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Discriminant Function Analysis to Distinguish the Performance of Information and Communication Technology (ICT) Companies (A Study of U.S. Companies Listed in U.S. Stock Market)

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Abstract. *The growing important role of ICT companies in digital era has attracted many institutions and researchers to conduct studies to measure the value creation created by digitalization. However, not many of them emphasize the importance of financial information as a performance measurement for ICT companies that are useful for their sustainability in the rapid pace of technology. Therefore, this study aims to find the importance of financial ratios in assessing the performance of ICT companies. This study uses discriminant function analysis to find the best financial ratios that distinguish the ICT companies' performance based on their grade in the credit ratings. The scope of this study is 70 US-based companies listed in US stock market within ICT groups with 35 companies in each group of Investment Grade and Non-investment Grade. There are 4 financial ratios that best discriminate the performance between the two groups which are ROA, CFO to current liabilities, total debt to EBITDA, and CFO to net sales. This model has a predictive accuracy or early warning ability of 87.1% in the latest full-year financial statements prior to rating date and 80% in the longer period (up to 3rd last full-year financial statements prior to rating date).*

Keywords: *Discriminant function analysis, financial ratio, performance, information and communication technology*

1. Introduction

Digitalization derived by innovation and technological disruption have influenced significantly to the multiple aspects of life, both aspects of the organization's business, industry, economy, even to society welfare (Weinelt, 2016). According to OECD (2014), definitions of digital economy involve two important key aspects: policies on digital technologies; and the growth of ICT and digitally oriented firms. The role of ICT business including hardware, software, telecommunication, internet infrastructure, digital products and services, are increasingly needed and relied upon. In 2018, 3.9 billion people (51.2% of global population) have used the internet (ITU, 2018). The five big-tech companies such as Microsoft, Apple, Amazon, Google, and Facebook, all of which are US companies, have attracted the global attention as their important role in driving the wave of digitalization. Those companies reached the combined value of 30% of US contribution in the top 100 global largest market capitalization (PwC, 2019). Among the top 100 global largest market capitalization companies, 54 companies are US-based including 18 companies in technology, communication, and consumer service sectors, especially retail internet. In terms of ICT value added based on GDP in 2010-2017, US has the world's largest ICT value added, almost twice the size of the second largest, China (UNCTAD, 2019). These proof that US is always in the forefront of digital technology innovation. Many institutions and researchers have conducted the studies to measure the value creation created by digitalization. As more modern business is often associated with the concept of value creation including many perspectives in the form of qualitative assessment, not many studies emphasize on the quantitative assessment such as financial ratios.

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The term digital economy was first introduced by Tapscott in 1996. The 1990s were the years that many internet-related companies conducted an IPO, which caused the dotcom bubble phenomenon to occur in the late 1990s to early 2000s. Although the scope is limited to internet-related companies, many studies have been conducted to find out what factors influence the growth and stock price in relation to financial and non-financial information, especially during those periods. However, those studies found that financial information could not explain much about its relationship to the growth and stock prices of internet-related companies (Bontis and Mill, 2000; Eisenmann, 2006; Graham, Cannice, & Sayre, 2002). US internet firms tend to have large expenditure on brand, R&D, and structural intangible that more destroying profit but have positive relationship with returns-to-scale (Hand, 2001).

Therefore, some argue that financial aspect is not reliable to be applied for the success measurement of digital companies in this digital era. Profit as a measurement of the digital economy has the disadvantage that some major firms such as Amazon invested back its all earnings in order to achieve continuous growth which would underestimate the value creation of digital economy (Evans, 2014). Govindarajan, Rajgopal, and Srivastava (2018), has an opinion on financial information, especially those which come from financial statements, are often be considered only as an accounting number that is not relevant to modern business because it cannot capture the principle value creator for digital companies which more decrease rather than increase profit. The same thing happens to Amazon, which is already known for its small operating margin despite of huge market capitalization. These conditions are certainly a challenge for this study. Considering that this study is not subjected only on digital companies but a broader scope of ICT companies and there were previous studies that found the relationship between financial ratios and ICT companies' performance, general useful financial information is expected to be drawn from this study.

Recent COVID-19 pandemic has impacted the economy significantly through the declining of business sector and purchasing power. The ICT sector is not an exception, many multinational ICT companies postpone and cancelled the production, event or conferences especially for the multi-countries business. Some of the ICT financial reports are below expectations. Covid-19 has forced every business and everyone to switch to a new working culture, a new style of many activities. Digital and technology become the foundation of many other businesses. Great opportunity arises on the other hand, providing plenty of rooms for innovation for the old business or new commers and tightening the rivalry. Companies must have guidance in order to sustain their business.

As explained in the background above, there is lack of research on the importance of financial ratios as one of the objective performance indicators, especially for ICT companies. Qualitative measurements may be appropriate to be applied to monitor the company in achieving its long-term growth. However, in the context of companies failing because of bankruptcy, qualitative measurements are less able to anticipate the company from financial failure because they put less emphasis on the financial aspects in the measurements. The importance of the emphasis on the financial aspect is that there are objective measurements that can complement the qualitative measurements as a guidance of achieving good performance in the future. However, not many studies are conducted to assess the ICT company performance from the aspect of financial information. Finally, the needs of an objective measurement that can be used to assess the current performance and to predict the future performance of ICT companies has motivated the author to conduct this study. This study is expected to be able to close the gap between the lack of research on the importance of financial ratios to assess the performance of ICT companies that can compensate the important growing role of ICT companies in the digital economy.

