PREDICTING FINANCIAL DISTRESS OF PUBLIC AND NON-PUBLIC CONSTRUCTION SUB-SECTOR COMPANIES

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Abstract

This study examines if there are variations among financial crisis models. It is intended to investigate whether it has the most significant level of accuracy in predicting potential corporate bankruptcies. This is a quantitative study; Secondary information from financial reports serves as the data source. The study population is public and non-public companies in the construction sector listed on the Indonesia Stock Exchange (IDX) for 2014–2020. In order to obtain a sample of eight businesses, targeted selection was used for sampling. The results of this study show that the conditions differ from those of financial distress models for public and non-public companies. For public companies, the most accurate models are Grover and Lavin's (2001), Karas and Srbová's (2019), Fulmer's (1984), and Ohlson's (1980) models proven to be 100 percent. In contrast, only Fulmer's model is entirely applicable to non-public companies. Forecast results and best-fit models can provide positive information or warnings for external and internal parties.

Keywords: Prediction Model, Financial Distress, Bankruptcy, Public Company, Non-Public Company

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1. INTRODUCTION

The infrastructure sector is one of the programs that the Indonesian government is focusing on. The construction industry contributes to the country's gross domestic product (GDP) by 10% (Badan Pusat Statistik [BPS], 2023). Infrastructure improvements are carried out to build good and quality connectivity and economic growth in the country. Indonesia is the largest construction market in the Association of South East Asian Nations (ASEAN), with Indonesia's contribution being over 67% (Ruhulessin & Alexander, 2021). Infrastructure sector companies must have considerable funding to run their projects. Based on this, public companies continue to add large amounts of debt and are threatened with financial difficulties, especially during the COVID-19 pandemic (Ruhulessin & Alexander, 2021). The public companies fell by 70% in average revenue (Mulyana, 2021).

One of the public companies, Jakarta — PT Waskita Karya Tbk (WSKT), through their subsidiary PT Waskita Toll Road (WTR), transferred 55% of its shares in the Cibitung-Cilincing toll segment to PT Akes Pelabuhan Indonesia (API) with a transaction value of Rp2.49 trillion. The sale reduced Wasquita's debt to Rp5 trillion. As a result, the concession of the Cibitung-Cilincing toll road that spans 34 kilometres (km) is owned by PT Cibitung Tanjung Priok Port Tollways (CTP) with 55% of its shares owned by WTR and 45% owned by API (Daelami, 2021). Selling one or more business units indicates signs of financial difficulties in the WSKT company.

Public companies have a higher risk in paying debts because public companies have a pre-financing project, so the company is paid after the project is completed the pre-financing scheme causes public company debt to increase. In addition, the financial performance of the public company (WSKT) declined due to acquisition projects, low occupancy projects, project delays and cash flow disruptions. In contrast, in non-public companies, financial performance decreased due to the lack of payments for projects and the lack of completed projects.

Companies in the building construction subsector had significant fluctuations in D/E ratio (debt-to-equity ratio) values between 2014 and 2020. Thus, WSKT demonstrated D/E ratio values of 354% in 2014, 212% in 2015, 266% in 2016, 330% in 2017, 331% in 2018, 321% in 2019, and 537% in 2020. One of the non-public companies, API, also had a fluctuating D\E ratio: 130% in 2014, 190% in 2015, 92% in 2016, 269% in 2017, 526% in 2018, 3547% in 2019, and 843% in 2020[1].

Judging by the indicators, the profitability of companies in the construction sub-sector also fluctuated in the period 2014–2020. WSKT had a profitability ratio of 5% in 2014, 7% in 2015, 8% in 2016, 9% in 2017 and 2018, 3% in 2019, and -59% in 2020. A non-public company, namely API, also had a fluctuating profitability ratio: 8% in 2014, 3% in 2015, 4% in 2016, 5% in 2017, 1% in 2018, -29% in 2019, and in 2020 it was -111%.

The above phenomenon shows that the company's D/E ratio is very high, but the resulting profitability is low. If cash and cash equivalents experience a very significant decrease and the company's debt swells, the risk of default will increase. Suppose the company's instability in managing financial conditions continues. In that case, it will impact the company in a state of technical insolvency, potentially leading to bankruptcy. According to Lizal (2002), financial distress can occur due to the neoclassical, financial, and corporate governance models.

