Syntax Literate: Jurnal Ilmiah Indonesia p–ISSN: 2541-0849 e-ISSN: 2548-1398
Vol. 7, No. 10, Oktober 2022

THE PERFORMANCE OF FINANCIAL DISTRESS PREDICTION MODELS: EVIDENCE FROM ASEAN COUNTRIES

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Abstract

The objective of this study is to scrutinise selected financial distress prediction models across several categories, such as country, sector, COVID-19 era, utilising binomial probability test, confusion matrix, and ROC curve. The sample of this study included 21,250 observations from 6 countries and 21 sectors. In addition, it was collected on an annual basis from 2012 to 2021, which included both the pre- and during COVID-19 eras. According to the results of the binomial probability test, the observed proportion are statistically different from the assumed probability based on accuracy and total positives. Meanwhile, based on the confusion matrix and ROC curve results, it was indicated that the Grover model performed best in predicting financial distress for all COVID-19 era, country, and sector observations. This suggests that the Grover model can be applied as a practical tool to predict financial distress in ASEAN. This study will contribute significantly to the literature on financial distress prediction since there are no studies that scrutinise and compare the performance of financial distress prediction models in ASEAN countries and different sectors.

Keywords: Financial Distress Prediction Models, ASEAN Countries, Performance Evaluation

Introduction

Financial distress is a significant area of research for corporate finance (Sun et al., 2014). Its core is the prediction of financial distress, which is a topic of extensive ongoing research. In general, financial distress predictions predict whether a firm will fall into financial distress based on current financial data using different models. It is critical in managerial decisions for businesses, investment decisions for investors, credit decisions for creditors, and other similar decisions (Balasubramanian et al., 2019; Sun et al., 2014). In addition, the financial distress models assist creditors in assessing the risk associated with a firm issuing new loans, and they can alert the firm's auditors to monitor the performance of financial activities. During business activities, stakeholders are frequently solicitous about the accuracy of financial distress predictions. In order to improve the

How to cite:	Jessica, Moch. Doddy Ariefianto (2022) The Performance of Financial Distress Prediction Models: Evidence From Asean Countries, *(7) 10,* http://dx.doi.org/10.36418/syntax-literate.v7i10.11940
E-ISSN:	2548-1398
Published by:	Ridwan Institute

accuracy of existing financial distress predictions, different models have been introduced in previous studies (Rafatnia et al., 2020).

It is essential to comprehend whether the firm has started to experience financial distress in order for the firm's management to be cautious and take appropriate action if there are indicators that something terrible is happening. Moreover, creditors can use this information to their advantage by discovering whether the potential debtor's business qualifies for a loan and being cautious when monitoring the debtor's financial condition. Furthermore, investors may supervise and monitor the firm's financial condition by employing the current financial distress prediction models, allowing them to make the best decisions while preparing for the worst-case scenario (Balasubramanian et al., 2019).

This study scrutinised certain financial distress prediction models to fill a gap in the literature using 21,250 observations of ASEAN non-financial sector firms over the period 2012-2021. There have been a number of studies on the financial distress prediction model in specific countries and sectors, such as Balasubramanian et al. (2019), Habib et al. (2020), Setiawan & Rafiani (2021), and Salim & Ismudjoko (2021), but there have been no studies about ASEAN or various sectors. Due to the establishment of the ASEAN Economic Community, which has the goal of creating a dynamic and highly competitive region which is fully integrated with the global economy (Silalahi, 2017), the ASEAN region was chosen as the sample of this study.

If the ASEAN countries are more integrated and better coordinated, they have the potential to increase market efficiency collectively, resulting in more substantial growth (K. Vu, 2020). According to ASEAN Economic Community, ASEAN will become more dynamic and competitive if it develops into a single market and production base. Moreover, creating a stable, prosperous, and highly competitive economic region is the goal of ASEAN economic integration. This will encourage a larger, more efficient production scale in more accessible locations and improve the response to consumer needs (Silalahi, 2017).

The primary contributions of this study are as follows: First, there is a difference in the research sample compared to previous studies. This study used ASEAN firms' data as samples, while the others only researched one or two countries as well as industry sectors. The study focused on the non-financial sector, which is divided into 21 sectors, whereas previous studies only researched on one or two sectors. Second, despite the fact that numerous studies about the Altman, Grover, and Springate models have been published, to the best of our knowledge, no research studies have assessed the impact of the FDP models on the non-financial sector in ASEAN. This study emphasised the findings which demonstrated that the FDP models can be implemented in a variety of countries and sectors. The findings of this study are expected to be used by management for internal assessment and evaluation. Furthermore, before making an investment, investors and creditors can assess the firm's financial performance.

The continuations of this study were explained as follows: section 2 provides a literature review and hypothesis development; section 3 explains research methodology;

section 4 presents the empirical findings and results; and section 5 provides the conclusion of the study.