2. Literature Study

2.1. Financial Ratios as Predictor Variables

Variables, or predictor variables, in this study is financial ratio. Although many previous studies had been analyzed financial ratios to predict the failures of a company using discriminant analysis, there is no theory that strongly underlie what appropriate financial ratios should be chosen as a predictor variable (Bunyaminu & Issah, 2012). Soekarno and Azhari (2010) applied financial ratios that are relevant to the insurance industry. However, there was no specific ratio developed for ICT sectors. Thus, instead of developing new ratios, this study will refer to financial ratios that has been examined in the previous researches in their relation to company performance measurement.

Although it has been widely used in the practices of performance measurement, profitability ratios (ROA, ROE, ROIC), liquidity ratios (current ratio and cash ratio), and leverage ratio (debt to assets), are still widely used by many authors as variables in their researches and it has been proven that these ratios can provide important and significant information as an indicator of company performance (Bunyaminu & Issah, 2012; Dženopoljac, Janoševic, & Bontis, 2016; Gan & Saleh, 2008). The ratios in the Altman Z-score model (EBIT to total assets, NWC to total assets, retained earnings to total assets, market value of equity to book value of debt, and sales to total assets.) have also been applied by other researchers for bankruptcy predictions in various countries and industries (Almamy, Aston, & Ngwa, 2016; Charalambakis & Garrett, 2016).

Ratios developed from the cash flow statement should supplement the traditional accrual-based ratios (ratios derived from balance sheet and income statements) to provide additional information on the financial strengths and weaknesses of an entity and have proven the potential to predict financial failure (Almamy et al., 2016). Some previous studies have examined the use of cash flow ratios such as cash flow to net sales, cash flow to current liabilities, cash flow to total liabilities, cash flow to net income, that significantly distinguishes between failed and non-filed firms (Almamy et al., 2016; Kamaluddin, Ishak, & Mohammed, 2019). More emphasizes on cash flow ratio such as the proportion of cash flow from operations to cash flow from investing activities, and the cash flow reinvested to the company after paying dividends, have also been introduced by the other researcher (Kamaluddin et al., 2019).

Some authors applied the growth capabilities of the company such as growth on net profit, total assets, and sales, as the predictor variables (Bunyaminu & Issah, 2012; Nimtrakoon, 2015). Bauer, Dehning, and Stratopoulos (2012) used the proportion of R&D expense to sales as a proxy for technological intensiveness that relates to the characteristics of the technology-based company. Pech, Noguera, and White (2015) proposed a set of financial ratios that the most preferred ratios by equity analysts and have predictive power on future stock returns, some of them are debt to equity, debt to EBITDA, price to book value, price to earnings, etc. S&P and Moody's also applied certain financial ratios in the credit rating assessment, yet it depends very much on which business environment a company belongs to. The most common financial ratios used by those two credit ratings agencies is debt to EBITDA. In addition, some common market ratios such as price to earnings and price to book value, can reflect the perception of investors about the prospect of the company.

This study has main challenges where there are thoughts about the incompatibility of financial information and financial ratios to be applied to modern businesses and their inability to explain the performance of internet and digital companies in previous studies. However, some previous studies used financial information and financial ratios as the measurement indicators in their researches related to ICT companies and found some useful information drawn from those financial ratios. Cochran, Darrat, & Elkhal (2005) investigated the key predictors of internet (dotcoms) firm's bankruptcy: in a calendar-time model, three key predictors of firm's failure are net income to total assets, cash flow to total liabilities, and total assets; in event-time model, liquidity becomes more important as a predictor than profit potential about one year prior to the failure. Halkos and Tzeremes (2007) analyzed competitive structure of the global ICT market with data envelopment analysis (DEA) method using input variables of number of employees, the R&D expenditure, and market capitalization and output variables of revenues and net income. Bauer et al. (2012) examined the cross-sectional financial performance among firms from the global ICT sector over the period 1998–2007 using ROA, ROE, ROS, and sales growth as the variables.

Some authors used pooled linear regression to explore the relationship between ICT firms' intellectual capital and financial performance in various countries. Gan and Saleh (2008) found that intellectual capital of ICT companies in Malaysian stock market is positive correlated with ROA and asset turnover but fails to explain market to book value ratio. Nimtrakoon (2015) found a positive relationship between intellectual capital and market value, ROS, and ROA, among ICT firms in ASEAN stock market. Dženopoljac et al. (2016) found that intellectual capital has significant effect on financial performance (ROA, ROE, ROIC, and asset turnover) of ICT firms in Serbian stock market.

2.2. Discriminant Analysis

Previous studies used a regression method to analyze the relationship between financial ratios and ICT company performance, while analysis of discriminant functions offered a different way. Discriminant analysis is a statistical method used to classified or categorized an observation or a case into one of two or more groups based on the characteristic of that observation or case (Altman, Danovi, & Falini, 2013). Below is the model of discriminant function:

$$Zjk = a + W1X1k + W2X2k + \ldots + WnXnk$$

Where,

Zjk = Discriminant Z score of discriminant function j for object k

a = Intercept

Wi = discriminant weight for independent variable i

Xik = independent variable i for object k

Altman's Z-score has been applied for predicting the bankruptcy in various industries or countries by many researchers. However, discriminant function analysis can also be used for various purposes. Soekarno and Azhari (2010) used discriminant function analysis to distinguish the performance of well-performed and less-performed companies in insurance industry by applying the ratios that are relevant and commonly used in insurance industries. Besides discriminant analysis, there are other methods used to create predictive models and determine the most important factors, namely logistic regression and hazard models. Altman et al. (2013) used data one year before failure and logistic regression was also considered as a single period model, while hazard model could solve the problem by examining all company-year observations. However, distinguishing the performance can be carried out in some further years unlike predicting failures which the occurrences can be clearly stated in the past. Logistic regression is also used in the case of classification into one of several populations. Both discriminant function analysis and logistic regression have discrete or categorical dependent variables. The contrast between discriminant function analysis and logistic regression is the underlying assumption that makes each of those two methods has certain condition to be applied to. In discriminant function analysis, the explanatory or independent variables must follow a multivariate normal distribution with the equal covariance matrix for each state of dependent variables that makes this method is very robust against violation of assumptions. However, if the explanatory or independent variables do not have a multivariate normal distribution, logistic regression is preferred because in logistic regression there is no assumption of normality. Tillmanns and Krafft (2017) have shown that logistic regression estimators are between one-half and two-thirds as efficient as discriminant function predictors when multivariate data are normal with equal covariance matrices. Thus, if the data are completely normal with the same covariance matrices, discriminant functions are more economical to calculate and more efficient than logistic regression.

2.3. Research Hypothesis Statement

Previous research found that financial ratios have a positive relationship with ICT company performance (Dženopoljac & Janoševic, 2016; Gan & Saleh, 2008; Nimtrakoon, 2015). Soekarno and Azhari (2010) found that discriminant analysis using financial ratios can be used to differentiate the performance of insurance companies. Therefore, the hypothesis in this study is developed as below:

H0: The financial ratios selected as variables of the discriminant function analysis in this study, cannot distinguish the performance of ICT companies between those that are in Investment Grade group and those that are in Non-investment Grade group based on the credit ratings.

H1: The financial ratios selected as variables of the discriminant function analysis in this study, can distinguish the performance of ICT companies between those that are in Investment Grade group and those that are in Non-investment Grade group based on the credit ratings.

3. Methodology

3.1. Sample

The sample selection is done by utilizing Yahoo Finance – Equity Screener feature (accessed on Dec 19, 2019) to obtain the companies based on the following criterion: (a) companies listed in US stock market; (b) companies within the Technology sector, Communication Service sector, Internet Retail industry (included in Consumer Cyclical sector); (c) companies with market capitalization over $2 billion. A company with a market capitalization of more than $2 billion is considered a mature company. The rise of startups in the ICT sector that has not yet gone public but has valuation above $1 billion is also a consideration of the authors. Out of more than 300 global unicorn companies valued at more than $1 billion, 12% of them are unicorn startups in the field of financial technology, followed by e-commerce and direct retail, internet software & services, and artificial intelligence, each with 11% (CB Insights, 2019). Therefore, a market capitalization of more than $2 billion was chosen by the author because it was considered mature and able to compete with unicorns in attracting investors' attention in the capital market.; (d) companies that are domiciled in US (US-based). Next, select the companies only for those which has been rated at corporate level by S&P and Moody's credit rating. Based on the criterion above, there are 538 US-based companies listed in US stock market within the selected sector and industry with market capitalization above $2 billion. Finally, 35 companies from each group are selected as sample ordered by the highest rating in Investment Grade and the lowest rating in Non-investment Group in order to get a significant result.

3.2. Variables

Based on the literature review, financial ratios selected as predictor variables of discriminant function analysis in this study, are listed as follows (see Table 1):

Table 1.
List of Financial Ratios selected as Predictor Variables

Financial Ratios (variables)	Formula
Profitability:	
Return on Asset *(X_1)*	net income / total assets
Return on Invested Capital *(X_2)*	net income / (total assets – current liability)
Return on Equity *(X_3)*	net income / total equity
EBIT to Total Assets *(X_4)*	(net income + interest + tax) / total assets
Liquidity:	
Current Ratio *(X_5)*	current assets / current liabilities
Cash ratio *(X_6)*	(cash and cash equivalent + short-term investment or marketable securities) / current liabilities
Working Capital to Total Assets *(X_7)*	(current assets – current liabilities) / total assets
CFO to Current Liabilities *(X_8)*	cash flow from operation / current liabilities
Solvency:	
Total Debt to Total Assets *(X_9)*	total debt / total assets
Total Debt to Total Equity *(X_{10})*	total debt / total equity
Total Debt to EBITDA *(X_{11})*	total debt / (net income + interest + tax + depreciation + amortization)
CFO to Total Liabilities *(X_{12})*	cash flow from operation / total liabilities
Cash Generating Ability:	
CFO to Net Sales *(X_{13})*	cash flow from operation / net sales
CFO to Net Income *(X_{14})*	cash flow from operation / net income
Cash Reinvestment *(X_{15})*	(cash flow from operation - dividend paid) / (non-current assets - net working capital)
CFO to Cash flow from Investing *(X_{16})*	cashflow from operation / cashflow from investing
Growth Ability:	
Growth on Net Income *(X_{17})*	(net income$_t$ - net income$_0$) / net income$_0$
Growth on Total Asset *(X_{18})*	(total assets$_t$ - total assets$_0$) / total assets$_0$
Growth on Net Sales *(X_{19})*	(net sales$_t$ - net sales$_0$) / net sales$_0$
R&D Expenses to Net Sales *(X_{20})*	R&D expenses / net sales
Retained Earnings to Total Assets *(X_{21})*	retained earnings / total assets
Market Ratio:	
Price to Book Value *(X_{22})*	share price / ((total assets - total liabilities) / outstanding shares)
Price to Earnings *(X_{23})*	share price / (net income / outstanding shares)