Predicting the company's condition can be done with various models of financial distress analysis. These models can be used to identify early symptoms or as a warning before financial distress or even bankruptcy occurs. At this time, many financial distress prediction models have been developed, including the model of Altman (1968), Grover and Lavin (2001), Springate (1978), Ohlson (1980), and others. There are several similar studies on financial distress analysis, including those conducted by Pratama and Mulyana (2020), and Masdiantini and Warasniasih (2020) showing differences in the predictions of the models they use.

In addition, studies by Gupita et al. (2020) and Zebua and Purnomo (2020) show that the most accurate model is Springate's model (S-score). However, as studied by Hastuti (2018), Hungan and Sawitri (2018), and Indriyanti (2019) argue Grover's model (G-score) achieves the most significant level of accuracy. Studies by Wulandari et al. (2012), and Salim and Ismudjoko (2021) demonstrate that Ohlson's model (O-score) is the most accurate. Research by Putri and Werastuti (2021), and Masdiantini and Warasniasih (2020) demonstrates that Fulmer's model has the most significant level of accuracy. Research by Oz and Yelkenci (2015), and Masdiantini and Warasniasih (2020) demonstrates that Taffler's model is the most accurate.

Previous studies showed different research results. The current study aims to re-examine the financial distress model in predicting potential bankruptcy in public and non-public companies in the building construction sub-sector. The financial distress prediction models that researchers use are Springate (1978), Ohlson (1980), Fulmer (1984), Taffler (1984), and Grover and Lavin (2001). The researchers also add the latest models developed by Hajdu and Virág (2001) and Karas and Srbová (2019), which are specially adapted and applicable to construction companies. These models can be used in Indonesia, a member of the Group of Twenty (G20). As a developing country, Indonesia is actively building infrastructure in all areas of the economy. The financial distress prediction model from developed countries is used for Indonesia by comparing public and non-public construction companies listed on the Indonesia Stock Exchange (IDX). During the observation period of 2014–2020, Indonesia faces a crisis due to COVID-19, affecting financial performance.

This study aims to evaluate the financial instability of construction firms in Indonesia by categorizing them into two distinct groups: public and private enterprises. To achieve this, newly developed models by Hajdu and Virág (2001) and Karas and Srbová (2019) are utilized, which are novel in the context of developing countries, in addition to previously employed models. This study aims to investigate the factors leading to financial difficulty and bankruptcy, with a specific focus on construction enterprises in Indonesia. The objective is to develop predictive models that can accurately forecast financial distress and insolvency.

The remainder of the paper is organized as follows. Section 2 considers the theoretical foundations of the proposed models and the formulation of hypotheses. Section 3 describes the research method and empirical data collected for the study. Section 4 presents the results and discussion of the results. Finally, Section 5 presents the conclusions of the study and some recommendations for future research.

2. LITERATURE REVIEW AND HYPOTHESES DEVELOPMENT

2.1. Signaling theory

Signaling theory refers to the proactive steps that management takes to inform investors about the company's prospects (Brigham & Houston, 2019). In addition, Morris (1987, as cited in Palm &

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[1] https://idx.co.id/id/perusahaan-tercatat/laporan-keuangan-dan-tahunan

Bohman, 2023) stated that signaling theory was developed to deal with the problem of information asymmetry in the company by providing more information signals to other parties. According to this signaling theory, external parties to the company or users of financial statements outside the company will determine whether the company's condition is positive or negative. Therefore, this study on financial crisis forecasting analysis will provide useful information to provide signals to external parties such as investors, creditors and other users of financial reports to find out whether the company's condition is in good condition or not, so that investors not make mistakes in investing, and creditors are not wrong to provide loan funds to a company.

