Predicting financial distress in an emerging market: corporate actions, accounting ratios, or both?

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Abstract: This paper investigates the utility of corporate actions in predicting financial distress in the context of an emerging country: Malaysia. Recognising the dominance of historical accounting ratios in distress prediction models, we set out to test if employing more current information in the form of corporate action fares better. To this end, we employ three logistic regression models on data from 54 firms and find that corporate actions, on a stand-alone basis, outperform pure accounting ratios and a pooled combination of both. The most significant corporate actions are frequency of capital issuance and shuffling of audit committees. These findings are novel for Malaysia and relatively scarce in broader empirical literature. Meanwhile, among the accounting ratios, working capital and sales volumes emerge as significant predictors of distress, both of which have extensive empirical precedents.

Keywords: financial distress; emerging market; bankruptcy; Malaysia; accounting ratio.

Reference to this paper should be made as follows: Mohamad, A., Azad, M. and Sifat, I.M. (2021) 'Predicting financial distress in an emerging market: corporate actions, accounting ratios, or both?', *American J. Finance and Accounting*, Vol. 6, Nos. 3/4, pp.314–331.

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1 Introduction

In this paper, we seek answers to two questions with important consequences in finance, accounting, and risk management. First, do corporate actions possess information in predicting bankruptcy among financially distressed firms? Second, do corporate actions outperform traditional accounting ratios in predictive modelling? Prior research concerning modelling financial distress has been explored largely through financial and accounting ratios. Since financial distress is followed by either bankruptcy or recovery of the company, earliest research on the topic relied on bankruptcy prediction models formulated by Altman (1968). Later, researchers used distress prediction models to assess credit worthiness, prudent portfolio management, and to appraise external and internal performances of a firm. As it stands, bankruptcy risk analysis and financial distress analysis have globally relied on ratios derived from the companies' financial statements. These ratios reflect the historical and non-current financial position of the company. Less attention is paid to publicly available non-financial information such as various corporate actions taken by public listed companies. Researchers in related sub-disciplines have found that non-financial information such as performance of the CEO, changes in shareholder base, and a change in company can have informational content on the future financial performances of a firm. Given that such information is more current and usually publicly available, under-utilisation of such information in distress modelling research is somewhat surprising. This paper is an attempt to address this gap.

We aim to contribute to the research gap identified above by studying the case of public listed companies on the Main Board of Bursa Malaysia (Malaysian Stock Exchange) classified as facing financially distressed. Malaysian companies facing financial distress are required to follow a certain set of standards regarding disclosure and company reorganisation. The regulation governing the financially distressed companies is Practice Note 17 (PN17). PN17 specifically points out factors that can lead a company to being classified as financially distressed. The factors are:

a If the shareholders' equity falls below 25% of the total assets, or if the shareholders' equity falls below RM 40 million.

b If receivers or managers have been appointed to oversee 50% of the company's assets.

c If the company wound up of subsidiary with 50% of the assets of the consolidated group.

d When the auditors opine adversely regarding the financial statements for the last year.

e When the auditors question the ability of the company as a going concern.

f If a default occurs in debt payments.

By studying these companies, we try to predict financial distress before it occurs using the corporate actions of these companies. Also, we compare their performances against traditional ratio-based metrics. Our approach differs from previous studies, who have mainly employed different statistical methods such as logistic regression, discriminant analysis, and neural networks on accounting ratios alone for financial distress prediction. In the case of Malaysia, the literature on listed companies' financial prediction analysis is particularly scarce. The few extant works focus on the Altman z-score and market-based variables. Those findings, too, suffer from weak generalisability. Yet, industry practitioners, risk managers, and investors require greater precision in financial distress modelling and higher classification rates. This is because the ability to predict financial distress can have a very significant impact on the credit analysis of corporations as well as in investment analysis. In addition, the ability to predict financial distress can help investors reduce risk, especially investors in fixed income assets such as bonds. This makes our research important for investors and risk managers who need more frequent and updated information to better predict financial distress.

