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Bankruptcy Prediction Models Applied on Companies Listed on the Indonesian Stock Exchange (IDX)

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Abstract

This study tries to determine the best BPM (bankruptcy prediction model) method in predicting the bankruptcy (delisting) event amongst the delisted companies from the IDX for the period of 2011-2015. To verify the acuracy rate of those 4 BPMs, that is Altman, Springate, Zmijewski, and Grover, we apply these 4 BPM methods in predicting the non-bankruptcy (non-delisting) event of the paired companies used as the sample. This also mean that we need to measure the Error Type-II (ET-II).

On average, the acuracy rate of 4 BPMs in predicting 7 companies NOT to be bankrupt (still-listed) was 82.14%, and coupled with the relevant ET-II at 17.86%. By restricting the prediction only on the bankruptcy (delisting) event, Altman is the best BPM method with an acuracy of 71.43%. Altman becomes the best BPM in predicting the bankruptcy (delisting) event as it has an error rate by 14.29%, lower than the Springate.

Although Springate has an acuracy of 71.43%, it has an error rate higher than Altman, that is by 28.57%. Grover and Zmijewski took the third and fourth place respectively in the overall acuracy and in predicting the bankruptcy (delisting) event. By companies, the 4 BPM can predict the bankrupty (delisting) event of PWSI (Panca Wiratama Sakti), that is with ET-I = 0, but not with the delisting event of KARK (Dayaindo Resource International) whose acuracy rate was 0%.

Introduction

Bankruptcy and delisted are 2 separate events. The similarities lie in their characteristics as verdicts. The first is a legal status made by the judges in the commercial court, either requested by the company itself or by the third parties. The latter was made by the IDX (Indonesian Stock Exchange, Bursa Efek Indonesia). It may be due to the self-delisting reasoning to go private or due to the violation of listing regulations.

The bankruptcy status provides some options for the companies defaulted on the loans to choose, to be liquidated or to be restructured, organisationally or financially. In French, failite is defined as a situation of a company deemed to fail to pay its debt. Financially, the company is said to be insolvent as it fails to settle one of its debt components, either the principal or the interest or both.

In Indonesia, Law No.37 Year 2004 was issued to regulate the defaulted loans and postponement of liabilities to service the loans. The law also provides some degree of protections to debtors, creditors, and investors. Shall there be sufficient trusts and convictions amongst the stakeholders of company's sustainability, the company may wither the storm and resurrect to operate normally.Corporate failures have become something to avoid. Early warning systems to detect the companies to fail have been developed for decades. It is due to its catastrophic nature to lenders, creditors, and investors. There's nothing better to predict the probability of companies to fail, but their financial indicators. That includes the indicators for illiquidity, insolvency, bankruptness, or other measures.

Paul J. FitzPatrick was known as the avant garde to predict the bankruptness of 20 companies by pairing them with the surviving 20 companies within the same 20 industries.[1] FitzPatrick interpreted the 13 accounting ratios and its trends as the indicators of bankruptcy. The observation time was 3 years. In 1932, it was considered to be a complex, multiple variables analysis. Nevertheless, it was Edward I. Altman in 1968 that known to formalize the multiple variable analysis by applying multiple discriminant analysis within a pair-matched sample to predict corporates to fail.[2] Two years before, in 1966, with its univariate analysis, Beaver concluded that 'Cash Earnings to Total Debt' was the best ratio for signaling bankruptcy.[3]

Some numbers may provide early signs of the companies beginning to step into the murky waters and troubled territories. Bankruptcy is another stage and status of troubling companies. The status can be obtained through voluntary filing and/or imposed by a court order. Liquidation is the last stage of life of a company. Some of liquidations don't need bankruptcy status beforehand. Others may also come from sustained unsuccessful attempts of the management of the troubled companies to weather the storm. Financial distress indicators can not necessarily be the main culprit for the management and/or the stakeholders to liquidate the company. Some non-financial figures may take a larger role.

Bleak revenue projections, either in short-terms and/or medium-terms, that fail to meet the schedules set over various debt restructuring efforts, may become the obvious reason to liquidate a company. Illiquidity and insolvency have been used as the measures and indicators of financial distress of any company. Some forced delisting of publicly held companies in any stock exchange may serve as the early signs of trouble, likewise the voluntary delisting policy to make the companies private again. Some forced delisting may originate from the authorities within the stock exchange, the supervisory body, and/or the court.

Some forms of protection given and provided along with the bankruptcy statutes have been alleged to be vulnerable as a means to be exploited and manipulated. Many have classified such acts as white-collar crimes. Some fraud activities during bankruptcy protection and status are as follows:[4]

1. concealment of assets,
2. concealment or destruction of documents,
3. fraudulent claims,
4. false statements or declarations (perjury),
5. fee fixing or redistribution arrangements.

Literature Review

Financial Analysis

In the Financial Accounting Standard (PSAK) No.1, the IAI (Institute of Indonesia Chartered Accountants) defines financial statement as a structured presentation of the financial position and financial performance of an entity. It is created to provide some degree of illustration and figures of an entity's financial statements to the outsiders and external parties such as investors, lenders, creditors, suppliers, customers, employees, government, and societies in general.

The usual and standard financial statements comprise of balance sheet, assets, liabilities, equity, cash flow, revenues and expenses, profit or loss. The analysis on financial statements shows a company's earning power, the past and future cash flows, debt service capability, and the performance and accountability of the management.