2.2. Financial distress

Financial distress is the first step that a company will face before going bankrupt; in these conditions, the company experiences liquidity difficulties in paying short-term obligations and company invoices (Gerritsen, 2015). The condition of financial distress can be seen in a company's net income with a negative value (Aviantara, 2023; Habib et al., 2020; Platt & Platt, 2002). Financial distress triggers corrective action by management to improve company performance (Veganzones & Severin, 2021; Wang et al., 2021; Whitaker, 1999). The types of financial distress: 1) economic failure, 2) business failure, 3) technical insolvency, 4) insolvency in bankruptcy, and 5) legal bankruptcy (Bringham & Gapenski, 1997; Lipi & Lipi, 2020; Tong & Serrasqueiro, 2021; Voda

et al., 2021). In addition, neoclassical, financial and corporate management models may be factors that caused the financial crisis of a company (Lipi & Lipi, 2020; Lizal, 2002; Voda et al., 2021).

2.2.1. Springate's model

Springate's model is a financial distress prediction model, developed in 1978 at Simon Fraser University by Gordon L. V. Springate. Springate's model is a measurement model that uses multiple discriminant analysis (MDA). The accuracy of this model is 92.5%. The following equation is (Springate, 1978):

$$S\_score = 1.03(Y_1) + 3.07(Y_2) + 0.66(Y_3) + 0.4(Y_4) \tag{1}$$

where,
- Y_1 — working capital / total assets;
- Y_2 — net profit before interest and taxes / total assets;
- Y_3 — earnings before taxes / current liabilities;
- Y_4 — sales / total assets;

Cut-off: $S\_score > 0.862$, non-distress (safe); $S\_score < 0.862$, distress and has the potential for bankruptcy.

2.2.2. Ohlson's model

Ohlson (1980) conducted research on financial distress inspired by previous studies. This model has a 96.4% level of accuracy in predicting bankruptcy. The equation for Ohlson's (1980) model is as follows.

$$O\_score = -1.03 - 0.407(Z_1) + 6.03(Z_2) - 1.43(Z_3) + 0.0757(Z_4) - 2.37(Z_5) - 1.83(Z_6) + 0.285(Z_7) - 1.72(Z_8) - 0.521(Z_9) \tag{2}$$

where,
- Z_1 — log (total assets / gross national product (GNP) price-level index);
- Z_2 — total liabilities / total assets;
- Z_3 — working capital / total assets;
- Z_4 — current liabilities / current assets;
- Z_5 — one if total liabilities exceed total assets, zero otherwise;
- Z_6 — net income / total assets;
- Z_7 — funds provided by operations / total liabilities;
- Z_8 — one if the net income has been negative for the past two years, zero otherwise;

- $Z_9 = (Net_{income_t} - Net_{income_{t-1}})/(|Net_{income_t} + Net\_income_{t-1}|)$.

Cut-off: $O\_score < 0.38$, non-distress (safe); $O\_score > 0.38$, distress and potentially bankruptcy.

2.2.3. Fulmer's model

Fulmer's model was developed in 1984. This model is one of the prediction models which uses nine financial ratio variables related to financial distress. Fulmer's model has an accuracy rate of 81%–98%. The following is the equation for Fulmer's model (Fulmer et al., 1984).

$$H\_score = 5.528(Y_1) + 0.212(Y_2) + 0.073(Y_3) + 1.27(Y_4) - 0.12(Y_5) + 2.335(Y_6) + 0.575(Y_7) + 1.083(Y_8) + 0.894(Y_9) - 6.075 \tag{3}$$

where,
- Y_1 — retained earnings / total assets;
- Y_2 — sales / total assets;
- Y_3 — earnings before taxes / total equity;
- Y_4 — cash flow from operations / total liabilities;
- Y_5 — total liabilities / total assets;
- Y_6 — current liabilities / total assets;
- Y_7 — logs (fixed assets);
- Y_8 — working capital / total liabilities;
- Y_9 — log of earnings before interest and taxes (EBIT) / interest expenses.

Cut-off: $H\_score > 0$, non-distress (safe); $H\_score < 0$, distress and potential for bankruptcy.

2.2.4. Taffler's model

Taffler's model was first published by Taffler, R. J. in 1977. This model was developed with a linear model and had five ratio indicators. The five indicators have been improved and modified to produce four ratio indicators. Taffler uses the MDA analysis technique with an accuracy rate of 95.7% for bankruptcy and 100% for non-bankruptcy companies. The following is the equation for Taffler's model (Pech et al., 2020; Taffler, 1984; Weiss et al., 2023).

$$T\_score = 0.53(T_1) + 0.13(T_2) + 0.18(T_3) + 0.16(T_4) \quad (4)$$

where,

- T_1 — earnings before taxes / current liabilities;
- T_2 — current assets / total liabilities;
- T_3 — current liabilities / total assets;
- T_4 — sales / total assets.