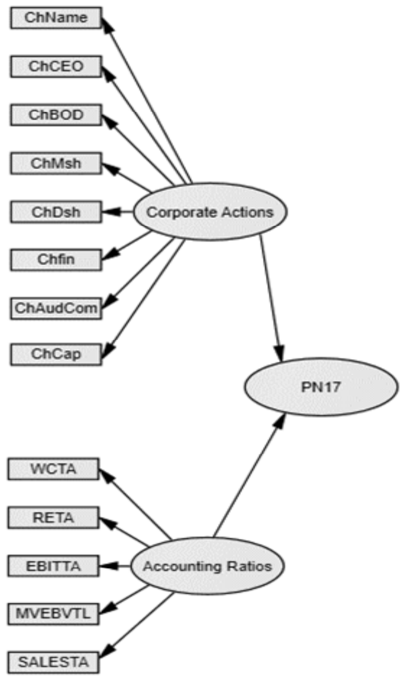
We claim three contributions in this study. First, this research helps improve the existing theoretical approaches on financial distress models and bankruptcy prediction models by combining accounting ratios and corporate actions into the same predictive framework. Second, in this study we develop a novel model which uses more current information than accounting ratios, which are published once or at-best quarterly in a year. Although many researchers use accounting information, this information has the drawback of not being available as it occurs. For example, corporate financial reports are usually published once a year or in every quarter. Contrarily, the relative immediacy of news on corporate actions makes it more attractive, which is usually available in most countries through the stock exchange websites, media outlets, and even social media feeds such as Twitter. Therefore, the ability to incorporate most recent information into financial distress models has the potential to improve its practical use in investment analysis and credit analysis. This aids in devising prompt reaction to risk and adjustment of exposure accordingly. Third, we compare the predictive ability of accounting ratios and corporate actions to test which predictors can forecast financial distress more accurately.

2 Review of literature

Researchers have experimented with a broad spectrum of variables in distress modelling of firms. To simplify the spectrum of differences, recent approaches can be demarcated by market-based information and accounting information. The differences in variables are sometimes associated with the country in which the research is conducted. Most of these works derive from Altman's seminal piece in 1968, where the author reports that in Japan, on average, all models utilise regression and factor reduction methods. Notable methodological exceptions in later years include discriminant analysis. Meanwhile, Beerman (1976) used ratios such as company profitability, fixed asset growth, cash flow, leverage, and turnover. Moreover, Pindado et al. (2008) estimate the likelihood of financial distress using companies in G7 countries for a period of 13 years through a logistic model. They find that the firm's return on assets, the resulting trade-off between this manner of generating money, and the company's need to meet its expenses during the financial period accurately explain likelihood of financial distress of the company. Mohammed (2012) also stresses that use of competitor's information or an industry average to compare between financially distressed firms is superior compared to other methods in case of Malaysian listed companies. Alifiah (2014) develops a financial prediction model using logistic regression which employs both financial and macro-economic variables. She finds that based on Malaysian evidence in trading and services segment, predictors of bankruptcy are debt ratio, total assets turnover ratio, working capital ratio, net income to total assets ratio, and base lending rate. She also remarks about the lack of literature in the area of financial distress modelling in the Malaysian trading and services segment which use both macro-economic variables as well as accounting ratios. Tian et al. (2015) find that some accounting ratios built from only financial data also contain important incremental information about future bankruptcy risk, and their importance in comparison to that of market-based predictors in bankruptcy forecasts increases with prediction time period. These ratios are current liabilities/total asset, total debts/total assets, net income / (market equity + total liabilities), total liabilities / (market equity + total liabilities), cash and short-term investment / (market equity + total liabilities), log (price), stock volatility, and excess return over S&P 500 index. Chen et al. (2013) classify the predictors into solvency, operation ability, and growth ability. Khan (1985) uses performance measures, solvency measures, liquidity measures, capital utilisation measures, and operational efficiency measures from financial statement ratios to predict bankruptcy risk. Dimitras et al. (1996) also find that working capital/total assets is the most often used financial ratio and that total debt/total assets, current assets/current liabilities, EBIT, total assets; net income/total assets are also often used variables by researchers in 12 countries. Foreman (2003) finds that lower values of earnings per share and return on assets correspond to higher probabilities of bankruptcy and that share prices do not reflect the likelihood of bankruptcy and weaker retained earnings to assets and total debt proportion suggest significantly higher probabilities of bankruptcy. In Taiwan, Lin (2009) studies four models that are used for bankruptcy prediction including logit, probit, and artificial neural networks (ANNs) methodology, multiple discriminate analysis (MDA) and finds that the logit model conceives the best classification accuracy among the models used.

Although many researchers use discriminant analysis models, these models have problems if the dataset is not normally distributed. Logit regressions do not cause this problem according to many theoreticians. Some of the researchers who utilise logit models for bankruptcy analysis include Zavgren (1985). Meanwhile some researchers use neural networks to analyse financial ratios' ability to predict bankruptcy risk: Wilson and Sharda (1994), Tsukuda and Baba (1994), Altman et al. (1994), Zhang et al. (1999) and Cheng et al. (2006).