Delisting

Based on the Decree of JSX's BOD No.Kep-308/BEJ/07-2004, Rule Number I-I (Concerning Delisting and Relisting of Securities at the Exchange) was issued and became effective as of 19 July 2004. Delisting was defined as the delisting of securities from the securities list listed at the Exchange; as a consequence, such shares are no longer tradable at the Exchange.

Delisting may originate from the companies listed on the Exchange. Some required procedures are the followings: approval from the GMS (General Meeting of Shareholders), the shares have been listed at the Exchange for a minimum period of 5 years, the company must absorb and repurchase the shares outstanding at the price above the current market price or at par, whichever is higher. The offered price must also include a premium of the investment return rate for 2 years. The return is calculated at equals to the initial price of shares multiply multiplied by an average interest rate of the SBI-3 month (Certificate of Bank Indonesia), or other equivalent government bond interest rates that prevails as of the stipulation date of the GMS resolution concerning the Delisting.

The third option was the proper and fair value of the stock set by the appraiser, an independent party that listed at the Bapepam and appointed by the company, or the willingly party approved by the GMS to make the company private again. This procedure is usually coined as the voluntary delisting of the listed company.

Table – Severity and stages of financial distress

Severity	Stage	Description
∇	State 0	Financial stability
⯯	State 1	Omitting or reducing dividend payments more than 40% over the previous year
	State 2	Technical default and default on loan payments
⟱	State 3	Protecting under Chapter X or XI of the Bankruptcy Act
	State 4	Bankruptcy and liquidation

Source: Wen-Ying Cheng, Ender Su, and Sheng-Jung Li, A Financial Distress Pre-Warning Study, 2006.

On the contrary, there is the involuntary delisting, which is termed as the delisting forced by the Exchange. The Exchange found that the company has experienced and suffered some condition(s) and/or an event(s) that may affect its existence and status as a listed and publicly held company. That includes the no-sign of recovery and sufficient progress to positive outcome. A condition that may force the Exchange to delist the company is as the company's shares have been suspended and only traded on the Negotiable Market for at least the last 24 months consecutively.

Bankruptcy

Bankruptcy in Indonesia was set, ruled, and regulated by the Law No.37/2004. It defines bankruptcy as a common confiscation to the whole assets of bankrupted debtor, in which its management and settlement is carried out by the curator supervised by the Supervisory Judge. The legal status gets directly attached, embedded, and stamped with the company as there is a request from the company, the creditors, and/or from the authority to suspend the obligation to settle the outstanding debts.

In regard to the publicly held companies, Bapepam Regulation No.X.K.5 set the company in question to disclose any information in relation to the petition of bankruptcy status. The Regulation was set in Bapepam Decree No.Kep- 46/PM/1998, dated 14 August 1998. In 2017, this regulation was revoked and replaced by the OJK Regulation No.30/POJK.04/2017. Issued on 21 June 2017, it set the share repurchase activity by the public companies.

Bankruptcy Prediction Model

Bankruptcy prediction models (BPM) have been generated and developed through theoretical and mathematical constructs. It begins with traditional statistics techniques (e.g. discriminant analysis and logistic regression), early artificial intelligence models (e.g. artificial neural networks), and later on the machine learning models (that support vector machines, bagging, boosting, random forest).[5] BPM has been developed to provide some substantial improvement upon the accuracy of prediction of companies to fail financially. The names vary according to the focus, intention, and purpose of the study. Some models have been commercially implemented such as KMV[6], EDF[7], LGD[8], Merton debt model (MDM), or elses. Rating agencies are the most common implementers and developers.

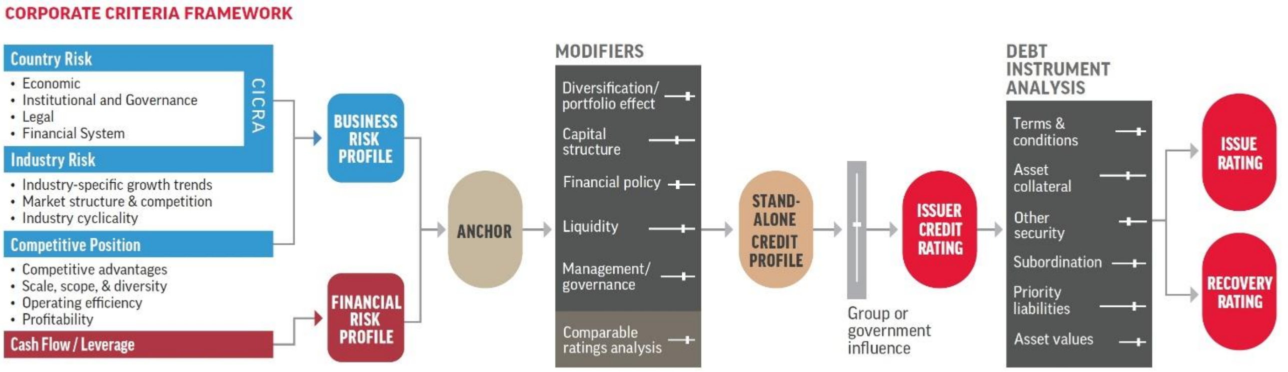

Chart – Score card in S&P rating system
Source: Standard & Poor's, Corporate Ratings Methodology: Transparency. Comparability, S&P's Ratings Services, McGraw Hill Financial, 20140501.

Some empirical results and research findings vary across the selection of models, variables, and the setting of default points (Distance to Default, DtD). Many considered the structural distance to default is timely mannered and to have some back-propagation characteristics. As is the case, to cope with this characteristics, the MLP[9] is considered to be adequate and sufficient to present as a form of neural network analysis and to serve as the simplest and most reliable classifier.