Cut-off: $T\_score > 0.3$, non-distress (safe); $0.2 \leq T\_score \leq 0.3$, gray area; $T\_score < 0.2$, distress and has the potential for bankruptcy.

2.2.5. Virag and Hajdu's model

Virág and Hajdu's (1996) model was a prediction model developed based on basic accounting for Hungarian companies from 1990–1991. The research sample was conducted in 154 companies, of which 77 companies were declared safe and 77 were declared bankrupt. This model has an accuracy of 98%. The following is the Hajdu and Virág (2001) model equation.

$$VH\_score = 1.3566(Y_1) + 1.63397(Y_2) + 3.6638(Y_3) + 0.03366(Y_4) \quad (5)$$

where,

- Y_1 — cash ratio;
- Y_2 — cash flow / total liabilities;
- Y_3 — current assets / total assets;
- Y_4 — cash flow / total assets.

Cut-off: $VH\_score > 2.61612$, non-distress (safe); $VH\_score < 2.61612$, distress and has the potential for bankruptcy.

2.2.6. Grover's model

Jeffrey S. Grover used a sample from the 1968 Altman Z-score model, adding thirteen new financial ratios and examining the period from 1982 to 1996. The sample included 70 companies; the results showed that 35 companies were declared bankrupt, and 35 other companies were considered safe. The following is the equation for the Gover model (Grover & Lavin, 2001).

$$G\_score = 1.650(Y_1) + 3.404(Y_2) - 0.016(Y_3) + 0.057(Y_4) \quad (6)$$

where,

- Y_1 — working capital/total assets;
- Y_2 — EBIT / total assets;
- Y_3 — net income / total assets;
- Y_4 — cash flow / total assets.

Cut-off: $G\_score > 0.01$, non-distress (safe); $G\_score < -0.02$, distress and potential bankruptcy.

2.2.7. Karas and Srbová's model

The model by Karas and Srbová (2019) was developed in the Czech Republic specifically for the construction industry. The reason for making this model is that many models are still not compelling enough for use in construction companies. In their research, this model produces a high accuracy of 85.71%. The following is the equation for the model (Karas & Srbová, 2019; Munir & Bustamam, 2020).

$$M\_score = 20.8(Y_1) - 12.054(Y_2) + 3.116(Y_3) - 2.399(Y_4) \quad (7)$$

where,

- Y_1 — earnings after taxes (EAT) / total assets;
- Y_2 — EBIT / total assets;
- Y_3 — retained earnings / total assets;
- Y_4 — current liabilities / sales.

Cut-off: $M\_score < 0.6$, non-distress (safe); $M\_score > -0.6$, distress and potential bankruptcy.

2.3. Bankruptcy

Bankruptcy is a condition where a company tend to experience deficits and company experience liquidation (Agustia et al., 2020; Gerritsen, 2015; Tron, 2021). Bankruptcy can be predicted long before the company goes bankrupt. Hanafi and Halim (2016) explained that the indicators of bankruptcy are as follows:

1) analysis of cash flow now or for the future;
2) an analysis of the corporate strategies that focus on the competition faces;
3) cost structure relative to its competitors;
4) quality and management's capacity to control costs.

2.4. Hypotheses development

Based on the theoretical background, the hypotheses of the study are as follows:

H1: There is a significant difference between the estimated financial distress models in predicting the bankruptcy of public and non-public companies in the building construction sub-sector in the Indonesian capital market.

H2: It is estimated that there is one financial analysis model that has the highest level of accuracy in predicting potential bankruptcy in public and non-public companies in the building construction sub-sector in the Indonesian capital market.

3. RESEARCH METHODOLOGY

The type of research used is quantitative research with a descriptive approach. The population in this study are public and non-public companies in the building construction sub-sector in the Indonesian capital market for 2014–2020. The sampling technique used the purposive sampling method so that eight sample companies were produced. The object of the study is IDX-listed companies that have issued audited financial statements during the observation period. After selecting the sample, the next step is determining the category of the company experiencing financial and non-financial distress. Platt and Platt (2008) explain the criteria for a sample experiencing financial distress as follows:

1) public and non-public companies in the building construction sub-sector which have negative net profits for two consecutive years;
2) public and non-public companies in the building construction sub-sector which has not paid dividends for two consecutive years.