4. Findings and Discussion

4.1. Data Analysis and Interpretation

In the multicollinearity test, each variable will be seen how it correlates with each of the other variables. This step is mainly to test the multicollinearity of the predictor variables to fulfil the assumption which predictor variables should be independent or no multicollinearity. In this study, value above 0.6 (in absolute manner) will be determined as high collinearity and will be excluded in the next steps of discriminant function analysis. In the Appendix (see Figure 1), there are 11 variables with high multicollinearity. Based on the judgmental basis, ROIC, EBIT to total assets, price to book value, current ratio, NWC to total assets, and CFO to net income will be excluded in the further analysis which it also means leaving 17 variables to be used in the next analysis.

The remaining 17 variables then are tested for the equality of covariance matrices to fulfil the assumption which predictor variables should have a multivariate normal distribution, an equal across groups and within-group variance-covariance matrices, and a mutually exclusive group membership (see Table 2). To meet the assumption, log determinants should be almost equal-to-one-another and Box's p-value should be more than 0.05 (or not significant). Note that larger number of the data observed may lead the small deviations from homogeneity to be found significant. Thus, if the p-value is found significant, we can ignore it as long as the log determinants show an almost equal-to-one-another value and continue with the discriminant function analysis. Otherwise, we should not continue with the discriminant function analysis in order to avoid the subjectivity which can lead bias in the final result of the analysis.

Table 2.
Box's Test of Equality of Covariance Matrices

Group	Rank	Log Determinant
Investment Grade	4	-12.055
Non-investment Grade	4	-11.328
Pooled within-groups	4	-11.311
Box's M	Sig.	0.007

The column "Rank" in Box's M table shows how many variables used in discriminant function analysis. From the data above, log determinants for group of Investment Grade, Non-Investment Grade, and within-groups are -12.055, -11.328, and -11.311 which can be considered equal-to-one-another. However, the Box's p value is found significant which means the groups covariances are not equal because the p value is 0.007, or < 0.05. Box's test is very sensitive towards any small deviation that differs against homogeneity. In this condition, we are allowed to ignore the significant Box's if the log determinants are equal-to-one-another. After meeting the previous assumptions, the last assumption which group membership is a truly categorical variable, will be fulfilled through stepwise method with further analysis (see Table 3). Stepwise test includes several steps in selecting variables that will be used in discriminant function analysis by entering and removing the variables which require one significance level to enter variables and one significance level to remove variables. The cutoff probability for entering variables should be less than the cutoff probability for removing variables. If a non-significant variable is found, it is removed from the model. This analysis use significance of 0.05 to enter and significance of 0.1 to remove. Stepwise in discriminant function analysis selects the variables that can lower the Wilks' lambda the most. Only the variables selected by stepwise method which then will be used in discriminant function analysis.

Table 3.
Variables Entered in the Analysis

Step	Entered	Statistic of Wilks' Lambda
1	TDEBITDA	0.700
2	CFOSALES	0.612
3	CFOCL	0.559
4	ROA	0.521

Stepwise test needs cutoff probability for entering and removing variables. With the maximum significance of F to enter of 0.05 and minimum significance of F to remove of 0.10, there are only 4 variables entered in this stepwise step: total debt to EBITDA (TDEBITDA); CFO to net sales (CFOSALES); CFO to current liability (CFOCL); and return on assets (ROA).
Eigenvalue provide information about the variance in the dependent variable explained by that function (see Table 4). The larger eigenvalue the more variance happened. Since there are only two groups of dependent variables, there will be only one discriminant function. The canonical correlation is the measure of association between the discriminant function and the dependent variable. Wilks' lambda is a measure of how well each function discriminates cases into groups (see Table 5). The value of Wilks' lambda range between 0 to 1. Smaller values of Wilks' lambda indicate greater discriminatory ability of the function. The p value of Wilk's lambda must be found significant, or < 0.05, to reject the H0 and accept the H1. The associated chi-square statistic tests the hypothesis that the means of the functions listed are equal across groups. The small significance value indicates that the discriminant function does better than chance at separating the groups.

Table 4.
Eigenvalue

Function	Eigenvalue	% of Variance	% of Cumulative	Canonical Correlation
1	0.919	100	100	0.692

Table 5.
Wilk's Lambda

Test of Function(s)	Wilk's Lambda	Chi-square	df	Sig.
1	0.521	43.027	4	0.000

The small eigenvalue of 0.919 means that variance in the dependent variable is low. The canonical correlation of 0.692 means that the variable used in discriminant function analysis has contribution of 69.2% to the dependent variable. Out of 0 to 1, Wilks' lambda is 0.521. It means that the ability of the 4 variables in discriminating between the two categories of dependent variables (group) can lower the Wilks' lambda to 0.521. The p value of Wilk's lambda is also found significant, so the H1 of this study is accepted, meaning that there is a significant difference in the performance of ICT companies between Investment Grade and Non-investment Grade explained by the predictor variables. The associated chi-square is 43.027 that means the means of the functions listed are equal across groups and the model is statistically significant. The standardized discriminant function coefficients indicate the relative importance of the independent variables in predicting the dependent variables (see Table 6).

Coefficients with large absolute values correspond to independent variables with greater discriminating ability.

