FDPM after the global price crisis in the coal industry

by Ni Nyoman Sawitri

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Ni Nyoman Sawitri

Universitas Trilogi,
Kalibata, Pancoran, Jakarta,
Selatan 12760, Indonesia
Email: sawitri@trilogi.ac.id
Email: ninyoman.sawitri@gmail.com

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Abstract: Using the Altman model, the Springate model and the Ohlson model, this study aimed to determine if these financial distress prediction models (FDPM) would perform well in forecasting financial distress in the coal industry companies listed on the Indonesia Stock Exchange (IDX) from 2012 to 2016. Furthermore, this study compared which of these models is the most appropriate for predicting financial distress. The results showed that it is possible to use FDPM to forecast financial distress in relation to the coal companies listed on the IDX. The calculations obtained from the three methods show that some coal companies are experiencing significant financial distress, and the Springate model is the most appropriate FDPM for predicting financial distress.

AQ2: Please check if the expansion of 'FEDM' is "financial distress prediction models" or "financial distress prediction methods".

Keywords: Altman *Z*-score model; coal industry; comparison; financial distress; Ohlson model; Springate model.

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Biographical notes: Ni Nyoman Sawitri is a Lecturer of Post-graduate Program. She has published several research papers in leading international journals including *European Research Studies Journal (ERSJ) 2018*, *International Journal of Economic Research (IJER) 2017*, *Journal Nasional Terakreditasi Dikti Jurnal Bisnis Manajemen (JBM) UNPAD 2017*, *Vector Europen Revista de Cercetari Socio-Umanistice, 2016*, *Ikonomika*, *Journal Ekonomi dan Bisnis Islam, 2016* and books including *Fostering Your Child to be a Great Leader in Crisis 2011* and *Prospek dan Srategi Pariwista Nusantara 2010–2015*.

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1 Introduction

The coal industry is one of the industrial sectors that make the largest contribution to a country's economy. In Indonesia, the coal industry contributes approximately 40 billion rupiahs (IDR) annually. The success of commodities in the 2000s resulted in significant profits for coal exporting firms. However, in 2008 the global crisis caused the commodity price to decline rapidly; this was followed by a global coal price crisis that occurred from the 2nd quarter of 2009 to the early part of 2011, during which coal prices rebounded sharply. The current decline experienced by the coal industry in Indonesia is a grave concern for that country's government because commodity exports (mainly for coal and palm oil) represent about 50% of the country's total exports. In 2009, this limited the gross domestic product (GDP) growth to 4.6% (which is still quite good, especially when it is supported by domestic consumption).

In Indonesia, about 125 coal companies in Kalimantan have stopped their operations since August 2015. Consequently, 5000 people lost their livelihood. Several coal companies listed on the Indonesia Stock Exchange (IDX) have also been impacted, as reflected in their negative profits.

Table 1 The 2012–2016 net income of coal companies listed on the IDX

AQ4: Please cite 'Table 1' in text.

Companies	*2012*	*2013*	*2014*	*2015*	*2016*
ADRO	383,307	229,263	183,244	151,003	340,686
ARII	(11,150)	(10,625)	(24,618)	(25,922)	(25,482)
ATPK	(16,740,643)	13,040,702	52,011,645	(161,555,929)	(288,021,991)
BSSR	9,783,589	4,734,891	2,544,925	26,376,125	27,421,577
BUMI	(705,626,038)	(660,103,477)	(448,409,910)	(2,185,480,487)	120,255,710
BYAN	54,946,917	(55,216,028)	(189,017,198)	(81,798,054)	18,015,433
DEWA	(41,424,551)	(51,744,184)	83,066	465,754	549,890
DOID	(15,255,620)	(29,369,973)	16,305,961	(8,306,595)	37,089,185
GEMS	178,934,525,099	170,268,433,795	10,818,904	2,088,781	34,988,248
HRUM	161,670,125	49,580,100	2,628,331	(18,996,829)	17,979,743
ITMG	432,043	230,484	200,971	63,107	130,709
KKGI	23,589,823	17,240,350	8,006,072	5,672,213	9,472,864
MYOH	36,149,791	173,784,084	22,580,872	24,732,565	21,258,922
PKPK	(9,064,094)	333,679	(26,919,603)	(61,713,327)	(13,670,278)
PTBA	2,909,421	1,854,281	2,019,214	2,037,111	2,024,405
PTRO	49,122	17,308	2,356	(12,691)	(7,825)
SMMT	15,119,883,204	19,337,808,450	(3,502,096,211)	(60,578,867,106)	(18,281,061,731)
TOBA	11,932,682	34,603,793	35,548,674	25,724,095	14,586,772

