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The Accuracy of Financial Distress Prediction Models: Empirical Study on the World's 25 Biggest Tech Companies in 2015–2016 Forbes's Version

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Abstract

Every company has the possibility to go bankrupt. Bankruptcy begins with a condition of financial distress. Reliable and accurate models prediction are needed as the early warning system to anticipate financial distress. This research aims to find the predictor model of financial distress that are the most accurate in predicting the condition of financial distress at technology companies. The population of this research is the technology companies that were listed on the World's 25 Biggest Tech Companies in 2015–2016 Forbes's version. The total sample of this research was 30 tech company. The data in this research is totaled to 60 annual reports. Determination of the accuracy level was based on the calculation of the correct number of prediction divided by the total data and multiplied by 100%. This study compares seven predictors model of financial distress. The result indicate that if Grover is the most accurate model in predicting financial condition after the year predict. Grover model has an accuracy rate of 96.6%.

Keywords: financial distress, bankruptcy, model prediction, accuracy

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1. Introduction

In an age of digital disruption, technology companies face increasing pressure to improve time to market and ensure their offerings are best in class (Sallomi, 2018). Not all technology companies are able to compete, in fact not a few of the technology companies that once dominated the market then faced financial distress until they went bankrupt. It means that even though a company has long been operating, it still has the risk of financial distress to bankruptcy. Financial distress is a condition of financial difficulties that faced by the company. While every company must be very avoiding the occurrence of financial distress.

Analysis to predict the condition of a company is very important to do early. It aims to minimize business risk. Assessing the financial strength of companies has traditionally

been the domain of parties external to the firm, such as investors, creditors, auditors, government regulators, and other stakeholders (Platt & Platt, 2002). This is due to the fact that external parties are the biggest recipients of risk in cases of financial distress (Vestari & Farida, 2013). Analysis to predict financial distress is used as an early warning system for external parties and is used to determine the condition of the company. This shows that a accurate predictive measurement model is needed to predict financial distress.

There are several models of measuring tools to predict financial distress such as Altman Model, Springate, Fulmer, Taffler, Grover, Ohlson and Zmijewski. This research aims to find predictor model of financial distress which are the most accurate in predicting the condition of financial distress at companies that listed in "the World's 25 Biggest Tech Companies in 2015 – 2016 Forbes's Version".

2. Literature Review

2.1. Financial distress

Financial distress refers to a condition in which a company cannot meet, or has difficulty paying off, its financial obligations to its creditors, typically due to high fixed costs, illiquid assets, or revenues sensitive to economic downturns. Altman & Hotchkiss (2006, p. 4) said that the unsuccessful business enterprise has been defined in numerous ways in attempts to depict the formal process confronting the firm and/or to categorize the economic problems involved. Four generic terms that are commonly found in the literature are *failure*, *insolvency*, *default*, and *bankruptcy*. Financial difficulties that may be experienced by the company include (a) dividend reduction (b) asset closure (c) loss (d) termination of employment (e) CEO turnover (f) decrease in stock price (Ardiani, 2016).

2.2. Financial distress prediction models

There are two ways of prediction broke or not broke. From number of research that occurred related with broke prediction, can be divided to two big groups, which are: (1) statistical analysis technique, such as linier regression, discriminant analysis, (2) computer base analysis, such as trait recognition, fuzzy system, etc. (Gamayuni, 2009). In this research compares seven predictors model of financial distress which are include in the Multiple Discriminant Analysis models.

There are several studies regarding the accuracy of prediction of financial distress that has been done before such as the research of Arasu, et al. (2013), Gunawan, Pamungkas, & Susilawati (2017), Rado (2013), Agarwal & Taffler (2007), and the research of Imanzadeh, Maran-Jouri, & Sepehri (2011). But all the results of the study show different results, it means there are inconsistencies in determining the most accurate prediction model.

3. Research Methodology

To answer the purpose of this study, below are the steps to determine the accuracy of the prediction model for financial distress:

1. The first step in determining the accuracy of the prediction model is that each prediction model calculates all available samples with the formula for calculating each model.

