phase of a deteriorating financial condition that precedes either bankruptcy or liquidation. A company's bankruptcy begins with financial difficulty, a circumstance in which the company struggles to generate profits or has a propethesity to run a deficit in its finances. Several types of financial difficulties, according to Hery (2016); The first possibility is an economic failure, which describes a situation in which the company's income is insufficient to cover all of its costs, including the cost of capital. Second, a company is considered to have failed if it has ceased operations while owing money to its creditors. Third, a company is said to be technically insolvent if it is unable to meet its current obligations when they become due. Fourth, insolvency in bankruptcy, which is a company condition that occurs when the book value of a company's debt is higher than the market value of the company's assets. The final option is known as legal bankruptcy, and it describes a situation in which a company is considered to be legally bankrupt if an official lawsuit has been filed against it by applicable laws.

Generally, the prediction model for company failure uses information regarding the company's finances, including balance sheets and income statements. But in addition, cash flow information can also be used as a predictor of financial distress (Zhang et al., 2010). Zhang et al. (2010) state that financial difficulty is when the company's operating cash flow is insufficient to meet current obligations, and the company must take corrective action. The prediction model for company failure has three types: the Statistical Model, Artificial Intelligence and Expert System (AIES), and the Theoretic model (Aziz & Dar, 2006; Kpodoh, 2009). Multiple Discriminant Analysis (MDA) and Logit models, as well as several AIES models that use Neural Networks, are said to be the most popular types of statistical software, as stated by Aziz & Dar (2006). In addition, according to Pech et al. (2020), the highest success rate of Czech bankruptcy prediction models was achieved by the Zmijevski model. Meanwhile, Zhang et al. (2010) modified Altman's MDA model into the Chinese version of the Z-score model using four variables and has a very high forecasting power to predict bankruptcy for companies with a problematic credit rating in China. But, in Slovakia, a creditworthy model confirmed that the sector appears financially healthy (Stefko et al., 2019).

2.2 Altman *Z-score* Model

Edward I. Altman developed a bankruptcy prediction model in 1968. The Altman model was initially applied to companies to distinguish between companies that were bankrupt and not bankrupt using financial ratios (Altman, 1968). The Altman model measures a company's financial health and predicts its potential for bankruptcy. Of the twenty-two variables used, The best financial ratios to predict corporate bankruptcy were identified by Altman (1968) as falling into one of five categories: X1 (working capital/total assets), X2 (retained earnings/total assets), X3 (earnings before interest and taxes/total assets), X4 (market value equity/book value of total debt), and X5 (sales/total assets).

At first, Altman developed a model based on manufacturing companies, then later made modifications for other sectors. The Altman model is considered sufficient to predict company failure, both in the financial and non-financial industries (Al-Sulaiti & Almwajeh, 2007; Hamid et al., 2016; Azim & Sharif, 2020). The first Altman model for manufacturing companies uses five ratios (X1, X2, X3, X4, and X5). However, Altman redeveloped the model in 1983 to apply the Z-Score to private, manufacturing, and non-manufacturing companies. Altman et al. (2014) divided the previous model into two different index groups: public and private companies. The first Altman model (see equations 1, 2 & 3) uses the firm's market value and thus only applies to public companies. However, the second Altman model (see equations 4 & 5) re-estimates the first model by replacing the value of X4, i.e., book value equity will now be used market value equity will be phased out. Furthermore, due to the lack of a secondary database on private companies, Altman tested the Z-Score model using four variables without including the X5 (Sales/Total assets) ratio due to potential industry effects. Altman argues that when the industry-sensitive variable X5 (asset turnover) is entered into the model, which allows the model to be applied to companies that are not involved in manufacturing and financial services, the likelihood of the industry effect occurring increases. Therefore, Altman estimates the second revised Z-Score model using four variables (Altman et al., 2014).