Source: idx.co.id

The declining condition of coal companies in Indonesia has created special concerns for the Indonesian government. Predicting firm financial distress is a very important task for companies and governments (Avramov et al., 2013; Jones and Hensher, 2004).

An organisation's financial problems are a concern for all stakeholders; this impacts an organisation's ability to make decisions, meet its objectives and provide services.

Delisting is the removal of a company from a stock exchange list due to its inability to satisfy the requirements of the exchange. When a company goes from being a public entity to being a private entity, it is delisted by the exchange. Delisting also occurs if companies listed in a stock exchange are unable to satisfy the applicable regulations meet the exchange's normal financial health requirements (Avramov et al., 2013; Christensen et al., 2016).

When a company is under financial distress, its cash flow is insufficient so it cannot pay its liabilities (such as debts or interests), and it is forced to take corrective actions (Li, 2012; Manab et al., 2015; Sun and Li, 2012; Omelka et al., 2013; Brahmana, 2007; Frydman et al., 1985) stated that financial default is defined as an insolvency that distinguishes between cash flow and stock basis. A company declares bankruptcy when its financial condition is unhealthy due to economic, internal or external factors (Ko et al., 2017; Salmar, 2018). Coal companies should establish a structure and implement a variety of strategies to understand the early warning signals related to financial distress (Laulajainen, 2000).

Various financial distress prediction methods (FDPM) and bankruptcy analysis tools are available, but the most widely used tools are the Springate model, the Ohlson model and the Altman model. These analytical tools have a high level of accuracy in predicting the potential bankruptcy of a company. Omelka et al. (2013) compare the financial distress model then Chen et al. (1995) and Dolejšová (2015) stated that to obtain appropriate results, it is best to use more than two prediction models. Lee et al. (2014) tested the Ohlson model and found that it can forecast future stock price movement with greater accuracy than any other prediction method. Lee et al. (2014) findings are supported by Lundholm (1995). Dolejšová (2015) and Matturungan et al. (2017) confirmed that the Altman and Springate models had 80% accuracy for predicting a company's financial status. This result was also supported by Syamni et al. (2018). Ghodrati and Moghaddam (2012) showed that the Springate model is better able to predict financial distress than other models. This result was also supported by Husein and Pambekti (2015), Alexakis (2008).

