BALANCE: Jurnal Akuntansi, Auditing dan Keuangan ISSN : 2620-4320 (Online)
Vol.21 No.1 Maret 2024 : 16 - 28. ISSN : 1693-9441 (Print)
Doi: https://doi.org/10.25170/balance.v21i1.5411

DETECTION OF FINANCIAL DISTRESS IN TECHNOLOGY COMPANIES LISTED ON THE INDONESIAN STOCK EXCHANGE

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ABSTRACT

The purpose of this study is to determine and analyse the sensitivity of the results of financial distress analysis using the Ohlson and Grover models to predict financial distress in technology companies listed on the IDX for the 2020-2022 period. The study employs quantitative data extracted from the financial statements of technology companies listed on the Indonesia Stock Exchange (IDX) from 2020 to 2022. Utilizing the Ohlson and Grover models, the research aims to detect financial distress within these technology firms and determine the sensitivity level of the two models. This descriptive research design relies on secondary data sources, emphasizing the objectivity and popularity inherent in data-driven analyses. The research results of financial distress detection analysis, Ohlson model detects 10 distress zones and 8 safe zones, while Grover model detects 5 distress zones, 1 gray zone and 12 safe zones. From this analysis, the Grover model shows a higher level of sensitivity in recognizing financial distress with 12 samples consistent with the results of the Grover model analysis.

***Keywords**:* Financial Distress, Ohlson, Grover, Technology Companies

1. INTRODUCTION

In recent years, the technology industry has experienced significant growth. Rapidly advancing innovations are bringing about changes in business paradigms, and digital transformation has become an inherent characteristic of the sector. The technology industry continues to grow, based on IDXTECHNO data from 1990 to 2023 there have been 42 companies (Indonesian Stock Exchange, 2023) , covering various subsectors within technology. The sector's expansion has been particularly accelerated by the Covid-19 pandemic, leading to a surge in online activities, from education to trade. Notably, internet services have become pervasive, with 86.54% of households, 98.17% of the population utilizing mobile internet, and 73.94% engaging in internet-based social media activities (Sutarsih & Maharani, 2022). Despite the industry's rapid development, it is important to note that not all aspects of its performance necessarily reflect positive outcomes.

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Table 1. 1
Sectoral Index Performance

No.	Sectoral Index	Percentage
1	IDXTRANS	1.38%
2	IDXENERGY	1.28%
3	IDXBASIC	0.97%
4	IDXCYLIC	0.67%
5	IDXINFRA	0.65%
6	IDXINDUST	0.62%
7	IDXPROPERT	0.48%
8	IDXFINANCE	0.38%
9	IDXHEALTH	0.29%
10	IDXNONCYC	0.15%
11	IDXTECHNO	-0.91%

Source: CNBC (2023)

Table 1.1 shows that in August 2023 the decline in technology sector performance of -0,91% was the last compared to other sectors (CNBC Indonesia, 2023). This happened continuously from 2022, where the companies GOTO, WIRG, EMTK, DMMX and ARTO experienced a fairly drastic decline in share prices. GOTO share price -75.94%, WIRG -86.03%, EMTK -70,93%, DMMX -61.42% and ARTO -82.10% (CNBC Indonesia, 2023). The same situation also occurred in global markets, with shares of major technology companies such as Facebook parent Meta Platforms Inc., Amazon.com Inc., Apple Inc., Netflix Inc. and Google owner Alphabet Inc. declining in the previous year. The decline in FAANG stocks, which eliminated more than US$3 trillion in market capitalization, impacted the broader stock market. Meta shares fell 64% in 2022, Netflix fell 51%, and three other stocks fell at least 27%. In the worst year since the 2008 financial crisis, the S&P 500 rose 19% (CNBC Indonesia, 2023).

Understanding a company's financial condition is crucial, as financial distress, defined by Patunrui & Yati (2017) as a continuous decline potentially leading to bankruptcy, can disrupt operations. Financial distress, according to Fahma (2020) and Octavera & Syafel (2022), involves difficulties in meeting obligations and a decline in operating income. Financial statement analysis techniques, such as financial ratios, serve as a signaling mechanism according to Ross (1977), signaling theory posits that these ratios convey important information about a company's financial health to external stakeholders. Managers utilize this information, particularly in times of financial distress, to formulate effective

strategies and policies for the future. By understanding the signals emitted by financial ratios, managers can not only assess the company's current situation but also communicate its financial status to investors. This analysis helps distinguish between positive and negative signals, aiding in decision-making (Octavera & Syafel, 2022; Rachmawati & Nur, 2021).

