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Analysis of Factors Affecting the Potential Bankruptcy of Construction Companies Before and During Covid-19

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ABSTRACT

Every company has goals to achieve, including construction companies. However, a problem that cannot be avoided in every company is bankruptcy. This study aimed to determine differences in the financial distress of construction companies before and during the COVID-19 pandemic and whether financial and macroeconomic factors affected financial distress before and during the COVID-19 pandemic crisis. The population in this research is all construction companies on the Indonesian Stock Exchange. The sampling technique used was purposive sampling. The samples obtained were 25 construction sector companies on the Indonesia Stock Exchange during 2017-2022. The research method uses a panel data regression model involving company financial and macroeconomic factors on the financial distress of companies as measured by the bankruptcy model Altman (1968) and Ohlson (1980). The study's results confirmed no differences between Z-scores and O-scores before and during the Covid-19 pandemic. However, there were differences in construction companies' Z-score and O-score patterns before and during the Covid-19 pandemic. In addition, it was also found that before and during the Covid-19 pandemic crisis, only the company's financial factors affected the Z-score and O-score model.

Keywords: Altman, Bankruptcy, Construction, Macroeconomics, Ohlson

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INTRODUCTION

The construction sector in Indonesia is the fourth largest contributor to the National Gross Domestic Product (GDP) from 2017 – 2021. Based on variable data on the business problem index from the Central Statistics Agency (2022), the three main problems in construction sector companies are very tight competition, a decrease in demand for construction services in general, and an increase in building/material prices (Acosta-González et al., 2019; Valaskova et al., 2021; Zizi et al., 2022). In 2020, there was a decrease in the value of construction work by 17.74% from 2019. This was accompanied by a decrease in the number of construction companies in Indonesia by -5.66% from 2019. The construction sector has different financial characteristics from other sectors (Rinofah et al., 2022; Rusydiana et al., 2019). High levels of uncertainty such as project duration, industry sensitivity to economic cycles, and so on, make the construction industry vulnerable to financial crises (Agarwal & Taffler, 2008; Alcalde et al., 2022).

For this reason, the analysis of the financial health of construction companies is important for investors, especially the infrastructure sector in determining the success and feasibility of the projects carried out. Bankruptcy prediction has been widely discussed in literature as an early warning of a company's financial condition. Two common bankruptcy models practitioners and academics use are the Z-score (Altman, 1968, 2005) *and the O-score* (Altman, 2005; Ohlson, 1980). Both models are based on information from financial statements to correlate with bankruptcy risk through financial ratios. Agarwal and Taffler (2008) show that traditional accounting ratio-based bankruptcy prediction models are not inferior to market-based models (Altman et al., 2017).

The Z-Score and O-Score models are two approaches commonly used to assess a company's bankruptcy potential. The Z-Score model uses discriminant analysis to combine several important financial ratios into a single score that reflects bankruptcy risk. Meanwhile, the O-Score Model uses logistic regression to take into account financial ratios and other economic factors in assessing the possibility of bankruptcy. Although both are useful in providing an indication of potential bankruptcy, they both have limitations, such as reliance on accurate financial data and certain assumptions in the analysis.

Gupta & Mahakud, (2023) used Altman and Ohlson's model measure to explain that financial distress increases the sensitivity of investment cash flows and negatively impacts company investments. Valaskova et al. (2021) measured a firm's financial stability using the Altman model to examine whether there is an interdependence between a firm's financial stability and profit management. Srebro et al., (2021) and Alcalde et al., (2022) believe the Altman Z-Score model presents a high-value instrument for all interested parties. However, Lisin et al. (2022) improved on a previous model that used the Altman Z-Score model *in predicting the probability of corporate bankruptcy by using the Ohlson O-Score model*. Ohlson's (1980) model provides high predictive accuracy in the original version, showing that it is stationary and valid for different periods and economic conditions (Ohlson, 1980; Oz & Simga-Mugan, 2018). Thus, Altman and Ohlson's accounting-based bankruptcy model has been widely used and is quite effective in predicting bankruptcy with an accuracy of 75% to 90% (Altman et al., 2017; Altman, 2018a).

Nurhayati et al. (2022) believe there is no significant difference in financial conditions in Healthcare sub-sector companies in Indonesia before and during the COVID-19 pandemic (Altman, 2018b; Fernández-Gámez et al., 2020). However, research on the crisis phenomenon during the Covid-19 pandemic whether it affects the potential bankruptcy of construction sector companies in Indonesia needs further research. This is because there has been a decrease in the value of work and the number of construction companies during the Covid-19 pandemic.