Figure 1 List of variables



Notes: This figure shows the conceptual framework of this study. We use frequency of changes in company name, frequency of changes in CEO, frequency of changes in board of directors, frequency of changes in majority shareholder, frequency of levy of fines and penalties on company and its executives, frequency of changes in audit committee and frequency of changes in capital as corporate actions that can predict financial distress. We also use working capital to total assets ratio, retained earnings to total assets ratio, EBIT to total assets ratio, market value of equity to book value of total liabilities ratio and sales to total assets ratio as financial ratios that can predict financial distress.

As the discussion above demonstrates, the existing body of literature mainly targets predicting financial distress using accounting ratios and other financial measures. On the other hand, the use of corporate actions in financial distress prediction is highlighted by a handful of researchers. They emphasise that the use of corporate actions can improve the classification accuracy of the existing models which use only accounting ratios. For example, Scott (1981) finds that bankruptcy prediction is both empirically feasible and theoretically explainable. Daily and Dalton (1994) find that a combination of corporate governance issues and financial ratios improves the accuracy of bankruptcy prediction models five years before bankruptcy. Others note that a combination of corporate governance issues and financial ratios can marginally improve the accuracy of the predictive models (Ciampi, 2015). Some have also observed that a change in board members is also a significant factor in financial prediction models (Chen et al., 2009). Karbhari et al. (2004), however, warn that unless the corporate name change is accompanied with announcement of an approved restructuring scheme by regulatory authorities, there is no statistically significant effect on shareholder wealth by a name change. Nevertheless, they find that on the announcement day, failed companies' share prices climb higher. Therefore, there is theoretical support in using corporate actions for predicting financial distress. This paper incorporates both corporate actions and accounting ratios to create a financial distress prediction model. We also assess the predictive capability of corporate actions separately as well as combined with the accounting ratios.

3 Methodology

This section outlines the three hypotheses posited in this study and the equations formulated to test them.

Hypothesis 1 Corporate actions taken by financially distressed companies are not the same compared with healthy companies three years prior to financial distress. To test this hypothesis, we formulate the following model.

$$\begin{aligned} Pn17_{i,t+1} = {} & \alpha + \beta_1 ChName + \beta_2 ChCEO + \beta_3 ChBOD + \beta_4 ChMSh \\ & + \beta_5 ChDSh + \beta_6 ChCap + \beta_7 ChFin + \beta_8 ChAudCom + \varepsilon_{i,t} \end{aligned} \tag{1}$$

Hypothesis 2 Predictive ability of financial variable and corporate actions are not same for financial distress. To test this hypothesis, we formulate the following model.

$$\begin{aligned} Pn17_{ci,t+1} = {} & \alpha + \beta_1 WCTA + \beta_2 RETA + \beta_3 ECITTA + \beta_4 MVEBVTL \\ & + \beta_5 SALESTA + \varepsilon_{i,t} \end{aligned} \tag{2}$$

Hypothesis 3 Combination of financial and corporate actions has different predictive ability of financial distress compared with using corporate actions separately and financial variables separately. To test this hypothesis, we formulate the following model using corporate action variables which are statistically significant in predicting financial distress. Therefore, we develop this model at the end of the analysis. Nonetheless, the model is stated here for clarity.

$$\begin{aligned} Pn17_{bi,t+1} = {} & \alpha + \beta_1 ChCap + \beta_2 ChAudCom + \beta_3 WCTA + \beta_4 RETA \\ & + \beta_5 EBITTA + \beta_6 MVEBVTL + \beta_7 SALESTA + \varepsilon_{i,t} \end{aligned} \tag{3}$$

In the three models, the dependent variable represents the status of the company and classifies whether the company is financially distressed or not. Independent variables are both corporate actions taken by the company and the financial ratios used in Altman Z-score. This study uses a significance level of 5% test the hypotheses. If the statistic is significant, we reject the null hypothesis and accept the alternate hypothesis. We select all the 19 companies classified as financially distressed companies by Bursa Malaysia as of 1 August 2015 as the initial sample. For most of the companies, the actual date of classification by Bursa Malaysia and the announcement data differs. This study uses the announcement date as the base year of financial distress. Table 1 provides the list of companies and the date on which the company was classified as financially distressed as well as the date of announcement of the classification by Bursa Malaysia.