Table – Summary of Strengths and Weaknesses of 5 credit risk measurement methodologies

	S&P's, Moody's, Fitch External Ratings	Moody's RiskCalc Accounting	KMV (DtD, MDM) Structural	JP Morgan CreditMetrics	CreditPortfolioView
Detailed Customer Specific Financial Analysis	H Detailed analysis of financials	H Detailed analysis of financials	L Only debt and asset values	H Based on external ratings which includes detailed financial analysis	H Based on external ratings which includes detailed financial analysis
Industry differentiation	M Industry factors incorporated at time of rating	L Most accounting models do not differentiate between industries	H Based on market fluctuations which will vary with industry risk	M Based on ratings which incorporate industry factors at time of rating	H Have a specific Industry transition adjustment
Fluctuates with market (no time delays)	L No fluctuations with market	L No fluctuations with market	H Highly responsive to market fluctuations	L No fluctuations with market	M Can update industry adjustment factors from time to time
Easy to model	H Ratings readily available to researchers	M Relatively easy to duplicate models on a spreadsheet	L Complex techniques	L Complex techniques	L Complex techniques
Accuracy	High at time of rating Lower as time passes	High at time of rating Lower as time passes	Medium - Does fluctuate with market but can over- or understate depending on market volatility. Calibration can improve accuracy	High at time of rating Lower as time passes	High at time of rating Lower as time passes

Source: David E. Allen and Robert J. Powell, Credit risk measurement methodologies, 2011.
Note: H shows that the criteria in column 1 is met to a high degree, M is moderate and L is low.

The Uses and Abuses of Predictive Analytics

As a tool of predictive analytics, any BPM outcome send mixed signals to the market. The nature of asymmetric information in the market gets easily exploited and manipulated relatively. It is to be up or down. The choice is simply classified and coined as the scenarios.[10] It can be worst case, least case, mainstream or niche, maximum likelihood or least probabilities, certain or uncertain, quadrants or zonation, contrary or minority reports, the changing scenes and themes.

The outcome of any prediction can lead to an inference of point estimates, nomograms, score charts or Likert scale, tree-based methods and/or graphical decision (tree) rules. Any predictive modelling is based on the detection theory, probability to occur, and lastly the classifiers as the ultimate predictor and judge. Some algorithm(s) may have and had been set and accepted as standard of measurement. Some coders familiar with it may have exploited and manipulated the codes, particularly when they get induced and stimulated. In sum, it is a matter of time to finally find and realise that BPM has become a tool that is easily used and abused relatively.[11]

PREVIOUS STUDIES

Studies on BPM Methodologies

The Altman Z-Score has paved the way for further development of corporate bankruptcy prediction models. The option pricing model developed by Black and Scholes in 1973 and Merton in 1974 provided the foundation upon which structural credit models were built. It was KMV the first model to commercialise the structural bankruptcy prediction model in the late 1980s.

The Distance to Default (DtD) is not an empirically created model, but a mathematical conclusion. It is built on some bases and assumptions such as:

1. a company will default on its financial obligations when its assets are worth less than its liabilities.
2. asset returns are log-normally distributed (the Black-Scholes option pricing model).

Table - Predictive Ability by Decade and Method

Period	Lowest Accuracy	Highest Accuracy	Method(s) used to obtain Highest Accuracy
1960's	79%	92%	Univariate DA [Beaver, 1966]
1970's	56%	100%	Linear probability [Meyer and Pifer, 1970] MDA ([Edmister, 1972]; [Santomero and Vinso, 1977])
1980's	20%	100%	MDA ([Marais, 1980]; [Betts and Behoul, 1982]; [El Hennawy and Morris, 1983]; [Izan, 1984]; [Takahashi et al.,1984]; [Frydman et al., 1985]) Recursive partitioning algorithm [Frydman et al., 1985] Neural network [Messier and Hansen, 1988]
1990's	27%	100%	Neural networks ([Guan, 1993]; [Tsukuda and Baba, 1994]; [El-Temtamy, 1995]) Judgmental [Koundinya and Puri, 1992] Cumulative sums [Theodossiou, 1993]
2000's	27%	100%	MDA [Patterson, 2001]

Source: J.L. Bellovary, D.E. Giacomino, and M.D. Akers, A Review of Bankruptcy Prediction Studies, 2007.

The DtD model has been used as the Morningstar's Financial Health Grade for public companies.[12] In 2009, Miller found that DtD has superior ordinal and cardinal bankruptcy prediction power within Morningstar's universe; a more durable bankruptcy signal, but less stable ratings than the Z-Score.[13] The primary performance indicator for both the Z-Score and DtD models is the Accuracy Ratio. The foci of financial research have shifted to seek earlier and more accurate predictions of financial distress. It is to permit intervention prior to an actual distress event, including bankruptcy. The inaccuracy factors may have come from the sampling biases, estimating model form, time period selection, breadth of industry type and distress indicator choice.[14]

The logit and probit models of predictive accuracy are known as the 2 relatively recent models. They are applied to a data set of known high-risk companies. The logit model (of Marchesini, Perdue, and Bryan)[15] was derived from a sample of bond defaulting versus nondefaulting firms. The probit model (of Zmijewski)[16] was derived from a sample of bankrupt versus non-bankrupt industrial firms.