Research Methodology

A. *Financial Distress Performance: Existing Empirics*

The summaries of each studies are presented in table 1 below.

Table 1
Existing Empirics

Author	Period	Model	Context	Results
Aminian et al. (2016)	2008-2013	Altman, Springate, Zmijewski, Grover	Textile and ceramic firms listed on the Tehran Stock Exchange	Grover model, with an accuracy rate of 98%
Djamaluddin et al. (2017)	2009-2015	Altman, Ohslon, Zmijewski	Japanese electronic manufacture firms listed on the Tokyo Stock Exchange	Ohlson model, with an accuracy rate of 62.14%
Indriyanti (2019)	2015-2016	Altman, Fulmer, Taffler, Zmijewski, Ohlson, Springate, Grover	World's 25 largest technology companies listed on Forbes	Grover model, with an accuracy rate of 96.6%
Rababah et al. (2020)	2013-2020	ROA, ROE	Chinese listed firms, extracted from CSMAR database	COVID-19 has had a negative impact on financial performance of the Chinese listed companies
Yendrawati & Adiwafi (2020)	2014-2018	Altman, Springate, Zmijewski	Property firms listed on the Indonesia Stock Exchange	Altman model, with an accuracy rate of 88.44%
Fauzi et al. (2021)	2014-2019	Altman, Springate, Zmijewski, Grover	Telecommunications firms listed on the Indonesia Stock Exchange	Altman, Springate, and Grover models, with

				an accuracy rate of 100%
Salim & Ismudjoko (2021)	2015-2019	Altman, Springate, Zmijewski, Ohlson, Grover	Coal mining firms listed on the Indonesia Stock Exchange	Altman and Ohlson models, with an accuracy rate of 90.91%
Muzanni & Yuliana (2021)	2015-2019	Altman, Springate, Zmijewski	Retail firms listed on Indonesia Stock Exchange and Singapore Stock Exchange	Zmijewski model, with an accuracy rate of 87% (Indonesia), Altman model, with an accuracy rate of 86% (Singapore)
Syaputri & Cakranegara (2021)	2016-2020	Altman, Grover, Zmijewski	Automotive and component companies listed on the Indonesia Stock Exchange	Grover model, with an accuracy rate of 85%
Rahmah & Novianty (2021)	2019-2020	Altman	Hotel, restaurant, and tourism firms listed on the Indonesia Stock Exchange, before and during COVID-19	COVID-19 has had a negative impact on the hotel, restaurant, and tourism firms

Source: Authors' own

B. Variable *definitions and measurements*

The definition and measurement of each variable are presented in Table 2 as follows:

Table 2
Variable Definitions and Measurements

Variable	**Definition**	**Measurement**
Financial Distress (*ACT_FD*)	A condition occurs when the income generated by a firm is insufficient to allow it to make timely debt payments to its creditors (Danilov, 2014).	*ACT_FD* = 1 if the firm in question has experienced losses for three consecutive

		years; otherwise, it is 0 (Kordestani et al., 2011).
Altman Model (*Z_SCORE*)	The most well-known and frequently used MDA prediction model was developed by Edward I. Altman (Altman et al., 2014).	$Z'' = 6.56X1 + 3.26X2 + 6.72X3 + 1.05X4$ Z'' = 1 means the firm in question is expected to experience financial distress; otherwise, it is 0.
Grover Model (*G_SCORE*)	The model was developed by Jeffrey S. Grover in 2001 by redesigning and reassessing the Altman Z-Score model (Fauzi et al., 2021).	$G = 1.650X1 + 3.404X2 - 0.016ROA + 0.057$ G = 1 means the firm in question is expected to experience financial distress; otherwise, it is 0.
Springate Model (*S_SCORE*)	The model was developed by Gordon L.V. Springate in 1978 by redesigning and reassessing the Altman Z-Score model (Aminian et al., 2016; TURK & KURKLU, 2017).	$S = 1.03X1 + 3.07X2 + 0.66X3 + 0.4X4$ S = 1 means the firm in question is expected to experience financial distress; otherwise, it is 0.
Working Capital/Total Assets (*WC_TA*)	This variable is used to assess the firm's liquidity (Salim & Ismudjoko, 2021).	$WC\_TA = \frac{\text{Current Assets – Current Liabilities}}{Total\ Assets}$
Retained Earnings/Total Assets (*RE_TA*)	*RE_TA* is used to measure the firm's overall profitability (Salim & Ismudjoko, 2021).	$RE\_TA = \frac{Retained\ Earnings}{Total\ Assets}$
Earnings before interest & tax/Total Assets (*EBIT_TA*)	*EBIT_TA* is used to calculate the firm's profitability (Salim & Ismudjoko, 2021).	$EBIT\_TA = \frac{Earnings\ before\ interest\ and\ tax}{Total\ Assets}$
Total Equity/Total Liabilities (*TE_TL*)	*TE_TL* is used to calculate the value of a firm based on the book value of equity and liabilities (Salim & Ismudjoko, 2021).	$TE\_TL = \frac{Total\ Equity}{Total\ Liabilities}$