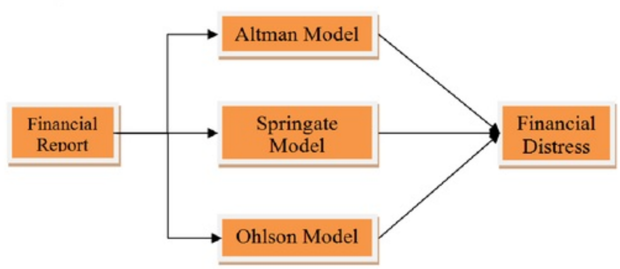
In the paper of "The creation of bankruptcy prediction methods using Springate and SAF models", Aghajani and Jouzbarkand (2012), Lee and Choi (2013) showed that, when the Springate model is combined with multiple discriminant analysis (MDA), it predicts bankruptcy with an accuracy rate of 90%, one year before bankruptcy is declared; the accuracy rate is 82% two years before the event occurs. The Multinomial Logit model is utilised to predict bankruptcy in manufacturing companies in Indonesia (Suteja et al., 2017), and the simple analysis of failure (SAF) method with logistic regression analysis predicts bankruptcy with an accuracy rate of 88.5% for a period of one year before bankruptcy is declared; the accuracy rate is 79% two years before the event occurs. Dewi and Hadri (2017), Jubaedah et al. (2016), Syamni et al. (2018) showed that there are differences between the Altman model and the Altman *Z*-score, the Altman model with the Springate model and the Altman model and the Zmijewski model. The Altman model is the most suitable prediction method applied to a food and beverage company because the accuracy is higher for this method than the other methods (Alexakis, 2008). Prusak (2018) reported that the average Altman *Z*-score and the Springate and Zmijewski methods had a similar ability to predict the potential for declaring bankruptcy. Aaron et al. (2017), Husein and Pambekti (2015) stated that it is possible to predict potential bankruptcy using three methods, the Altman *Z*-score, the Springate model and the Zmijewski model. Matturungan et al. (2017) mentioned that the Altman method is the most appropriate bankruptcy predictor for food and beverage companies listed on the IDX. This result is supported by Husein and Pambekti (2015), Karaca and Ercan (2017), Nandhini et al. (2012), Oz and Simga-Mugan (2018), Sinarti and Sembiring (2015) and Zhou et al. (2015). Janson et al. (2016) and Kumar and Kumar (2012) showed that the O-score from the Ohlson model is the best bankruptcy predictor for the Texmo Industries because it uses nine predictable components of bankruptcy, including inflation, short-term and long-term liquidity and profit before and after tax. This result is supported by Ghodrati and Moghaddam (2012), Oude Avenhuis (2013), Poklepovic et al. (2013) and Syamni et al. (2018).

2 Theoretical framework

The present study will use a company's financial report as the data source to consider its level of financial distress. The numbers in the financial report will be used to calculate the financial ratios, which will then be included in the calculations for each of the three tested models to determine a company's financial distress. The present study will utilise financial reports of the companies in the coal industry that are listed on the IDX from 2012 to 2016 as the data source. The numbers in the financial reports will be utilised to calculate the financial ratios, which will then be included in the calculations of each model.

Figure 1 Conceptual framework used in the research study (see online version for colours)

AQ5: Please cite 'Figure 1' in text.



Financial reports are able to provide information regarding the possibility of corporate financial distress. The models that are utilised in numerous studies are the Altman, Springate and Ohlson models. In this study, researchers aim to determine which of the three models is the best at predicting financial distress. The criteria are on the basis of the "Accuracy and Error Level Test".

3 Data, methods and results

Population in this research study is the coal companies listed in the IDX for 2012–2016. Purposive sampling was used to select the 18 coal companies that comprised the sample. The data used in this study consist of secondary data obtained from the official website of

IDX in the form of annual financial reports (have been audited) by accessing the website: www.idx.co.id. The Springate model, the Ohlson model and the Altman model are the variables that are analysed in this study. Secondary data analysis methods were used to analyse the financial statements associated with the companies studied; the findings of that analysis were used to calculate a formula for each of the three studied models.

3.1 Altman model

1. Working capital-to-total asset ratio
2. Retained earnings-to-total assets ratio
3. Earning power of the total investment ratio
4. Debt-to-equity ratio
5. Total asset turnover

Altman method:

$$Z = 0.717Z_1 + 0.874Z_2 + 3.107Z_3 + 0.420Z_4 + 0.998Z_5$$

Information:

Z_1 = working capital/total asset

Z_2 = retained earnings/total assets

Z_3 = earnings before interest and taxes/total asset

Z_4 = book value of equity/book value of debt

Z_5 = sales/total asset.

3.2 Springate model

1. Working capital-to-total asset ratio
2. Earning power of the total investment ratio
3. Net profit before tax-to-current liabilities ratio
4. Total asset turnover

Springate method:

$$S = 1.03A + 3.07B + 0.66C + 0.4D$$

Information:

A = working capital/total asset

B = net profit before interest and taxes/total asset

C = net profit before taxes/current liabilities

S = sales/total assets.