Table – Bankruptcy Prediction Models Typology

Period	Discriminant Analysis	Logit Analysis	Probit Analysis	Neural Networks	Other
1960's	2	0	0	0	1
1970's	22	1	1	0	4
1980's	28	16	3	1	7
1990's	9	16	3	35	11
2000's	2	3	0	4	3
Total	63	36	7	40	26

Source: J.L. Bellovary, D.E. Giacomino, and M.D. Akers, A Review of Bankruptcy Prediction Studies, 2007.
Note: 7 studies applied more than 1 method which could-be considered primary; this makes the number of total studies listed to 165. "Other" methods include linear probability, judgmental, Cusp catastrophe, and Cox proportional hazards models.

Studies on Selected BPM Methodologies

To choose the best method in predicting non-bank companies to be delisted from the IDX during 2003-2007, Hadi and Anggraeni utilised 3 different BPM methods, that is the Altman's, Springate's, and Zmijewski's, and compared the research results. By using the logistic regression, they concluded that the Altman model is the best delisting predictor, followed by the Springate model, but not the Zmijewski model.[17]

Similar finding with different period of observation and analysis, that is between 2007-2011, was also concluded by Savitri in 2012.[18] The studies on 4 bankruptcy predicton models are recapitulated in the following table.

Table – Gap analysis and the studies on 4 bankruptcy prediction models

Pub. Date	Author (s)	Industry	Coys	Period	Significancy Hi	Significancy Lo	Critics
2013	Ni Made Evi Dwi Prihanthini dan Ratna Sari	F&B	10	2008-2012	G	A	Method of inference and acuracy is explained within the analysis.
201412	Yusni Warastuti and Elizabeth Lucky Maretha Sitinjak	Bank	-	2006-2012	S	Z	NO amounts of sample; weighted coefficients of predicting variables; method of inference; R2 is not used as the explaining determinants; which model is the highest predictor. Funny way to make conclusion.
20141210	M. Fakhri Husein and Galuh Tri Pambekti	Daftar Efek Syariah	132	2009-2012	Z	G	NO cut off values, method of inference. -acuracy.
20150313	Lili Syafitri dan Trisnadi Wijaya	F&B	INDF	2009-2013	Z, G	A	NO explanation about Error Type I & II
20150310	Citra Dewi Lestari	Mining & Mining Service	7	2009-2013	G	S	Method of inference and acuracy is explained within the analysis. The amount of sample was mentioned at 35, but only 7 coys were detailed.
20150311	Enny Wahyu Puspita Sari	Transportation	66	2009-2013	A	Z	Least error, NOT net acurate. Good advice
20180831	Patrisius Gerdian Bimawiratma	Manufacturing	8	2009-2013	G	A	★★★★
20150819	Anissa Agustina Rahmadini	Telecommunication s	FREN	2010-2014	A	G	NO alternative of financial distress indicators.
2015	Queenaria Jayanti dan Rustiana	Manufacturing	432	2008-2011	G	S	BPM vs voluntary auditor switching: the relationship and causalities were unclear.
20160108	Andrianti	Delisted coys	12	2010-2014	S	Z	★★
201607	Abolfazl Aminian, Hedayat Mousazade, and Omid Imani Khoshkho	Textile, ceramic, tile	35	2008-2013	G	Z	Misleading conclusion in abstract.
2016	Junaidi	Islamic Bank	10	2010-2014	S, G	Z	Misleading conclusion and inferences.

Table – Gap analysis and the studies on 4 bankruptcy prediction models

Pub. Date	Author (s)	Industry	Coys	Period	Significancy		Critics
201605	Desmawati, Kamaliah, dan Errin Yani Wijaya	Manufacturing	140	2013	-	S	NO method of inference. -acuracy. Z-score in 2013. Actual delisting events in 2015.
20170526	Anis Kurniawati	Jakarta Islamic Index	12	2011-2015	A	Z, G	★
201707	Niken Savitri Primasari	FMCG	29	2012-2015	A	G	NO model estimation, method of inference, -acuracy. Out of the blue: negative net income, dividend payment
2017	Dimas Priambodo	Mining & Mining Service	19	2012-2015	S	Z	★★★
201710	Januri, Eka Nurmala Sari, and Armida Diyanti	Cement	3	2011-2015	Z	A	NO definitions of code, rank, and error type.
2017	Harsono Yoewono and Ridwan Ali	Delisted coys	14	2011-2015	A	Z	★★★★

Note: A: Altman. S: Springate. Z: Zmijewski. G: Grover.

The Altman Z-Score Model

In 1968, Altman developed an intuitive appealing scoring method when traditional ratio analysis was losing favor with academics. By using multiple discriminant analysis (MDA), Altman narrowed a list of 22 potentially significant ratios to 5 that, as a set, proved significant in predicting bankruptcy in his sample of 66 corporations (33 bankruptcies and 33 non-bankruptcies).[19]

The scored figure is noted as Z, whilst the surviving 5 variables are working capital/total asset; retained earnings/total asset; earnings before interest and taxes/total asset; market capitalization/book value of debt; and sales/total asset. The weighted index for the respective 5 variables are 1.2, 1.4, 3.3, 0.64, and 1.05. It is written as $Z = 1.2X1 + 1.4X2 + 3.3X3 + 0.6X4 + 1.05X5$. This model has a cutoff value of $Z \leq 1.81$ (bankrupt), $Z \geq 2.99$ (not bankrupt), $1.81 < Z < 2.99$ (grey zone). Altman later revised the numerator in the 4^{th} variable from market cap to book value of equity, with the book value of debt as the denominator remained unchanged. The score was 95% acurate to predict a company to bankrupt in 1 year, and 72% acurate in 2 years.