Return on Assets (*ROA*)	*ROA* is a measure of the income generated by the firm's total assets (Akben-Selcuk, 2016).	$ROA = \frac{Net\ Income}{Total\ Assets}$
Profit or loss before Tax/Current Liabilities (*PBT_CL*)	*PBT_CL* is used to calculate the firm's profitability (Salim & Ismudjoko, 2021).	$PBT\_CL = \frac{Profit\ or\ loss\ before\ tax}{Total\ Assets}$
Sales/Total Assets (*S_TA*)	*S_TA* is used to assess a firm's capacity to generate sales from its current assets (Salim & Ismudjoko, 2021).	$S\_TA = \frac{Net\ Sales}{Total\ Assets}$

The dependent variable selected and used for this study is the actual results of the number of firms experiencing financial distress or not (*ACT_FD*). Moreover, the independent variables in this study were the prediction results represented by the Altman, Grover, and Springate prediction models (*Z_SCORE*, *G_SCORE*, and *S_SCORE*). Meanwhile, the other variables, such as *WC_TA*, *RE_TA*, *EBIT_TA*, *TE_TL*, *ROA*, *PBT_CL*, and *S_TA*, were ratios applied to selected prediction models based on the existing literature.

C. Sample *Selection*

The population used in this study were all companies from ASEAN countries collected from the OSIRIS database. The ASEAN region was chosen as it has aimed to be a dynamic and highly competitive region which is fully integrated with the global economy since the establishment of the ASEAN Economic Community (Silalahi, 2017). The ASEAN countries selected are Indonesia, Malaysia, Philippines, Singapore, Thailand, and Vietnam. Only these six countries were chosen because they have a lot of firms which could be analysed for this study, so the sample proportions were not too varied. The sample of this study is non-financial sector companies listed on the OSIRIS database from 2012 to 2021, and the data were collected annually. This study used that specific sample period because it is a perfect period following the global financial crisis, a period when the ASEAN Economic Community was established, and a period when the COVID-19 pandemic was still ongoing, all of which may have influenced the actual and prediction results. Due to the fact that banking and finance firms are highly regulated industries with particular characteristics, only non-financial sector firms were chosen (Jamal Zeidan, 2012), which might have influenced the results of this study. The research selection and sampling were conducted using the purposive sampling method. The method was done by selecting samples using specific criteria mentioned above and 2,125 firms with a total of 21,250 observations were used as the sample.

D. *Research Framework*

The source of data collection in this study was secondary data. The data was obtained and collected from other parties; in this study, it was from the OSIRIS database.

The data was collected using the documentation study technique by re-recording or documenting the received data, especially for the firms from ASEAN countries in the non-financial sector which were used as our research sample. This study used a quantitative approach because the data were collected and used in the form of numbers calculated by statistical methods. The stages of data analysis in this study were descriptive statistics, ROC (Receiver Operating Characteristics) curve, and confusion matrix.