The first Altman model for public companies:

$$Z = 0{,}012(X_1) + 0{,}014(X_2) + 0{,}033(X_3) + 0{,}006(X_4) + 0{,}999(X_5) \quad (1)$$

$$Z = 1{,}2(X_1) + 1{,}4(X_2) + 3{,}3(X_3) + 0{,}6(X_4) + 1{,}0(X_5) \quad (2)$$

A first revised model for private/non-public companies:

$$Z' = 0{,}717(X_1) + 0{,}847(X_2) + 3{,}107(X_3) + 0{,}420(X_4) + 0{,}998(X_5) \quad (3)$$

A second revised model for non-manufacturing/financial companies:

$$Z'' = 3{,}25 + 6{,}56(X_1) + 3{,}26(X_2) + 6{,}72(X_3) + 1{,}05(X_4) \quad (4)$$

$$Z'' = 6{,}56(X_1) + 3{,}26(X_2) + 6{,}72(X_3) + 1{,}05(X_4) \quad (5)$$

Conclusions on the calculation of the Z-Score value of the first Altman model, namely, if the Z-Score is below 1.81, the company can go bankrupt. Furthermore, if the Z-Score value is between 1.81–2.99, then the company is in the gray area, in which the zone may go bankrupt if there is no protection, whereas if the Z-Score is above 2.99, then the company is declared not bankrupt. Meanwhile, the revised Altman model Z-Score values for non-manufacturing are; if Z-Score<1.10, announced bankrupt/distressed; if Z-Score>2.60, declared not bankrupt/safe; and if the Z-Score is between 1.10–2.60, being in the gray zone to bankruptcy.

2.3 Financial and Non-Financial Variables

The financial variables used in this study are financial ratios, including liquidity ratios (current ratio, cash flow operations), leverage (debt to total assets), and profitability (gross profit margin, return on assets). Financial ratio analysis can reveal conditions and trends that are difficult to detect by examining each component that makes up the ratio. Financial ratios are proper when the goal is future-oriented (Subramanyam, 2019). Financial ratio analysis makes it possible to determine the level of liquidity, solvency, operating effectiveness, and profitability of the company (Munawir, 2014; Hanafi & Halim, 2018). Similarly, Altman (1968) had already established five categories of financial ratios into one model in the past to the level of health and the potential for bankruptcy. The use of financial ratios is an essential component in determining whether or not a company is financially stable. This function contributes to the upkeep of an organization's competitive position, with the accomplishment of stable development helping to contribute to the elimination of potential financial risks (Kliestik et al., 2020). Meanwhile, financial statements are the object of ratio analysis, and the results evaluate the company's financial performance, including measuring the potential for financial distress. Non-financial variables used in this study include; going concern opinion, audit report lag, opinion shopping, additional stated capital, and subsidies. This variable is one of the innovations of the financial distress prediction model that was previously by Keasey & Watson (1987); Chen (2008); Hu & Sathye (2015); Assagaf (2017); Assagaf et al. (2017); Sayidah et al. (2019); Sayidah et al. (2020); Elbannan (2021); Li et al. (2021); and Alexeyeva & Sundgren (2022).

2.3 Hypotheses Development

We formulated three five models to predict financial distress; namely, Model 1 uses financial variables, Model 2 uses non-financial variables, Model 3 uses financial and non-financial variables, Model 4 uses financial and non-financial variables in the sample of listed SOEs, while Model 4-5 on the selection of non-listed SOEs. To test the five models, we developed four hypotheses.

H1: The financial distress prediction model’s ability to use financial variables is better than the model using non-financial variables.

H2: The financial distress prediction model’s ability to use a combination of financial and non-financial variables is better than the model that only uses financial variables.

H3: The financial distress prediction model’s ability to use a combination of financial and non-financial variables is better than the model that only uses non-financial variables.

H4: The ability of the financial distress prediction model in listed SOEs is higher than in non-listed SOEs.