During the COVID-19 pandemic, there has been a decline in the number of construction companies in line with deteriorating economic conditions and business climate. Losses borne by contractors due to delays in implementing construction projects during the Covid-19 pandemic (Zahrina & Suryanto, 2021). Alaka et al. (2018), Schonfeld et al. (2018), and Svabova and Kliestik (2018) believe that traditional bankruptcy prediction models are not suitable for analyzing modern companies because they are in dynamic macroeconomic and business conditions (Frank & Goyal, 2003; Gelashvili et al., 2023). In addition to financial factors originating from internal companies, macroeconomic factors as external factors cannot be ignored to predict a company's bankruptcy.

Altman et al. (2017) developed a model to explain the financial difficulties of European companies but have not consider factors from countries or heterogeneity between countries (Lisin et al., 2022). Lisin et al. (2022) have improved on a previous model that used the Altman Z-Score *model in predicting the probability of corporate bankruptcy by using the Ohlson O-Score model* (Altman et al., 2017). Fernandez-Gamez et al. (2020) continued research that considered country and macroeconomic factors with the results that EBITDA/Sales, EBITDA/Total Assets, Total Liabilities/Total Assets, Current Assets/Current Liabilities, Depreciation Amortization/EBIT, risk premiums, and inflation rates had a significant effect on the financial difficulties of European companies. In the construction sector industry, Giriūniene et al., (2019) found that the company's financial *factors (current* ratio, debt ratio*, sales revenue*/*net working capital*) and macroeconomic factors (unemployment rate, inflation, and construction costliness index) have a significant effect on the potential for bankruptcy.

Different from previous research, the novelty of this research is that the research object used is a construction company that has been registered on the IDX and has had the influence of the COVID-19 pandemic on its financial performance. Then a comprehensive analysis was carried out before and during the pandemic so that it focused on the context of the COVID-19 pandemic. Therefore further research needs to be expanded to developing countries that are more economically heterogeneous by analyzing factors that can affect the potential bankruptcy of companies due to the COVID-19 pandemic crisis. The results of this study are expected to reveal what factors need to be considered to reduce the potential bankruptcy of large-scale construction companies listed on the Indonesia Stock Exchange (IDX).

METHODS

This research uses quantitative methods. According to Sujarweni, (2014) quantitative research is a type of research that produces discoveries that can be achieved (obtained) using statistical procedures or other means of quantification (measurement). The object to be studied is a construction sector company listed on the Indonesia Stock Exchange. To see the difference before and during the Covid-19 pandemic crisis, financial statement data for six years from 2017 to 2022 is needed. . The population in this research is all construction companies on the Indonesian Stock Exchange. The sampling technique used was purposive sampling. The samples obtained were 25 construction sector companies on the Indonesia Stock Exchange during 2017-2022. The criteria for the sample used are being registered on the IDX, company size, financial performance for 6 years, length of operation, the influence of the COVID-19 pandemic on financial performance, and transparency of financial reports.The sample consists of 25 companies operating in the Infrastructure sector (J), Building Construction Sub-sector (J2), Building Construction Industry (J21), and Building Construction Sub-industry (J211).

This study used two dependent variables and seven independent variables. The dependent variables in this study were Z-score *and O-score*. Z-score calculation *refers to equation (1) and O-score calculation refers to equation (*2). The independent variables used in this study are secondary data derived from the calculation of accounting data or company financial ratios and macroeconomic indicators. Each variable is described in table 1.

Table 1. Independent Variables

Financial Factors of the Company	
Variable	**Operationalization**
Current Ratio (CR)	$CR = \frac{Current\ Assets}{Current\ Liabilities}\ x\ 100\%$ (3)
Debt to Asset Ratio (DA)	$DAR = \frac{Total\ Debt}{Total\ Assets} x\ 100\%$ (4)
Return on Asset (RoA)	$RoA = \frac{Net\ Income}{Total\ Aset}$ (5)
Sales Growth (SG)	$the\ oneSG = \frac{Sales_t - Sales_{t-1}}{Sales_{t-1}}$ (6)
Firm Size (SIZE)	*SIZE = ln(Total Assets)* (7)
Macroeconomic Factors	
Variable	**Operationalization**

Financial Factors of the Company	
Variable	**Operationalization**
Exchange rate USD to Rupiah (end of period)	*KURS = ln [(selling rate + buying rate)/2]* (8)
Real interest rate (end of period)	*RIR = Interest rate – Inflation rate* (9)

Source: Processed author data

The initial stage carried out in this study is to collect data, but not limited to financial ratios used as variables in calculations in Altman and Ohlson models and corporate financial and macroeconomic factors shown in Table 1. Data in the form of financial ratios of construction companies collected are processed to calculate Z-Score *and* O-Score *as* well as regression models of panel data involving company financial and macroeconomic factors. Average Difference Test Before and During COVID-19. Thus, the data analysis stage begins with data collection, data presentation, data calculation, and drawing conclusions.