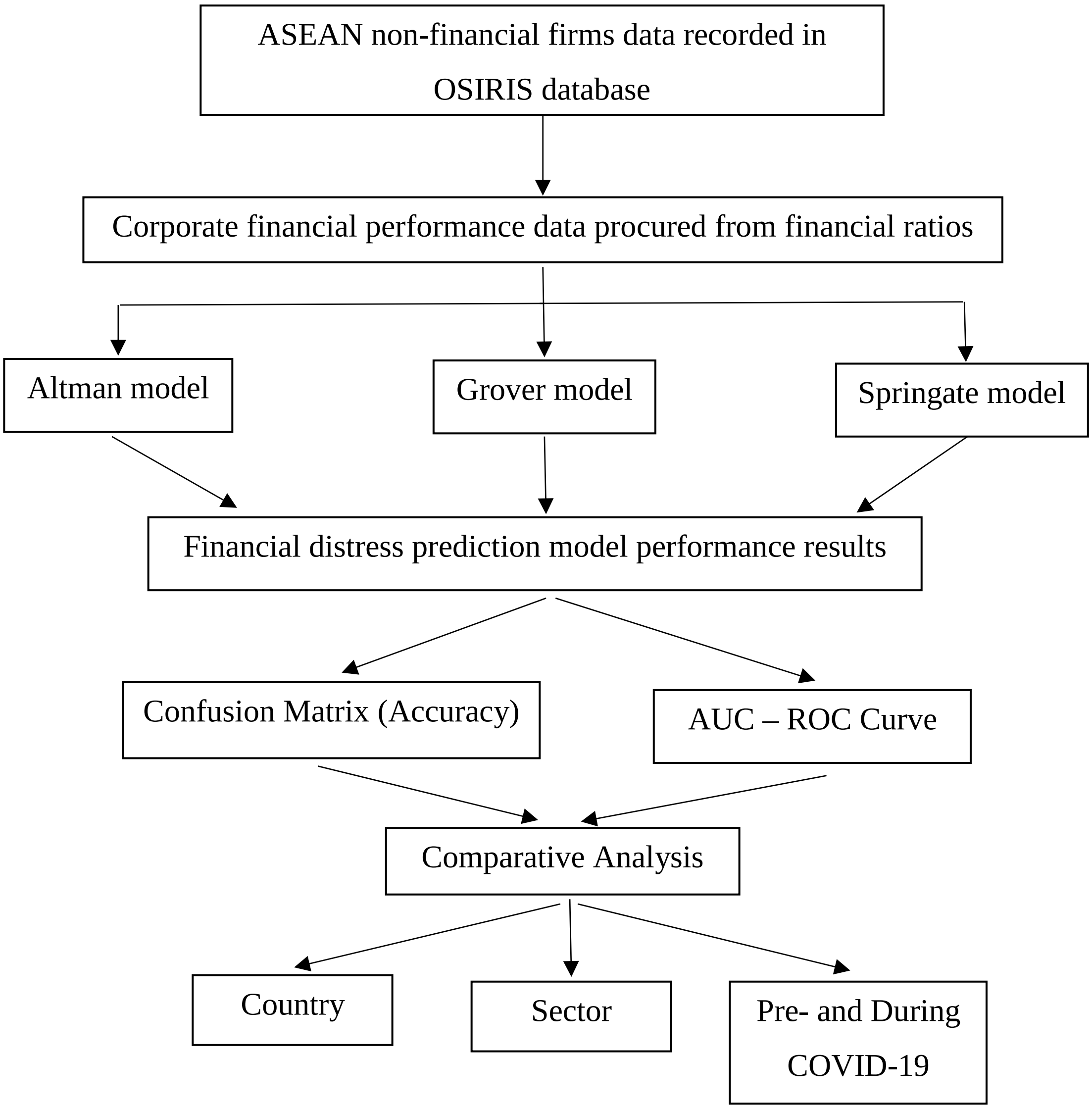
Data derived from population or sample research can be organised and summarised with the assistance of descriptive statistics (Holcomb, 2016). In addition, descriptive statistics provide a summary of the researched sample with results such as frequency distribution tables, percentages, and other measures of data concentration (average, maximum, minimum, standard deviation, and others). Descriptive statistics can help in summarising data in the form of simple quantitative measures such as percentages or in the form of visual summaries. Descriptive statistics can be used to describe one variable or more (Kaliyadan & Kulkarni, 2019).

The collected data were analysed using the ROC (Receiver Operating Characteristics) curve and confusion matrix in STATA 15 and Excel to test the accuracy of each model and determine whether the prediction models have an excellent ability to predict financial distress or not. The ROC (Receiver Operating Characteristics) curve portrays the sensitivity (true positive rate) to 1-specificity (false positive rate), then displays it graphically. The further the curve is from the diagonal line, the larger the area under the ROC curve—the larger the area under it, the better the curve is at distinguishing true positives from true negatives (Bhatia & Singh, 2022). The ROC curve was used as a tool to test the sample because it is an effective curve for assessing the performance of financial distress prediction models. Furthermore, it may demonstrate and provide an idea of the models' usefulness. The confusion matrix is a two-way frequency table with actual and predicted variables. This matrix consists of four elements: true positive (TP), true negative (TN), false positive (FP), and false negative (FN). The confusion matrix was chosen as a tool to test the sample because it is an important measure to evaluate the accuracy of the prediction models. The confusion matrix can be used to demonstrate the accuracy of each prediction model by comparing the predicted value with the actual value. Accuracy is the ratio of correct predictions to the number of total observations tested (Hoo et al., 2017; Mailund, 2017; Zeng, 2020).

A probability test, a binomial probability test, was needed to be conducted to compare the probability of firms which were predicted to experience financial distress with those that did not before conducting the confusion matrix and ROC curve tests. A value of $p < 0.05$ is considered statistically significant (Klug, 2014). In addition, the test was conducted to determine whether the selected model performed better than the coin toss method (<50%). Once all the tests were completed, the findings were compared to determine the most accurate financial distress prediction model in general and in the context of country, sector, and COVID-19 period.