Based on the hypothesis that has been proposed, we also developed conceptual framework, as shown in Figure 1 below:

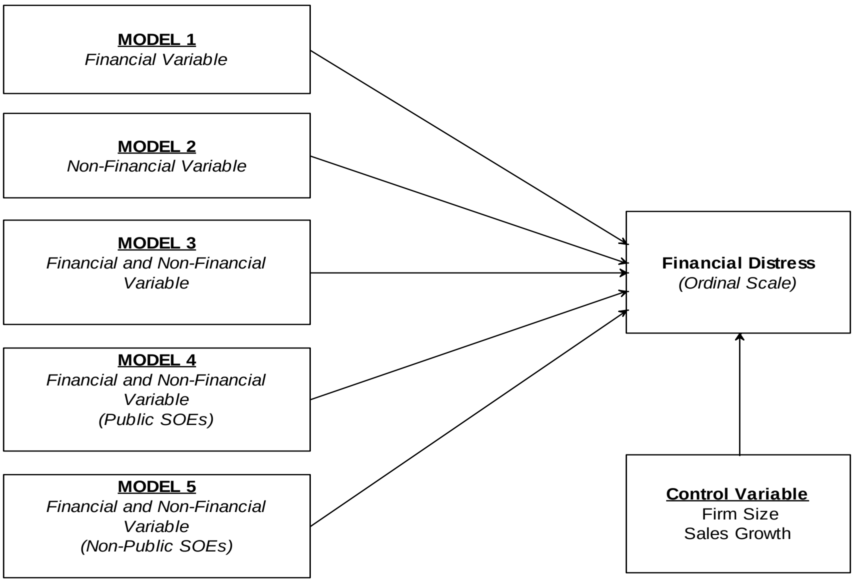

Figure 1: Conceptual Framework

3 Research and Methods

3.1 Materials, Methods, and Models

In the course of this research, panel data have been utilized. The analysis was conducted using a method called ordinary logistic regression. The use of ordinal logistic regression is since the dependent variable in this investigation is ranked on a scale consisting of three categories (Ghozali & Ratmono, 2017). Our research data source uses panel data from the Indonesia Stock Exchange, the company's website, with an observation period of 2016-2022. This study's sample of people to whom it was applied is all state-owned companies, both listed and non-listed, with as many as 107 companies. Determination of the research sample using the purposive sampling method is based on the researcher's criteria (Sekaran & Bougie, 2017) and (Efferin et al., 2008). Based on the purposive sampling method, 50 companies met the sample criteria, consisting of 21 listed SOEs and 29 non-listed SOEs. We innovate on previous research that has never used both types of samples simultaneously in research. The sample selection criteria in this study can be seen in Table 1.

Table 1: Research Sampling Criteria

No	Research Sampling Criteria	Amount
1.	Total population of state-owned enterprises in Indonesia	107
2.	Financial statements and annual reports that are not fully accessible	(57)
3.	Companies that meet the criteria as a sample	50
4.	Total observation for 7 years	350

To answer our research hypotheses, we formulated the following research model as follows (equation 6):

$$\textit{Z-Score} = \alpha_1 + \beta_1 CR + \beta_2 CFO + \beta_3 LEV + \beta_4 GPM + \beta_5 ROA + \beta_6 GCO + \beta_7 ARL + \beta_8 SHOP + \beta_9 ADD + \beta_{10} SUB + \varepsilon \qquad (6)$$

3.2 Measurements of Variable

The measurement of each variable can be seen in Table 2 below.

Table 2: Measurement of Variables

Variable	Variable Indicator	Measurement
Financial Distress (FDIS)	1=distress, 2=grey-area, 3=safe	Ordinal
Financial variable:		
Current Ratio (CR)	Curr. Asset/Curr. Liabilities	Ratio
Cash Flow Operation (CFO)	CFO/Curr. Liabilities	Ratio
Debt to Asset (LEV)	Tot. Liabilities/Tot. Asset	Ratio
Gross Profit Margin (GPM)	Gross Profit/Tot. Sales	Ratio
Return On Asset (ROA)	EAT/Tot. Asset	Ratio
Non-financial variable:		
Going Concern Opinion (GCO)	1=GCO, 0=Non-GCO	Dummy
Audit Report Lag (ARL)	Number of days issuance audit report	Nominal
Opinion Shopping (SHOP)	1=Changing auditor, 0=None	Dummy
Additional State Capital (ADD)	1=Additional state capital, 0=None	Dummy
Subsidies (SUB)	1=Receiving subsidies, 0=None	Dummy
Control variable:		
Firm Size	FSize=Ln (Tot. Asset)	Nominal
Growth	(Curr.Sales-Prev.Sales)/Prev. Sales	Ratio