3.3 Ohlson model

1 Log (total assets/GNP price-level index)

2 Debt ratio

3 Working capital-to-total asset ratio

4 Current liabilities-to-current asset ratio

5 Score 1 if total liabilities > total assets; 0 if otherwise

6 Return on assets

7 Cash flow-to-total asset ratio

8 Score 1 if net income is negative; 0 if otherwise

9 (*NIt* – *NIt*–1)/(*NIt* + *NIt*–1)

Ohlson method:

$$0 = -1.32 - 0.407Y_1 + 6.032Y_2 + 0.0757Y_4 - 2.37Y_5 - 1.83Y_6 + 0.285Y_7 - 1.72Y_8 - 0.521Y_9$$

Information:

Y_1 = Log (total assets/GNP price-level index)

Y_2 = Total liabilities/total assets

Y_3 = Working capital/total assets

Y_4 = Current liabilities/current assets

Y_5 = 1 if total liabilities > total assets; 0 if otherwise

Y_6 = Net income/total assets

Y_7 = Cash flow from operations/total liabilities

Y_8 = 1 if net income is negative; 0 if otherwise

Y_9 = (*NIt* – *NIt*–1)/(*NIt* + *NIt*–1)

3.4 Accuracy level tests

The best financial distress prediction method can be seen at the highest accuracy level. The accuracy level shows the percentage of the method in predicting the right company condition, based on the total sample.

$$\text{Accuracy level} = \frac{\text{Total Right Prediction}}{\text{Total Sample}} \times 100\%$$

4 Results and discussion

4.1 Financial distress analysis

4.1.1 Analysis of the Altman model

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The Altman model categorises a company in a state of bankruptcy based on the *Z*-score. If the *Z*-score is less than or equal to –0.02 (Z – 0.02), the company is said to have no bankruptcy potential. If the *Z*-score is greater than or equal to 0.01 (Z_0, 01), the company is said to have bankruptcy potential. The Altman model analysis results are shown in Table 2.

Table 2 Analysis results for the Altman model

Company code	*2012 X score*		*2013 X score*		*2014 X score*		*2015 X score*		*2016 X score*	
ADRO	1.48	GA	1.33	GA	1.84	GA	1.44	GA	1.57	GA
ARII	0.61	FD	0.73	FD	–0.08	FD	–0.33	FD	–0.15	FD
ATPK	1.85	GA	2.09	GA	3.05	HA	2.35	GA	–0.22	FD
BSSR	2.61	GA	2.28	GA	2.68	GA	3.84	HA	3.85	HA
BUMI	0.87	FD	0.38	FD	–0.64	FD	–2.05	FD	–1.15	FD
BYAN	1.43	GA	1.27	GA	0.9	FD	1.37	GA	1.99	GA
DEWA	1.66	GA	0.99	FD	1.33	GA	1.3	GA	1.22	FD
DOID	1.1	FD	1	FD	1.19	FD	1.28	GA	1.35	GA
GEMS	4.38	HA	3.08	HA	4.62	HA	3.04	HA	3.53	HA
HRUM	6.06	HA	5.45	HA	4.15	HA	5.58	HA	4.3	HA
ITMG	4.65	HA	4.19	HA	3.73	HA	3.72	HA	3.8	HA
KKGI	17.9	HA	14.77	HA	3.74	HA	4.43	HA	5.29	HA
MYOH	2	GA	2.48	GA	3.08	HA	3.33	HA	3.92	HA
PKPK	4.94	HA	8.52	HA	0.75	FD	–0.36	FD	–0.01	FD
PTBA	3.89	HA	3.51	HA	2.98	HA	2.73	GA	2.71	GA
PTRO	1.92	GA	1.9	GA	1.88	GA	1.38	GA	1.3	GA
SMMT	5.79	HA	1.52	GA	0.79	FD	0.49	FD	0.59	FD
TOBA	2.31	GA	2.46	GA	3.06	HA	2.71	GA	2.28	GA

Remarks: FD = *Financial Distress*, GA = Grey Area, HA = Healthy Area.