The average difference between two populations can be tested using two methods, namely through parametric and non-parametric statistical tests. The parametric statistical test is an independent sample t-test, while the non-parametric statistical test is the Mann-Whitney U.

Panel Data Regression Analysis

The use of regression panel data with dependent variables Z-score or O-Score, and independent variables namely corporate financial and macroeconomivariable. The panel data regression equation can be written as follows. $Y_{it} = \alpha_i + \beta_1 X_{1it} + \beta_2 X_{2it} + \beta_3 X_{3it} + \beta_4 X_{4it} + \beta_5 X_{5it} + \beta_6 X_{6it} + \beta_7 X_{7it} + e_{it}$(10)

Y	: Z-*Score* or O-*Score*	X5	: *firm size*
αi	: *constant*	X6	: *exchange rate*
βi	: *regression coefficient*	X7	: *real interest rate*
X1	: *current ratio*	eit	: *residual/error*
X2	: *total debt/total assets*	i	: *Company* i
X3	: RoA	t	: *time period* t
X4	: *sales growth*		

The flow of the research process is described from beginning to end according to Figure 1.

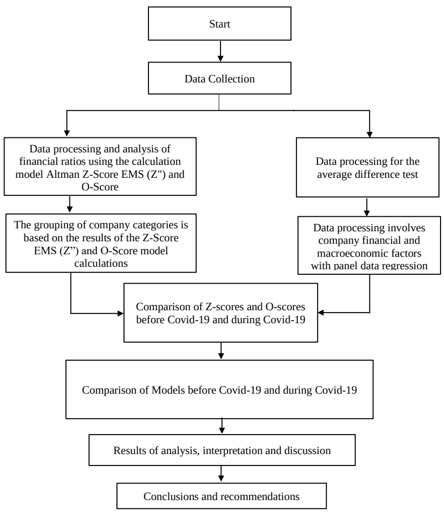

Figure 1. Research mindset
(Source: Primary Data is Processed, 2024)

RESULTS AND DISCUSSION

The research observation period was carried out from 2017 to 2022 so that 20 companies already had complete data to be used as research samples. This is because as many as five incomplete companies did not publish *audited financial statements* from 2017-2022. With the number of company samples studied, as many as 20 companies, and the research observation period starting from 2017-2022, the number of observation data becomes 120 firm years.

Table 2. Descriptive Statistics Before and During COVID-19

Variable	Min	Max	Mean	Std. Deviation
Before Covid-19				
O-*score*	-3.84	2.52	-1.06	1.45
Z-score	2.18	12.14	6.53	2.32
CR	0.35	5.93	1.48	0.83
OF	0.18	0.98	0.61	0.19
Roa	-0.11	0.41	0.05	0.07
SG	-0.53	3.89	0.25	0.69
Size	18.02	25.55	21.95	1.89
Course	9.51	9.58	9.55	0.03
LAUGH	0.64	2.87	1.93	0.95
During Covid-19				
O-*score*	-4.92	1.98	-1.35	1.61
Z-score	-6.44	16.91	5.54	4.03
CR	0.16	5.85	1.46	1.00
OF	0.12	0.97	0.58	0.21
Roa	-1.28	0.16	-0.04	0.19
SG	-0.98	4.01	0.01	0.69
Size	18.65	25.36	21.93	1.85
Course	9.56	9.66	9.60	0.05
LAUGH	-0.01	2.07	1.23	0.90

Source: Processed author data

Table 2 shows that the average O-score and Z-score in the period before COVID-19 were -1.06 and 6.53, while the average O-score and Z-score during *the period during Covid-19 were -1.35 and 5.54.* The greater the Z-score, the company *shows the healthier, while the greater the O-score*, the more *distress* the company. The average O-score and Z-score *were* higher before the pandemic than during the pandemic. From these conditions, it can be concluded that based on the O-score value, the company's condition before the pandemic was more *distressed* than during the pandemic crisis. Meanwhile, based on the Z-score, *the* company's condition was more healthy before the pandemic than during the crisis.

The average DA and SIZE values did not differ much before and during the pandemic. Average CR, RoA and SG values were higher before the pandemic than after. The average exchange rate is higher during the pandemic than before, while the average *real interest rate* is higher before than during the pandemic crisis.

Average Difference Test Results

The mean difference test is used to see if there is a significant difference between the Z-score *and* O-score before and during the pandemic crisis. Before performing the mean difference test, a data distribution test is carried out to determine whether the data follows the normal distribution or not. The results of the data normality test can be found in table 3. next.