   - Altman Revised Model

$$Z\text{-}score = 0.717X_1 + 0.847X_2 + 3.107X_3 + 0.420X_4 + 0.998X_5 \tag{1}$$

   Z-score > 2.90 non-bankrupt

   1.21 < Z-score < 2.90 grey area

   Z-score < 1.21 bankrupt

   X_1 = *working capital/total assets*

   X_2 = *retained earnings/total assets*

   X_3 = *earnings before interest and taxes/total assets*

   X_4 = *book value of equity/book value of total debt*

   X_5 = *sales/total assets*

   - Springate Model

$$S\text{-}Score = 1.03X_1 + 3.07X_2 + 0.66X_3 + 0.4X_4 \tag{2}$$

   S-score < 0.862 bankrupt

   S-score > 0.862 non-bankrupt

   X_1 = *Working capital/total assets*

   X_2 = *Earnings before interest and taxes/total assets*

   X_3 = *Earnings before taxes/current liability*

   X_4 = *sales/total assets*

- Fulmer Model

$$H = 5.528V_1 + 0.212V_2 + 0.073V_3 + 1.270V_4 - 0.120V_5$$
$$+2.335V_6 + 0.575V_7 + 1.083V_8 + 0.894V_9 - 6.075 \tag{3}$$

H < 0 bankrupt

V_1 = Retained Earning/Total Assets

V_2 = Sales/Total Assets

V_3 = EBT/Equity

V_4 = Operating Cash Flow/Total Debt

V_5 = Debt/Total Assets

V_6 = Current Liabilities/Total Assets

V_7 = Log Tangible Total Assets

V_8 = Working Capital/Total Debt

V_9 = Log EBIT/Interest

- Taffler Model

$$Z_{\text{Taffler}} = 3.20 + 12.18X_1 + 2.50X_2 - -10.68X_3 + 0.0289X_4 \tag{4}$$

Ztaffler < 0 bankrupt

X_1 = *EBT/Current Liabilities*

X_2 = *Current Assets/Total Liabilities*

X_3 = *Current Liabilities/Total Assets*

X_4 = (*quick assets – current liabilities)/((sales – PBT – depreciation)/365*)

- Grover Model

$$G\text{-score} = 1.650X_1 + 3.404X_3 - 0.016ROA + 0.057 \tag{5}$$

G-score < –0.02 bankrupt

X_1 = *Working capital/Total assets*

X_3 = *EBIT/Total assets*

ROA = *net income/total assets*

- Zmijewski Model

$$X\text{-Score} = -4.3 - 4.5X_1 + 5.7X_2 - 0.004X_3 \tag{6}$$

X-score < 0 non-bankrupt

X-score > 0 bankrupt

X_1 = *return on asset* (NI/TA)

X_2 = *debt ratio* (TL/TA)

X_3 = *current ratio* (CA/CL)

• Ohlson Model

$$Ohlson_{score} = -1.3 - 0.4X_1 + 6.0X_2 - 1.4X_3 + 0.8X_4 - 2.4X_5 - 1.8X_6$$
$$+0.3X_7 - 1.7X_8 - 0.5X_9$$

(7)

O-score < 0.38 bankrupt

O-score > 0.38 non-bankrupt

X_1 = log (TA/GNP price-level index)

X_2 = Total Liabilities/Total Assets

X_3 = Working Capital/Total Assets

X_4 = Current Liabilities/Current Assets

X_5 = 1 jika TL > TA, 0 jika tidak

X_6 = Net Income/Total Assets

X_7 = *Cash flow from operation/*TL

X_8 = 1 jika NI negatif selama 2 tahun, 0 jika tidak

X_9 = $(NI_t - NI_{t-1})/(NI_t + NI_{t-1})$

2. Analysis of the accuracy of the prediction model is determined based on the calculation of the correct estimation between the results of the prediction of the reality of the company. The reality of the company is based on the company are delisted from the stock exchange.

3. Determination of the accuracy level based on the calculation of the correct number of prediction devided by the total data and multiplied by 100%.

4. The most accurate prediction model is the model with the highest percentage of accuracy that is close to 100%.

5. After getting the results of the accuracy analysis of the financial distress prediction model, then robustness check is carried out. The purpose of doing robustness check is (1) The official reason, as it were, for a robustness check, is to see how your conclusions change when your assumptions change, (2) to demonstrate that your main analysis is still good (Gelman, 2017).