There are several financial distress prediction models with financial ratios, namely Springate, Zmijewski, Altman Z-Score, Ohlson, Grover, Fulmer and others. This study only uses Ohlson and Grover model. This model was chosen because it has ratios suitable for the type of technology company, namely service companies. Wulandari & Aprilia (2023) highlight the Grover model's 83% accuracy, while Indriyanti (2019) and Lababan (2022) affirm Grover and Ohlson's high accuracy rates, with the latter showing 100% accuracy. Despite various studies favoring these models, limited focus on technology companies during the challenging 2020-2022 period, especially amidst the COVID-19 pandemic, underscores the uniqueness of this research. The author's approach, utilizing only Ohlson and Grover models, specifically on technology companies listed on the Indonesia Stock Exchange from 2020 to 2023, distinguishes this study from previous research.

So, based on the background description above, the purpose of this study is to determine and analyse the sensitivity of the results of financial distress analysis using the Ohlson and Grover models to predict financial distress in technology companies listed on the IDX for the 2020-2022 period. The researchers are interested in analyzing the financial distress conditions of the Ohlson and Grover models in the technology companies with the title "Detection of Financial Distress in Technology Companies Listed on the Indonesia Stock Exchange".

2. LITERATURE REVIEW

Signalling Theory

Signaling theory posits that strong financial statements indicate business success, prompting managers to fulfill their duty of conveying signals to stakeholders. Asymmetry of information between companies and external parties, especially investors and creditors, motivates companies to share financial information. Applied to corporate leverage levels, larger companies are incentivized to adopt

higher leverage, creating a separating equilibrium where high-value firms use more debt while smaller companies opt for more equity to avoid bankruptcy risks. This theory allows investors to differentiate between high and low-value firms based on their capital structure, attributing high valuations to stable equilibrium firms. In the context of financial distress, declining financial performance serves as a signal for managers to avert distress and bankruptcy, enabling them to strategize and communicate effectively with investors about the company's financial condition.

Financial Distress

Financial distress encompasses economic, financial, working capital, inability to pay, and increased sales perspectives. Sun et al. (2014) emphasize the importance of early warning systems for financial distress, bankruptcy, or corporate failure, highlighting its significance in corporate finance. Generally, financial distress prediction aims to foresee a company's financial troubles using current financial data, with Irawan (2023) defining it as a weakening phase preceding bankruptcy, characterized by inadequate revenue or profit generation. Octavera and Syafel (2022) echo this, emphasizing the need for businesses to anticipate deteriorating financial conditions to prevent operational disruptions. Fahma (2020) describes financial distress as a state where a company's financial performance declines, leading to difficulty in meeting short-term and long-term obligations, along with a decrease in net profit operating income. Lieu, Lin, and Yu (2008) contribute by developing an early-warning model, using indicators like debt ratio, times interest earned, interest expense ratio, operation expense ratio, net income ratio, retention ratio, cash flow ratio, and ownership structure to predict financial trouble one, two, or three years in advance.

3. RESEARCH METHODOLOGY

This study uses a descriptive research design, focusing on technology companies listed on the Indonesia Stock Exchange (IDX) from 2020 to 2022 as research subjects. The selection of technology companies as research subjects was carried out deliberately. Secondary data sources were used, specifically financial reports obtained from the Indonesia Stock Exchange covering the period 2020 to 2022.

This study classifies a company as financially distressed if it experiences net losses for one year or two years or three years. This study is to determine and analyse the sensitivity of the results of financial distress analysis using the Ohlson and Grover models to predict financial distress in technology companies listed on the IDX for the 2020-2022 period. This study uses a financial distress model that has been studied by previous researchers, namely the Ohlson Model by Fahma (2020) and the Grover Model by Wulandari & Aprilia (2023).

Sample selection criteria include:

1. Technology companies listed on the Indonesia Stock Exchange during the period 2020 to 2022.
2. Technology companies that consistently publish complete financial reports on the Indonesia Stock Exchange during the period 2020 to 2022.
3. Technology companies that experienced a decrease in profit (loss) during the period 2020 to 2022.

