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EVALUATION AND RE-ESTIMATION OF BANKRUPTCY PREDICTION MODELS IN FACING THE CRISIS PERIOD IN INDONESIA (2017-2022)

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Abstract

This research was conducted to see how suitable the existing bankruptcy prediction models that have been used in other countries to be used during the crisis in Indonesia. The data used in research are companies in Indonesia registered in the Indonesia Stock Exchange (IDX). The re-estimate of the coefficient of variables models is carried out and then the bankruptcy prediction of the re-estimation model is re-calculated. The results of the bankruptcy prediction of the re-estimate model are then compared with the results of the bankruptcy prediction of the original model to see whether the model can be used during the crisis in Indonesia. The results of the study is that Springate original model is the most suitable model for the conditions in Indonesia during the crisis caused by the COVID-19 pandemic. The Springate model has the highest financial distress prediction accuracy, while the Altman Emerging Market model produces the highest Error Type I.

Keywords: Financial distress, bankruptcy, re-estimate models, developing countries, Altman, Ohlson, Springate

Introduction

The COVID-19 pandemic that is occurring globally has actually had a lot of impact on the global economy. The COVID-19 pandemic has triggered substantial risk across financial markets, which is also highly correlated with the level of investor panic. COVID-19 has been shown to significantly increase risks in global stock, bond, crude oil and foreign exchange markets respectively in the short term. The COVID-19 pandemic also increases risks that have a domino impact on global financial markets in the medium and long term, and the magnitude of the risk is highly correlated with the level of investor panic in financial markets (Fang et al., 2023).

The COVID-19 pandemic is not the first economic crisis the world has faced. There have been various economic crises. One of the crises experienced by Indonesia occurred in 1998. In fact, one of the impacts of the economic crisis that occurred in Indonesia in 1998 was the high bank interest rates in Indonesia. The average interest margin in Indonesia after the 1998 crisis reached 6.36%, which is the highest figure compared to other Asian countries (Lin et al., 2012).

During times of crisis, companies usually have large working capital due to the large inventory which is not accompanied by any liabilities. In general, working capital consists of accounts receivable, inventory, and accounts payable. During the global financial crisis, working capital levels increased due to reasons such as unexpectedly

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excessive inventory levels, many delayed payments for goods and services resulting in large trade receivables, and a decline in company sales resulting in a decrease in accounts payable. (Tsuruta & Uchida, 2019). With the decline in company sales during the crisis, purchases of goods also decreased, causing a decrease in accounts payable (Tsuruta & Uchida, 2013).

There are also various possibilities for credit constraints for companies that cause companies to have to use other financial sources. Companies must adjust working capital levels to the company's specific targets during and after the crisis period (Tsuruta, 2019). One of the efforts that companies can make to get through the crisis is restructuring. In fact, the restructuring coefficient is one of the variables in the recovery equation with a significance of 0.0578 (Koh et al., 2015). The various bankruptcy prediction models that have previously been studied by previous researchers may not necessarily be able to be used generally in various types of economic environments. This is because these models are used to predict bankruptcy in developed countries (Oz & Simga-Mugan, 2018). Apart from that, to test the generality of these models it is necessary to carry out a re-estimation test (Grice & Dugan, 2003).

From previous studies, it can be seen how previous studies that examined bankruptcy prediction models tended to focus on developed economies so they did not provide an understanding of the impact of the pandemic on companies in developing countries. Therefore, this research aims to fill this gap by evaluating existing bankruptcy prediction models in the context of the Indonesian economy during the pandemic period. As a basis, this research will test prediction models that have been proven effective in advanced economies, namely Altman 1968, Ohlson 1980, and Springate 1978 with a special focus on the applicability of these models to companies in Indonesia. To support this analysis, accurate and up-to-date economic data from the Indonesian Central Bureau of Statistics will be used as the main source of information to describe the impact of the pandemic on the financial condition of companies in Indonesia.