Source: Processed data

The Altman model was able to predict that, in 2012, three companies were classified as experiencing financial distress, eight companies were classified as being in a grey area and seven companies were classified as healthy. In 2013, four companies were classified as experiencing financial distress, eight companies were classified as being in the grey area and six companies were classified as healthy. In 2014, six companies were classified as having financial distress, four companies were classified as being in the grey area and eight companies were classified as healthy. In 2015, four companies were classified as having financial distress, eight companies were classified as being in the grey area and six companies were classified as healthy. In 2016, six companies were classified as having financial distress, six companies were classified as being in the grey area and six companies were classified as healthy.

For five consecutive years (2012–2016), two companies, Atlas Resources and Bumi Resources were classified as having financial distress. In this method, as a company's *Z*-score decreases, its financial condition worsens. Both companies experienced financial distress, so their working capital value and retained earnings were negative. The Z_1 score for the working capital-to-total asset ratio and the Z_2 score for the retained earnings-to-total asset ratio were also negative. This shows that when a company's working capital and profits are small, it is experiencing financial distress based on its Altman *Z*-score.

4.1.2 Analysis of the Springate model

The Springate model uses four financial ratios to predict the potential for financial difficulties within an enterprise. This method can be used to predict bankruptcy with an accuracy rate of 92.5%. If $S > 0.862$, then the company is classified as healthy. If $S < 0.862$, then the company is classified as potentially having to declare bankruptcy. The Springate model analysis results are shown in Table 3.

Table 3 Analysis results for the Springate model

Company code	*2012* *S score*		*2013* *S score*		*2014* *S score*		*2015* *S score*		*2016* *S score*	
ADRO	1.55	HA	1.2	HA	1.09	HA	1.23	HA	1.47	HA
ARII	–0.07	FD	–0.14	FD	–0.41	FD	–0.52	FD	–0.6	FD
ATPK	1.42	HA	0.42	FD	1.08	HA	–0.57	FD	–1.38	FD
BSSR	1.6	HA	1.09	HA	1.55	HA	2.6	HA	2.49	HA
BUMI	0.37	FD	0.05	FD	–0.86	FD	–1.8	FD	–0.07	FD
BYAN	0.97	HA	0.71	HA	0.24	FD	0.31	FD	1.43	HA
DEWA	0.46	FD	0.1	FD	0.88	HA	0.83	HA	0.78	HA
DOID	0.89	HA	0.77	HA	1.22	HA	1.02	HA	1.25	HA
GEMS	2.13	HA	1.74	HA	2.33	HA	1.62	HA	2.69	HA
HRUM	4.94	HA	3.29	HA	1.82	HA	0.74	HA	1.77	HA
ITMG	3.84	HA	3.05	HA	2.52	HA	2.19	HA	2.46	HA
KKGI	11.52	HA	9.08	HA	2.18	HA	2.13	HA	2.99	HA
MYOH	1.77	HA	2.2	HA	2.71	HA	2.88	HA	3.48	HA
PKPK	0.91	HA	0.85	HA	0.11	FD	–0.95	FD	–0.38	FD
PTBA	4.06	HA	2.71	HA	2.15	HA	1.77	HA	1.71	HA
PTRO	1.52	HA	1.25	HA	1.23	HA	0.57	FD	0.39	FD
SMMT	0.83	HA	0.83	HA	0.03	FD	–0.38	FD	–0.22	FD
TOBA	1.72	HA	1.91	HA	2.61	HA	2.15	HA	1.54	HA

Remarks: FD = *Financial Distress*, GA = Grey Area, HA = Healthy Area.