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Table 3. Normal Assumption Test Results

Variable	p-value Anderson-Darling	
	Before	For
Z-Score	0.2669	0.0019
O-Score	0.1984	0.8549

Source: Processed author data

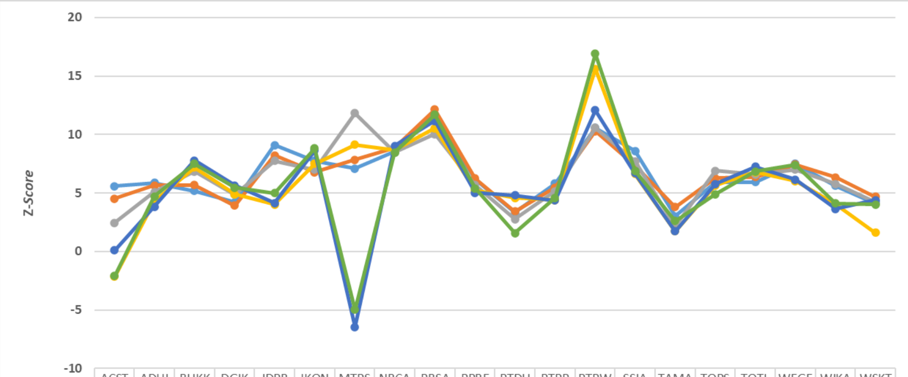
Based on the normality test results, the Z-score data during the pandemic was not normally distributed, while previously it was normally distributed. Because some groups do not meet the Normal assumption, the average difference test uses the non-parametric Mann-Whitney U approach. While the O-Score data meet the Normal assumption, the average difference test uses the parametric t-test approach. The average difference test results can be seen in table 4. next.

Table 4. Average Difference Test Results

Variable	$\bar{X}$ Before	$\bar{X}$ For	Test	p-value	information
Z-score	6.532	5.535	Mann-Whitney U	0.075	Not Significant
O-Score	-1.062	-1.354	t-test	0.299	Not Significant

Source : processed author data

Based on the results of the average difference test, for *Z-score and O-score, it can be seen that there is no difference in Z-score* and O-score values between before and during the pandemic. In other words, the state of bankruptcy of construction companies does not differ markedly between before and during the pandemic, however, from *the Z-score pattern before and during the pandemic, as shown in Figure 2. Below, it can be seen that most companies experienced a decrease in Z-score during the pandemic.* So that more construction companies during the pandemic experience *financial distress conditions*.



	ACST	ADHI	BUKK	DGIK	IDPR	JKON	MTPS	NRCA	PBSA	PPRE	PTDU	PTPP	PTPW	SSIA	TAMA	TOPS	TOTL	WEGE	WIKA	WSKT
2017	5.601	5.874	5.191	4.222	9.106	7.768	7.108	8.572	11.72	6.17	3.349	5.809	10.57	8.585	3.005	5.904	5.945	7.496	5.633	4.104
2018	4.523	5.645	5.678	3.924	8.221	6.796	7.847	8.875	12.14	6.262	3.412	5.46	10.3	7.332	3.795	6.279	6.39	7.439	6.333	4.667
2019	2.457	5.093	6.858	4.871	7.756	7.013	11.82	8.472	10.03	5.67	2.769	5.15	10.58	7.715	2.183	6.92	6.593	6.997	5.778	4.203
2020	-2.14	4.295	7.202	4.916	4.026	7.505	9.125	8.684	10.54	5.213	4.599	4.388	15.62	6.624	1.724	5.652	6.775	6.015	4.038	1.606
2021	0.112	3.837	7.787	5.654	4.161	8.62	-6.44	9.04	11.17	5.017	4.795	4.381	12.09	6.678	1.732	5.79	7.258	6.166	3.642	4.408
2022	-2.11	4.703	7.491	5.454	5.002	8.81	-4.98	8.474	11.7	5.408	1.584	4.581	16.91	6.895	2.621	4.892	6.851	7.394	4.118	4.019

Figure 2. Construction Company Z-score Before and During the Pandemic
Source: Processed author data

While the O-score pattern of construction companies is shown in Figure 3. It can be seen that most construction companies have experienced an increase in O-score value during the pandemic, so more construction companies during the pandemic experience *financial distress*.

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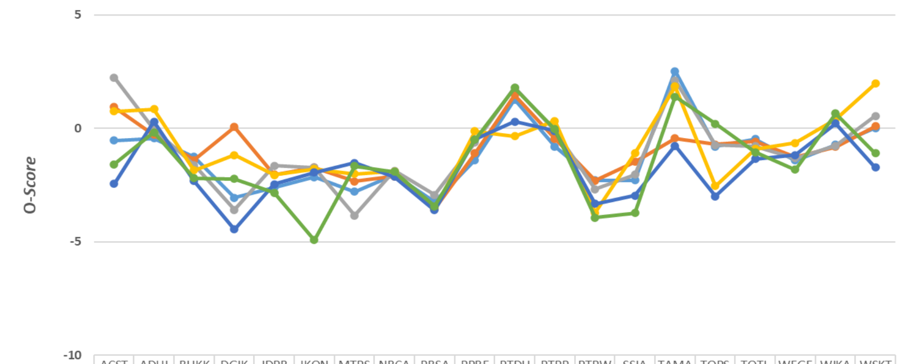