Table 1 List of firms under study

#	*Symbol*	*Company name*	*Date of PN17*	*Announcement date*
1	7315	AHB Holdings Berhad	31.10.2014	03.11.2014
2	9954	Asia Knight Berhad	31.10.2014	03.11.2014
3	7193	Biosis Group Berhad	26.06.2013	27.06.2013
4	5214	China Stationary Limited	08.07.2014	08.07.2014
5	7986	CN Asia Corporation Berhad	29.05.2015	01.06.2015
6	7110	Haisan Resources Berhad	09.06.2010	11.06.2010
7	5187	HB Global Limited	07.05.2013	08.05.2013
8	7220	IRM Group Berhad	31.05.2013	03.06.2013
9	7170	LFE Corporation Berhad	01.10.2012	02.10.2012
10	3581	Lion Corporation Berhad	25.10.2013	28.10.2013
11	6548	Malaysia Pacific Corporation Berhad	28.11.2014	01.12.2014
12	7059	Metal Reclamation Berhad	29.08.2014	02.09.2014
13	7002	Nakamichi Corporation Berhad	29.04.2015	30.04.2015
14	7109	Octagon Consolidated Berhad	08.06.2012	12.06.2012
15	5146	Perwaja Holdings Berhad	26.11.2013	27.11.2011
16	7027	Petrol One Resources Berhad	30.08.2012	03.09.2012
17	7176	TPC Plus Berhad	28.02.2014	28.02.2014
18	7595	VTI Vintage Global (ML Global)	25.02.2010	01.03.2010

Notes: This table shows the companies which are classified as PN17 companies on 1st August 2015 with the date of classification and the date of publication of the classification by Bursa Malaysia. We use data three years before each company is classified to compile the variables in the study.

From the initial 19 PN17 companies, we exclude MAA Group Berhad as the company is in insurance business, which is considered to be in financial sector. Companies in financial sector have different risk factors and dissimilar ways of measuring risk compared to other industries. This difference in risk factors composition of balance sheet renders a fair comparison of financial companies and other companies unreliable. This notion also has considerable precedent in prior literature. Moreover, companies in the financial sector have to abide by global regulations regarding liquidity and risk management, which is not applicable to companies in other sectors. Lo (1986) analyses the use of discriminant analysis and logit analysis based on an initial sample of 184 firms, which faced bankruptcy. He excludes 4 from this sample, as they are in the financial sector. Many other researchers also eliminate financial firms from their analysis as these firms have different risk factors and different measures of bankruptcy. Besides, other scholars have suggested that the inclusion of companies from different sectors of the economy other than financial sector in the same data set in financial distress prediction does not cause classification problems.

To compare between healthy firms, which are traded on the Bursa Malaysia main board, and the financially distressed firms, we choose healthy companies based on two very important criteria. First, we narrow down the companies for each PN17 company and then we reduce this sample further by only including companies, which have comparable market capitalisations similar to PN17 companies. Based on this narrowed down sample, we choose two companies randomly for each financially distressed company. Some researchers such as Lee and Yeh (2004) also use the two healthy firms to one financially distressed firm ratio. Table 2 shows the companies that are of the same industry and comparable size. Although the comparison of financial ratios of different sizes of companies may not cause problems in the analysis, frequency of corporate actions may differ across them. By selecting companies of the same size, we are able to eliminate this effect from the analysis. The use of company size and industry when selecting the matching samples of companies that are not financially distressed is supported by literature. For example, Easterwood et al. (2012) use company size in matching the sample selection.

Table 2 Market capitalisation of firms under study

#	*Symbol*	*Company name*	*Industry*	*Market map*
1	7315	AHB Holdings Berhad	Trading and services	28.1 million
2	9954	Asia Knight Berhad	Manufacturing and hotel	24.13 million
3	7193	Biosis Group Berhad	Pharmaceuticals	2.10 million
4	5214	China Stationary Limited	Consumer products	86.29 million
5	7986	CN Asia Corporation Berhad	Petro chemical parts manufacturer	15.43 million
6	7110	Haisan Resources Berhad	Engineering	5.24 million
7	5187	HB Global Limited	Food processing	37.44 million
8	7220	IRM Group Berhad	Manufacturing	1.95 million
9	7170	LFE Corporation Berhad	Engineering	17.40 million
10	3581	Lion Corporation Berhad	Diversified (steel, property and furniture)	46.07 million
11	6548	Malaysia Pacific Corporation Berhad	Property	41.71 million
12	7059	Metal Reclamation Berhad	Metal recycling	23.88 million
13	7002	Nakamichi Corporation Berhad	Timber	6.93 million
14	7109	Octagon Consolidated Berhad	Manufacturing	11.68 million
15	5146	Perwaja Holdings Berhad	Iron and steel	84 million
16	7027	Petrol One Resources Berhad	Shipping and oil	2.79 million
17	7176	TPC Plus Berhad	Poultry farming	37.60 million
18	7595	VTI Vintage Global (ML Global)	Manufacturing	33.61 million