6. In this study, robustness check was used to re-test the accuracy level of the prediction model. Analysis of accuracy of the prediction model is determined based on the calculation of the correct estimation between the results of the prediction model and the results of the interest coverage ratio (ICR). Companies are called financial distress if the interest coverage ratio is less than one (Claessens, Djankov, & Klapper, 1999).

4. Result and Discussion

4.1. Data description

In this study, each company will be observed by their last trade. Last trading indicates that the company is still active and not delisted on the stock exchange. In addition, the company will also be observed after a year of prediction whether the company has merged or acquired with another company or not. It aims to analyze and compare the predictive results of each prediction model with the current real condition of the company.

The time of observation of the company's last trading is done on August 5, 2018 on each stock exchange which is the place where the company are listing. The stock exchanges include Nasdaq, New York Stock Exchange, Korea Stock Exchange, London Stock Exchange, India Stock Exchange, and National Stock Exchange of India. In addition to seeing the reality of the company's condition, ICR was also calculated for Robustness check analysis.

4.2. Accuracy level

The determination of the accuracy of the prediction model in this study is based on the high percentage level of each prediction model. The percentage of results is obtained from the comparison of the results of the predictions of each model compared to the reality of the company after the year predict. The model with a percentage level approaching 100% is the most accurate model in predicting the financial distress of a company that has the potential to bankrupt in the future.

The result show that the prediction models which are the most accurate to predict reality of the company is Grover models. Grover models can predict with accurate until

Company	Reality	ICR
Apple	Listing	Non-distress
Samsung	Listing	Non-distress
Microsoft	Listing	Non-distress
Alphabet	Listing	Non-distress
IBM	Listing	Non-distress
Intel	Listing	Non-distress
Cisco	Listing	Non-distress
HonHai	Listing	Non-distress
Oracle	Listing	Non-distress
TSMC	Listing	Non-distress
HPE	Listing	Non-distress
Qualcomm	Listing	Non-distress
Alibaba	Listing	Non-distress
SAP	Listing	Non-distress
Facebook	Listing	Non-distress
Tencent	Listing	Non-distress
Amazon	Listing	Non-distress
HP	Listing	Non-distress
Ericson	Listing	*Distress*
Baidu	Listing	Non-distress
Nokia	Listing	Non-distress
SKY HNIX	Listing	Non-distress
TCS	Listing	Non-distress
TI	Listing	Non-distress
Micron	Listing	Non-distress
ADP	Listing	Non-distress
Lenovo	Listing	Non-distress
Yahoo	*Delisting*	*Distress*
TE Connectivity	Listing	Non-distress
Canon	Listing	Non-distress

96,6%, and it is close to 100%. After Grover model, Altman model can predict with accurate until 86,6%, and then Taffler model 85%, Zmijewski model 85%, Springate model 70%, Ohlson model 46,6%, and the last Fulmer model 40%.

Table 2 show the result of Robustness Check which are based on compares calculation models with interest coverage ratio. And the results prove that the Grover model which is the highest accuracy model is correct and still accurate.

Although the percentage rate decreased from 96.6% to 95%, the Grover model remains the prediction model of financial distress with the highest accuracy compared to the Altman, Zmijewski, and Taffler models with an accuracy rate of 83.3%, the Springate

TABLE 1: Accuracy level based on reality.

Model	Correct Predict	Total Data	Accuracy
Grover	58	60	96%
Altman	52	60	86,6%
Taffler	51	60	85%
Zmijewski	51	60	85%
Springate	42	60	70%
Ohlson	28	60	46,6%
Fulmer	24	60	40%

TABLE 2: Robustness check.

Model	Correct Predict	Total Data	Accuracy
Grover	57	60	95%
Altman	50	60	83,3%
Taffler	50	60	83,3%
Zmijewski	50	60	83,3%
Springate	43	60	71,6%
Ohlson	28	60	46,6%
Fulmer	27	60	45%

model with 71,6% accuracy rate, Ohlson's model with a 46.6% accuracy rate, as well as the prediction model with the lowest accuracy rate is the Fulmer model with an accuracy rate of 45%.

Acknowledgment

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