4 Results and Discussion

4.1 Distribution of sample

Table 3 shows the distribution of sample units of SOEs based on three categories: companies experiencing distress, being in the grey zone, and non-distressed. Based on 350 observation units, after analyzing the dependent variable, it was found that 236 companies (67.43 percent) experienced distress (value 1). Furthermore, as many as 64 companies (18.29 percent) are in a distress-prone condition (score 2), while the remaining 50 companies (14.29 percent) are in a healthy/good financial situation (score 3).

Table 3: Dependent Variable Description

Value	Count	Percent
1 = Distress	236	67.43
2 = Grey area	64	18.29
3 = Non distress	50	14.29
Total	350	100.00

4.2 Descriptive Statistics

The results of descriptive statistical tests in this study are shown in Table 4. According to the information in the table, the financial distress variable (FDIS), if it is worth 3, is declared healthy; if it is worth 2, it is declared vulnerable; if it is worth 1, it is declared unhealthy. Meanwhile, the descriptive statistical test results show a mean value of 1.468, indicating that most companies are in a harmful condition (distress).

Table 4: Descriptive Statistics

Variable	Minimum	Maximum	Mean	Std. Dev.
(Y) FDIS	1.000	3.000	1.468	0.732
(X1) CR	0.031	85.999	2.575	5.999
(X2) CFO	-29.158	29.975	0.217	2.400
(X3) LEV	0.071	3.463	0.592	0.341
(X4) GPM	-6.895	1.960	0.195	0.478
(X5) ROA	-0.430	0.632	0.030	0.077
(X6) GCO	0.000	1.000	0.191	0.393
(X7) ARL	12.000	200.000	63.322	32.197
(X8) SHOP	0.000	1.000	0.288	0.453
(X9) ADD	0.000	1.000	0.188	0.391
(X10) SUB	0.000	1.000	0.131	0.338
Control SIZE	11.889	21.185	16.714	2.033
Control GROWTH	-4.525	5.104	0.139	0.454

The current ratio (CR) has a mean value of 2.57, indicating that the average CR of the companies in this study is 2.57 percent. This means that corporate liquidity is still quite good as measured by the current ratios. However, the minimum value of 0.03 indicates that none of the samples in this study has a negative current ratio (current assets<current liabilities). The cash flow operation (CFO) has a minimum value of -29.16, a maximum of 29.97, and a mean of 0.21. The mean value

of 0.21 indicates that the company's average operating cash flow ratio is still relatively low; even in some companies, it is negative, although there are also companies with very high ratio values. The leverage (LEV) has a minimum value of 0.07, a maximum of 3.46, and a mean of 0.59, indicating that this study's average level of leverage is 59-60 percent. Meanwhile, the lowest leverage value is 7 percent, and the highest is 340 percent. Finally, the gross profit margin (GPM) has a minimum value of -6.89, a maximum of 1.96, and a mean of 0.19, indicating that this study's average gross profit margin ratio is 19 percent. This value shows that most companies have a fairly good gross profit level. Meanwhile, the return on asset (ROA) has a mean value of 0.03 which means this study's average level of profitability is 3 percent.