Notes: This table shows the market capitalisation of the companies classified as financially distressed by Bursa Malaysia and their sector of business. We use this information to select comparable sample of companies which are not classified as financially distressed.

Based on the above classification of PN17 companies into different industries and based on the market capitalisation of these PN17 companies, we select two companies for each of PN17 company, which make up a total sample of 54 companies. The data for the corporate action variables is collected through the Bursa Malaysia official website, whereas the data for the accounting ratios are collected through Bloomberg. Next, we provide theoretical justifications for some of the key variables invoked to answer our research questions.

3.1 Frequency of company name change (ChName)

According to some researchers the change in company name may be accompanied by financial distress of the company. Many companies often change their name to portray a different image of the company to the general public including investors. Logically, we expect companies that are going to face financial distress to change name more often than healthy companies.

3.2 Frequency of CEO change (ChCEO)

Another variable suggested by previous researchers that may contribute to the prediction of financial distress is the change in CEO. Although research is scant on the relationship between CEO changes and financial distress, we find some literature such as Weisbach (1988), Simpson and Gleason (1999) and Brookman and Thistle (2009) that suggest that during times of financial distress the top management of the company as well as CEO changes more often than in healthy companies.

3.3 Frequency of board of directors change (ChBOD)

Another corporate action, which is often taken by companies facing financial difficulties, is to change the composition of the board. The board may change, based on the influence of the CEO and top management within the company or vice versa as suggested by Easterwood et al. (2012), Manzaneque et al. (2015) and Iqbal and French (2007).

3.4 Frequency of audit committee change (ChAudCom)

Some experts such as Klein (2002) also suggest that as the company faces financial difficulties the company may change the Audit Committee more frequently in order to portray a more favourable audited financial statements and to exercise more flexibility in accounting adjustments.

3.5 Frequency of substantial shareholder change

Another corporate action that may help to predict financial distress is frequency of changes in substantial shareholder of the company. Substantial shareholders may change their position in the company when the company repeatedly faces financial hard times. This relationship is supported in literature, as evidenced through work of Jostarndt (2007).

3.6 Frequency of changes in directors' shareholding

The same way that substantial shareholders may change their position in the company, directors of the company may also change their shareholding in the company. But in case of directors some literature such as Iqbal and French (2007), Gilson and Vetsuypens (1993), Huson et al. (2004), Denis and Denis (1995), Murphy and Zimmerman (1993), Hatfield et al. (1999), Parrino (1997), Kang and Shivdasani (1995), Zopounidis (1987) and Shaw and Gentry (1988) suggest that directors may increase shareholding during financially difficult times to reduce the possibility of their expulsion from the board.

3.7 Frequency of new share issues

During financial distress the companies may resort to issue new shares to fill up shortage in funds. Issuing debt may not be cost efficient, as the interest rate increases during times of financial distress of the company. This variable evaluates Bursa Malaysia New Share Issue Regulation 'Chapter 6' new share issues including convertible shares, bonus issues, dividend reinvestment issues and directors' allotments and other new issues. Therefore, we can expect to have a higher frequency of new share issues just before the company is classified as being in financial distress.

3.8 Frequency of fines for misconduct of the company and directors

During times of financial distress some companies may resort to unethical practices of improving financial performance of the company, thereby may face fines for misconduct by regulatory organisations. For example, Douglas (2001) finds that when the company is facing bankruptcy risk, management is more likely to be investigated and penalised. Therefore, we expect in our research that companies facing financial distress will be penalised more frequently than companies which are financially healthy.

3.9 Financial ratios

This study incorporates working capital/total assets, retained earnings/total assets, earnings before interest and taxes/total assets, market value equity/book value of total liabilities and sales/total assets as financial variables. These are the same variables used by Altman's (2000) enhanced model.