Table 3.1
Operational Variable

Variables	Variable Definition	Indicator	Scale
Ohlson Model	The Ohlson model uses logical analysis to avoid assumption problems with the Multiple Discriminant Analysis (MDA) model created by Altman (Kristanti, 2019). In this model, company size is included as a research variable.	O = -1.32 – 0.407X1 + 6.03X2 – 143X3 + 0.0757X4 – 2.37X5 – 1.83X6 + 0.285X7 – 1.72X8 – 0.521X9 Description: X1: SIZE (Log [Total assets / GNP price-level index]) X2: TLTA (Total Liabilities / Total Assets) X3: WCTA (Working Capital / Total Assets) X4: CLCA (Current Liabilities / Current Assets) X5: DUM.TLTA (1 if total liabilities > total assets; 0 otherwise) X6: NITA (Net Income / Total Assets) X7: CFOTL (Cash Flow from Operation / Total Liabilities)	Interval Fahma (2020), The result of the Ohlson model, O-Score < 0.38 is safe zone and O > 0.38 is distress zone.

		X8: DUM.NI (1 if net income is negative, 0 otherwise) X9: NI.NOW ([Nit-Nlt-1] / [Nlt+ Nit-1])	
Grover Model	The Altman Z-Score bankruptcy prediction model, created by Altman in 1968, was further developed by Jeffrey S. Grover. In his research, Grover used samples that fit the Altman Z-Score model. (Irfani, 2020)	G = 1.650X1 + 3.404X2 + 0.016X3 + 0.057 Description: X1: WCTA (Working Capital / Total Assets) X2: EBITTA (Earnings Before Interest and Tax / Total Assets) X3: NITA (Net income / Total Assets)	Interval Wulandari & Aprilia (2023), G-Score results ≥ 0.01 are safe zone and G-Score ≤ -0.02 are distress zone. G-Score values between > -0.02 and < 0.01 grey zone
Financial Distress	Financial distress prediction aims to predict whether a company will face financial difficulties using current financial data (Sun et al., 2014).	The results of the Ohlson and Grover model	Interval

4. RESULTS AND DISCUSSIONS

The number of samples in this study were six samples. The following is a list of companies that are sampled:

Table 4. 1
Sample Studied

No.	Company Code	Company Name
1	ATIC	PT Anabatic Technologies Tbk.
2	KIOS	PT Kioson Komersial Indonesia Tbk
3	LUCK	PT Sentral Mitra Informatika Tbk.
4	HDIT	PT Hensel Davest Indonesia Tbk.
5	PGJO	PT Tourindo Guide Indonesia Tbk.
6	CASH	PT Cashlez Worldwide Indonesia Tbk.

Source: Data processed (2023)

In the discussion of this chapter, the author will use abbreviations of words that appear frequently as in table 4.1 above. This study classifies a company as financially distressed if it experiences net losses for one year or two years or three years.

Results of Descriptive Analysis of Financial Distress

Table 4. 2
Results of Descriptive Analysis of Financial Distress Ohlson Model

No.	Company Code	Company Name	Year	O-Score	Description
1	ATIC	PT Anabatic Technologies Tbk.	2020	3.566	Distress Zone
			2021	6.644	Distress Zone
			2022	8.135	Distress Zone
2	KIOS	PT Kioson Komersial Indonesia Tbk.	2020	2.235	Distress Zone
			2021	1.806	Distress Zone
			2022	0.330	Safe Zone
3	LUCK	PT Sentral Mitra Informatika Tbk.	2020	0.935	Distress Zone
			2021	2.101	Distress Zone
			2022	1.162	Distress Zone
4	HDIT	PT Hensel Davest Indonesia Tbk.	2020	0.293	Safe Zone
			2021	-2.819	Safe Zone
			2022	-2.274	Safe Zone
5	PGJO	PT Tourindo Guide Indonesia Tbk.	2020	-4.005	Safe Zone
			2021	-4.421	Safe Zone
			2022	-0.930	Safe Zone
6	CASH	PT Cashlez Worldwide Indonesia Tbk.	2020	1.530	Distress Zone
			2021	0.465	Distress Zone
			2022	0.045	Safe Zone

Source: Data processed (2023)

Based on table 4.2, the financial distress analysis using the Ohlson model on technology companies listed on the Indonesia Stock Exchange during 2020-2022 reveals varying conditions. In 2020, ATIC, KIOS, LUCK, and CASH faced potential financial distress, as indicated by O-Score values exceeding 0.38. Conversely, HDIT and PGJO demonstrated stable financial conditions with O-Score results below 0.38. In 2021, ATIC, KIOS, LUCK, and CASH continued to show potential financial distress, while HDIT and PGJO maintained stable financial sustainability. In 2022, ATIC and LUCK persisted in financial distress, while KIOS exhibited a recovery with O-Score results below 0.38. CASH also showcased

financial improvement, while HDIT and PGJO maintained stable financial conditions.