Measurement of financial distress uses Taffler's, Fulmer's, Springate's, Ohlson's, Karas and Srbová's, Grover's, and Virág and Hajdu's models.

Data normality was tested using the Shapiro-Wilk test (1965), according to which data are normally (typically) distributed if the p-value is > 5%; and if the p-value < 5%, the data is not normally distributed. Hypothesis testing uses the Kruskal-Wallis test or H-test, a non-parametric test created by William H. Kruskal and W. Allen Wallis (Kruskal & Wallis, 1952) with a Sig. value < 5%. From the test results, if the Sig. < 5%, then there is a difference and vice versa if the value is Sig. > 5%, then there is no difference. Accuracy test and type of error according to Altman (1968). The accuracy level formula is as follows:

$$Accuracy = \left(\frac{Accurate\ count}{N\ sample}\right) \times 100\% \quad (8)$$

The type of error is divided into two, namely *type I error* (in fact, there is financial distress, but the results of the prediction show otherwise), and *type II error* (in fact, it is non-financial distress, but the predicted results of the model are experiencing financial distress). The following is the type of calculation formula error:

$$Type\ I\ error = \left(\frac{type\ I\ error}{N\ a}\right) \times 100\%$$

$$\qquad\qquad\qquad\qquad (9)$$

$$Type\ II\ error = \left(\frac{type\ I\ error}{N\ sample}\right) \times 100\%$$

4. RESULTS AND DISCUSSION

Table 1 (Panel A) presents the results of calculations for public and non-public companies using Springate's model, predicting that all companies will file for bankruptcy. Meanwhile, Ohlson's, Fulmer's, Grover's, and Karas and Srbová's models predict all safe companies. Taffler's model predicts three safe cases and one grey area. Virág and Hajdu's model predicts three safe companies and one bankruptcy.

Table 1. Model calculation results in public and non-public companies

Model	ADHI	PTPP	WIKA	WSKT	Model	ACST	DGIK	NRCA	SSIA
			Panel A					*Panel B*	
Springate	0.58792	0.67279	0.61312	0.37377	Springate	0.33238	0.34526	1.26390	0.82353
	bankruptcy	bankruptcy	bankruptcy	bankruptcy		bankruptcy	bankruptcy	safe	bankruptcy
Ohlson	-2.19015	-2.72748	-1.61533	-2.28907	Ohlson	0.32308	-3.13244	-4.02356	-3.89405
	safe	safe	safe	safe		safe	safe	safe	safe
Fulmer	3.15030	3.45201	1.74732	2.97884	Fulmer	-0.58503	1.66676	6.35651	4.15950
	safe	safe	safe	safe		bankruptcy	safe	safe	safe
Taffler	0.36440	0.36085	0.35152	0.26564	Taffler	0.35224	0.29527	0.59031	0.36566
	safe	safe	safe	gray area		safe	gray area	safe	safe
Virág and Hajdu	3.31827	3.26943	3.07185	2.20875	Virág and Hajdu	3.16641	2.33664	3.81441	2.46602
	safe	safe	safe	bankruptcy		safe	bankruptcy	safe	bankruptcy
Grover	0.54499	0.61270	0.52177	0.28046	Grover	0.27309	0.27626	0.97893	0.69953
	safe	safe	safe	safe		safe	safe	safe	safe
Karas and Srbová	-3.37070	-2.56328	-2.67148	-3.42457	Karas and Srbová	-4.57786	-2.47802	0.37563	-0.34075
	Safe	safe	safe	safe		safe	safe	bankruptcy	bankruptcy

Note: ADHI — PT Adhi Karya Tbk, PTPP — PT PP Tbk, WIKA — PT Wijaya Karya Tbk, WSKT — PT Waskita Karya Tbk, ACST — PT Ascet Indonusa Tbk, DGIK — PT Nusa Konstruksi Enjiniring Tbk, NRCA — PT Nusa Raya Cipta Tbk, SSIA — PT Surya Semesta Internusa Tbk.