Table 6.
Standardized Canonical Discriminant Function

	Function
	1
ROA	-0.472
CFOCL	0.794
TDEBITDA	0.693
CFOSALES	-0.881

The function allows to compare the discriminating power of the variable relatively to another, or in other words it can be used to rank the importance of each variables. The function of the 4 variables are: ROA (-0.472); CFOCL (0.794); TDEBITDA (0.693); and CFOSALES -0.881). In the absolute value, the variable that best discriminate the two dependent variables (group) is CFOSALES which followed by CFOCL, TDEBITDA, and ROA in the least discriminating ability.

Canonical discriminant function coefficient is the unstandardized coefficient used to construct the actual prediction equation which can be used to classify new cases (see Table 7). Same with the regression analysis, the model in discriminant analysis consists of constant and variables which each has a coefficient that will determine the value of the score (Z-score).

Table 7.
Canonical Discriminant Function Coefficient

	Function
	1
ROA	-8.172
CFOCL	1.296
TDEBITDA	0.416
CFOSALES	-8.384
(Constant)	0.247

Functions at group centroids are the mean discriminant scores of each group which will be used to determine the cut-off point for classifying cases (see Table 8). The value of functions at group centroids are more of informational values rather than a strict value because it is resulted by computerized calculation. For the two groups that are equal in size, the best approach to determine the cutting point is by dividing half-way between the values of the functions at group centroids (that is, the average). If the groups are unequal, the optimal approach it is the weighted average of the two values.

Table 8.
Functions at Group Centroids

Group	Function
	1
Investment Grade	-0.945
Non-investment Grade	0.945

Since the two dependent variables (groups) observed in this analysis each has equal number of observations, the function at group's centroids are in the same range, which is -0.945 in Investment Grade group and 0.945 in Non-investment Grade group. Thus, the cut-off point used in this discriminant function is 0, that is the mean between -0.945 and 0.945. Therefore, when this discriminant function is applied to classify a new case, if the case has Z-score value below 0, it will be classified into Investment Grade group, while if the case has Z-score value above 0, it will be classified into Non-investment Grade group.

Predicted group membership provides information about how well the ability of discriminant function in this model in classifying the cases into the different group (see Table 9).

Table 9.
Classification Results

Classification[a, c]		**Group**	**Predicted Group Membership**		**Total**
			Investment Grade	**Non-investment Grade**	
Original[a,c]	Count	Investment Grade	31	4	35
		Non-investment Grade	5	30	35
	%	Investment Grade	88.6	11.4	100
		Non-investment Grade	14.3	85.7	100
Cross-validated[b]	Count	Investment Grade	30	5	35
		Non-investment Grade	6	29	35
	%	Investment Grade	85.7	14.3	100
		Non-investment Grade	17.1	82.9	100

[a]87,1% of original grouped cases correctly classified.
[b]Cross validation is done only for those cases in the analysis. In cross validation, each case is classified by the functions derived from all cases other than that case.
[c]84,3% of cross-validated grouped cases correctly classified.

The discriminant function resulted in the analysis contains of ROA, CFOCL, TDEBITDA, and CFOSALES that best discriminate between the two groups of Investment Grade and Non-investment Grade. In the original group, the discriminant function can correctly classify the group member as of 87.1% in total count, which among the 35 cases in each group, 31 cases are correctly classified as Investment Grade (88.6%) and 30 cases are correctly classified as Non-Investment Grade (85.7%). In cross validation that each case is classified by the functions derived from all cases other than that case, the discriminant function can correctly classify the group member as of 84.3% in total count, which among the 35 cases in each group, 30 cases are correctly classified as Investment Grade (85.7%) and 29 cases are correctly classified as Non-Investment Grade (82.9%).

4.2. The Prediction Model

Among 23 financial ratios used as original variables (predictor variables) or 17 financial ratios that are met the assumptions of no multicollinearity, there are 4 financial ratios that best discriminate the performance between the two groups. This is in line with Soekarno and Azhari (2010) where discriminant analysis with financial ratios can be used to distinguish the performance of companies that are in the groups of top and least companies. The prediction model resulted from this analysis is as follows: Z-score = 0.247 – 8.172 Return on Assets + 1.296 CFO to Current Liabilities + 0.416 Total debt to EBITDA – 8.384 CFO to net sales, with cut-off point of 0 that when this discriminant function is applied to classify a new case, if the case has Z-score value below 0, it will be classified into Investment Grade group, while if the case has Z-score value above 0, it will be classified into Non-investment Grade group.

Return on Assets (ROA), is already a well-known ratio for evaluating the financial performance of companies in various industries because of its ease in formula and interpretation. ROA measures how much a company's profitability or ability to generate net income from its effectiveness in managing its all resources. In the academic field, ROA appears as a ratio that has a great significance to its relation to financial performance in many studies (Dženopoljac & Janoševic, 2016; Gan & Saleh, 2008; Nimtrakoon, 2015). Although some ICT companies, especially e-commerce, often result small returns despite the huge growth of their revenue or share price, this ratio still has the ability to distinguish the performance between companies in the Investment Grade group and the Non-Investment Grade group.