Table 4. 3
Results of Descriptive Analysis of Financial Distress Grover Model

No.	Company Code	Company Name	Year	G-Score	Description
1	ATIC	PT Anabatic Technologies Tbk.	2020	-0.367	Distress Zone
			2021	-0.241	Distress Zone
			2022	0.117	Safe Zone
2	KIOS	PT Kioson Komersial Indonesia Tbk.	2020	0.669	Safe Zone
			2021	1.068	Safe Zone
			2022	0.808	Safe Zone
3	LUCK	PT Sentral Mitra Informatika Tbk.	2020	0.543	Safe Zone
			2021	0.635	Safe Zone
			2022	0.823	Safe Zone
4	HDIT	PT Hensel Davest Indonesia Tbk.	2020	1.242	Safe Zone
			2021	1.349	Safe Zone
			2022	1.098	Safe Zone
5	PGJO	PT Tourindo Guide Indonesia Tbk.	2020	-1.475	Distress Zone
			2021	-0.660	Distress Zone
			2022	-1.524	Distress Zone
6	CASH	PT Cashlez Worldwide Indonesia Tbk.	2020	0.275	Safe Zone
			2021	0.277	Safe Zone
			2022	-0.004	Grey Zone

Source: Data processed (2023)

Based on table 4.3, the financial distress analysis using the Grover model on technology companies listed on the Indonesia Stock Exchange from 2020 to 2022 reveals significant variations. In 2020, ATIC and PGJO faced financial distress, indicated by G-Score values below -0.02, while KIOS, LUCK, HDIT and CASH maintained stable financial conditions with G-Score values above 0.01. In 2021, ATIC and PGJO continued to experience financial distress, while the other companies sustained stability. In 2022, ATIC improved, PGJO persisted in financial distress, and CASH entered a grey zone, signaling potential distress. The rest of the

companies maintained stable financial sustainability with G-Score values above 0.01.

Sensitive Model to Detect Financial Distress

During the research period of 2022-2022, there were different results in the detection of financial distress in technology companies between Ohlson and Grover models. This study aims to identify the model that shows a higher level of sensitivity by comparing financial distress classifications, focusing on the net profit (loss) parameter.

Table 4. 4
Sensitive Model to Detect Financial Distress

No.	Company Code	Year	O-Desc	G-Desc	Clasifies Financial Distress
1	ATIC	2020	Distress Zone	Distress Zone	Loss
		2021	Distress Zone	Distress Zone	Loss
		2022	Distress Zone	Safe Zone	Profit
2	KIOS	2020	Distress Zone	Safe Zone	Loss
		2021	Distress Zone	Safe Zone	Profit
		2022	Safe Zone	Safe Zone	Profit
3	LUCK	2020	Distress Zone	Safe Zone	Loss
		2021	Distress Zone	Safe Zone	Profit
		2022	Distress Zone	Safe Zone	Profit
4	HDIT	2020	Safe Zone	Safe Zone	Profit
		2021	Safe Zone	Safe Zone	Loss
		2022	Safe Zone	Safe Zone	Loss
5	PGJO	2020	Safe Zone	Distress Zone	Loss
		2021	Safe Zone	Distress Zone	Loss
		2022	Safe Zone	Distress Zone	Loss
6	CASH	2020	Distress Zone	Safe Zone	Loss
		2021	Distress Zone	Safe Zone	Loss
		2022	Safe Zone	Grey Zone	Loss

Source: Data processed (2023)

Based on the findings presented in table 4.4, the Ohlson and Grover models yield divergent results in detecting financial distress for ATIC during 2020-2022. In 2020 and 2021, both models indicate financial distress, but in 2022, only the Grover model detects distress. A closer examination reveals that the sensitivity of O-Score and G-Score aligns with the company's financial performance, as losses in 2020 and 2021 trigger distress detection, while profits in 2022 favor Grover's sensitivity.

Examining KIOS in table 4.4, the Ohlson model places it in the distress zone for 2020 and 2021, while the Grover model categorizes it as safe. Interestingly, in 2022, both models indicate a safe zone. Comparative analysis with the distress classification in this study shows that KIOS incurred losses in 2020 but reported profits in 2021 and 2022. Consequently, Ohlson effectively detects distress in 2020, whereas Grover shows sensitivity in 2021 and 2022.