Company failure in financial difficulties leading to bankruptcy is usually the result of financial difficulties and economic difficulties. Company financial difficulties often arise from cash flow deficiencies required to meet the company's debt obligations. Meanwhile, even in conditions of economic difficulty, companies often have a sustainable business model. In practice, corporate difficulties that lead to bankruptcy are often a combination of both (Altman, 2006). Altman formulated the bankruptcy prediction model to take into account developments in emerging markets. While there are not many changes to the variables, Altman adds a new constant to the bankruptcy prediction model equation for emerging markets. The equations are:

$$Z = 6.56\,\frac{NWC}{TA} + 3.26\frac{RE}{TA} + 1.05\frac{EBIT}{TA} + 6.72\frac{BVE}{TL} + 3.25 \qquad \ldots (2.1)$$

NWC/TA = Net Working Capital to Total Asset
RE/TA = Retained Earning to Total Asset
EBIT/TA = Earning Before Interest and Tax to Total Asset
BVE//TL = Book Value of Equity to Total Liabilities

The next model used besides the Altman model is the Ohlson model which uses nine independent indicators as depicted in the following equation (Ohlson, 1980):

$O = -1{,}32 - 0{,}407\,SIZE + 6{,}03\frac{TL}{TA} - 1{,}43\frac{WC}{TA} + 0{,}0757\frac{CL}{CA} - 2{,}37\,ONEGG - 1{,}83\frac{NI}{TA} + 0{,}285\frac{FU}{TL} - 1{,}72\,INTWO - 0{,}521\,CHINN$ …(2.2)

SIZE = log (total assets / GNP price level index)
TL/TA = total liabilitas / total aset
WC/TA = working capital / total assets
CL/CA = current liabilities / current assets
ONEGG = 1 (if total liabilities > total asset) ; 0 (if total liabilities < total asset)
NI/TA = net income / total assets
FU/TL = funds provided by operations / total liabilities
INTWO = 1 (if net income is negative for the last 2 years) ; 0 (if else)
CHINN = $(\text{Net income}_t - \text{Net income}_{t-1}) + (|\text{Net income}_t| + |\text{Net income}_{t-1}|)$

The calculation of the Ohlson model value will also be considered based on the cut-off which is also the result of Ohlson's research. If the calculated value exceeds 3.8%, or 0.038, it can indicate that the company is likely to experience bankruptcy (Ohlson, 1980). From the results of the calculation of the Ohlson value, the probability of bankruptcy of the company concerned can also be obtained using the following logistic method (Utama & Lumondang, 2009):

$$\frac{e^{o-score}}{1+e^{o-score}} \quad \ldots(2.3)$$

The next bankruptcy prediction model is the model proposed by Gorgon L.V Springate in 1978, namely the Springate Model. This model was tested on 40 manufacturing companies in Canada. The results of this modeling were that 20 of the 40 companies were predicted to experience bankruptcy with an accuracy rate of 92.5% (Ghodrati, 2012). The equation of the Springate Model uses 4 ratios as follows:

$$S = 1.03X_1 + 3.07X_2 + 0.66X_3 + 0.4X_4 \quad \ldots(2.4)$$

Where X1 is working capital / total assets, X2 is EBIT / total assets, X3 is EBT / current liabilities, and X4 is sales / total assets. The interpretation of the S-score value is to look at the value of the S-score of each company, where companies with an S-score value of more than 0.862 are predicted not to experience bankruptcy or be in good health, while on the contrary, companies with an S-score value below 0.862 are predicted to experience bankruptcy.

Multi Discriminant Analysis (MDA) is a statistical technique as well as a branch of discriminant analysis used in finance and investment to evaluate the potential of various investments when the number of variables used is large. MDA is used to group variables by reducing differences between variables. In the Altman Model itself, for example, MDA helps identify variables that are considered to be the most important variables in the equation (Ishmah et al., 2022). Multi Discriminant Analysis is used in the Altman Model and Springate Model so that in this research it is used to re-estimate the coefficients of the variables from the two equations.