Ratios in this model, two of which are cash flow ratios, which in previous studies, Almamy et al. (2015); and Kamaludin et al. (2019) found the ability of cash flow ratios to predict financial failure. In accordance with the results of their research, CFO to current liabilities and CFO to net sales are significant in differentiating the company performance. CFO to Current Liabilities, is a ratio that measures how much company's ability to generate CFO proportionally to current liabilities. Such liabilities as operating expenses, payables, and debt and interest expenses that all of which are due in the short-term, cannot wait any longer and must be paid immediately. A sufficient amount of cash is needed primarily from the company's operation activities to avoid taking out the other debt or loans that will only add to the company's burden. Therefore, CFO is considered as should be in good proportion to current liabilities. However, in this model, companies in Investment Grade group tend to have a smaller CFO to current liabilities ratio, on the contrary, companies in the Non-investment Grade group have a greater value. The are some probable reasons that can explain this condition: companies in Non-investment Grade group have smaller proportion of current liabilities than companies in Investment Grade group; or, companies in Investment Grade group are mostly has been in the mature business cycle that their capacity to generate more cash flow has met the optimum level, it is different with companies in Non-investment Grade group that might still have a lot of room to grow.

Total debt to EBITDA, is a ratio to measures how much income the company generates that can be used to pay debt before covering the interest, taxes, and depreciation and amortization expenses (EBITDA). It is a widely-used ratio to measure company's solvency and profitability. It is also a common ratio used by rating agencies in assessing the possibility of defaults of a company in meeting its long-term commitments (Pech et al., 2015). Total debt to EBITDA can also reflect the characteristics of technology-based companies well. Such companies tend to require a large amount of funding in the form of long-term debt or obligations, other than capital market, to finance their huge investments that are mostly on physical assets such as PPE or technology, or non-physical assets such as software or intellectual capital. It also relates that EBITDA is more capable to reflect earnings from main business, rather than operating income or net income because expenses associated with debt or physical and intangible assets, and taxes in addition, are added back to net income.

CFO to Net Sales, is a ratio to measures the company's ability to generate sales into cash flow after covering its operations. Cash flow from operations (CFO) is very liquid cash and should be sufficient to pay expenses and short-term or other liabilities, before taking the external funding. ICT companies tend to prioritize the rapid growth of net sales or revenue to attract investors' interest to invest in the companies, however neglect the efficiency in converting the net sales or revenue into cash. Although the proportion of CFO to net sales which is relatively small may also be a result from high R&D expenses or technological development expense that cannot be capitalized, yet the ratio shows its contribution to the discriminant function model that distinguishes between companies in Investment Grade group and Non-investment Grade group.

4.3. Early Prediction Test

This test is conducted to find out how the discriminant function that has been obtained from this analysis can be used as a prediction or early warning if the company starts to show good or poor performance. To know this, the discriminant function will be applied to sample companies over a longer period, using the 2nd and 3rd last full-year financial statements prior to rating date (see Table 10).

Table 10.
Early Prediction Test Result

Year(s) of last financial statements prior to rating date		**Investment Grade**		**Non-investment Grade**		**Total**	
		Correct	**Wrong**	**Correct**	**Wrong**	**Correct**	**Wrong**
1	Count	31	4	30	5	61	9
	%	88.6	11.4	85.7	14.3	87.1	12.9
2	Count	29	6	27	8	56	14
	%	82.9	17.1	77.1	22.9	80.0	20.0
3	Count	30	5	26	9	56	14
	%	85.7	14.3	74.3	25.7	80.0	20.0

Predictive accuracy for the Investment Grade group from the latest full-year financial statements prior to rating date is decreasing in the longer period of time. Using the 2nd and 3rd last full-year financial statements prior to rating date, the predictive accuracy is 82.9% and 85.7% respectively, decrease from 88.6% in the latest full-year financial statements prior to rating date. The decreasing predictive accuracy in the longer period of time also happen in Non-investment Grade group. Using the 2nd and 3rd last full-year financial statements prior to rating date, the predictive accuracy is 77.1% and 74.3% respectively, decrease from 85.7% in the latest full-year financial statements prior to rating date. In total, prediction accuracy in the latest full-year financial statements prior to rating date is 87.1% and decrease to 80.0% in the 2nd and 3rd last full-year financial statements prior to rating date. From these results, the predictive accuracy of the discriminant function in this study has predictive accuracy or early warning ability up to 3rd last full-year financial statements before the rating date with an overall accuracy of more than 80%.

5. Conclusions

The result of this study concluded that H0 is rejected and H1 is accepted which means that the financial ratios selected as variables of the discriminant function analysis in this study can distinguish the performance of ICT companies between those that are in Investment Grade group and those that are in Non-investment Grade group based on the credit ratings. Among the 23 financial ratios selected as predictor variables, there are only 4 financial ratios that are best and consistently distinguish between ICT companies that are in Investment Grade and those that are in Non-investment Grade based on the credit ratings that establish this prediction model which are ROA, CFO to Current Liabilities, Total Debt to EBITDA, and CFO to Net Sales. All of these ratios should be applied together within the model of discriminant function established from this study. In addition, this model also proofs that financial ratio still has the ability to assess the ICT company's performance in the current digital era. Based on the results, it can be concluded that this model has a predictive ability of 87.1% in the latest full-year financial statements prior to rating date, and in a longer period, the predictive ability is 80% (up to 3^{rd} last full-year financial statements prior to rating date). Therefore, the prediction model in this study is highly recommended because it is able to predict the ICT company's performance in the future very well. By the data we have today, we can predict whether the companies will perform well (equivalent to Investment Grade) or not (equivalent to Non-investment Grade) over the next year with accuracy of 87.1% and over the next three years with accuracy of 80%.

