1-1-2023

Accounting-based variables as an early warning indicator of financial distress in crisis and non-crisis periods

Robert J. Powell
Edith Cowan University

Dung V. Dinh
Edith Cowan University

Nam T. Vu

Duc H. Vo

10.1002/ijfe.2864
Powell, R. J., Dinh, D. V., Vu, N. T., & Vo, D. H. (2023). Accounting-based variables as an early warning indicator of financial distress in crisis and non-crisis periods. International Journal of Finance & Economics. Advance online publication. https://doi.org/10.1002/ijfe.2864

Received: 22 September 2020 | Revised: 20 June 2023 | Accepted: 23 June 2023

DOI: 10.1002/ijfe.2864

RESEARCH ARTICLE

WILEY

Accounting-based variables as an early warning indicator of financial distress in crisis and non-crisis periods

Robert J. Powell[1] | Dung V. Dinh[1] | Nam Thanh Vu[2] | Duc Hong Vo[2,3]

[1]School of Business and Law, Edith Cowan University, Joondalup, Australia

[2]Research Centre in Business, Economics and Resources, Ho Chi Minh City Open University, Ho Chi Minh City, Vietnam

[3]Department of Accounting and Finance, University of Western Australia, Crawley, Australia

Correspondence
Duc Hong Vo, Research Centre in Business, Economics and Resources, Ho Chi Minh City Open University, Ho Chi Minh City, Vietnam.
Email: duc.vhong@ou.edu.vn

Abstract

Financial integration in the Association of Southeast Asian Nations (ASEAN) region is a key focus of the ASEAN Economic Community. Whereas many studies focus on modelling corporate default, this paper identifies early warning indicators of financial distress before a default, using multiple discriminant analysis (MDA) models with a sample of listed and delisted companies in the ASEAN region. The analysis examines 720 companies in 10 different industries across six ASEAN countries from 1997 to 2016. The study constructs individual models for each country as well as an overall model for the entire region, using both in-sample and out-of-sample approaches. This overall model could be useful for an integrated banking system. To ensure robustness, the study also separately examines the predictive performance of the MDA models across different economic crises: the Asian financial crisis (AFC) from 1997 to 2000, the global financial crisis (GFC) from 2007 to 2009 and their pre- and post-crisis periods. We find that profitability ratios are the best indicators of financial distress in the ASEAN region, followed by liquidity and leverage ratios. In addition, our findings reveal common indicators that can be used to predict financial distress across ASEAN countries. The single model performs reasonably well in predicting financial distress 1 year ahead. In addition, the model is extended to incorporate a market-based indicator into the MDA models, the distance to default. However, the inclusion of this indicator does not significantly improve the accuracy of the models in predicting financial distress at listed firms in the ASEAN region.

KEYWORDS

ASEAN, corporate financial distress, distance to default, early warning indicator, multiple discriminant analysis

1 | INTRODUCTION

In the Association of Southeast Asian Nations (ASEAN) region, a key focus of the ASEAN Economic Community (AEC) is financial and economic integration, including banking. The push for banking integration leads countries within the region to make strenuous efforts to strengthen their domestic banking networks. This study examines financial distress in the emerging market context of the ASEAN region, specifically its six members: Indonesia, Malaysia, Singapore, Thailand, the Philippines, and Vietnam. In 2018, these six countries had a combined gross domestic product (GDP) of US$2.84 trillion (World Bank, 2019), accounting for 95.71% of the total GDP among ASEAN members. Other countries in this region are excluded from the study as insufficient information is available for the studied period from 1997 to 2016.

Corporate financial distress and default are serious issues with potentially damaging social and economic consequences (Cao et al., 2020). A company in financial distress cannot generate sufficient revenues to cover its financial obligations (Pindado et al., 2008), which can lead to corporate default. Banks have various models for measuring and forecasting default risk, and studies on them can be divided into two research streams: (1) market-based models, such as the Merton (1974) distance to default (DD) model, and (2) accounting-based models, such as the multiple discriminant analysis (MDA) models (Altman, 1968; Altman et al., 2017; Chijoriga, 2008; Deakin, 1972; Koh & Killough, 1990; Taffler, 1983).