3.10 Number of years included in the study

This study uses information three years prior to each firm being classified as financially distressed. The research on the financial distress prediction models conducted by Takahashi et al. (1984), Grice and Ingram (2001), Hamer (1984), Lin (2009) and Laitinen and Laitinen (2001) suggest that the accuracy of classification of companies as financially distressed improves largely when three years prior to company being classified as financially distressed is chosen.

3.11 Logistic regression analysis

The two methods of bankruptcy prediction analysis researchers utilise most often are linear and logistic regression analysis. Linear model accepts full linear compensation among the independent predictors, although this rarely happens. Quadratic discriminant analysis suggests a broader relationship, which is a quadratic equation. However, both linear and quadratic discriminant analyses are subtle to deviations from normal distributions. Logistic regression analysis can solve this problem as it does not assume multivariate normality (see Tam and Kiang, 1992; Wilson and Sharda, 1994). Logistic regression analysis is used for predicting bankruptcy analysis by researchers such as Martin (1977), Lo (1986), Zavgren (1985) and Keasey and McGuinness (1990). Researchers who compared the use of various methods of bankruptcy predicting who suggest that logistic regression is better include Lennox (1999), Collins and Green (1982) and Lin (2009). Based on the available literature this study analyses the data using logistic regression analysis as it reduces problems with normality of data. Logistic regression predicts the likelihood of dependent variable, which is a categorical outcome, occurring based on a number of independent variables. In binary logistic regression there are two states of dependent variables, whether the company is in financial distress or otherwise. The outcome of the logistic regression ranges between 0 and 1, values closer to 0 indicates that the outcome is unlikely while values closer to 1 suggest that outcome is probably likely while F-ratio to calculate how well the three models proposed in this paper fits the overall data. Logistic regression calculates several log-likelihood outcomes through a process of iteration, which refines the parameters. This process provides us with an initial model and a final model. The success of the model is measured against this initial model using chi-square. We also check the correlation between the variables using Wald statistic. We expect the variables to have correlation, which is below 0.8. We also use Cox and Snell's R-square and Nagelkerke's R-square to measure to what extent variance is explained by the variables. By using logistic regressions, we model the equations to represent both financially distressed firms and financially healthy firms in the same equation.

4 Findings, analysis and discussion

4.1 Predictive ability of corporate actions in financial distress modelling

As per equations (1) to (3) outlined previously to measure the predictive ability of corporate actions in predicting financial distress of the Malaysian public listed companies, we find that frequency of changes in board of directors and frequency of changes in the issue of new shares as reliable predictors of financial distress. With a final sample of 54 companies including both financially healthy and financially distressed companies, we find that although the baseline model classifies all the companies as not financially distressed, the inclusion of the corporate actions in the equation in the final model improves the classification accuracy of the model to 92.6% compared with the baseline model of 66.7%. With this improvement in the final model, only four companies are misclassified by the model. Although in the baseline model the variables ChName, ChBOD, ChCap, ChFin and ChAudCom are significant, suggesting inclusion of these variables can improve the final model, we find that variables ChBOD and ChCap are significant at predicting financial distress.

As suggested by Pompe and Bilderbeek (2005) the sequence of entry of variables into the equation do not cause a problem in case of financial distress prediction modelling and therefore we use enter method to analyse data in which all variables are entered at the same time into the equation unlike other options which involve some sort of step-wise regression. In this way we can analyse the impact of all variables simultaneously. The final model reduces the –2LL from 68.744 to 25.3766 and the highly significant chi-square suggests that the final model is better at predicting financial distress than the baseline model. Cox and Snell R^2 shows that 55.2% can be explained by the model while base on Nagelkerke R^2 76.7% can be explained by this model. Moreover, the model does not have a problem of multicollinearity as the VIF is less than 10 and tolerance is close to '0' for most of the variables and no variables have tolerance below 0.2 (Table 3).

Table 3 Model 1

Variables	*B*	*Sig.*	*Exp (B)*	*VIF*	*Tolerance*	*df*	*Chi-square*	*Cox and Snell R^2*	*Nagelkerke R^2*
		0.000				8	43.368	0.552	0.767
ChName	21.173	0.999	1,568.053	1.576	0.634				
ChCEO	–2.314	0.206	0.099	1.095	0.914				
ChBOD	0.156	0.321	1.168	3.165	0.316				
ChMsh	0.010	0.703	1.010	1.719	0.582				
ChDsh	–0.052	0.267	0.950	1.777	0.563				
ChCap	0.603	0.046	1.828	1.587	0.630				
ChFin	1.456	0.257	4.290	1.895	0.528				
ChAudCom	0.701	0.041	2.016	4.317	0.232				
Constant	–4.405	0.001	0.012						

Notes: A logistic regression using enter method is run and this table shows the important results. The model does not have multicollinearity problem and the highly significant chi-square shows that the model is statistically significant at explaining the financial distress and the model is able to explain more than 55%. By using a significance level of 5% we find that variables frequency of changes in capital and frequency of changes in audit committee as potential predictors of financial distress. The exp (B) in the table shows the magnitude of changes in the variables in terms of probability.