Furthermore, the going concern opinion (GCO) has a minimum value of 0 and a maximum of 1, with a mean value of 0.19, indicating that the average company does not get a going concern opinion in its audit report. So far, the audit opinion received is mostly "fairly in all material respects" or without "emphasis of matter." The audit report lag (ARL) has a mean value of 63.32, a minimum of 12.00, and a maximum of 200.00. Therefore, completing an auditor's audit report requires an average completion time of 63.32 days, while the fastest completion time is 12 days and the longest is up to 200 days. Next, opinion shopping (SHOP) has a mean value of 0.28, a minimum of 0.00, and a maximum of 1.00. The mean value of 0.28 is close to the minimum value; this shows that most companies tend not to change auditors in a fast time. Instead, companies tend to use the services of the same audit firm for the next few years. Finally, additional stated capital (ADD) and subsidy (SUB) have mean values of 0.18 and 0.13, respectively, with a minimum value of 0.00 and a maximum value of 1.00. The average weight of close to 0.00 indicates that most companies do not receive additional capital or subsidies from the state. This means that even though companies are state-owned, they do not always have to receive capital injections from the government. At the same time, state subsidies are only given to companies with special assignments to carry out public service obligations.

4.3 Percentage Correctly Predicted

The value of a regression model's ability to accurately predict the future is described by the percentage of observations that were correct. The model is considered to be of higher quality the higher the value of each prediction percentage for Model 1, Model 2, Model 3, Model 4, and Model 5 is as follows: 5 are presented in Table 5. Also presented is the value of each prediction percentage for Model 6.

According to Table 5, the proportion of times that Model 3 correctly predicted a value was higher than that of both Model 1 and Model 2. The results of the tests conducted on all of the samples demonstrated that Model 3 had a higher level of accuracy in its predictions compared to Model 1 and Model 2. On the other hand, when contrasted to Model 4 and Model 5, which were only evaluated on a specimen of listed and non-listed SOEs, Model 4 has a greater degree of precision than some other models. Therefore, it is possible to make the inference that Model 4, which is a model that uses a sample of listed SOEs as opposed to Model 1, Model 2, Model 3, and Model 5, possesses a forecasting accuracy value that is superior to the other modeling techniques.

Table 5: Percentage Correctly Predicted Model

Model	Obs.	Correct	Incorrect	% Correct	% Incorrect
Model 1	350	301	49	86.000	14.000
Model 2	350	258	92	73.714	26.286
Model 3	350	311	39	88.857	11.143
Model 4	147	141	6	95.918	4.082
Model 5	203	179	24	88.177	11.823

4.4 Output Ordinal Logistic Regression (Model 1, Model 2, Model 3)

Putting the hypothesis that this study is based on through its paces by employing the approach of ordinal logistic regression The findings of the ordinal logistic regression test are as follows: that was based on Model 1, Model 2, and Model 3 are presented in the table that is referenced as Table 6, which can be found below. Putting the hypothesis that this study is based on through its paces by using the technique of ordinal logistic regression The results of the ordinal logistic regression test that were based on Model 1, Model 2, and Model 3 are presented in Table 6.

The results of testing the data in Table 6 show that the significant variables in Model 3 are liquidity (CR), leverage (LEV), gross profit margin (GPM), return on assets (ROA), and subsidies (SUB). These variables affect financial distress at a confidence level of 1% (0.01), 5% (0.05), and 10% (0.1). This indicates that these variables affect the level of financial distress in SOEs companies in Indonesia. However, cash flow operation (CFO), going concern opinion (GCO), audit report lag (ARL), opinion shopping (SHOP), and additional state capital (ADD) have significance values above 1%, 5%, or 10%, so that indicates that the variable is not a variable that affects financial distress.

In addition, Model 1 shows that the current ratio (CR), leverage (LEV), gross profit margin (GPM), and return on asset (ROA) are significant at the 1% and 5% levels. Furthermore, when re-tested on Model 3, the results of the current ratio (CR), leverage (LEV), gross profit margin (GPM), and return on asset (ROA) remain consistent in significance. Furthermore, testing on Model 2 shows that only subsidies (SUB) are significant (at the 1% level), as well as in Model 3. Meanwhile, going concern opinion (GCO), audit report lag (ARL), opinion shopping (SHOP), and additional paid-in capital (ADD) are not significant in Model 2 or Model 3. In addition, the control variable company size (SIZE) consistently has a significant effect (at the 1% level).