The next algorithm is Logit Regression Model, which is similar to Multi Discriminant Analysis, is also used for classification as well as being a tool for predictive analytics. The Logit Regression Model is used to estimate the possibility or probability of an event based on available data with the dependent variable expressed in binary form, namely 0 and 1. From this probability, an evaluation is then carried out on how well the model predicts the dependent variable. Logit Regression Analysis is used in the Ohlson

Model so that in this research it is used to re-estimate the coefficients of the variables from the Ohlson Model equation itself. Moreover, this research was conducted to find out how suitable the existing bankruptcy prediction models that have been used in other countries to be used during the crisis in Indonesia

Research Methods

This research was conducted using secondary data in the form of financial reports from 60 companies in Indonesia which were recorded from the closest period to the pre-crisis period, data recorded during the crisis period itself, and data recorded for several years after the global COVID pandemic crisis. -19, namely in 2017, 2018, 2019, 2020, 2021 and 2022. This was done to see the effects of the global financial crisis which was the effect of the COVID-19 pandemic on the financial condition of these companies.

The data is downloaded from Revinitif Eikon and must contain the variables needed in the five bankruptcy prediction models used in this research. In this research, there are 7 stages starting from data collection, sorting data according to research criteria as well as outlier data based on confidence levels, predicting company bankruptcy using the models that have been chosen for this research which is also continued with re-estimating the coefficients used. on these models, validity testing, accuracy testing and error type analysis, and ending with drawing conclusions. These stages are summarized in the research workflow below:

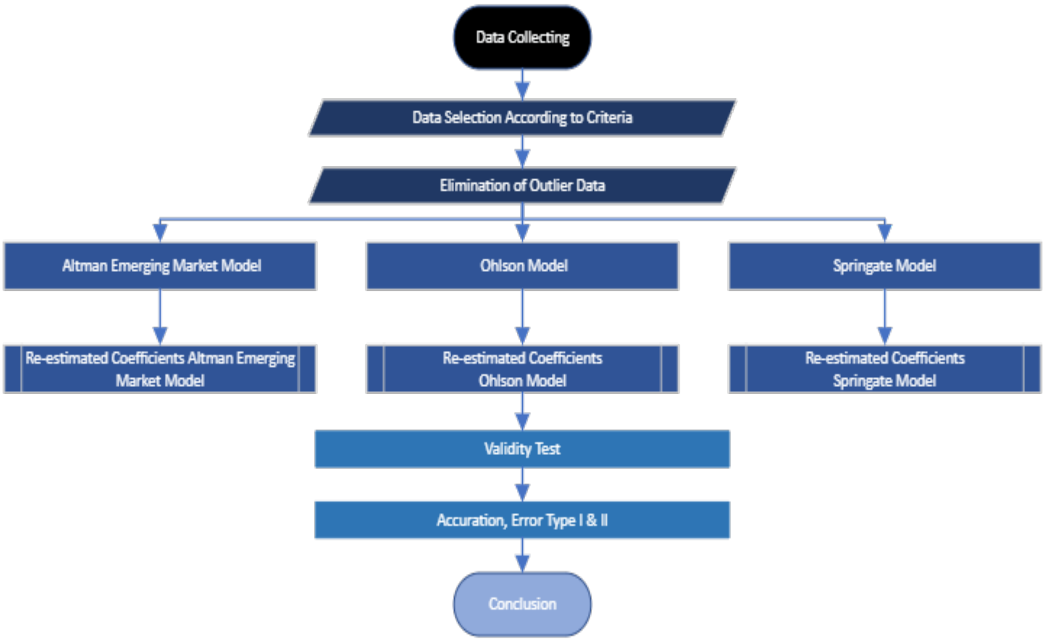

Figure 1. Research Flow Diagram

The data processed are financial reports of companies in Indonesia registered on the Indonesian Stock Exchange that experienced financial distress when hit by the pandemic in 2020. The financial reports used as data are financial reports for 2016, 2017, 2018, 2019, 2020, 2021, 2022 and 2023 where financial reports in 2016, 2017, 2018, 2019 act as pre-crisis data, financial reports in 2020 and 2021 as data during the crisis, and data in 2021 as post-crisis data. This was done to see how significant the changes experienced by these companies were due to the crisis. The data taken must contain the variables needed in the five bankruptcy prediction models used in this research. The data used in the research was taken from Revinitif Eikon.