The analysis extends to LUCK, as depicted in table 4.4, where the Ohlson model identifies distress for all three years, while the Grover model designates safe zones. Considering the distress classification in this study, losses in 2020 lead to Ohlson's heightened sensitivity, whereas Grover's efficacy is noted in 2021 and 2022 when LUCK reports profits.

Moving on to HDIT, both the Ohlson and Grover models consistently categorize it as a safe zone from 2020 to 2022, despite the company experiencing losses throughout these years. Consequently, neither model effectively detects distress in HDIT during this period.

Analyzing PGJO in the same context, the Ohlson model designates all three years as safe zones, while the Grover model detects distress. In alignment with the distress classification in this study, PGJO's continuous losses from 2020 to 2022 highlight Grover's heightened sensitivity in detecting financial distress.

Finally, the examination of CASH in the aforementioned table reveals that the Ohlson model identifies distress in 2020 and 2021 but designates a safe zone in 2022. Conversely, the Grover model categorizes 2020 and 2021 as safe zones and 2022 as a grey zone. Comparative analysis with the distress classification indicates that CASH incurred losses from 2020 to 2022. As a result, Ohlson demonstrates sensitivity in 2020 and 2021, while Grover exhibits sensitivity in 2022.

Based on the financial distress detection analysis, Ohlson model detects 10 distress zones and 8 safe zones, while Grover model detects 5 distress zones, 1 grey zone and 12 safe zones. From this analysis, the Grover model shows a higher level of sensitivity in recognizing financial distress with 12 samples consistent with the results of the Grover model analysis. This finding is consistent with research by Wulandari & Aprilia (2023) who researched financial distress in digital companies on IDX during the 2018-2021 period, with the accuracy of the Grover model

reaching 83% and stating that Grover is effective in predicting bankruptcy. These results are reinforced by Indriyanti's (2019) study which evaluated the accuracy of the financial distress model on the 25 largest technology companies according to Forbes during 2015-2016, with an accuracy of 96.6%. Furthermore, Liew, Lam, & Lam (2023) studied financial distress in technology companies on the Bursa Malaysia during the period 2016-2020, and concluded that the Grover model is a good recommendation for measuring company performance in various sectors.

5. CONCLUSIONS AND RECOMENDATIONS

Conclusions

1. In employing the Ohlson model for financial distress detection, it identifies ten distress zones and eight safe zones. PT Anabatic Technologies Tbk. and PT Sentral Mitra Informatika Tbk. remain in distress for three years, while PT Kioson Komersial Indonesia Tbk. and PT Cashlez Worldwide Indonesia Tbk. transition from distress in 2020-2021 to a safe zone in 2022. PT Hensel Davest Indonesia Tbk. and PT Tourindo Guide Indonesia Tbk. consistently remain in the safe zone for three consecutive years.
2. The Grover model detects five distress zones and thirteen safe zones. PT Tourindo Guide Indonesia Tbk. experiences three consecutive years of distress, while PT Anabatic Technologies Tbk. transitions to a safe zone in 2022 after distress in 2020-2021. PT Cashlez Worldwide Indonesia Tbk. shifts to the grey zone in 2022 after two safe years in 2020-2021. PT Kioson Komersial Indonesia Tbk., PT Sentral Mitra Informatika Tbk., and PT Hensel Davest Indonesia Tbk. consistently remain in the safe zone for three consecutive years.
3. The Grover model demonstrates higher sensitivity in recognizing financial distress with 12 consistent samples, outperforming the Ohlson model.

Recomendations

1. For academic research, explore financial distress detection using alternative models such as Fulmer, Springate, Zmijewski, Altman, etc.
2. Technology companies should continually monitor and manage factors influencing potential financial distress. PT Anabatic Technologies Tbk. and PT

Sentral Mitra Informatika Tbk. may consider financial improvement, while PT Kioson Komersial Indonesia Tbk. and PT Cashlez Worldwide Indonesia Tbk. should evaluate factors leading to the shift to a safe zone in 2022. Stable companies like PT Tourindo Guide Indonesia Tbk. and PT Hensel Davest Indonesia Tbk. can optimize their financial policies.

3. Creditors are advised to consider information from both Ohlson and Grover models for more informed credit decisions. Given Grover's higher sensitivity, integrating data from both models can mitigate credit risk and enhance accurate lending decisions.

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