Table 6: Output Ordinal Logistic Regression (Model 1, 2, 3)

Variable	**Model 1**		**Model 2**		**Model 3**	
(X1) CR	0.101	(0.037)**			0.095	(0.065)*
(X2) CFO	-0.162	(0.297)			-0.153	0.383
(X3) LEV	-10.076	(0.000)***			-10.231	(0.000)***
(X4) GPM	-2.253	(0.013)**			-2.212	(0.016)**
(X5) ROA	41.163	(0.000)***			46.312	(0.000)***
(X6) GCO			-0.385	0.251	0.324	0.526
(X7) ARL			-0.003	0.545	0.008	0.224
(X8) SHOP			-0.159	0.567	-0.242	0.557
(X9) ADD			-0.662	0.095	-0.851	0.122
(X10) SUB			2.334	(0.000)***	2.510	(0.000)***
Control SIZE	-0.556	(0.000)***	-0.697	(0.000)***	-0.741	(0.000)***
Control GROWTH	-0.893	(0.090)*	0.006	(0.978)	-0.495	0.348
Pseudo R-squared	0.614		0.210		0.651	
LR statistic	367.358		125.794		389.102	
Prob (LR statistic)	0.000		0.000		0.000	
% Correctly Predicted	86.000		73.714		88.857	
Observations	350		350		350	

*Notes: Level of sig. *(0.1), **(0.05), ***(0.01)*

4.5 Output Ordinal Logistic Regression (Model 4, Model 5)

After testing Models 1, 2, and 3, the next step is to conduct separate tests on samples of listed SOEs (Model 4) and non-listed SOEs (Model 5). Table 7 will compare the results of ordinal logistic regression statistical tests on Model 4, Model 5, and Model 3. Table 7 explains that the financial variables in Model 4 that are significant at the 1%, 5%, and 10% level are leverage (LEV), gross profit margin (GPM), and return on assets (ROA). Meanwhile, for the non-financial variable group, only going concern opinion (GCO) is significant. In addition, the subsidy (SUB) is not included in Model 4 because none of the samples of listed SOEs in this study received government subsidy funds. However, the subsidy (SUB) is included in Model 5 because several non-listed SOEs receive state subsidies. Furthermore, findings obtained from statistical analysis on a sample of unlisted state-owned enterprises (Model 5) indicate significant financial variables, namely the current ratio (CR), leverage (LEV), gross profit margin (GPM), and return on assets (ROA), while the only significant non-financial variable is additional state capital (ADD). Furthermore, the control variable for firm size (SIZE) remains consistently significant.

The Pseudo R-squared value in the sample of listed SOEs is 0.859 higher than that of non-listed SOEs at 0.645. This value means that the variability of the financial distress variable, which can be explained by the variability of the independent variable in Model 4, is 85.9 percent. In contrast, in Model 5, it is 64.5 percent. Meanwhile, the Prob value (LR statistic) of 0.000 means that Model 4 and Model 5 used in the test are excellent. For example, the percentage value of Model 4 prediction accuracy of 95.92 percent is higher than that of Model 5, which is 88.18 percent. Suppose look at the overall model used in the sample of listed SOEs compared to non-listed SOEs. In that case, it is known that the consistently significant variables are leverage (LEV), gross profit margin (GPM), and return on assets (ROA). Likewise, the three variables remain consistently considerable in Model 3, which uses a sample of listed and non-listed SOEs. However, if we look at the consistency of non-financial variables in Model 3, Model 4, and Model 5, only subsidies (SUB) are consistent in Model 3 and Model 5. Overall, the model that uses a sample of listed SOEs is better at predicting financial distress than the model that uses an example of non-listed SOEs or models that combine both listed and non-listed.