	ACST	ADHI	BUKK	DGIK	IDPR	JKON	MTPS	NRCA	PBSA	PPRE	PTDU	PTPP	PTPW	SSIA	TAMA	TOPS	TOTL	WEGE	WIKA	WSKT
2017	-0.53	-0.43	-1.25	-3.06	-2.6	-2.14	-2.78	-2.04	-3.24	-1.39	1.281	-0.8	-2.28	-2.28	2.522	-0.79	-0.46	-1.4	-0.71	0.023
2018	0.938	-0.27	-1.39	0.076	-2.04	-1.71	-2.33	-2.11	-3.53	-1.09	1.481	-0.45	-2.3	-1.46	-0.43	-0.7	-0.57	-1.27	-0.8	0.092
2019	2.244	-0.03	-1.6	-3.58	-1.63	-1.71	-3.84	-1.85	-2.93	-0.61	1.803	-0.09	-2.67	-2.03	2.122	-0.74	-0.78	-1.31	-0.77	0.551
2020	0.759	0.855	-1.85	-1.18	-2.05	-1.78	-1.99	-1.89	-3.57	-0.12	-0.35	0.332	-3.71	-1.09	1.852	-2.53	-0.91	-0.63	0.398	1.984
2021	-2.44	0.3	-2.31	-4.44	-2.46	-1.94	-1.52	-2.13	-3.6	-0.48	0.307	-0.11	-3.32	-2.96	-0.76	-2.99	-1.34	-1.17	0.218	-1.72
2022	-1.58	-0.17	-2.18	-2.21	-2.83	-4.92	-1.65	-1.91	-3.42	-0.5	1.787	-0.02	-3.92	-3.72	1.397	0.213	-1.04	-1.81	0.659	-1.09

Figure 3. Construction Company O-score Before and During the Pandemic
Source: Processed author data

Correlation Analysis Results

Correlation analysis evaluates the relationship between two variables, be it between the independent and dependent variables or between the independent variable itself. Correlation can also be used to identify indications of multicollinearity between independent variables. Suppose there is a strong correlation between two independent variables. In that case, this indicates a multicollinearity relationship. One of those independent variables may need to be removed from the model or reduced without removing the number of original variables. The results of the correlation analysis can be seen in Tables 5. and 6.

Table 5. Correlation Analysis Before Covid-19

Correlation (prob.)	Z_SCORE	O_SCORE	CR	DA	ROA	SG	SIZE	KURS	RIR
Z_SCORE	1.000 -----								
O_SCORE	-0.806*** 0.000	1.000 -----							
CR	0.531*** 0.000	-0.481*** 0.000	1.000 -----						
DA	-0.869*** 0.000	0.850*** 0.000	-0.460*** 0.000	1.000 -----					
ROA	0.545*** 0.000	-0.390*** 0.002	0.110 0.398	-0.365*** 0.004	1.000 -----				
SG	0.008	-0.092	-0.006	0.020	0.204	1.000			

Correlation (prob.)	Z_SCORE	O_SCORE	CR	DA	ROA	SG	SIZE	KURS	RIR
	0.950	0.479	0.966	0.879	0.115	-----			
SIZE	-0.261	0.247	-0.164	0.412***	-0.234	-0.063	1.000		
	0.042	0.055	0.207	0.001	0.069	0.632	-----		
KURS	-0.082	0.182	-0.067	0.054	-0.128	-0.068	-0.052	1.000	
	0.531	0.161	0.605	0.678	0.326	0.601	0.690	-----	
RIR	-0.107	0.206	-0.032	0.050	-0.205	-0.159	-0.055	0.934***	1.000
	0.411	0.112	0.808	0.703	0.112	0.222	0.674	0.000	-----

*** significant level <0,1%, ** significant level 1%, * significant level 5%
Source: Processed author data

Based on table 5. above, *Current Ratio, Debt to Asset, and* Return on Asset *significantly correlate with the Z-score and O-score, while* sales growth, size, *exchange rate,* and real interest rate *do not significantly correlate with the Z-score and O-score. The current ratio* with debt to asset and debt to asset *with RoA and* size has a significant correlation, but the correlation coefficient is below 0.6 which is moderate, so it does not cause multicollinearity. While the *real interest rate* and exchange rate correlation are very strong at 0.934, these two variables will cause multicollinearity so that they can be simplified into one Principal *Component Analysis* (PCA) factor.