Based on Table 1 (Panel B), the results of calculations using Springate's model predict that one company will be declared safe and three will be declared bankrupt. Meanwhile, Ohlson's and Grover's models predict safety for all companies. Fulmer's model predicts three safe cases and one bankruptcy.

Taffler's model predicts three safe zones and one gray zone. Virág and Hajdu's model predicts two safeties and two bankruptcies. Karas and Srbová's model predicted two safe companies and two bankruptcies.

Table 2. Descriptive statistics

Model	Public companies				Count	Non-public companies			
	Min	Max	Mean	SD		Min	Max	Mean	SD
Springate	-0.351	0.959	0.562	0.256	28	-1.405	1.596	0.691	0.619
Ohlson	-3.295	-0.725	-2.206	0.684	28	-4.632	2.611	-2.682	1.972
Fulmer	1.142	3.715	2.832	0.737	28	-3.698	7.188	2.899	2.849
Taffler	0.047	0.448	0.336	0.081	28	0.034	0.754	0.401	0.169
Virág and Hajdu	1.171	3.868	2.967	0.613	28	1.669	4.291	2.946	0.702
Grover	-0.327	0.812	0.489	0.228	28	-1.363	1.291	0.557	0.519
Karas and Srbová	-8.587	-1.644	-3.008	1.658	28	-12.23	1.917	-1.755	3.0126

Based on Table 2, each model uses 28 samples, of which Springate's model has a minimum value of -0.351 obtained by WSKT in 2020, so it is predicted to be the most distressed company and has the potential to experience bankruptcy. In addition, PTPP obtained a maximum value of 0.959 in 2014. This value shows that the company is predicted to be in a non-distress (healthy) condition. The mean value of 0.562 illustrates that, on average, all state-owned companies in the building construction subsector for the 2014–2020 period are distressed and have the potential to experience bankruptcy, while the standard deviation value is 0.256.

The resulting standard deviation value is lower than the mean value, so the distribution of varying data is more minor.

From Ohlson's model, with a minimum value of -3.295 obtained by PTPP in 2016, it is predicted to be the most non-distressed (healthy) company. In addition, WIKA obtained a maximum value of -0.725 in 2020. This value shows that the company is predicted to be in a non-distress (healthy) condition. The mean value of -2.206 illustrates that, on average, all state-owned companies in the building construction subsector for the 2014–2020 period are in a non-distress (healthy) condition, while the standard

deviation value is 0.684. The resulting standard deviation value is higher than the mean value, so the data distribution varies from the mean value.

Fulmer's model shows a minimum value of 1.142 obtained by WIKA in 2020, which is predicted to be the most non-distressed (healthy) company. The maximum value of 3.715 was obtained by PTPP in 2016. This value shows that the company is predicted to be in a non-distress (healthy) condition. The mean value of 2.832 illustrates that, on average, all state-owned companies in the building construction subsector for the 2014–2020 period are in a non-distress (healthy) condition, while the standard deviation value is 0.737. The resulting standard deviation value is lower than the mean value, so the distribution of varying data is more minor.

Taffler's model showed a minimum value of 0.047 for WSKT in 2020, so it is predicted to be the most distressed company and has the potential to experience bankruptcy. The maximum value of 0.448 was obtained by PTPP in 2014, so the company was predicted to be in a non-distress (healthy) condition. The mean value of 0.336 illustrates that, on average, all state-owned companies in the building construction subsector for the 2014–2020 period are in a non-distress (healthy) condition, while the standard deviation value is 0.081. The resulting standard deviation value is lower than the mean value, so the distribution of varying data is more minor.

The Virág and Hajda model shows a minimum value of 1.171 obtained by WSKT in 2020, so it is predicted to be the most distressed company and has the potential to experience bankruptcy. ADHI obtained a maximum value of 3.868 in 2015. This value shows that the company is predicted to be in a non-distress (healthy) condition. The mean value of 2.967 illustrates that, on average, all state-owned companies in the building construction subsector for the 2014–2020 period are in a non-distress (healthy) condition, while the standard deviation value is 0.613. The resulting standard deviation

value is lower than the mean value, so the distribution of varying data is more minor.