Some known facts regarding the Altman Z-Score are as follows:

1. commonly used to gauge the financial health of all companies,
2. the most widely recognised and applied model for predicting financial distress.[20]

In July 2000, Altman[21] published the updated version of 1968 paper and its collaboration to build the ZETA[22] model with Halderman and Narayanan in 1977. Some improvements regarding this new model are as follows:

1. effective in classifying bankrupt companies up to 5 years prior to fail, the sample corporations of retailers and manufacturers.
2. can classify bankruptcy above 90% acuracy 1 year prior and 70% accuracy up to 5 years.
3. outperformed alternative bankruptcy classification strategies in terms of expected cost criteria utilising prior probabilities and explicit cost of error estimates.

The Springate Model

In 1978, Springate utilised 40 Canadian companies as the sample and changed the earnings variable to net profit as the numerator in 2 variables. From 19 ratios examined, only 4 variables were known to be significant. This model has a cutoff value of $Z \leq 0.862$ (bankrupt) and $Z > 0.862$ (not-bankrupt). This model can predict its accuracy of up to 92.5%. The surviving 4 variables are working capital/total assets; net profit before interests and taxes/total assets; net profit before taxes/current liabilities; and sales/total asset. The weighted index for the respective 4 variables are 1.03, 3.07, 0.66, and 0.4. It is written as Z = 1.03X1 + 3.07X2 + 0.66X3 + 0.4X4.

The Zmijewski Model

In 1983, Zmijewski used probit regression as the statistical method and random sampling as sample selection methods.[23] He estimated the coefficients of the models using industrial firms from 1972-1978. Developed with the data of bankrupted companies, the model failed to specify its use in identifying the firms that are likely to go bankrupt or are financially distressed.[24] Instead of using the matched-pair sampling technique that was deemed bias, Zmijewski employed 840 companies as the sample, in which 40 of them were considered has already bankrupted. This model has a cutoff value of $Z \geq 0$ (bankrupt), and $Z < 0$ (not bankrupt). This model can predict its acuracy of up to 94.9%.[25]

The model has a constant value of -4.3 and 3 independent variables. The respective weights are -4.5 for ROA (net profit / total assets) (X1); 5.7 for debt ratio (total liabilities / total assets) (X2), and -0.004 for current ratio (X3). It is written as Z = – 4.3 – 4.5 X1 + 5.7 X2 – 0.004 X3.

Some findings of Grice and Dugan in regard to the Zmijewski model are as follows:

1. sensitive to time periods. The accuracy of the model declined when applied to time periods different from those used to develop the models.
2. not sensitive to industry classifications.
3. not sensitive to financial distress situations.
4. useful for predicting financial distress in general, not just bankruptcy.[26]

The Grover Model

In 2001, Grover and Lavin applied a revised version of the Altman Z-Score models on 80 companies in the service industry, in which the working capital to total asset ratio variable was replaced by the current ratio.[27] However, most articles have cited 70 companies as the sample in the Grover model, without refering any industry and the original (title) of the paper.

The most cited parts are that the model has a constant value of +0.057, 3 independent variables; and a cutoff value of $Z \leq 0.02$ (bankrupt), and $Z > 0.02$ (not bankrupt). The respective weights are 1.65 for working capital to total assets ratio (X1); 3.404 for EBIT to total assets ratio (X2); and -0.016 for ROA (net income / total assets) (X3). It is written as Z = 0.057 + 1.650 X1 + 3.404 X2 – 0.016 X3.

Studies on Selection of Variables

In their paper published in 2006, Pindadoa, Rodrigues, and de la Torre chose the explanatory variables based on a theoretical justification.[28] The parsimonious selection is expected to provide a more stable model in terms of magnitude, sign, significance of the variables, and a maximum level of efficiency. They are EBIT, Financial Expenses (FE), and Retained Earnings (RE). The parsimonious thing in variable selection was defended by Scott in 1981.[29] He argued that the selection of explanatory variables should not be based on sequential processes of elimination of variables according to a maximum prediction capacity criterion. He also added that this method often leads to over-adjusted models with counter-intuitive coefficient signs and results.

In 2007, Bellovary, Giacomino, and Akers made a review of bankruptcy prediction studies from 1930 onward. The most common financial ratios used as the explanatory variables can be found in the attached Table – Factors included in five or more studies. In 2009, du Jardin made an analysis on choosing the most relevant variables. His findings were summarised in attached 2 tables, that is:

1. Criteria used to select explanatory variables to include in bankruptcy models.
2. Typology of explanatory variables commonly used in bankruptcy prediction models in 190 studies.

Research Methodology

The methodology used in this research is quantitative descriptive research. The financial statements of companies delisted involuntarily from the IDX for the period of 2011-2015 are the object in this research. Companies from the financial industries are disqualified in this study. In order to distinguish with the still listed companies, the involuntary delisted companies need to be matched with their pair sample as a comparison. The pair companies should still be listed on the IDX, in the same (sub) industry, having similar asset size relatively, same periods of financial statements published, and profiting for 3 consecutive years.