Source: Processed data

As seen, the Springate model was able to predict that, in 2012, three companies were classified as experiencing financial distress and 15 companies were classified as healthy. In 2013, four companies were classified as having financial distress and 14 companies were healthy. In 2014, five companies were classified as having financial distress and 13 companies were healthy. In 2015, seven 7 companies were classified as experiencing financial distress and 11 companies were healthy. In 2016, six companies were classified as having financial distress and 12 companies were healthy.

For five consecutive years (2012–2016), two companies, Atlas Resources and Bumi Resources were classified as having financial distress. In this method, as a company's *S* score decreases, its financial distress worsens. Both companies experienced financial distress because their working capital value and net profit before tax were negative. Their working capital-to-total asset ratio and their net profit before tax-to-current liabilities ratio were also negative. This shows that when a company has a small amount of working capital and low before tax profit, it is experiencing financial distress.

Table 4 Analysis results for the Ohlson model

Company code	*2012 O Score*		*2013 O Score*		*2014 O Score*		*2015 O Score*		*2016 O Score*	
ADRO	–1.33	HA	–1.49	HA	–1.49	HA	–1.69	HA	–1.14	HA
ARII	1.72	FD	1.07	FD	1.07	FD	2.3	FD	2.94	FD
ATPK	5.01	FD	–3.25	HA	–3.25	HA	7.45	FD	6.84	FD
BSSR	–2.64	HA	–2.17	HA	–2.17	HA	–1.36	HA	–2.71	HA
BUMI	1.95	FD	2.41	FD	2.41	FD	9.6	FD	0.2	HA
BYAN	–2.13	HA	408.81	FD	408.81	FD	–1.5	HA	–3.64	HA
DEWA	–1.28	HA	–1.57	HA	–1.57	HA	–1.81	HA	–2.32	HA
DOID	–0.42	HA	–0.25	HA	–0.25	HA	–3.92	HA	–0.01	HA
GEMS	4.65	FD	5.39	FD	5.39	FD	0.6	FD	2.31	FD
HRUM	–2.28	HA	–3	HA	–3	HA	–0.86	HA	–39.2	HA
ITMG	–1.6	HA	–2.19	HA	–2.19	HA	–2.57	HA	–1.83	HA
KKGI	–1.73	HA	–1.59	HA	–1.59	HA	–3.58	HA	–3.29	HA
MYOH	5.91	FD	6.09	FD	6.09	FD	4.53	FD	4.01	FD
PKPK	5.44	FD	3.11	FD	3.11	FD	5.94	FD	4.92	FD
PTBA	6.18	FD	5.94	FD	5.94	FD	6.42	FD	6.35	FD
PTRO	–1.99	HA	–2.56	HA	–2.56	HA	0.07	HA	–1.11	HA
SMMT	4.19	FD	4.3	FD	4.3	FD	7.03	FD	7.93	FD
TOBA	–3.06	HA	–1.44	HA	–1.44	HA	–2.71	HA	–2.69	HA

Remarks: FD = *Financial Distress*, GA = Grey Area, HA = Healthy Area.

Source: Processed data

4.1.3 *Analysis of the Ohlson method*

Ohlson built three models; each consists of the same variables. The Ohlson method has nine variables consisting of several financial ratios. Ohlson (1980) stated that this method has an optimal cut-off point value (*O*-score) of 0.38. Ohlson chose this cut-off value because it makes it possible to minimise the number of errors. An *O*-score > 0.38 is an indicator that a company is or will be experiencing financial distress. Conversely, if a company's *O*-score < 0.38, it is predicted that it will not experience financial distress. The Ohlson analysis results are shown in Table 4.

As seen in Table 4, the Ohlson model predicted that, in 2012, eight companies were classified as experiencing financial distress and seven companies were classified as healthy. In 2013, eight companies were classified as having financial distress and 10 companies were healthy. In 2014, eight companies were classified as having financial distress and 10 companies were healthy. In 2015, eight companies were classified as having financial distress and 10 companies were healthy. In 2016, seven companies were classified as having financial distress and 11 companies were healthy.