Meanwhile, Grover's model shows a minimum value of -0.327 obtained by WSKT in 2020, is predicted to be the most distressed company and has the potential to experience bankruptcy. PTPP obtained a maximum value of 0.812 in 2014, so the company is predicted to be in a non-distress (healthy) condition. The mean value of 0.489 illustrates that, on average, all state-owned companies in the building construction subsector for the 2014–2020 period are in a non-distress (healthy) condition, while the standard deviation value is 0.228. The resulting standard deviation value is lower than the mean value, so the distribution of varying data is more minor.

Based on Table 3, for public companies, only Ohlson's model has a p-value > 5%, which is equal to 0.463. This demonstrates that Ohlson's model has normally distributed data. Meanwhile, the remaining six models had p-values < 5%, namely Fulmer's (0.003), Springate's (0.004), Taffler's (0.002), Karas and Srbová's (0.000), Grover's (0.002), and Virág and Hajdu's (0.031) models. This shows that the six models have data that are not normally distributed. Meanwhile, for non-public companies with a degree of freedom (df) of 28 samples, Fulmer, Taffler, Virág and Hajdu have p-values > 5%, which is equal to 0.273, 0.898, and 0.760, respectively. This demonstrates that the three prediction models have normally distributed data. Meanwhile, the other four models had p-values <5 %, namely the Springate's, Ohlson's, Grover's, and Karas and Srbová's models of 0.018, 0.000, 0.001, and 0.000, respectively. This demonstrates that the four models have data that are not normally distributed. The parametric test requirements are not fulfilled based on the test results of the seven prediction models applied to public and non-public companies. Therefore, the next test is carried out with a non-parametric different test (Kruskal-Wallis test).

Table 3. Results of the normality test (Shapiro-Wilk test)

Model		Public companies			Non-public companies		
		Stats.	df	Sig.	Stats.	df	Sig.
Score	Springate	0.881	28	0.004	0.908	28	0.018
	Ohlson	0.965	28	0.463	0.790	28	0.000
	Fulmer	0.873	28	0.003	0.956	28	0.273
	Taffler	0.867	28	0.002	0.982	28	0.898
	Virag and Hajda	0.918	28	0.031	0.976	28	0.760
	Grover	0.870	28	0.002	0.848	28	0.001
	Karas and Srbová	0.716	28	0.000	0.778	28	0.000

Table 4. Kruskal-Wallis test results

	Public companies	Non-Public companies
Kruskal Wallis H	175.025	122.830
df	6	6
Asymp. Sig.	0.000	0.000

The test results in Table 4 demonstrate that public companies have a Kruskal-Wallis-H value of 175.025, df of six, and Asymp. Sig. equals 0.000 < 0.05. In addition, non-public companies have a Kruskal-Wallis-H value of 122.830, df of six, and Asymp. Sig. equals 0.000 < 0.05. Thus, it can be concluded that *H1* is accepted, which means that there is a significant difference between Fulmer's, Springate's, Ohlson's, Taffler's, Karas and Srbová's, Grover's, and Virág and Hajdu's calculation models

in predicting bankruptcy in public and non-public companies in the registered building construction subsector on the IDX for the 2014–2020 period. Differences in conditions from the results of the analysis in predicting potential bankruptcy are caused by the different values, cut-offs, and financial ratios used in each model.

This study's results align with Pratama and Mulyana's (2020) research which also demonstrates that the model used can predict financial distress. Altman predicted 8 distressed, 16 gray areas, and 31 safe; Springate predicted 37 distressed and 18 safe; Ohlson predicted three distressed and 52 safe; and Zmijewski predicted 1 distressed. Research by Gupta et al. (2020) shows differences between the Altman Z-score, Grover's, and Springate's models. Research by

Zebua and Purnomo (2020) demonstrate that Grover, Springate, and Zmijewski have significant differences. According to Hajdu and Virág (2001), there are differences in bankruptcy prediction using the Altman model, Springate's model, Zmijewski's model, Taffler's model, and Fulmer's model. In addition, the models of Hajdu and Virág (2001) and Karas and Srbová (2019) show that the percentage of accuracy differs from other models, resulting in conditions that are also different from other models.