Based on the explanation above, the research framework of this study is shown in Figure 1 as follows:

Figure 1
Research Framework



Result and Discussion

A. *Descriptive statistics*

Table 3 provides the descriptive statistics of the variables as previously mentioned. In order to control outliers, the variables at the first and 99th percentiles of their distributions were winsorized.

Table 3
Descriptive statistics

Variable	Average	Median	Max	Min	Std. Dev.	Percentile 1%	Percentile 99%	Obs
Z_SCORE	4.742	3.669	32.322	-8.692	5.452	-8.692	32.322	21,250
G_SCORE	0.596	0.570	2.009	-1.251	0.555	-1.251	2.009	21,250

S_SCORE	0.988	0.882	4.251	-1.677	0.919	-1.677	4.251	21,250
WC_TA	0.202	0.185	0.766	-0.480	0.238	-0.480	0.766	21,250
RE_TA	0.123	0.148	0.725	-1.852	0.360	-1.852	0.725	21,250
EBIT_TA	0.061	0.056	0.359	-0.263	0.090	-0.263	0.359	21,250
TE_TL	2.473	1.253	26.219	-0.044	3.779	-0.044	26.219	21,250
ROA	0.041	0.040	0.300	-0.299	0.085	-0.299	0.300	21,250
PBT_CL	0.362	0.187	3.963	-1.373	0.719	-1.373	3.963	21,250
S_TA	0.875	0.719	3.981	0.026	0.731	0.026	3.981	21,250

Source: Authors' own

As shown in Table 3, the average values of Z_SCORE, G_SCORE, and S_SCORE (4.742, 0.596, and 0.988, respectively) exceeded the safe zone cut-off value (2.6, 0.01, and 0.862, respectively). This indicates that the majority of the observations fell within the safe zone, demonstrating that they are in a healthy financial condition and unlikely to experience financial distress. Moreover, the mean values of G_SCORE, S_SCORE, and S_TA are greater than the standard deviation value, indicating that these variables varied. The remaining variables, on the other hand, have mean values that are less than the standard deviation value, indicating that they are not varied.

B. *Binomial probability test*

Table 4
Binomial Probability Test

	Model	Observed k	Expected k	Assumed p	Observed p	p-value
Accuracy	Altman	14,379	10,625	0.5	0.6767	0.0000
	Grover	19,186	10,625	0.5	0.9029	0.0000
	Springate	12,278	10,625	0.5	0.5778	0.0000
Total Positives	Altman	7,552	10,625	0.5	0.3554	0.0000
	Grover	2,295	10,625	0.5	0.1080	0.0000
	Springate	10,377	10,625	0.5	0.4883	0.0006
True Positives	Altman	1,089	10,625	0.5	0.0513	0.0000
	Grover	864	10,625	0.5	0.0407	0.0000
	Springate	1,451	10,625	0.5	0.0683	0.0000
True Negatives	Altman	13,290	10,625	0.5	0.6254	0.0000
	Grover	18,322	10,625	0.5	0.8622	0.0000
	Springate	10,827	10,625	0.5	0.5095	0.0057

Source: Authors' own

According to Table 4, all p-value results are less than 0.05, which means that the results are statistically significant. The observed proportion are statistically different from assumed probability based on accuracy and total positives. The test results additionally demonstrated that the observed proportion of accuracy for each model is actually higher than the assumed proportion of 0.5. This implies that the accuracy of all models is higher than that of coin-tossing. The observed proportion of each model's total positives, on the other hand, is less than the assumed probability of 0.5. This happened because the total positives are less than the total negatives, indicating that the distressed samples are typically less than normal samples. Moreover, the observed proportion of each model's total true positives is less than the assumed probability of 0.5. This indicates that the majority of the samples collected are true negatives, which represent healthy firms.

C. *Overall evaluation*

Table 5
Confusion matrix for predicting financial distress

	Actual	
Predicted	Distress observation	Safe observation
Distress observation	True Positive (TP)	False Positive (FP)
Safe observation	False Negative (FN)	True Negative (TN)

Source: Authors' own

Using the confusion matrix provided in Table 5, the actual and predicted values of each model were compared. From the matrix results, it can be seen that there are correct and incorrect prediction results. The incorrect predictions are referred to as errors. Errors can be classified into type I and type II. Type I error occurs when the model predicts that the sample is in distress when, in fact, it is not (false positive). Meanwhile, type II error occurs when the model incorrectly predicts that the sample is not in financial distress when, in fact, it is (false negative) (Balasubramanian et al., 2019).