Table 6. Correlation Analysis During Covid-19

Correlation (prob.)	**Z_SCORE**	**O_SCORE**	**CR**	**DA**	**ROA**	**SG**	**SIZE**	**KURS**	**RIR**
Z_SCORE	1.000 -----								
O_SCORE	-0.538*** (0.000)	1.000 -----							
CR	0.602*** (0.000)	-0.519*** (0.000)	1.000 -----						
DA	-0.612*** (0.000)	0.787*** (0.000)	-0.556*** (0.000)	1.000 -----					
ROA	0.713***	-0.150 (0.251)	0.118 0.370	-0.113 0.389	1. 000 -----				

	(0.000)								
SG	0.201 0.125	-0.089 0.497	0.042 0.750	0.002 0.985	0.234 0.072	1.000 -----			
SIZE	-0.024 0.853	0.278* 0.032	-0.184 0.160	0.574*** 0.000	0.236 0.070	-0.066 0.618	1.000 -----		
KURS	-0.010 0.939	-0.049 0.708	0.028 0.834	-0.001 0.995	0.071 0.591	0.128 0.330	-0.003 0.980	1.000 -----	
RIR	0.019 0.888	0.084 0.523	-0.019 0.885	0.006 0.967	-0.058 0.661	-0.184 0.160	0.004 0.974	-0.987*** 0.000	1 ------

*** significant level <0,1%, ** significant level 1%, * significant level 5%
Source: Processed author

Based on Table 6. above, *Current Ratio, Debt to Asset, and* Return on Asset *have a significant correlation with the Z-score, while* sales growth, size, exchange rate, and *real interest rate* do not have a significant correlation with the Z-score. *Current Ratio, Debt to Asset, and* size *correlate significantly with the O-score, while* Return on Asset, sales growth, *exchange rate, and* real interest rate do not significantly correlate with the O-score. *The current ratio* with debt to asset *and* debt to asset with *size* has a significant correlation, but the correlation coefficient below 0.6 is moderate, so it does not cause multicollinearity. While the *real interest rate* and correlation rate are very strong at -0.987, these two variables will cause multicollinearity so that they are summarized into one Principal *Component Analysis* (PCA) factor.

Model Selection Test Results

In the panel model, there are 3 (three) model choices, namely *Pooled Least Square* (PLS), *Fixed* Effect Model (FEM) and *Random Effect* Model (REM). The results of the model selection test can be seen in Table 7. next.

Table 7. Model Selection Test Results

Testing	**Statistics**	**p-value**	**Conclusion**
Model before the Covid-19 Pandemic			
Dependent: Z-score			
PLS vs FEM	Fstat = 11,821	0,000	FEM is more accurate
PLS vs REM	LM test = 31,793	0,000	REM is more accurate
FEM vs REM	Chi-square = 7,873	0,248	REM is more accurate
Dependent: O-score			
PLS vs FEM	Fstat = 1,619	0,111	PLS is more accurate
PLS vs REM	LM test = 0,124	0,725	PLS is more accurate
FEM vs REM	Chi-square = 9,805	0,133	REM is more accurate
Model during the Covid-19 Pandemic			
Dependent: Z-score			
PLS vs FEM	Fstat = 40,325	0,000	FEM is more accurate
PLS vs REM	LM test = 4,242	0,039	REM is more accurate
FEM vs REM	Chi-square = 0,000	1,000	REM is more accurate
Dependent: O-score			

PLS vs FEM	Fstat = 1,600	0,114	PLS is more accurate
PLS vs REM	LM test = 0,361	0,548	PLS is more accurate
FEM vs REM	Chi-square = 6,296	0,391	REM is more accurate

Source: Processed author data

The results of the Z-score model selection test before the pandemic were obtained, the conclusion of the right model was REM, the O-score model before the pandemic was obtained, the conclusion of the right model was PLS, the Z-score model during the pandemic was obtained, the conclusion of the right model was REM, and *the* O-score model During the pandemic, the conclusion of the right model was PLS. Next, the model estimation uses the most appropriate selected model.

Classical Assumption Test Results
In the REM model, several assumptions must be met, namely, residuals are normally distributed and there is no multicollinearity among independent variables. The results of the assumption test can be seen in table 8.