As shown in Table 3, the variables WCTA and SALESTA are significant at predicting financial distress while other variables representing accounting ratios are not significant at predicting financial distress. The exp (B) shows the magnitude of the effect on probability of changes in the ratio. One unit increase in working capital/total assets is associated with 0.001 decreases in likelihood of the company facing financial distress. Likewise, one unit increase in sales/total assets is associated with 0.065 decreases in likelihood of company facing financial distress.

4.2 Predictive ability of accounting ratios in financial distress

We also measure which variables explain financial distress among the accounting ratios we choose using equation (3). In the case of financial ratios, the baseline model shows that it can be improved by adding variables WCTA, RETA and SALESTA into the equation as these variables are statistically significant. Based on the Malaysian public listed companies accounting ratios have significant capability of predicting financial distress as shown by the highly significant chi-square. This model can be explained based on Cox and Snell R^2 43.6% and Nagelkerke R^2 of 60.6%. The final model also improves the classification of financially distressed firms from 66.7% to 87%. Moreover, as VIF is less than 10 and no variables have tolerance below 0.2, this suggests there is no multicollinearity (Table 4).

Table 4 Model 2

Variables	*B*	*Sig.*	*Exp (B)*	*VIF*	*Tolerance*	*df*	*Chi-square*	*Cox and Snell R^2*	*Nagelkerke R^2*
		0.000				5	30.947	0.436	0.606
WCTA	–6.635***	0.004	0.001	1.943	0.515				
RETA	–1.866	0.132	0.155	1.835	0.545				
EBITTA	9.787	0.225	177.101	1.853	0.540				
MVEBVTL	0.302	0.200	1.352	1.727	0.579				
SALESTA	–2.739**	0.031	0.065	1.128	0.886				
Constant	1.051	0.274	2.860						

Notes: The result of the logistic regression using enter method for accounting ratio variables are shown in this table. The model does not have multicollinearity problem and the highly significant chi-square shows that the model is statistically significant at explaining the financial distress and the model is able to explain more than 43.6%. By using a significance level of 5% we find that variables working capital to total assets and sales to total assets as potential predictors of financial distress. The exp (B) in the table shows the magnitude of changes in the variables in terms of probability.

As shown in Table 4, the variables WCTA and SALESTA are significant at predicting financial distress while other variables representing accounting ratios are not significant at predicting financial distress. One unit increase in working capital/total assets is associated with 0.001 decrease in likelihood of the company facing financial distress and one unit increase in sales/total assets is associated with 0.065 decrease in likelihood of company facing financial distress as shown by exp (B). Because WCTA and SALESTA have exp (B) which is lower than 1 that represent increase in these variables reduces the likelihood of financial distress. Because the co-efficient of WCTA is –6.635 and SALESTA is –2.739, we conclude that increases in WCTA and SALESTA are associated with lower likelihood of financial distress.

4.3 Predictive ability of combination of financial ratios and corporate actions

To test whether a combination of corporate action variables and accounting variables can predict financial distress better than using them individually in a model we use equation (3). Based on the two corporate action variables which are significant at predicting financial distress in combination with the accounting ratios, we find that inclusion of ChCap, ChAudCom, WCTA, SALESTA and RETA in the model can improve the financial prediction model. The highly significant chi-square shows that the model is significant at predicting financial distress and the model can explain 58.3% based on Cox and Snell R^2 and 81% based on Nagelkerke R^2. Moreover, the final model improves the classification of financially distressed firms from 66.7% to 88.9%, although it is better than the base line model the classification rate of the model 3 is less than models 1 and 2. In other words, using accounting ratios separately and by using corporate actions separately to predict financial distress classifies the distressed companies and other companies better than a combination model. The check on multi-collinearity shows that the VIF is less than 10 and tolerance is close to ‘0’ for most of the variables (Table 5).