In this study, we focus on the accounting-based MDA model for the following reasons. The MDA is straightforward and well established, making it easy to evaluate and compare the results with the existing studies on financial distress. The approach stems from the work by Altman (1968), whose bankruptcy model is the one most widely cited (Shi & Li, 2019). Another feature is that the MDA approach identifies companies in financial distress using financial ratios, which are regarded by managers and analysts as an effective method of evaluating companies' financial health. The financial ratio approach can also control for the size effect (du Jardin, 2009; Salmi & Martikainen, 1994), as these ratios can be standardized across firms and regions, which makes the accounting-based approach suitable for examining financial distress across ASEAN countries.

One main concern regarding the use of MDA models is that MDA models developed for specific situations (e.g., periods or samples) do not perform well when applied to other situations. (Grice & Ingram, 2001; Ohlson, 1980). However, like all models, the MDA has limitations, the extensive use of MDA models over time has revealed those limitations, enabling us to identify and address the key limitations in our models. Recent evidence also reveals that the MDA model performs reasonably well, especially in the international context (Altman et al., 2017). Therefore, we develop individual and overall models for six ASEAN countries over a 20-year period from 1997 to 2016 to address this concern, covering different economic crises. Moreover, we perform both in-sample and out-of-sample analysis, in order to validate the financial distress models constructed.

Another concern is that the accounting-based MDA model is a static model and thus focuses exclusively on static accounting data. Thus, various studies suggest that incorporating accounting-based as well as market-based indicators will improve the predictive ability of financial distress models (Allen et al., 2015; Dinh et al., 2021; Gharghori et al., 2006; Pham et al., 2018; Vassalou & Xing, 2004). Therefore, we extend our analysis by including a market-based variable in our accounting-based models to examine whether doing so can improve the performance of the models in predicting financial distress.

Our extensive analysis, therefore, performs several tasks, using extensive in-sample and out-of-sample approaches. First, our analysis enables the identification of important accounting-based indicators across ASEAN countries and different periods. Second, our study identifies similarities and differences in accounting-based indicators, which are statistically significant in predicting financial distress for different countries and periods. Third, our study develops and compares individual and overall models for predicting financial distress among companies in ASEAN countries. Fourth, the study examines whether including a market-based variable, particularly the distance to default (DD), improves the predictive performance of the accounting-based models.

The study makes several contributions. *First*, by performing an extensive MDA study across six ASEAN countries using a sample of 720 firms, spanning six periods of different economic circumstances, including crisis periods, we fill a gap in the research, which lacks a detailed accounting-based MDA analysis of distressed firms in the ASEAN region across economic periods. *Second*, by comparing prediction models across different periods and utilizing diverse combinations of explanatory variables, we determine the financial ratios that are most effective in identifying distressed companies under different economic circumstances. *Third*, this study constructs prediction models that provide early warning signals of financial distress for firms in the ASEAN region. Such models can assist banks, regulators, and even investors in detecting financial distress before default.

The remainder of this study following this introduction is structured as follows. Section 2 reviews the literature. Section 3 explains the data and research methodology used. Section 4 discusses the empirical results, followed by concluding remarks and policy implications in Section 5.

2 | LITERATURE REVIEW

In an era of financial integration, modelling corporate distress, default, and bankruptcy is a continual concern in the literature on corporate finance. The trend toward developing models to predict these events has grown over the past few decades. This review summarizes the key findings in earlier and recent studies on the determinants of corporate financial distress.

Measure the risk of distress is a primary concern in empirical research on corporate financial distress because the validity of the findings is evaluated based on the reliability of the measurement. Early researchers often used financial ratios based on the balance sheet and profit and loss statement as indicators of distress (Altman, 1968; Beaver, 1966). Beaver (1966) wrote a pioneering study that offered providing evidence on the use of accounting data as an indicator of financial distress. Beaver determined that a single financial ratio, the ratio of funds provided by operations to total liabilities, was the best predictor of bankruptcy. Altman (1968) performed the next analysis of corporate distress, developing a Z-score equation with multiple discriminant analysis (MDA). Then he constructed a model for forecasting a firm's bankruptcy:

$$Z = 0.012X_1 + 0.014X_2 + 0.033X_3 + 0.006X_4 + 0.999X_{5,}$$

where X_1 = working capital/total assets (WC/TA); X_2 = retained earnings/ total assets (RE/TA); X_3 = earnings before interest and taxes/total assets (EBIT/TA); X_4 = market value of equity/ book value of total liabilities (MVE/TL); and X_5 = sales/total assets (S/TA).