Once collected, the data is then sorted according to the required criteria and outliers are eliminated. The criteria used as the basis for sample selection consist of four criteria. First, company year data must come from the fiscal year-end financial statements. Second, all firm-year observations must include every variable required by the models tested in this study. Third, company year data points must be continuous for the entire observation period. Fourth, outliers are removed at a confidence level of 95% to increase the robustness of the research results (Oz & Simga-Mugan, 2018).

After all the required variables have been collected, financial distress indicators are calculated using the bankruptcy prediction models selected in this research, namely the Altman Z Score, Beneish M Score, Ohlson Score and Springate Score. The Altman model used in this research is the Altman model for emerging markets, namely a model for calculating financial distress indicators specifically for developing countries.

This calculation was carried out on data from the pre-crisis year, the crisis period itself, and the post-crisis period from year to year with the aim of seeing differences in the financial condition of companies before and after the crisis and then comparing them. From the comparison results, companies that experienced significant and insignificant changes in financial conditions will also be analyzed.

The next step, after obtaining the bankruptcy prediction values for each company with each model, is to re-estimate the coefficients from the equations for each model. To carry out re-estimations, various methods can be used such as Multi Discriminant Analysis (MDA), Linear Discriminant Analysis (LDA), Logit. After re-estimating the coefficients on the models selected in the research, the score calculations were carried out again using these models. The results of this calculation are then compared with the company's real financial distress value, followed by Chi-square and t-stat validity tests.

The next step is to carry out accuracy tests and Type I and Type II error analysis. Test errors include two types of errors, namely Type I and Type II errors. Type I error is an error condition where the calculation classifies a company experiencing financial difficulties as a healthy company, while Type II error is an error where the calculation results classify a healthy company as experiencing financial difficulties). Type 1 errors are riskier than Type 2 errors because errors in identifying companies that are actually experiencing financial difficulties as healthy can have serious consequences, whereas Type 2 errors, although important, are not as fatal as I errors.

Conclusions were drawn based on the research objectives, namely finding out whether the Altman Z Score, Beneish M Score, Springate Score, Ohlson O Score bankruptcy prediction models can be used to detect bankruptcy during the crisis due to the pandemic in Indonesia, as well as knowing the best bankruptcy prediction models. good for use in times of crisis due to the pandemic in Indonesia.

Results and Discussion

From the data collection stage, data was obtained with 375 company data in Indonesia consisting of companies belonging to the automotive, energy, manufacturing industry, health, food and real estate sectors. The companies belonging to the automotive sector consist of 21 companies, companies belonging to the energy sector consist of 56 companies, companies belonging to the industrial sector consist of 85 companies, companies belonging to the health sector consist of 34 companies, companies belonging to the the food sector consists of 106 companies and companies belonging to the real estate sector consist of 84 companies.

The first stage carried out was to sort the data to see the continuity and completeness of the data by eliminating companies that were detected as having incomplete data. This is done so that data distribution can be obtained properly at the next stage. In addition, sorting was carried out to ensure that all companies processed had all the variables needed in the research. From the results of this sorting, the remaining number of companies was 185 companies, of which 11 companies in the automotive sector were eliminated, 24 companies in the energy sector were eliminated, 48 companies in the manufacturing sector were eliminated, 20 companies in the health sector were eliminated, 50 companies in the food sector were eliminated, and 42 companies in the real estate sector eliminated.

After eliminating companies that did not have data continuity and completeness, the next thing to do was to carry out descriptive statistics on the data for the 185 companies. Data that is eliminated is data with a Z value below -3 and above 3 with reference to a confidence level of 95% (Venkataanusha, et al., 2019). Z itself is a standardization score used in statistics to measure the extent to which a value in a data distribution differs from the average in standard deviation units. This process is carried out using SPSS software. From the elimination of outliers, there were 45 companies eliminated in the combined data of all sectors. The coefficients resulting from the reestimation are as follows:

Table 1. Comparison of original coefficients (β) and re-estimated coefficients from the Altman EM (Emerging Market), Ohlson and Springate models for combined data for all sectors (ˆ), automotive sector (ˆ1), energy sector (ˆ2), industrial manufacture sector (ˆ3), health sector (ˆ4), food and beverage sector (ˆ5), real estate sector (ˆ6)

Altman EM								
X	β	$\hat{\beta}$	$\hat{\beta}^1$	$\hat{\beta}^2$	$\hat{\beta}^3$	$\hat{\beta}^4$	$\hat{\beta}^5$	$\hat{\beta}^6$
WC/TA	6.52	*0.494	*5.906	*2.544	*-0.762	*4.806	*1.175	*-0.606
RE/TA	3.26	*1.11	*1.405	*-0.045	*0.709	*0.428	*1.559	*1.201
OI/TA	6.72	*16.782	*-3.129	*10.612	*19.173	*10.705	*20.199	*26.424
BE/TL	1.05	*-0.087	*-0.008	*0.077	*-0.77	*-0.095	*-0.224	*-0.008
(Constant)	3.25	*-1.111	*-0.773	-1	*-0.867	*-2.518	*-1.441	*-1.14

Ohlson								
X	β	$\hat{\beta}$	$\hat{\beta}^1$	$\hat{\beta}^2$	$\hat{\beta}^3$	$\hat{\beta}^4$	$\hat{\beta}^5$	$\hat{\beta}^6$
SIZE	-0.407	-0.258	-2.921	-0.655	-0.725	6.245	0.648	-0.052
TLTA	6.03	-0.029	21.095	3.879	0.703	-108.157	*-12.785	0.81
WCTA	-1.43	0.222	-54.935	-3.101	-3.157	22.048	3.759	0.027
CLCA	0.076	0.313	-20.117	-0.362	-3.427	126.12	4.111	-0.453
NITA	-2.37	*-55.739	-104.085	*-26.486	*-50.293	120.846	*-101.11	*-72.011
OCFTL	-1.83	-0.007	-0.041	*0.050	-0.005	-0.067	-0.086	-0.007
OINEG	0.285							
CHIN	-1.72	*-0.457	-0.281	-1.251	-0.708	-28.003	0.213	-0.391
INTWO	-0.521	*1.048	-4.327	1.736	2.157		20.046	0.575
(Constant)	-1.32	*-1.123	8.207	-4.28	1.015	-51.288	2.861	-0.934

Springate								
X	**β**	**$\hat{\beta}$**	**$\hat{\beta}1$**	**$\hat{\beta}2$**	**$\hat{\beta}3$**	**$\hat{\beta}4$**	**$\hat{\beta}5$**	**$\hat{\beta}6$**
WCTA	1.03	*0.417	*6.602	*1.295	*-1.672	*5.281	*-0.794	*-0.637
EBITTA	3.07	*13.022	*-2.066	*3.099	*9.380	*8.503	*18.798	*18.764
EBTCL	0.66	*0.713	*-0.459	*1.015	*2.967	*-0.422	*0.404	*1.202
SALESTA	0.4	*0.252	*0.930	*1.396	*0.333	*0.724	*0.273	*1.884
(Constant)		*-1.181	*-1.143	*-1.306	*-0.702	*-3.616	*-1.783	*-1.104

*Represent Statistical significance at 5%

After the entire model was recalculated using the original coefficients and re-estimations, interpretation results were obtained for companies experiencing financial distress (0) and healthy companies (1). After seeing the differences in results between models and re-estimating each model, the next step is to test for type I and II errors. Type I error is an error condition where the calculation results classify a company experiencing financial difficulties as a healthy company, while Type II error is an error where the calculation results classify a healthy company as a company experiencing financial difficulties. The benchmark for the actual condition of a company is a situation where a company experiencing financial distress is a company that has a negative net profit for two consecutive years.

Type I errors are riskier than Type II errors because errors in identifying companies that are truly experiencing financial difficulties as healthy companies can have serious consequences, while Type 2 errors, although important, are not as serious as error I. And besides type error tests, they are also carried out. accuracy test on each model in each sector. Accuracy testing is important in evaluating the performance of a predictive model or system after conducting type I and type II error testing.