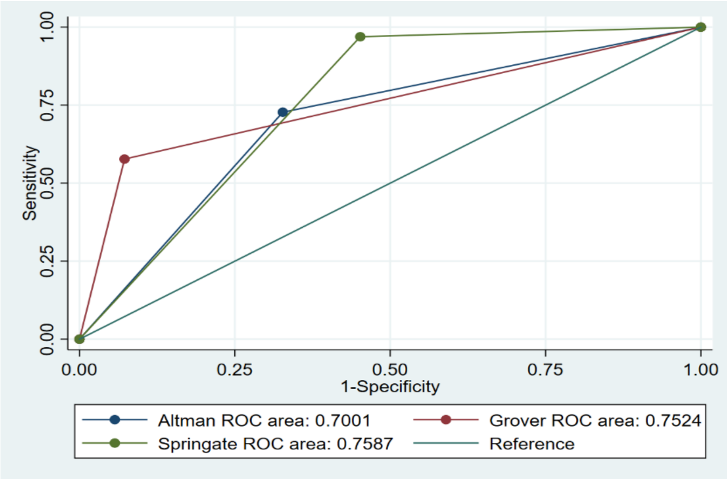
Table 6
Confusion matrix results for all observations

Model	**Correct Prediction**	**Type I Error**	**Type 2 Error**	**Total Obs**	**Accuracy (%)**
Altman	14,379	6,463	408	21,250	67.67
Grover	19,186	1,431	633	21,250	90.29
Springate	12,278	8,926	46	21,250	57.78

Source: Authors' own

According to the confusion matrix results, which are shown in Table 6, the Grover model has the highest accuracy rate (90.29%) compared to all other models that were chosen for the entire sample. In addition, the Grover model has the most correct predictions (19,186 predictions) and the fewest type I errors (1,431 errors), although it has more type 2 errors (633 errors) compared to other models. This suggests that the model misclassified such distressed firms as safe firms, indicating critical issues because it mistook positives for negatives. This type II error can lead to financial loss for the firm if it is too late to recognise the signs of financial distress. Meanwhile, the Springate model has the lowest accuracy rate (57.78%). The Springate model also has the most type I errors (8,926 errors), which means the model misclassified the safe firms as distressed firms. This results in the firm losing out on beneficial business opportunities since stakeholders felt that the firm would bankrupt after being misclassified as a distressed firm when it is not. Based on the accuracy rate analysis, the Grover model has the best performance to predict financial distress for the entire observation.

Figure 2
ROC curve (all observations)



The ROC analysis was conducted with a trust level of 95 percent. The ROC curve plots the sensitivity as a function of 1-specificity for different cut-off points. If the area under the curve (AUC) value is close to 1, the model performs excellently (Balasubramanian et al., 2019). Since there are a lot of cut-off points, the curve will only show the most relevant cut-off point for all related observations. Moreover, as can be seen in Figure 2 above, the ability of all models to predict financial distress in all observations is satisfactory. It is evidenced by the position of the curve line, which is above the diagonal line. Despite the fact that all models imply great performance, the Grover and Springate models have a higher AUC than Altman. The Springate model has the highest true positive rate (sensitivity) among other models despite having the lowest accuracy rate and the highest false positive rate (1-specificity). It denotes the high probability that an actual positive will coincide with its predicted result and that the probability of a false alarm will increase. Meanwhile, the AUC for Grover somehow resembles Springate. Despite being the most accurate model when the accuracy rate is the only thing discussed, the Grover model has the lowest true positive rate because it predicts a lot of false negatives. This model also has the lowest false positive rate because it predicts many true negatives. If we take into account the accuracy rate and AUC value, the Grover model performs best overall in predicting financial distress for all observations. These results are in line with several studies, including Indriyanti (2019), Aminian et al. (2016), Pakdaman (2018), Hertina et al. (2020), and Hungan & Sawitri (2018). They concluded that the Grover model is the best model, with the most accurate prediction results.

D. *Context evaluation*

Table 7
Confusion matrix results for pre- and during COVID-19 observations

	Model	Correct Prediction	Type I Error	Type 2 Error	Total Obs	Accuracy (%)
Pre-COVID-19	Altman	11,610	5,100	290	17,000	68.29
	Grover	15,521	1,036	443	17,000	91.30
	Springate	10,127	6,839	34	17,000	59,57
During COVID-19	Altman	2,769	1,363	118	4,250	65.15
	Grover	3,665	395	190	4,250	86.24
	Springate	2,151	2,087	12	4,250	50.61

Source: Authors' own

Table 7 shows that, of all the models considered, the Grover model has the highest accuracy rate (91.30% and 86.24%, respectively), for both pre- and during COVID-19 observations. As before, the Grover model also has the most correct predictions and the fewest type I errors, although it has more type II errors compared to other models. Meanwhile, the Springate model has the lowest accuracy rate (59,57% and 50.61%) compared to other models. The most type I errors are also present in the Springate model. In terms of predicting financial distress for both pre- and during COVID-19 observations, the Grover model gives the best result, according to the accuracy rate analysis. Moreover, the ROC curve results show that the ability of all models to predict financial distress on both pre- and during COVID-19 observations is satisfactory, as evidenced by the position of the curve line, which is above the diagonal line. Even though all models suggest remarkable performance, the Springate model is definitely better at predicting financial distress during the pre-COVID-19 era. On the contrary, the Grover model performed better than the Springate during the during COVID-19 era. Meanwhile, the AUC for Grover somehow resembles Springate. If we take into account the accuracy rate and AUC value, the Grover model performs best overall in predicting financial distress for all pre- and during COVID-19 observations.