Table 5 Model 3

Variables	*B*	*Sig.*	*Exp (B)*	*VIF*	*Tolerance*	*df*	*Chi-square*	*Cox and Snell R^2*	*Nagelkerke R^2*
		0.000				7	47.239	0.583	0.810
ChCap	0.457*	0.096	1.579	0.457	0.096				
ChAudCom	0.807**	0.015	2.242	0.807	0.015				
WCTA	–9.808**	0.037	0.000	–9.808	0.037				
SALESTA	–3.708*	0.065	0.025	–3.708	0.065				
RETA	0.296	0.887	1.344	0.296	0.887				
EBITTA	23.663*	0.077	1,898.271	23.663	0.077				
MVEBVTL	0.259	0.401	1.296	0.259	0.401				
Constant	–1.219	0.429	0.296	–1.219	0.429				

Notes: The result of the logistic regression using enter method for accounting ratio variables and corporate actions variables are shown in this table. The model does not have multi collinearity problem and the highly significant chi-square shows that the model is statistically significant at explaining the financial distress and the model is able to explain more than 58.3%. By using a significance level of 5% we find that variables working capital to total assets and frequency of changes in audit committee as predictors of financial distress. The exp (B) in the table shows the magnitude of changes in the variables in terms of probability.

Table 6 Classification accuracy comparison

Details	*Model 1*	*Model 2*	*Model 3*
Initial classification	66.7%	66.7%	66.7%
Final classification	92.6%	87%	88.9%

Notes: This table shows a comparison of the classification accuracy of the models we use in this paper. Classification accuracy shows how well the model is able to identify PN17 companies. Model 1 which uses only corporate actions as variables has the highest classification accuracy compared with other models.

As can be seen in Table 5 the variables ChAudCom and WCTA are significant at predicting financial distress, while other variables representing corporate actions and accounting ratios are not significant when combined together. One unit increase in working capital/total assets is associated with less than 0.0001 decrease in likelihood of the company facing financial distress. In this case the likelihood ratio fell considerably. Likewise, one unit increase in frequency of changes in audit committee is associated with 2.242 unit increases in likelihood of company facing financial distress. When we combine corporate actions and accounting ratios, the predictability of the variables changes because the loss of degrees of freedom for estimating the error does not compensate the reduction in the sum of squares of the error. A predictor with a relevant effect can be relevant, simply because of its effect. The significance may be low because the model cannot decide which of the collinear variables actually should be made responsible for the changes in the outcome. Because the co-efficient of ChAudCom is 0.807, we conclude that increases in the frequency of changes in audit committee are associated with higher likelihood of financial distress.

5 Conclusions

In the present investigation on predictive ability of corporate actions vis-à-vis financial distress, we arrive at the following salient findings with important implications for banks, risk managers, and investors. Firstly, incorporating corporate action variables in a predictive model substantially increases distress prediction. Secondly, frequent equity issuance and switching audit committees are both significant predictors of financial distress. Thirdly, changes in major shareholding patterns and/or directors' interest fail to predict impending distress. Lastly, though useful separately, the combination of corporate action and accounting ratios is not an improvement on stand-alone models.

The importance of the main results notwithstanding, we remind the reader that among the firms within our sample window, no company changed its name or underwent a change in CEO. As such, we are unable to comment on the importance of these variables within our empirical setting. Moreover, an idiosyncrasy of the Malaysian capital market, not unlike neighbouring ASEAN markets or other emerging economies, is that many of the financially distressed firms happen to be family-controlled businesses. As such, corporate power is concentrated within only a handful of related shareholders. The reluctancy of these shareholders to relinquish control of the firm regardless of imminent distress is not surprising. In fact, even after being classified as a distressed firm, these companies avoid filing for bankruptcy. The controlling major shareholders utilise the grace period before filing for bankruptcy to restructure in a bid to surmount the prevalent financial distress. Family-based firms' controlling shareholders, in such situations, appear to be obstinate in retaining controlling interest to forestall a dip in the share price while the firm undergoes financial distress. In this regard, our findings cohere with conclusions of Boone et al. (2007) and Linck et al. (2008), who also note the inordinate influence wielded by CEOs in such circumstances. Some of our tertiary findings are both intuitive and support prior research. For instance, our second model finds that working capital and sales values are good predictors of financial distress for the main board companies. This finding is reasonable since a high value of both indicators suggest a firm's ability to honour its immediate-term obligations as well as core business activities. A dip in either is likely a cause for alarm.

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