However, prediction model resulted from this analysis is not separated from limitations and weaknesses. One of the limitations of this study that was explained in the previous section is that this study is limited to the use of credit rating as a reference in determining the good or not of a company performance because there are no benchmarks specifically used to evaluate the financial performance of ICT companies. It affects the weakness of this model to generalize all existing ICT companies because the selected sample is limited only to companies that have been rated. Another limitation is that the discriminant function analysis is strongly influenced by the predictor variables used. The use of different predictor variables will result different variables selected in discriminant functions as well. Therefore, the author's efforts to choose the right predictor variables along with good underlying considerations are needed. In addition, the selection of predictor variables in this study has limitation because big companies such as Apple or Microsoft have no debt and interest expenses, so that ratios with denominator 0 (interest coverage or CFO to debt) cannot be used in this analysis to avoid mislead information.

Since this study sampled the ICT companies in the US, the model drawn from this study reflects the success of US top-rated ICT companies in creating and maintaining superior financial performance. In theory, this study does not create a new theory but it supports the application of discriminant analysis because the independent variables in this study form a multivariate normal distribution and homogeneity of the variance-covariance matrices of the independent variables so that the differences between the two groups of dependent variables can be found significantly.

The main stakeholders targeted by this study are investors, company's internal management, and future researchers. This model is recommended for investors because this model is a quantitative model that can complement the qualitative aspects such as economic aspects or future business prospects of ICT so that it can help investors in making decisions to invest in ICT companies. For internal company management, this model can be used as an internal control of the company's financial performance so that it is possible to take precautionary measures when the company starts to indicate a decline in performance. This study can be used as reference for further research especially on the relation of financial information and ICT companies' performance. In addition for regular audiences, this study is useful to acknowledge that financial information that is considered irrelevant to ICT company businesses in the digital era turns out from the results of this study that financial information, especially financial ratios, can

actually help them assess or predict the future company performance of ICT companies by implementing functions discriminant resulting from this study.
The results of this study are still valid as long as the benchmarks used to categorize the performance are credit ratings, considering that one of the limitations of this study is the use of credit ratings which in addition to influencing generalization also affect the financial ratios that less reflect the characteristics of ICT companies. ICT and science that will increasingly develop in the future are expected to be accompanied by developments in research that not only emphasize the qualitative aspects but also the quantitative aspects, especially financial information. The important one is a benchmark specifically created to classify the ICT company performance. Therefore, the method in this study can still be done with some adjustments that may be needed related to the selection of samples or financial ratios.

References

Almamy, J., Aston, J., & Ngwa, L. N. (2016). An evaluation of Altman's Z-score using cash flow ratio to predict corporate failure amid the recent financial crisis: Evidence from the UK. *Journal of Corporate Finance*, *36*, 278-285.

Altman, E. I., Danovi, A., & Falini, A. (2013). Z-score models' application to Italian companies subject to extraordinary administration. *Journal of Applied Finance (Formerly Financial Practice and Education)*, *23*(1), 1-10.

Bauer, T. D., Dehning, B., & Stratopoulos, T. C. (2012). The financial performance of global information and communication technology companies. *Journal of Information Systems*, *26*(2), 119-152.

Bontis, N., & Mill, J. (2000). *Web-based metrics and internet stock prices* (Working Paper No.93). Retrieved from McMaster University, Management of Innovation and New Technology Research Centre website: https://macsphere.mcmaster.ca/handle/11375/5360.

Bunyaminu, A., & Issah, M. (2012). Predicting corporate failure of UK's listed companies: Comparing multiple discriminant analysis and logistic regression. *International research journal of finance and economics*, *94*, 6-22.

CB Insight. (2019). $1B+ Market Map: The World's 390+ Unicorn Companies in One Infographic. Retrieved from https://www.cbinsights.com/research/unicorn-startup-market-map/.

Charalambakis, E. C., & Garrett, I. (2016). On the prediction of financial distress in developed and emerging markets: Does the choice of accounting and market information matter? A comparison of UK and Indian Firms. *Review of Quantitative Finance and Accounting*, *47*(1), 1-28.

Cochran, J. J., Darrat, A. F., & Elkhal, K. (2006). On the bankruptcy of internet companies: An empirical inquiry. *Journal of Business Research*, *59*(10-11), 1193-1200.

Dženopoljac, V., Janoševic, S., & Bontis, N. (2016). Intellectual capital and financial performance in the Serbian ICT industry. *Journal of Intellectual Capital 17*(2), 373-396.

Eisenmann, T. R. (2006). Internet companies' growth strategies: determinants of investment intensity and long-term performance. *Strategic Management Journal*, *27*(12), 1183-1204.

Evans, B. (2014). Why Amazon has no profits (And why it works). Retrieved from https://www.ben-evans.com/benedictevans/2014/9/4/why-amazon-has-no-profits-and-why-it-works.

Gan, K., & Saleh, Z. (2008). Intellectual capital and corporate performance of technology-intensive companies:

Malaysia evidence. *AJBA*, *1*(1), 113-130.

Govindarajan, V., Rajgopal, S., & Srivastava, A. (2018). Why financial statements don't work for digital companies. *Harvard Business Review*, 2-6.

Graham, C. M., Cannice, M. V., & Sayre, T. L. (2002). The value-relevance of financial and non-financial information for Internet companies. *Thunderbird International Business Review*, *44*(1), 47-70.