Table 8. Classical Assumption Test Results

Testing	Statistics	p-value	Conclusion
Model before the Covid-19 Pandemic			
Dependent: Z-score (REM)			
Normality	Jarque berra=36,289	0,000	Unfulfilled
Multikolinearitas		VIF:	Fulfilled
	CR	1.664482	
	DR	1.803191	
	RoA	1.187130	
	SG	1.101287	
	Size	1.192040	
	Factor	1.093229	
Dependent: O-*score* (PLS)			
Normality	Jarque berra=71,249	0,0000	Unfulfilled
Multikolinearitas		VIF:	Fulfilled
	CR	1.272765	
	DR	1.650528	
	RoA	1.286865	
	SG	1.068731	
	Size	1.304484	
	Factor	1.050856	
Model during the Covid-19 Pandemic			
Dependent: Z-*score* (REM)			
Normality	Jarque berra=6,926	0,031	Unfulfilled
Multikolinearitas		VIF:	Fulfilled
	CR	1.488943	
	DR	1.713151	
	RoA	1.160139	
	SG	1.053786	
	Size	1.377619	
	Factor	1.039947	
Dependent: O-*score* (PLS)			
Normality	Jarque berra=7,287	0,026	Unfulfilled
Multikolinearitas		VIF:	Fulfilled
	CR	1.516308	
	DR	2.398823	
	RoA	1.280732	
	SG	1.125809	

Size	1.863665

Source: Processed author

Based on the results of the assumption test above, the Z-score *and O-score* models both before the pandemic and during the pandemic did not meet normal assumptions. To overcome violations of the Normal assumption can be done with robust regression, *so the estimation of the four models uses* robust regression.

Panel Data Regression Results

Regression analysis of panel data in this study was used to see the influence of financial and macroeconomic factors on *the financial distress* condition of construction companies. The model estimation results using selected estimates can be seen in Table 9. Next.

Table 9. Model Estimation Results

Factor	Before Covid-19		During Covid-19	
	Coefficient	p-value	Coefficient	p-value
		Depend: Z-score		
CR	1.876***	0.000	1.523***	0.000
OF	-4.339***	0.000	-7.048***	0.000
Roa	10.403***	0.000	10.200***	0.000
SG	0.331**	0.005	0.149	0.262
Size	0.157**	0.001	0.220**	0.001
Factor	0.095	0.241	0.016	0.854
Constant	2.267	0.349	3.026	0.014
Adj R2	0,5929		0,5883	
		Depend: O-score		
CR	-0.160**	0.002	-0.025	0.877
OF	6.794***	0.000	7.296***	0.000
Roa	-3.368***	0.000	0.468	0.542
SG	-0.169**	0.003	-0.209	0.299
Size	-0.253***	0.000	-2.228*	0.022
Factor	0.042	0.292	-0,080	0.549
Constant	0.909	0.084	-0.478	0.796
Adj R2	0,7374		0,5069	

*** significant level <0,1%, ** significant level 1%, * significant level 5%
Source: Processed author

Based on Table 9. above, *current ratio (*CR), *debt to asset ratio* (DA), *Return on Assets* (RoA) and *firm size* (size) significantly affected Z-score both before and during the Covid-19 pandemic crisis. Meanwhile, *sales growth* (SG) only significantly affected the Z-score before the Covid-19 pandemic crisis. The combined rate and RIR factors did not significantly affect the Z-score before or during the COVID-19 pandemic. CR, RoA, SG, and size positively affect the Z-score, *while DA hurts the Z-score*. The higher the Z-score, the healthier the company's condition (*solvent*). Thus, it can be concluded that the higher the CR, RoA, *sales growth*, and *size*, the healthier the company's condition. Meanwhile, the higher the DA ratio, the company's condition is increasingly unhealthy (*distress*). The Z-score both before the pandemic and during the pandemic is only influenced by the company's financial factors.

The results of this research are supported by previous research conducted by Gustiyah & Sihono (2023) which stated that DER, CR, TATO, ROA, FS and SG simultaneously influence Stock Returns in real estate & property sector companies listed on the Indonesia Stock Exchange (BEI) for the period 2021 to 2022. Kristiawan and Sapari (2023) stated that profitability (ROA) can be used as a basis for determining changes in stock return variables. Meanwhile, liquidity (CR), solvency (DR), and sales growth (SG) cannot be used as a basis for determining changes in stock return variables.

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In contrast to the results of Fitriyani (2022) which states that there is no significant difference in EBITTA, ROA and financial distress in transportation in Indonesia before and during the spread of the corona virus. In pandemic conditions, there is actually a significant increase in the average net working capital compared to before the spread of the corona virus in transportation companies in Indonesia, so that this sector is still able to operate despite the economic recession during the pandemic. The average ability of companies to generate profits by utilizing all the assets they have does not show a significant difference both in the 2 years before the pandemic (2018-2019) and 2 years since the pandemic (2020-2021).

Globally, millions of employees lost their jobs amid the Covid 19 crisis. In the construction industry, all employees lost their jobs and most of those affected were small businesses that could not pay employee salaries (Jumas et al., 2022). In order to prevent and minimize the company going bankrupt, companies and investors can analyze the financial situation, so as to identify whether there is financial distress as the beginning of the bankruptcy period. Financial distress is a state of financial difficulty that begins when the company is unable to pay its maturing obligations. A company experiences financial distress if the company cannot fulfill its financial obligations by violating debt covenants accompanied by the elimination or reduction of dividend financing (Putri & Friyatmi, 2023).