Table 7: Output Ordinal Logistic Regression (Model 3, 4, 5)

Variable	**Model 3** *Listed & Non-Listed*		**Model 4** *Listed*		**Model 5** *Non-Listed*	
(X1) CR	0.095	(0.065)*	2.105	0.280	0.141	(0.044)**
(X2) CFO	-0.153	0.383	-2.715	0.301	-0.230	0.285
(X3) LEV	-10.231	(0.000)***	-24.156	(0.008)***	-13.553	(0.000)***
(X4) GPM	-2.212	(0.016)**	-16.315	(0.098)*	-1.946	(0.0600)*
(X5) ROA	46.312	(0.000)***	138.218	(0.003)***	20.728	(0.000)***
(X6) GCO	0.324	0.526	4.038	(0.033)**	0.420	0.517
(X7) ARL	0.008	0.224	0.031	0.209	-0.007	0.491
(X8) SHOP	-0.242	0.557	-1.971	0.409	0.284	0.557
(X9) ADD	-0.851	0.122	-31.277	0.989	-0.967	0.147
(X10) SUB	2.510	(0.000)***	-	-	2.320	(0.001)***
Control SIZE	-0.741	(0.000)***	-1.952	(0.033)**	-0.799	(0.000)***
Control GROWTH	-0.495	0.348	0.474	0.310	-0.399	0.481
Pseudo R-squared	0.651		0.859		0.645	
LR statistic	389.102		154.816		254.065	

Prob (LR statistic)	0.000	0.000	0.000
% Correctly Predicted	88.857	95.918	88.177
Observations	350	147	203

*Notes: Level of sig. *(0.1), **(0.05), ***(0.01)*

4.6 Discussion

Based on Table 6 and Table 7, the findings in this study accept hypothesis 1 (H1), which states that the capacity for accurate forecasting of economic hardship Model 1 is better than Model 2. This assertion, following the value of the Pseudo R^2 Model 1, is greater than the value of Model 2. That is, the variability of the variable financial distress, which can be explained by the variability of the independent variables in Model 1, is 61.4 percent higher than in Model 2, where it is only 2.10 percent. This can be demonstrated by comparing the two models' respective standard deviations. In addition, judging from the prediction accuracy value of Model 1 of 86.0 percent, it is also higher than Model 2 of 73.7 percent. Thus, the findings of this study support hypothesis 1. This finding is consistent with the previous study by Vo et al. (2019) and Li et al. (2021), which revealed that the accuracy of predicting financial distress using financial variables was quite good compared to those using non-financial variables. However, this finding differs from Hu & Sathye (2015) and Keasey & Watson (1987), which state that the financial distress prediction accuracy model using non-financial variables is better than using financial variables alone.

The findings of this study also accept hypothesis 2 (H2), which states that the predictive ability of financial distress Model 3 is better than Model 1. This statement is in line with the value of Pseudo R^2 Model 3, which is higher than Model 1. independent in Model 3 by 65.1 percent, a little higher than Model 1 by only 61.4 percent. Furthermore, judging from the prediction accuracy value of 88.8 percent in Model 3, it also increased compared to Model 1 of 86.0 percent. Thus, the findings of this study accept hypothesis 2 (H2). This finding is consistent with those found by Li et al. (2021), as well as those found by Vo et al (2019), Hu & Sathye (2015), Tinoco & Wilson (2013), and Keasey & Watson (1987). According to them, the model for predicting financial distress that makes use of both financial and non-financial variables has a higher level of predictive accuracy than the model that only makes use of financial and non-financial variables separately. Even Alexeyeva & Sundgren (2022), Karas (2022), Li et al. (2021), Vo et al. (2019), and Tinoco & Wilson (2013) combine financial ratio variables with audit opinion, audit switch, public firms, corporate governance, stock market information, and macroeconomic conditions.