Accuracy tests provide a comprehensive picture of the extent to which a model can make correct and useful predictions. While type I error and type II error testing provide insight into specific errors, accuracy testing provides a general idea of the model's ability to make correct and accurate predictions. Apart from that, accuracy tests also present data that is easier to understand.

Apart from the overall accuracy test, the author also carried out specific accuracy tests, namely accuracy tests carried out on each model that succeeded in predicting non-financial distress and succeeded in predicting financial distress. This was done with the aim of seeing more clearly the accuracy of each model from a closer perspective, namely predicting non-financial distress and financial distress respectively. Then, to facilitate the analysis, the author carried out a comparison of each analysis tool, namely the accuracy value, both total accuracy and specific accuracy, with type I error and type II error. This is to be able to see how accuracy values and error values can build or bring down each other as the model chosen to analyze bankruptcy predictions during the COVID-19 crisis.

In the combined data of all sectors (table 2), the highest error value was obtained from the original Altman EM model, which was 99% of the type I error. As discussed previously, the type I error is a more dangerous type of error than the type II error because it predicts a firm year that experiencing financial distress as a healthy firm year. Therefore, for combined data for all sectors, the original Altman EM model is not recommended. From a type I error point of view, the most recommended model is the original Springate model because it has the lowest type I error value, namely only 5%.

Meanwhile, from a specific accuracy perspective, financial distress accuracy values are more important than non-financial distress accuracy values. This is because financial distress accuracy describes how accurate the model is in predicting the number of firm years with financial distress conditions, which is different from non-financial distress accuracy which describes how accurate the model is in predicting firm years with non-financial distress conditions.

From the highest financial distress accuracy value, the original Springate model is also the recommended model for analyzing bankruptcy predictions during the COVID-19 crisis for all sectors as a whole. However, this model has a specific accuracy value for firm years experiencing non-financial distress of only 54%, while the highest specific accuracy value for non-financial distress comes from the original Altman EM model. The highest total accuracy was obtained from the Ohlson re-estimation model, although the accuracy value for financial distress from this model was only 61%.

Table 2. Summary of type I and II error classification, FD and non-FD accuracy and total accuracy for all sectors

Model	Error Type I	Error Type II	FD Accuracy	Non-FD Accuracy	Total Accuracy	Chi-square	Prob
Altman EM Ori	99%	0%	1%	100%	75%		
Altman EM RE	57%	3%	43%	97%	83%	*332.22	0
Ohlson Ori	45%	21%	55%	79%	73%		
Ohlson RE	39%	4%	61%	96%	87%	*21.49	0.006
Springate Ori	5%	46%	95%	54%	65%		
Springate RE	54%	2%	46%	98%	85%	*337.34	0

*Represent Statistical significance at 5%

Table 3. Summary of type I and II error classification, FD and non-FD accuracy and total accuracy for automotive sectors

Model	Error Type I	Error Type II	FD Accuracy	Non-FD Accuracy	Total Accuracy	Chi-square	Prob
Altman EM Ori	100%	0%	0%	100%	62%		
Altman EM RE	31%	8%	69%	92%	83%	*17.440	0.002
Ohlson Ori	50%	8%	50%	92%	76%		
Ohlson RE	100%	0%	0%	100%	62%	3.430	0.904
Springate Ori	0%	58%	100%	42%	64%		
Springate RE	38%	12%	63%	88%	79%	*17.836	0.001

*Represent Statistical significance at 5%

From the automotive sector (table 3), when analyzing bankruptcy prediction in the context of the COVID-19 crisis for the automotive sector, caution should be exercised in relying on the original Altman EM value and the re-estimated Ohlson model, as they exhibit the highest type I error values. Conversely, the original Springate model stands out with the lowest type I error value and a balanced 100% specific accuracy for financial distress. Although the Altman EM re-estimation model achieves the highest total accuracy at 83%, it is important to note that its specific accuracy for financial distress is moderate at 69%. Therefore, considering both type I error and specific accuracy, the original Springate model emerges as a more robust choice for bankruptcy prediction in the challenging circumstances brought about by the COVID-19 crisis in the automotive sector.