Table – The delisted companies with their pairs

Delisted companies			Listed companies		Industry - Sub-Industry
Date	Company name	Ticker	Ticker	Company name	
20141127	Asia Natural Resource Tbk	ASIA	AIMS	Akbar Indomakmur Stimec Tbk	Trade, Services and Investment - Wholesale
20150121	Davomas Abadi Tbk	DAVO	ULTJ	Ultra Jaya Milk Industry Tbk	Consumer Goods - Food and Beverages
20131227	Dayaindo Resource International Tbk	KARK	TURI	Tunas Ridean Tbk	Trade, Services and Investment - Wholesale
20110124	New Century Development Tbk	PTRA	LAMI	Lamicitra Nusantara Tbk	Property and Real Estate
20130517	Panca Wiratama Sakti Tbk	PWSI	COWL	Cowell Development	Property and Real Estate
20131031	Surabaya Agung Industry Pulp Tbk	SAIP	SPMA	Suparma Tbk	Basic Industry and Chemicals - Pulp and Paper
20120228	Suryainti Permata Tbk	SIIP	LPCK	Lippo Cikarang Tbk	Property and Real Estate

Research Variables

Table – Operationalization of research variables

Measures	Short	Description	BPM Type			
			A	S	Z	G
Liquidity	WCTA	Working Capital / Total Asset	✓	✓		✓
Profitability	RETA	Retained Earnings / Total Asset	✓			
Profitability	EBITTA	Earnings Before Interest and Taxes / Total Asset	✓	✓		✓
L>A → MV	MVEBVTL	Market Value of Equity / Book Value of Total Liability	✓			
Profitability	STA	Sales / Total Asset	✓	✓		
Profitability	EBTCL	Earnings Before Taxes / Current Liability		✓		
Profitability	NITA	Net Income / Total Asset			✓	✓
Leverage	TLTA	Total Liability / Total Asset			✓	
Liquidity	CACL	Current Asset / Current Liability			✓	

Note: Working Capital = Current Asset- Current Liability. MVE = total of share issued x market share price

Data Processing

Table – Variables used in 4 BPMs (bankruptcy prediction models) compared

	Altman (1968)		Springate (1978)		Zmijewski (1983)		Grover (2001)	
Variable	Weigth	Variable	Weigth	Variable	Weigth	Variable	Weigth	Variable
Constant					-4.3		0.057	
x1	1.2	working capital / TA	1.03	working capital / TA	-0.004	current ratio (liquidity, volatility)	1.65	working capital / TA
x2	1.4	retained earnings / TA	0.66	net profit before taxes / current liabilities				
x3	3.3	EBIT / TA	3.07	net profit before interest and taxes / TA	-4.5	net profit / TA (ROA)	3.404	EBIT / TA
x4	0.6	market cap. / BV of debt		-			-0.016	net income / TA
		BV of equity / BV of debt		-	5.7	total liabilities / TA		
x5	1.05	sales / TA	0.40	sales / TA				
Cut-off								
NB		Z ≥ 2.99		Z > 0.862		Z < 0		Z > 0.02
GZ		1.81 < Z < 2.99						
B		Z ≤ 1.81		Z ≤ 0.862		Z ≥ 0		Z ≤ 0.02

Note: TA: total assets. BV: book value. EBIT: earnings before interest and taxes. NB: not bankrupt, GZ: grey zone. B: bankrupt.

Method of Inference

To classify the prediction is either correct or incorrect with the actual and reality status, the types of errors are distinguished in the Table – Error type of prediction vs actual. ET-I or errors of type I is a condition of a company predicted to be non-bankrupt (NB, non-defaults), but not actually. Therefore, the ET-I is called α-error or false negative proportion.[30] ET-I ⇔ Predicted = NB and Actual = B.

Table – Error type of prediction vs actual

	Prediction		
Actual	B	NB	∑
B	✓	ET-I	100%
NB	ET-II	✓	100%
∑	100%	100%	

Note: B: Bankrupt. NB: Not Bankrupt. ET: Error Type.

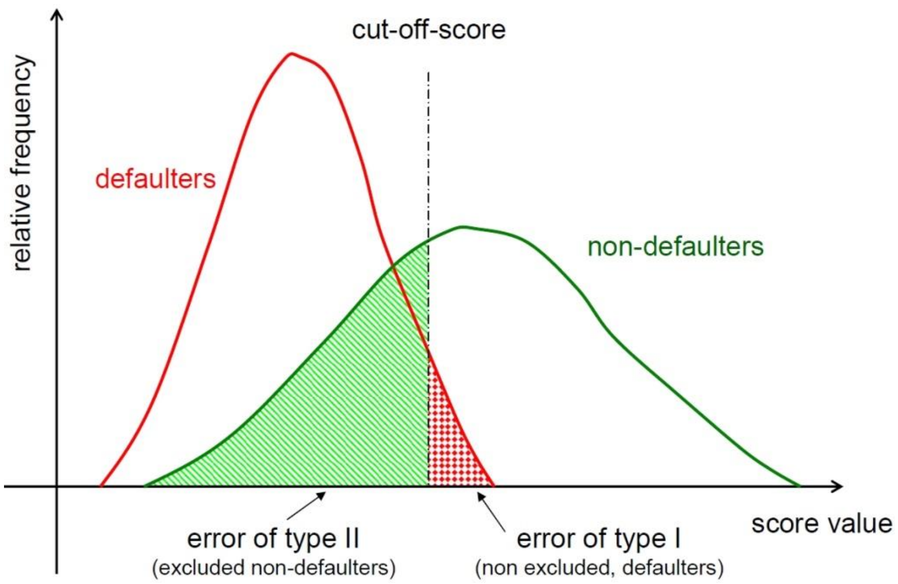

Chart – Classification errors subject to chosen cut-off-score and rating score probability density functions for defaulters and non-defaulters

Source: Martin Bemmann, Improving the Comparability of Insolvency Predictions, 2005.
Note: *cf* (1) "Chart – Probability densities of the rating scores and classification error rate" in Deutsche Bundesbank, Approaches to the validation of internal rating system, 2003, p.70. (2) Dirk Tasche, 'Rating and probability of default validation', 2005, p.37. (3) Bern Engelmann, Evelyn Hayden, and Dirk Tasche, Measuring the Discriminatory Power of Rating Systems, 2003, p.5. (4) Günther Thonabauer (OeNB) and Barbara Nösslinger (FMA), eds, Guidelines on Credit Risk Management. Rating Models and Validation. 2004, p.103.