Table 8
Confusion matrix results for country observations

Country	Model	Correct Prediction	Type I Error	Type 2 Error	Total Obs	Accuracy (%)
Indonesia	Altman	1,861	946	43	2,850	65.30
	Grover	2,570	184	96	2,850	90.18
	Springate	1,635	1,204	11	2,850	57.37
Malaysia	Altman	3,643	1,065	152	4,860	74.96
	Grover	4,354	291	215	4,860	89.59

	Springate	2,834	2,017	9	4,860	58.31
	Altman	828	387	25	1,240	66.77
Philippines	Grover	1,126	90	24	1,240	90.81
	Springate	568	671	1	1,240	45.81
	Altman	2,330	772	98	3,200	72.81
Singapore	Grover	2,810	220	170	3,200	87.81
	Springate	1,717	1,462	21	3,200	53.66
	Altman	2,921	1,548	81	4,550	64.20
Thailand	Grover	3,972	457	121	4,550	87.30
	Springate	2,605	1,941	4	4,550	57.25
	Altman	2,796	1,745	9	4,550	61.45
Vietnam	Grover	4,354	189	7	4,550	95.69
	Springate	2,919	1,631	0	4,550	64.15

Source: Authors' own

According to Table 8, the Grover model has the highest accuracy rate and has made the most correct prediction for each country. At the same time, the Springate model has the lowest accuracy rate and is the one with the most type I errors in each country, except Vietnam. The Altman model has the lowest accuracy rate and the most type I errors found in Vietnam. In addition, the Grover model has the most type II errors in comparison to the other two models, with the exception of Philippines and Vietnam. The model which has the most type II error in the Philippines and Vietnam is the Altman model. In terms of predicting financial distress for all country observations, the Grover model performed best, according to the accuracy rate analysis. According to the ROC curve results, which show that the curve line is above the diagonal line, the models' accuracy in predicting financial distress on all country observations is excellent. Despite the fact that all models show remarkable performance, the Springate model is unquestionably superior at predicting financial distress in Malaysia and Thailand. In the other four countries, however, the Grover model outperformed the Springate. Meanwhile, Grover's AUC is close to Springate's, with the exception of Vietnam, which is practically at 1. If we take into account the accuracy rate and AUC value, the Grover model outperformed all other models in predicting financial distress for all country observations.

Table 9
Confusion Matrix Results For Sector Observations

Sector	Model	Correct Prediction	Type I Error	Type 2 Error	Total Obs	Accuracy (%)
Automobiles and Components	Altman	281	88	1	370	75.95
	Grover	340	20	10	370	91.89
	Springate	232	138	0	370	62.70
Capital Goods	Altman	2,546	1,454	60	4,060	62.71
	Grover	3,735	208	117	4,060	92.00

	Springate	2,049	1,997	14	4,060	50.47
Commercial and Professional Services	Altman	417	107	6	530	78.68
	Grover	487	28	15	530	91.89
	Springate	346	182	2	530	65.28
Consumer Durables and Apparel	Altman	582	207	31	820	70.98
	Grover	728	43	49	820	88.78
	Springate	562	255	3	820	68.54
Consumer Services	Altman	562	260	28	850	66.12
	Grover	728	86	36	850	85.65
	Springate	431	418	1	850	50.71
Energy	Altman	625	393	22	1,040	60.10
	Grover	893	106	41	1,040	85.87
	Springate	636	393	11	1,040	61.15
Food and Staples Retailing	Altman	112	96	2	210	53.33
	Grover	189	14	7	210	90.00
	Springate	168	39	3	210	80.00
Food, Beverage, and Tobacco	Altman	1,400	592	28	2,020	69.31
	Grover	1,852	139	29	2,020	91.68
	Springate	1,320	699	1	2,020	65.35
Health Care Equipment and Services	Altman	322	132	6	460	70.00
	Grover	419	33	8	460	91.09
	Springate	281	179	0	460	61.09
Household and Personal Products	Altman	119	20	1	140	85.00
	Grover	133	6	1	140	95.00
	Springate	109	31	0	140	77.86
Materials	Altman	2,087	1,027	56	3,170	65.84
	Grover	2,836	256	78	3,170	89.46
	Springate	1,873	1,296	1	3,170	59.09
Media and Entertainment	Altman	412	110	18	540	76.30
	Grover	481	32	27	540	89.07
	Springate	361	178	1	540	66.85
Pharmaceuticals, Biotechnology, and Life Sciences	Altman	250	48	2	300	83.33
	Grover	293	4	3	300	97.67
	Springate	245	54	1	300	81.67
Real Estate	Altman	1,879	547	64	2,490	75.46
	Grover	2,280	119	91	2,490	91.57
	Springate	1,034	1,454	2	2,490	41.53
Retailing	Altman	575	220	15	810	70.99
	Grover	725	58	27	810	89.51
	Springate	585	225	0	810	72.22
	Altman	152	22	6	180	84.44
	Grover	164	8	8	180	91.11