In the energy sector (table 4), despite the original Ohlson model exhibiting the highest type I error value at 91% and a very low specific accuracy of 9% for financial distress in the energy sector, the original Springate model emerges as the recommended choice due to its lowest type I error value and a relatively high specific accuracy of 97% for financial distress in the context of bankruptcy prediction during the COVID-19 crisis. It is noteworthy, however, that the Altman EM re-estimation model, despite achieving the highest total accuracy at 81%, should be approached with caution, as its specific accuracy for financial distress is only 44%. Therefore, while the original Springate model offers a more balanced performance, the Altman EM re-estimation model's higher total accuracy should be considered alongside its lower specific accuracy for financial distress in the decision-making process for bankruptcy prediction analysis in the energy sector during the COVID-19 crisis.

Table 4. Summary of type I and II error classification, FD and non-FD accuracy and total accuracy for energy sectors

Model	Error Type I	Error Type II	FD Accuracy	Non-FD Accuracy	Total Accuracy	Chi-square	Prob
Altman EM Ori	65%	5%	35%	95%	80%		
Altman EM RE	56%	6%	44%	94%	81%	*42.898	0.000
Ohlson Ori	91%	12%	9%	88%	67%		
Ohlson RE	3%	40%	97%	60%	70%	2.170	0.976
Springate Ori	3%	50%	97%	50%	62%		
Springate RE	47%	3%	53%	97%	86%	*53.495	0.000

*Represent Statistical significance at 5%

Table 5. Summary of type I and II error classification, FD and non-FD accuracy and total accuracy for industrial manufacture sectors

Model	Error Type I	Error Type II	FD Accuracy	Non-FD Accuracy	Total Accuracy	Chi-square	Prob
Altman EM Ori	100%	0%	0%	100%	77%		
Altman EM RE	34%	27%	66%	73%	71%	*51.838	0.000
Ohlson Ori	49%	29%	51%	71%	67%		
Ohlson RE	37%	5%	63%	95%	87%	*7.649	0.469
Springate Ori	9%	53%	91%	47%	57%		
Springate RE	63%	2%	37%	98%	84%	*57.113	0.000

*Represent Statistical significance at 5%

If you look at table 5 from the perspective of the highest type I error value, then in the manufacturing industry sector the original Altman EM model is the least recommended model because the type I error value of this model reaches 100%, accompanied by a specific financial distress accuracy value of 0%. The lowest type I error value was obtained from the original Springate model, namely only 9%, accompanied by a specific financial distress accuracy value of 91%. Therefore, the original Springate model is the most recommended model for analyzing bankruptcy predictions during the COVID-19 crisis for the manufacturing industrial sector. The highest total accuracy was obtained from the Ohlson re-estimation model, namely 87% even though the specific accuracy value for financial distress was medium, namely only 63%.

In the health sector (Table 6), almost all models obtained the highest type I error value, namely 100%. These models are the original Altman EM model, the original Ohlson model, and the re-estimated Ohlson model. These three models also have a low specific financial distress accuracy value, namely 0%. With the type I error value being very high and the financial distress accuracy value being very low, these three models are not recommended for use in bankruptcy prediction analysis during the COVID-19 crisis for the health sector. The recommended model is the original Springate model, with the lowest type I error value, namely only 0%, with the highest specific accuracy value for financial distress, namely 100%. If the analysis is carried out from a total accuracy value perspective, then the model with the highest total accuracy value is the Springate re-estimation model, which is 98%, even though the specific accuracy value for financial distress is medium, which is only 50%.