For five consecutive years (2012–2016), six companies, Atlas Resources, Golden Energy Mines, Myoh Technology, Perdana Karya Perkasa, Bukit Asam Coal Mine and Golden Eagle Energy, were experiencing financial distress. The greater a company's *O*-score, the worse its financial condition. For the six companies experiencing financial distress during that period, the gross national product (GNP) price level index, total assets, total liabilities, current liabilities and current assets were all positive. This indicates that when a company's GNP price level, assets and debts are either normal or excessive, it will experience financial distress based on the Ohlson calculation formula.

4.2 *Accuracy and error level tests*

4.2.1 *The Altman model*

Table 6 shows the results of the comparison of the prediction methods and the status of the sample companies using the Altman model.

Calculation:

$$\text{Accuracy Level} = \frac{\text{Total Right Prediction}}{\text{Total Sample}} \times 100\% = \frac{7}{18} \times 100\% = 39\%$$

$$\text{Error Level} = \frac{\text{Total Error}}{\text{Total Sample}} \times 100\% = \frac{3}{18} \times 100\% = 17\%$$

$$\text{Grey Area} = \frac{\text{Total Grey Area}}{\text{Total Sample}} \times 100\% = \frac{8}{18} \times 100\% = 44\%$$

Based on the analysis of 18 companies (Table 5), the Altman *Z*-score method has an accuracy of 39%. As shown in Table 6, the accuracy of the Altman *Z*-score prediction method can be seen from the seven companies in which the model correctly predicted financial distress. The Altman model predictions consider seven companies that are predictably healthy and in fact do not experience delisting. The Altman *Z*-score method has an error rate of 17%. This error rate can be seen from three companies for whom the predictions were not accurate; in fact, while the model predicted that those companies would be financially distressed or declare bankruptcy, none of them was delisted.

For the grey area results (Table 6), eight companies did not go bankrupt. However, the grey area category is not included in the calculation of the accuracy or error rates because this category cannot determine whether or not a company has the potential to go bankrupt or has declared bankruptcy.

Table 5 Average recapitulation of financial distress results for coal companies in the Indonesian stock exchange, 2012–2016

S. No.	*Company code*	*Altman model*		*Springate model*		*Ohlson model*	
1	ADRO	1.53	GA	1.31	HA	–1.41	HA
2	ARII	0.15	FD	–0.35	FD	1.79	FD
3	ATPK	1.82	GA	0.19	FD	4.25	FD
4	BSSR	3.05	HA	1.87	HA	–2.28	HA
5	BUMI	–0.52	FD	–0.46	FD	3.96	FD
6	BYAN	1.39	GA	0.73	HA	80.36	FD
7	DEWA	1.3	GA	0.61	FD	–2.11	HA
8	DOID	1.18	FD	1.03	HA	–1.97	HA
9	GEMS	3.73	HA	2.1	HA	64.08	FD
10	HRUM	5.1	HA	2.51	HA	–9.79	HA
11	ITMG	4.02	HA	2.81	HA	–2.01	HA
12	KKGI	9.23	HA	5.58	HA	–2.75	HA
13	MYOH	2.96	HA	2.61	HA	5.35	FD
14	PKPK	2.77	GA	0.11	FD	5.23	FD
15	PTBA	3.16	HA	2.48	HA	6.25	FD
16	PTRO	1.68	GA	0.99	HA	–1.71	HA
17	SMMT	1.84	GA	0.22	FD	5.55	FD
18	TOBA	2.56	GA	1.98	HA	–2.45	HA

Remarks: FD = *Financial Distress*, GA = Grey Area, HA = Healthy Area.

Source: Processed data

Table 6 Accuracy and error levels for the Altman model

	Altman Z-score prediction results			
	Healthy area	*Grey area*	*Financial distress*	*Total*
Number of listed companies	7	8	3	18
Accuracy level			39%	
Error level			17%	
Grey area			44%	

Source: Data processed

4.2.2 The Springate model

Table 7 shows the results of the comparison of the prediction methods and the status of the sample companies using the Springate model.