Semiconductors and Semiconductor Equipment	Springate	127	53	0	180	70.56
Software and Services	Altman	333	82	25	440	75.68
	Grover	386	22	32	440	87.73
	Springate	311	128	1	440	70.68
Technology Hardware and Equipment	Altman	547	200	13	760	71.97
	Grover	698	42	20	760	91.84
	Springate	532	226	2	760	70.00
Telecommuni-cation Services	Altman	130	186	4	320	40.63
	Grover	272	44	4	320	85.00
	Springate	138	182	0	320	43.13
Transportation	Altman	669	382	19	1,070	62.52
	Grover	922	122	26	1,070	86.17
	Springate	582	485	3	1,070	54.39
Utilities	Altman	379	290	1	670	56.57
	Grover	625	41	4	670	93.28
	Springate	356	314	0	670	53.13

Source: Authors' own

Table 9 shows that the Grover model has the highest accuracy and correct prediction rates for each sector. On the contrary, the Springate model has the lowest accuracy rate, apart from energy, food and staples retailing, retailing, and telecommunication services. Moreover, the Altman model has the lowest accuracy rate among models in the four sectors. The Springate model also has the most type I errors in each sector, with the exception of telecommunication services and food and staples retailing. In those two sectors, the model with the most type I errors is the Altman model. Furthermore, the most type I errors were discovered in the energy sector for both the Altman and Springate models. The Grover model also has the most type II errors in each sector. In household and personal products and telecommunication services, both Grover and Altman models have the most type II errors. According to the ROC curve results, which show that the curve line is above the diagonal line, all models' abilities to predict financial distress based on all sector observations are satisfactory. Despite the fact that all models suggest remarkable performance, the Grover model is unquestionably superior at predicting financial distress in the capital goods, energy, food and beverage, health care, materials, telecommunication, transportation, and utilities sectors. Unexpectedly, the Altman model is the most accurate prediction model in the automobile and commercial sectors. Meanwhile, the Springate model outperformed other models in the remaining eleven sectors. When the accuracy rate and AUC value were analysed, the Grover model performed best in predicting financial distress for all sector observations.

Conclusions

Some conclusions could be drawn based on the findings of this study. If we take into account the accuracy rate and AUC value, the findings showed that the Grover model performed best in predicting financial distress for all COVID-19 era, country, and sector observations. The observed proportion is statistically different from the assumed probability based on accuracy. The test results also showed that the actual observed accuracy proportion for each model is higher than the assumed accuracy proportion of 0.5. This implies that the accuracy of all models is higher than that of coin tossing. The majority of the samples collected are true negatives, which represent healthy companies.

Our findings can be beneficial to all stakeholders in a firm. In order to prevent significant losses, these stakeholders must be aware if a firm fails. A forewarning of an impending collapse might reduce their losses, considering that these stakeholders are the last to receive compensation in bankruptcy and litigation. By providing managers with advance warning of declining profitability, net worth, and rising debt load, this study enables them to take remedial action to prevent significant losses. It is essential to comprehend whether the firm has started to experience financial distress in order for the firm's management to be cautious and take appropriate action if there are indicators of something terrible is happening. Moreover, creditors can use this information to their advantage by discovering whether the potential debtor's business qualifies for a loan and being cautious when monitoring the debtor's financial condition. Furthermore, investors may supervise and monitor the firm's financial condition by employing the current financial distress prediction models, allowing them to make the best decisions while preparing for the worst-case scenario.

Although our findings have implications for research on financial distress, there are several limitations. First of all, the sample period chosen in this study imposes limits on the sample size. Further study in this area can increase the sample size by extending the sample period to cover more than ten years. In addition, the sample scope can be expanded. Second, we limited the prediction of financial distress to one year in advance of its occurrence. In addition, a longer time period than the years prior to financial distress should be used to evaluate the model's accuracy. Third, other prediction models should be taken into account, such as Ohlson model derived from the results of logit analysis, Zmijewski model derived from the results of probit analysis, or Blums model (D-Score) which uses accounting and market-based variables with a strong conceptual framework.

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