These two early studies were expanded by using different research samples, periods, or explanatory financial ratios (Altman et al., 1977; Deakin, 1972; Taffler, 1983). Deakin (1972) found WC/TA an important ratio in predicting bankruptcy. Altman et al. (1977) then constructed a Zeta model with 27 indicators of distress. Taffler (1983) derived a Z-score for manufacturing firms listed on the London Stock Exchange using linear discriminatory analysis. Other studies also used logit or probit models to raise the model's predictive performance (Jung & Kim, 2008; Ohlson, 1980; Zmijewski, 1984).

Empirical research has also identified the determinants of corporate financial distress, divided into the following three categories: (1) firm-level determinants, (2) macro-level determinants, and (3) corporate governance determinants.

With respect to firm-level determinants, the existing literature reveals that firms with a wide book-tax difference or high R&D investment are more likely to experience financial distress (Al-Dhamari et al., 2023; Dang & Tran, 2021; Noga & Schnader, 2013; Zhang, 2015). Other firm-level determinants that contribute to the likelihood of distress are also identified: corporate hedging strategies, employee relations, and corporate social responsibility (CSR) activities. For example, empirical evidence shows that hedging can mitigate distress risk by minimizing volatility in firm value, reducing tax payments, and increasing debt capacity (Magee, 2013). Moreover, adequate investment in employees is demonstrated to reduce distress risk. It is also confirmed in the literature that firms with good CSR performance are less likely to be financially distressed (Boubaker et al., 2020; Farooq et al., 2022; Farooq & Noor, 2021).

Second, macro-level determinants are used in empirical studies to predict corporate distress during turbulent periods, such as the global financial crisis or the Covid-19 pandemic (Altman et al., 2017; Crespí-Cladera et al., 2021; Nguyen et al., 2023; Tinoco & Wilson, 2013). They argue that adding macro-level determinants to distress prediction models can raise their predictive performance because they account for nearly half the variation in firms' earnings (Bonsall et al., 2013). Accordingly, many empirical studies have confirmed that a firm's probability of distress could be influenced by current economic events (Giesecke & Weber, 2006; Pham et al., 2018). Firms' vulnerability to certain variables, such as investment intensity and debt financing, can change in times of crisis (Lopez & Saidenberg, 1999; Männasoo et al., 2018). Other macro-level determinants of corporate distress are inflation rates, interest rates, employment rates, credit availability, and monetary policy (Liou & Smith, 2007).

Third, many studies have examined the importance of corporate governance determinants in predicting corporate distress (Chen et al., 2020; Liang et al., 2020; Mariano et al., 2021), and Johnson et al. (2000) see them as more important than firm- or macro-level variables. Shleifer and Vishny (1997) define corporate governance as a mechanism for reassuring suppliers of finance of a return on their investment in corporations. Various researchers shed light on the relationship between corporate governance and financial distress, such as the nexus between board characteristics and distress risk, though the findings on this nexus are inconclusive (Adusei & Obeng, 2019). CEO characteristics, including personality, gender, and even CEO duality (i.e., a separation of decision management from decision control), are other factors that contributing significantly to the possibility of financial distress (García & Herrero, 2021), and so can other characteristics, such as ownership structure, a firm's political connections, and cultural dimensions. However, more empirical evidence on these issues is still needed (Li et al., 2021; Mangena et al., 2020; Shahwan & Habib, 2020).

As noted earlier, we use the interest coverage ratio (ICR), identified by Asquith et al. (1994) as an indicator of financial distress. If a firm's earnings are less than its interest costs for two consecutive years, it is categorized as financially distressed. We use it because predicting the likelihood of financial distress at an early stage can play a significant role in corporate governance. For example, financial distress is demonstrated to be expensive for creditors, and timely action to detect and address financial distress can minimize or prevent such expenses (Tinoco & Wilson, 2013). In addition, investors are inclined to assess financial distress at an early stage, which probably influences the allocation of payments linked to their investment.

Few studies have examined financial distress in the ASEAN region. Pongsata et al. (2004) compare the logit model by Ohlson (1980) and Altman's *Z*-score model (1968) to study prediction performance in Thailand. They conclude that both models can predict financial distress at Thai firms, regardless of their size. Sirirattanaphonkun and Pattarathammas (2012) use MDA and logit models to predict financial distress at Thai small and medium-sized enterprises (SMEs) using data from 2000 to 2010. Both models have a predictive accuracy rate of more than 80%. Thai et al. (2014) use MDA to predict financial distress at Thai companies between 2009 and 2013. They find WC/TA the most important variable in distinguishing between distressed and non-distressed businesses and conclude that their model predicts corporate distress with an accuracy rate of 76.7%. Dinh et al. (2021) find that a market-based DD model can be a good early warning indicator of financial distress for firms in Southeast Asia, but forecasting accuracy varies across countries. Vu et al. (2023) suggest a Lasso-based model that is superior in predicting financial distress for Vietnam.