Table 6. Summary of type I and II error classification, FD and non-FD accuracy and total accuracy for health sectors

Model	Error Type I	Error Type II	FD Accuracy	Non-FD Accuracy	Total Accuracy	Chi-square	Prob
Altman EM Ori	100%	0%	0%	100%	96%		
Altman EM RE	50%	2%	50%	98%	96%	*9.514	0.049
Ohlson Ori	100%	13%	0%	87%	83%		
Ohlson RE	100%	0%	0%	100%	96%	0.000	1.000
Springate Ori	0%	8%	100%	92%	93%		
Springate RE	50%	0%	50%	100%	98%	*9.90	0.042

*Represent Statistical significance at 5%

Table 7. Summary of type I and II error classification, FD and non-FD accuracy and total accuracy for food and beverage sectors

Model	Error Type I	Error Type II	FD Accuracy	Non-FD Accuracy	Total Accuracy	Chi-square	Prob
Altman EM Ori	100%	0%	0%	100%	82%		
Altman EM RE	59%	1%	41%	99%	89%	*145.947	0.000
Ohlson Ori	46%	10%	54%	90%	83%		
Ohlson RE	81%	0%	19%	100%	86%	0.674	1.000
Springate Ori	16%	25%	84%	75%	77%		
Springate RE	54%	0%	46%	100%	90%	*109.223	0.000

*Represent Statistical significance at 5%

In assessing bankruptcy prediction during the COVID-19 crisis in the food sector (Table 7), it is crucial to note that the original Altman EM model presents the highest type I error value at 100%, coupled with an extremely low specific accuracy for financial distress at 0%. In contrast, the original Springate model stands out with the lowest type I error value, merely 16%, and concurrently boasts the highest specific accuracy for financial distress at 84%. Consequently, the recommended model for robust bankruptcy prediction analysis in the food sector during the COVID-19 crisis is the original Springate model. Despite the Springate re-estimation model exhibiting the highest total accuracy, reaching 46% for specific financial distress, its lower specific accuracy compared to the original Springate model underscores the latter's superior performance in this context.

In the real estate sector (Table 8), careful consideration is crucial when selecting a bankruptcy prediction model for the COVID-19 crisis. The original Altman EM model, with the highest type I error value and a minimal 0% specific accuracy for financial distress, is strongly discouraged for use in this context. On the other hand, the original Springate model emerges as the recommended choice, displaying an impressively low type I error rate of 2% and a substantial specific accuracy for financial distress at 98%. While the Altman EM re-estimation model attains the highest total accuracy value at 83%, it is essential to note that its specific accuracy for financial distress stands at 50%. Therefore, in the real estate sector during the COVID-19 crisis, the original Springate model is preferred for its balanced performance, striking a commendable trade-off between type I error and specific accuracy for financial distress.

Table 8. Summary of type I and II error classification, FD and non-FD accuracy and total accuracy for real estate sectors

Model	Error Type I	Error Type II	FD Accuracy	Non-FD Accuracy	Total Accuracy	Chi-square	Prob
Altman EM Ori	100%	0%	0%	100%	75%		
Altman EM RE	50%	6%	50%	94%	83%	*54.409	0
Ohlson Ori	39%	41%	61%	59%	60%		
Ohlson RE	23%	6%	77%	94%	90%	14	0.072
Springate Ori	2%	75%	98%	25%	44%		
Springate RE	50%	2%	50%	98%	86%	*70.112	0

*Represent Statistical significance at 5%

Conclusion

In the research conducted, it can be seen how the three models, namely Altman EM, Ohlson and Springate, show different responses to each sector that is the object of research, including when all sectors are combined into one large data set. From the 7 datasets that are the object of research, including when all sectors are combined into one large data set, the original Springate model always produces the lowest type I error value as well as the highest accuracy value in predicting firm years experiencing financial distress. The original Altman EM model always produces the highest type I error value, except in the energy sector, as well as the lowest accuracy value in predicting firm years experiencing financial distress. The original Altman EM, Ohlson re-estimation and Springate re-estimation models always produce the highest type II error values as well as the lowest accuracy values in predicting a healthy firm year. The Ohlson model is superior on 3 of the 7 datasets in obtaining the highest total accuracy value, while the Springate re-estimation model is also superior on 3 of the t datasets in obtaining the highest total accuracy value. The Altman EM re-estimation model was only superior in 1 of 7 data sets in obtaining the highest total accuracy value. Apart from that, it can be seen that the original Springate model is the model that produces the lowest type I error value so that this model is the most recommended model for predicting bankruptcy during the crisis due to the pandemic in Indonesia.

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