Calculation:

$$\text{Accuracy Level} = \frac{\text{Total Right Prediction}}{\text{Total Sample}} \times 100\% = \frac{12}{18} \times 100\% = 67\%$$

$$\text{Error Level} = \frac{\text{Total Error}}{\text{Total Sample}} \times 100\% = \frac{6}{18} \times 100\% = 33\%$$

Based on the analysis of 18 companies (Table 5), the Springate model has an accuracy rate of 67%. As seen in Table 7, the Springate model accurately predicted that 12 companies were healthy; in fact, they did not experience delisting. The Springate model has an error rate of 33%; this can be seen from the six companies for whom the predictions were not accurate; the Springate model predicted that six companies would experience financial distress or declare bankruptcy; however, none of those companies was delisted.

Table 7 Accuracy and error levels for the Springate model

	Springate prediction results		*Total*
	Healthy area	*Financial distress*	
Number of listed companies	12	6	18
Accuracy level	67%		
Error level	33%		

Source: Processed data

Table 8 Accuracy and error levels for the Ohlson model

	Ohlson prediction results		*Total*
	Healthy area	*Financial distress*	
Number of listed companies	9	9	18
Accuracy level	50%		
Error level	50%		

Source: Processed data

4.2.3 The Ohlson model

Table 8 shows the results of the comparison of the prediction methods and the status of the sample companies using the Ohlson model.

Calculation:

$$\text{Accuracy Level} = \frac{\text{Total Right Prediction}}{\text{Total Sample}} \times 100\% = \frac{9}{18} \times 100\% = 50\%$$

$$\text{Error Level} = \frac{\text{Total Error}}{\text{Total Sample}} \times 100\% = \frac{9}{18} \times 100\% = 50\%$$

As seen in Table 8, based on the analysis of 18 companies (Table 5), the Ohlson model has an accuracy rate of 50%. The Ohlson model was able to accurately predict that nine companies were healthy and did not experience delisting. The Ohlson model has an error rate of 50%; this can be seen from the nine companies that were inaccurately predicted to have financial distress or to have declared bankruptcy; however, none of those companies was delisted.

4.2.4 Comparison of the precision of the predictions using the Springate, Ohlson and Altman models

Comparison based on a level of accuracy from each model. The accuracy result is shown in Table 9.

Table 9 Prediction comparison of the three models

Prediction method	*Accuracy rate* (%)
Springate	67
Ohlson	50
Altman	39

Source: Processed data

As seen in Table 9, the Springate model had the highest accuracy rate (67%), followed by the Ohlson model with an accuracy rate of 50% and the Altman model had the lowest accurate rate (39%). Thus, the Springate model is the most accurate method for analysing financial distress in the coal industry. This finding agrees with the results reported by Aghajani and Jouzbarkand (2012), which found that the Springate model combined with MDA had a bankruptcy prediction accuracy rate of 90% one year before declaring bankruptcy and an accuracy rate of 82% two years before bankruptcy occurred. The SAF method with logistic regression analysis predicts bankruptcy with an accuracy rate of 88.5% within one year of declaring bankruptcy and an accuracy rate of 79% two years before bankruptcy occurs. The Springate model is the best model because of having the highest accuracy rate.

Based on this result, the best model to predict financial distress is the Springate Model, because this model has the best precision result. This will affect the company response as an early warning system, so the company can anticipate bankruptcy faster. Because of the precision result of Springate model, the Investor also can make faster and better decision to save their investment. In contrary this result can't be generalised in different place and condition, so to choose the best model should do the whole test of few models.

5 Concluding remarks

The results of this research study show that FDPM can be used to forecast financial distress and predict bankruptcy for the coal companies listed on the IDX. The calculation results from the three models show that some of the coal companies are considered to be experiencing financial distress. The Springate model can predict financial distress with

67% accuracy, followed by the Ohlson model with 50% accuracy and then Altman model with 39% accuracy. Therefore, the Springate model is the most appropriate method for predicting financial distress and bankruptcy in the coal commodity sector in Indonesia.

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