ET-II or errors of type II is a condition of a company predicted to be bankrupt (B, defaults), but not bankrupt actually. Therefore, the ET-II is called β-error or false positive proportion. ET-II ⇔ Predicted = B and Actual = NB. In short, ET-I is in relation to the number of real defaulters and ET-II is in relation to the number of real non-defaulters. Either one, Bayesian error exists in the examined sample or in the basic population. The so-called hit rate for a condition of ET-I=100% and false alarm rate for ET-II might be somewhat misleading. The average of both error rates, either weighted or not, is a matter of choice to utilise the comprehensive predictive quality measures. The summarised measures are no longer categorial, but can be ordinal or cardinal.

Some conflict of objectives concerning the rates of ET-I or ET-II occur on all rating models. The ET-I may be scored at 0% and ET-II at 100% simulatenously, vice versa. The trade-offs between these two extremes are usually feasible, arbitrarily. The graphical presentation is illustrated in the 'Chart – Classification errors subject to chosen cut-off-score and rating score probability density functions for defaulters and non-defaulters'.

Result

This research tries to find the best BPM (bankruptcy prediction model) method in predicting the bankruptcy amongst the delisted companies from the IDX for the period of 2011-2015. Therefore, ET-I becomes the relevant error type with the acuracy rate. By companies, the 4 BPM can predict the bankrupty (delisting) event of PWSI (Panca Wiratama Sakti), that is with ET-I = 0, but not with the delisting event of KARK (Dayaindo Resource International) whose acuracy rate was 0%.

Table – Bankruptcy prediction by companies and methods on **delisted companies**

IDX Code	BPM				Acuracy	ET-I	ET-II
	A	S	Z	G			
DAVO (2015)	NB	B	NB	B	50%	50%	-
ASIA (2014)	B	B	NB	NB	50%	50%	-
KARK (2013)	GZ	NB	NB	NB	0%	75%	-
SAIP (2013)	B	NB	NB	B	50%	50%	-
PWSI (2013)	B	B	B	B	100%	0%	-
SIIP (2012)	B	B	NB	NB	50%	50%	-
PTRA (2011)	B	B	NB	NB	50%	50%	-
Acuracy	71.43%	71.43%	14.29%	42.86%	50%	46.43%	
GZ	14.29%	-	-	-			
ET-I	14.29%	28.57%	85.71%	57.14%			
ET-II	-	-	-	-			

Note: B: Bankrupt. NB: Not Bankrupt. GZ: Grey Zone. ET: Error Type. A: Altman. S: Springate. Z: Zmijewski. G: Grover.

Table – Bankruptcy prediction by companies and methods on **listed companies**

IDX Code	BPM				Acuracy	ET-I	ET-II
	A	S	Z	G			
ULTJ	NB	NB	NB	NB	100%	-	0%
AIMS	NB	NB	NB	NB	100%	-	0%
TURI	NB	NB	NB	NB	100%	-	0%
SPMA	B	NB	NB	NB	75%	-	25%

COWL	NB	NB	NB	NB	100%	-	0%
LPCK	B	B	NB	NB	50%	-	50%
LAMI	B	B	NB	NB	50%	-	50%
Acuracy	57.14%	71.43%	100.00%	100.00%	82.14%	-	17.86%
GZ	0.00%	0.00%	0.00%	0.00%			
ET-I	-	-	-	-			
ET-II	42.86%	28.57%	0.00%	0.00%			

Note: B: Bankrupt. NB: Not Bankrupt. GZ: Grey Zone. ET: Error Type. A: Altman. S: Springate. Z: Zmijewski. G: Grover.

To verify the acuracy rate of those 4 BPMs in predicting the non-delisting (non-bankruptcy) event, we found that ET-II occurs in 3 companies, that is SPMA (Suparma) by 25%, and LPCK (Lippo Cikarang) and LAMI (Lamicitra Nusantara) by 50% each. On average, the acuracy rate of 4 BPMs in predicting 7 companies NOT to be bankrupt (still-listed) was 82.14%, and coupled with the relevant ET-II at 17.86%.

Conclusion

Apart from acurate prediction of bankruptcy (delisted) and not bankrupt (still-listed) by companies, the highest overall acuracy rate in predicting the bankruptcy (delisting) and NOT-BANKRUPT (still-listed) events occurred in 2 BPMs, that is Springate and Grover. By restricting the prediction only on the bankruptcy (delisting) event, Altman is the best BPM method with an acuracy of 71.43%.