Table 5. Calculation of accuracy level and error type in public companies

	Real	Predictions						
		Springate	*Ohlson*	*Fulmer*	*Taffler*	*Virág and Hajdu*	*Grover*	*Karas and Srbová*
Distress	0	4	0	0	0	1	0	0
Gray area	-	-	-	-	1	0	-	-
Non-distressed	4	0	4	4	3	3	4	4
Total	4	4	4	4	4	4	4	4
Level of accuracy		0%	100%	100%	75%	75%	100%	100%
Type I error		0%	0%	0%	0%	0%	0%	0%
Type II error		100%	0%	0%	0%	25%	0%	0%
Gray area		-	-	-	25%	-	-	-

Based on the comparison of the test results by accuracy level and error type in Table 5, it can be concluded that Olson's, Fulmer's, Grover's, and Karas and Srbová's models are the most accurate models in predicting the probability of bankruptcy of public companies in the building construction sub-sector with a percentage of 100% and type of error for 0%. They were followed by Taffler's and Virág and Hajdu's models with an accuracy rate of 75% and a type error of 25%. And finally, the lowest accuracy rate of 0% and a type of error of 100 owned by the Springate.

Table 6. Calculation of the accuracy level and type of error in non-public companies

	Real	Predictions						
		Springate	*Ohlson*	*Fulmer*	*Taffler*	*Virág and Hajdu*	*Grover*	*Karas and Srbová*
Distress	1	3	0	1	0	2	0	2
Gray area	-	-	-	-	1	-	-	-
Non-distressed	3	1	4	3	3	2	4	2
Total	4	4	4	4	4	4	4	4
Level of accuracy		50%	75%	100%	50%	25%	75%	25%
Type I error		0%	25%	0%	25%	25%	25%	25%
Type II error		50%	0%	0%	0%	50%	0%	50%
Gray area		-	-	-	25%	-	-	-

The results of Table 6 for non-public companies show that only Fulmer's model has the most significant accuracy rate of 100% and an error type of 0%, followed by Ohlson's and Grover's models with an accuracy rate of 75% and a type of error of 25%. In addition, Springate's and Taffler's models have an accuracy of 50% and an error type of 50%. Moreover, the models of Virág and Hajdu, and Karas and Srbová have the lowest accuracy rate of 25% and a type of error of 75%. This demonstrates that *H2* is accepted, which means that there is a financial distress analysis model with the most significant accuracy in predicting potential bankruptcy in public and non-public companies.

The results of research on public companies are in line with research conducted by Wulandari et al. (2012), Oz and Yelkenci (2015), and Salim and Ismudjoko (2021), which show that Ohlson's model is the most accurate. Research by Putri and Werastuti (2021), and Masdiantini and Warasniasih (2020) demonstrate that Fulmer's model has the most significant level of accuracy. Research by Hastuti (2018), Hungan and Sawitri (2018), and Indriyanti (2019) demonstrate that Grover's model achieves the most significant level of accuracy. Research by Karas and Srbová (2019) states that the model they created is very suitable for use in construction. However, for non-public companies the situation is different: only Fulmer's model has 100% accuracy. This is in line with studies conducted by Putri and Werastuti (2021), Mustofa and Fahad Noor (2020), Oz and Yelkenci (2015), Masdiantini and Warasniasih (2020), which show that Fulmer's model is the most accurate.

5. CONCLUSION

The results of this study showed differences in conditions of the seven models used in predicting the potential for bankruptcy in public and non-public companies in the building construction subsector listed on the IDX for the 2014–2020 period. Public companies show that Ohlson's, Fulmer's, Grover's, and Karas and Srbová's models accurately predict bankruptcy potential. In non-public companies, only Fulmer's model has the most significant accuracy rate of 100% and a type of error of 0%. The difference in these conditions is caused by the different cut-offs, values, and financial ratios used in each model. Companies may get advantages from this study by considering the use of financial ratios found in Ohlson's, Grover's, Fulmer's, and Karas and Srbová's models as a viable option for forecasting a company's situation. In addition, this study may serve as an anticipatory measure in the future, enabling internal stakeholders to enhance corporate performance and implement necessary enhancements prior to the onset of financial trouble, which may ultimately result in bankruptcy. Investors may get advantages from this study by using Ohlson's, Grover's, and Fulmer's models as viable alternatives to accurately forecast the state of a business. This enables investors to avoid errors when allocating their capital.

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