Halkos, G. E., & Tzeremes, N. G. (2007). International competitiveness in the ICT industry: Evaluating the performance of the top 50 companies. *Global Economic Review*, *36*(2), 167-182.

Hand, J. R. (2001). Evidence on the Winner-Takes-All Business Model: The Profitability Returns-to-Scale of Expenditures on Intangibles Made by US Internet Firms, 1995-2001. *Available at SSRN 292099*.

ITU. (2018). *Measuring the Information Society Report 2018*. International Telecommunication Union.

Kamaluddin, A., Ishak, N., & Mohammed, N. F. (2019). Financial distress prediction through cash flow ratios analysis. *International Journal of Financial Research*, *10*(3), 63-76.

Nimtrakoon, S. (2015). The relationship between intellectual capital, firms' market value and financial performance. *Journal of Intellectual Capital,16*(3), 587-618.

OECD. (2014). *Measuring the Digital Economy: A New Perspective*. OECD Publishing.

Pech, C. O. T., Noguera, M., & White, S. (2015). Financial ratios used by equity analysts in Mexico and stock returns. *Contaduría y Administración*, *60*(3), 578-592.

PwC. (2019). *Global Top 100 Companies by Market Capitalization*. PwC.

Soekarno, S., & Azhari, D. A. (2010). Analysis of Financial Ratio to Distinguish Indonesia Joint Venture General Insurance Company Performance using Discriminant Analysis. *Asian Journal of Technology Management*, *3*(2), 101-122.

Tillmanns, S., & Krafft, M. (2017). Logistic regression and discriminant analysis. In C. Homburg, M. Klarmann, & A. Vomberg. *Handbook of market research* (pp. 1-39). Springer, Cham.

UNCTAD. (2019). *Digital Economy Report 2019: Value creation and capture– Implications for developing countries*. United Nations Conference on Trade and Development.

Weinelt, B. (2016). Digital Transformation of Industries: Digital Enterprise. In *World Economic Forum White Paper, World Economic Forum*.

APPENDIX

Insert Figure 1 here

	X1	X2	X3	X4	X5	X6	X7	X8	X9	X10	X11	X12	X13	X14	X15	X16	X17	X18	X19	X20	X21	X22	X23
X1	1,00																						
X2	0,93	1,00																					
X3	0,36	0,51	1,00																				
X4	0,91	0,90	0,37	1,00																			
X5	0,40	0,19	-0,02	0,31	1,00																		
X6	0,39	0,22	-0,01	0,27	0,74	1,00																	
X7	0,35	0,17	-0,09	0,30	0,71	0,80	1,00																
X8	0,50	0,29	0,01	0,45	0,63	0,57	0,37	1,00															
X9	-0,11	-0,12	-0,02	-0,09	-0,16	-0,24	-0,26	0,02	1,00														
X10	-0,09	-0,04	0,21	-0,08	-0,11	-0,16	-0,20	0,04	0,34	1,00													
X11	-0,39	-0,38	-0,20	-0,45	-0,26	-0,25	-0,35	-0,12	0,66	0,34	1,00												
X12	0,56	0,43	0,06	0,54	0,49	0,58	0,48	0,67	-0,43	-0,12	-0,41	1,00											
X13	0,27	0,18	0,02	0,26	0,26	0,37	0,10	0,68	0,03	0,00	0,11	0,47	1,00										
X14	-0,20	-0,19	-0,05	-0,10	-0,11	-0,12	-0,08	-0,11	-0,04	-0,06	-0,02	-0,05	0,08	1,00									
X15	0,55	0,72	0,48	0,59	-0,04	0,05	-0,07	0,17	-0,20	0,06	-0,26	0,42	0,27	0,04	1,00								
X16	0,13	0,15	-0,01	0,17	0,06	0,08	0,07	0,22	-0,06	-0,01	0,16	0,22	0,40	-0,01	0,36	1,00							
X17	-0,02	-0,04	-0,03	-0,11	-0,09	-0,02	-0,24	0,06	0,09	0,22	0,12	-0,06	0,04	-0,11	0,01	-0,12	1,00						
X18	0,17	0,09	0,05	0,06	0,15	0,21	0,32	0,06	-0,13	-0,01	-0,17	0,22	-0,10	-0,04	0,01	-0,18	-0,03	1,00					
X19	0,16	0,13	0,03	0,18	0,03	0,06	0,05	0,21	-0,06	-0,06	-0,08	0,18	0,09	-0,07	0,13	-0,01	0,05	0,38	1,00				
X20	0,27	0,34	0,44	0,21	0,20	0,39	0,42	0,01	-0,33	-0,07	-0,27	0,32	0,19	0,08	0,35	0,02	-0,18	0,14	-0,04	1,00			
X21	0,34	0,34	0,23	0,26	0,18	0,25	0,11	0,33	-0,03	-0,02	-0,07	0,36	0,25	0,02	0,35	-0,02	0,29	0,09	-0,04	0,16	1,00		
X22	0,13	0,29	0,88	0,15	-0,09	-0,08	-0,15	-0,11	0,00	0,38	-0,10	-0,03	-0,05	-0,03	0,38	-0,07	0,03	0,02	-0,02	0,46	0,18	1,00	
X23	-0,19	-0,17	-0,01	-0,13	-0,14	-0,14	-0,12	-0,19	-0,05	-0,07	-0,04	-0,07	-0,02	0,84	0,02	-0,17	-0,11	0,02	-0,09	0,21	0,05	0,04	1,00

Figure 1. Pooled Within-groups Matrices