Table – Accuracy and error in prediction in 4 bankruptcy prediction models: Altman, Springate, Zmijewski, Grover

Model	Altman				Springate			Zmijewski			Grover		
Actual	B FD	NB L	Total	GZ	B FD	NB L	Total	B FD	NB L	Total	B FD	NB L	Total
Prediction													
B	5	3	8		5	2	7	1	0	1	3	0	3
NB	1	4	5		2	5	7	6	7	13	4	7	11
GZ	1	0	1										
Correct	5	4	9		5	5	10	1	7	8	3	7	10
Sample	7	7	14		7	7	14	7	7	14	7	7	14
Acuracy	**71.43**	57.14	64.29		**71.43**	71.43	71.43	14.29	100	57.14	42.86	100	71.43
Error	**14.29**	42.86	35.71	7.14	28.57	28.57	28.57	85.71	0	42.86	57.14	0	78.57

Note: B: Bankrupt; NB: Not Bankrupt; GZ: Grey Zone; FD: Forced delisting; L: Listed

Altman becomes the best BPM in predicting the bankruptcy (delisting) event as it has an error rate by 14.29%, lower than the Springate. Although Springate has an acuracy of 71.43%, it has an error rate higher than Altman, that is by 28.57%. Grover and Zmijewski took the third and fourth place respectively in the overall acuracy and in predicting the bankruptcy (delisting) event.

Table – Accuracy rate of bankruptcy prediction by methods

Model name	Accuracy Rate		
	Overall	Delisted	Listed
Altman	64.29%	71.43%	57.14%
Springate	71.43%	71.43%	71.43%
Zmijewski	57.14%	14.29%	100.00%
Grover	71.43%	42.86%	100.00%

In general, bankruptcy prediction models (BPM) do not take the accounts of scale or score of other financial distress indicators. Financial distress indicators should have the ability to classify which stages of distress the companies financially.

Recommendation

BPMs should have encountered with the factors and variables, both directly and indirectly related with the companies. The theoretical and industrial approaches from the perspectives of Porter's Five Forces should have been considered as well.

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Attachments

Table – Criteria used to select explanatory variables to include in bankruptcy models

Popularity in the literature or predictive ability assessed in previous studies	40%
Univariate analysis: t test, F test, correlation test, signs of coefficients	17%
Stepwise search + Wilks's lambda	16%
Stepwise search + likelihood criterion	10%
Genetic algorithms, special algorithms (Relief, Tabu)	6%
Expert	4%
Methods that fit non-linear modelling techniques (such as neural networks)	3%
Other (multiple regression, regression tree, theoretical model)	4%

Source: Pierre du Jardin, Bankruptcy prediction models, 2009.

Table – Typology of explanatory variables commonly used by bankruptcy prediction models (BPM) in 190 studies

Variables	Frequency
Financial ratio (ratio of two financial variables)	93%
Statistical variable (mean, standard deviation, variance, logarithm, factor analysis scores… calculated with ratios or financial variables)	28%
Variation variable (evolution over time of a ratio or a financial variable)	14%
Non-financial variable (any characteristic of a company or its environment other than those related to its financial situation)	13%
Market variable (ratio or variable related to stock price, stock return)	6%
Financial market variable (data coming a balance sheet, an income statement or any financial documents)	5%

Source: Pierre du Jardin, Bankruptcy prediction models, 2009.
Note: The total is greater than 100 as several types of variables may have been used at the same time.

Table – Factors included in five or more studies

Factor/Consideration	Number of Studies
Net income / Total assets	54
Current ratio	51
Working capital / Total assets	45
Retained earnings / Total assets	42
Earnings before interest and taxes / Total assets	35
Sales / Total assets	32
Quick ratio	30
Total debt / Total assets	27
Current assets / Total assets	26
Net income / Net worth	23
Total liabilities / Total assets	19
Cash / Total assets	18
Market value of equity / Book value of total debt	16
Cash flow from operations / Total assets	15
Cash flow from operations / Total liabilities	14
Current liabilities / Total assets	13
Cash flow from operations / Total debt	12
Quick assets / Total assets	11
Current assets / Sales	10
Earnings before interest and taxes / Interest	10
Inventory / Sales	10
Operating income / Total assets	10
Cash flow from operations / Sales	9
Net income / Sales	9
Long-term debt / Total assets	8
Net worth / Total assets	8
Total debt / Net worth	8
Total liabilities / Net worth	8
Cash / Current liabilities	7
Cash flow from operations / Current liabilities	7
Working capital / Sales	7
Capital / Assets	6
Net sales / Total assets	6
Net worth / Total liabilities	6
No-credit interval	6
Total assets (log)	6
Cash flow (using net income) / Debt	5
Cash flow from operations	5
Operating expenses / Operating income	5
Quick assets / Sales	5
Sales / Inventory	5
Working capital / Net worth	5

Source: J.L. Bellovary, D.E. Giacomino, and M.D. Akers, A Review of Bankruptcy Prediction Studies, 2007.

Table – Descriptive statistics of the paired companies

Indicators	N	Delisted coys			Listed coys		
		Min	Max	Mean	Min	Max	Mean
WCTA	21	-1.849	0.496	-0.04285	0.043	0.98	0.32375
RETA	21	-6.897	0.248	-2.08735	0.035	0.522	0.21875
EBITTA	21	-1.146	0.0993	-0.07588	0.005	0.233	0.07911
MVEBVTL	21	0.007	29.216	2.64205	0.149	261.25	15.89708
STA	21	0.001	0.889	0.20689	0.147	5.535	1.35068
EBTCL	21	-8101.992	571.733	-359.166	0.005	5.121	0.52509
NITA	21	-1.074	0.123	-0.07237	0.003	0.175	0.05405
TLTA	21	0.065	2.239	0.78311	0.019	0.866	0.45663
CACL	21	0.152	1004.823	100.7215	1.158	51.413	4.32319
Valid N (listwise)	21						