Because financial distress can be a warning for companies as a stage before bankruptcy, it is appropriate for companies to conduct early detection of financial distress, especially in the midst of the COVID-19 pandemic which resulted in mass bankruptcy events. Dwijayanti (2010) states that if financial distress is predicted early, the company management can make efforts to improve the company's financial condition. These predictions will provide encouragement for companies to improve their financial performance, prepare business plans to minimize the impact of financial distress and find solutions to get out of this position. Other efforts to avoid bankruptcy can also be done by knowing an understanding of the factors that can trigger financial distress (Islamy et al., 2021).

Companies in predicting financial distress can be known by analyzing financial ratios. Companies use financial ratios as a form of warning in predicting financial distress, so that it will make companies act quickly to overcome so that financial difficulties do not occur. The ratios used in this study are debt to equity ratio, fixed asset ratio, net profit margin, current ratio and firm size which are calculated using the natural logarithm (Ln) of the company's total assets (Yosandra & Sembiring, 2022).

In the O-score model, there is a difference in results between before and during Covid-19. Conditions before COVID-19, CR, DA, RoA, SG, and size significantly affected the O-score, *while the combined exchange rate and RIR factors did not significantly affect the O-score* (Goh et al., 2022; Jang et al., 2021). Meanwhile, in conditions during COVID-19, only DA and size significantly affect the O-score, *while CR, RoA*, SG, exchange rate, and RIR factors do not significantly affect the O-score. CR, RoA, *sales growth*, and *size* negatively affect the O-score, *while DA positively affects the O-score*. The higher the O-score, the more unhealthy the company's condition (*distress*). Conversely, the lower the O-score, the healthier the company's condition (*solvent*). Thus, it can be concluded that the higher the CR, RoA, SG, and size, the healthier the company's condition. Meanwhile, the higher the DA ratio, the company's condition is increasingly unhealthy (*distress*). The company's financial factors influenced the O-score value before and during the pandemic (Hall & McDermott, 2019; Lisin et al., 2022).

Referring to the results obtained, it means that these factors have a high potential for causing bankruptcy. Bankruptcy in the economic system, continuous entry and exit of entities is a natural thing (Santoso et al., 2023). The cause of bankruptcy is not only due to financial pressure but also other reasons which vary depending on the condition of each company, including:

a. The condition of the industry is bad.

b. Deregulation of key industries such as aviation, financial services, healthcare, energy)
c. High real interest rates in a certain period.
d. International competition.
e. Increased debt levels of companies.
f. The rate of new business formation is relatively higher in certain periods.

Thus, it can be concluded that both Z-score *and O-score* methods before the pandemic had the same mechanism in responding to the company's financial factors. In the model during the pandemic, the O-score *has a different mechanism, and the Z-score has* almost the same mechanism as before the pandemic. Macroeconomic factors of the exchange rate and RIR do not affect the Z-score *or O-score.* The contribution of CR, DA, RoA, SG, size, and combined exchange rate; RIR factors to the increase/decrease in Z-score before and during the pandemic crisis was 59.29% and 58.83% respectively. The contribution of CR, DA, RoA, SG, size, and combined exchange rate; RIR factors to the increase/decrease in O-score before and during the pandemic crisis was 73.74% and 50.69%, respectively.

CONCLUSION

Based on the results of the study, the average difference test results for the Altman Z-score *and O-score models* concluded that there was insufficient evidence to state that *the financial distress* condition of construction companies in Indonesia during the Covid-19 pandemic crisis was significantly different from the period before the *Covid-19* pandemic crisis. However, when viewed from the pattern of O-score and Z-score of construction companies before and during the COVID-19 pandemic crisis, there is a difference between before and during COVID-19.

Using Altman's bankruptcy model, the company's financial factors, including current ratio (CR), debt to asset ratio (DA), return on assets (RoA), sales growth (SG), and firm size (size) had a significant influence on Z-score in the period before and during the COVID-19 pandemic. Macroeconomic factors do not affect the Z-Score during or before the pandemic. CR, RoA, SG, and size positively affect Z-Score *while DA hurts Z-Score.*

Meanwhile, using Ohlson's bankruptcy model, financial factors, including *current ratio (CR),* debt to asset ratio *(DA), return on* assets (ROA*), sales growth* (SG), *and* firm *size* (size) have a significant effect on the O-Score in the period before the Covid-19 pandemic. Meanwhile, during the COVID-19 pandemic, only DA and size significantly affected the O-Score. CR, ROA, SG, and size negatively affected the O-Score before the Covid-19 pandemic. DA had a positive effect on O-Score before the COVID-19 pandemic.

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