This finding also accepts hypothesis 3 (H3), which states that the predictive ability of financial distress Model 3 is better than Model 2. This statement is supported by the Pseudo R^2 Model 3 value, which is much higher than Model 2. This means that the independent variable can explain the variability of the financial distress variable. For example, in Model 3, by 65.1 percent, while in Model 2, it is only 2.1 percent. In addition, the prediction accuracy value of Model 3 of 88.8 percent also increased compared to Model 2 of 73.7 percent. This finding is also in agreement with Li et al. (2021), Vo et al. (2019), Hu & Sathye (2015), and Tinoco & Wilson (2013). They state that in financial distress the accuracy of predictions made using models that take into account both financial and non-financial factors is significantly improved relative to the accuracy of predictions made using alternative models. that only use financial and non-financial variables. Just. However, much earlier research by Keasey & Watson (1987) revealed that the predictive model of financial distress combining financial and non-financial variables has the same results compared to a model that only uses non-financial variables.

In conclusion, the findings of this research confirm the validity of hypothesis 4 (H4), which asserts that a predictive ability exists of the financial distress model of Model 4 is better than Model 5.

This statement is supported by the value of Pseudo R^2 Model 4, which is 76.80 percent higher than Model 5, which is 59.20 percent. Furthermore, Model 4's prediction accuracy value of 95.9 percent is also higher than Model 5 (88.2 percent). In addition, this finding provides empirical evidence that only financial variables have a significant effect as predictors of financial distress in Model 4. In contrast, essential variables in Model 5 include financial and non-financial variables. This finding provides empirical evidence in Model 4 that the financial variables current ratio (CR), leverage (LEV), gross profit margin (GPM), and return on asset (ROA) are the leading indicators in measuring financial distress. Meanwhile, in Model 5, only non-financial variables subsidies (SUB) affect financial distress and financial variables. So, it can be concluded that the performance of several samples of non-listed SOEs is highly dependent on injections of government funds.

The results of this study re-proven several previous studies that used additional state capital as a predictor, namely Handaka & Akbar (2020), which stated that additional state capital could improve the performance of SOEs, thereby reducing opportunities for financial distress. Zeitun & Tian (2007) also say that increasing government ownership participation is one way to improve company performance. In addition, the results of this study also confirm previous research related to state subsidies to SOEs in Indonesia, namely Assagaf (2017), Assagaf & Ali (2017), Assagaf et al. (2017), Sayidah et al. (2019). They state that increasing subsidies can reduce financial performance, thereby increasing financial distress. Marimuthu (2020) also says that the continuous provision of government subsidies can worsen financial performance, encourage SOEs to become too dependent on the government and burden the national fiscal.

5 Conclusion

The test results show the disparity between the five models' respective average values of the financial and non-financial variables that were used in the study. This investigation offers proof grounded in empirical studies. that the predictive model of financial distress in listed and non-listed SOEs using financial variables (Model 1) is better than models using non-financial variables (Model 2). In addition, the model for predicting financial distress in listed and non-listed SOEs that combines financial and non-financial variables (Model 3) is better than the model that only uses financial variables (Model 1). Likewise, the ability of the financial distress prediction model for SOEs and the listed and non-listed that combine financial and non-financial variables (Model 3) is also better than the model that only uses non-financial variables (Model 2). This study's results also prove that the predictive model of financial distress in listed SOEs (Model 4) is better than that of non-listed SOEs (Model 5).

Other empirical evidence shows that consistently significant variables in all test models are leverage, gross profit margin, and return on assets. Furthermore, if we look at the pseudo-R-squared value and prediction accuracy, Model 4 has the highest value compared to other models. However, when comparing listed SOEs with non-listed SOEs, it is known that the non-financial variables, additional state capital, and subsidies are only significant for non-listed SOEs. This finding shows that listed SOEs do not depend on further state equity participation or subsidies. At the same time, some non-listed SOEs still use state equity participation funds and subsidies to carry out their operational activities. The study has several limitations. Due to limited data and research time, we only used five financial and five non-financial variables. Although further research can add other financial and non-financial variables, other indicators, such as corporate governance or macroeconomic conditions, can be added to the model. This research model is also still limited to ordinal logistic regression testing, so testing additional moderating or intervening variables can strengthen the study's results.

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