The prior literature has some gaps and limitations, and the main one is that, although some use credit risk models to study the ASEAN region, none apply MDA models comprehensively across a large number of countries in the region over a sustained period encompassing the AFC, GFC, and noncrisis periods. Moreover, whereas many studies focus on distress or bankruptcy prediction, few focus on early warning indicators of financial distress (especially when it occurs before bankruptcy), using accounting-based MDA models to study the ASEAN region.

Logit and probit models have been used as substitutes for MDA models because they require less stringent assumptions than MDA models. Bellovary et al. (2007) review 165 bankruptcy studies, finding no significant difference in predictive accuracy among the MDA, logit, and probit models, though the accuracy rate is slightly higher for the MDA model than the other two models. Altman et al. (2017) find that the MDA model's performance is similar to that of the logit model.

In summary, the literature survey reveals the importance of financial distress models, which can be used as an indicator to give early warnings of distress across samples and economic conditions. Our methodology, as shown in the next section, addresses these issues and limitations by incorporating a range of countries (six ASEAN countries), a range of companies and industries (720 companies across 10 industries), and different periods (including crisis and noncrisis periods), using ICR as an early warning indicator of financial distress. The study also uses comprehensive in-sample and out-of-sample testing techniques to develop the MDA models.

3 | RESEARCH DESIGN

3.1 | Data

Our data were collected from the DataStream and Bloomberg databases, forming a dataset with the following criteria. First, companies in the financial sector were excluded, as the structure of their balance sheets differs from that of other industries—for example, most liabilities are deposits. Second, only companies with historical data that cover at least one of the two major financial crises (AFC or GFC) are considered. Third, delisted companies are included to mitigate survivorship bias and ensure that all the countries have an equal sample of companies that are no longer trading.

The number of listed and delisted companies for each country in the sample is in Table A1. The largest companies in the sample that satisfy the above-mentioned criteria were selected based on total liabilities (rather than total assets or market capitalization) because our study focuses on predicting financial distress at listed firms. Therefore, we select 100 listed companies and 20 delisted companies for each country. Our approach produces a uniform dataset for each country, making the results easier to compare and interpret. However, this sampling approach might suffer from choice-based sample bias, making the prediction models less precise for companies with low total liabilities (Platt & Platt, 2002).

The final sample comprises 720 companies, made up of 100 listed and 20 delisted companies for each of the six ASEAN countries. The listed companies are the largest companies (by total liabilities) and must have a minimum of 10 years of available data. Such long historical data enables us to consider the periods before, during, and after the crisis and compare the model's performance across these periods. The companies delisted are the largest companies (by total liabilities) and must have at least 5 years of available data because most delisted companies have a relatively short data lifespan. DataStream does not provide the reasons for delisting. Therefore, we performed numerous searches and ascertained that the vast majority were voluntary delisting, primarily due to acquisition or privatization. The other nonvoluntary delisting was generally due to failure to meet stock exchange requirements. For example, they did not provide the required reports or meet financial requirements.

3.2 | Variables

Accounting-based MDA is used to measure the ability of explanatory variables to discriminate among different groups of distressed or non-distressed firms, which are measured using the ICR. The first step is to divide the firms in this study into these two groups. Faelten and Vitkova (2014) use the ICR as an indicator of distress. The interest coverage is measured by the ratio of EBIT to interest expenses. An ICR of less than 1 indicates that the firm cannot cover its interest payments from its earnings (Faelten & Vitkova, 2014). Therefore, we use the interest coverage ratio as the threshold for determining whether firms are distressed (ICR <1) or non-distressed (ICR ≥ 1). The model divides firms into those that are non-distressed (0) and distressed (1).

In the literature, 14 variables are identified as important for the prediction of financial distress and can serve as a starting point for developing our discriminatory models. Table 1 summarizes these key accounting variables, which are divided into profitability, liquidity, and leverage groups.

Table 2 gives the descriptive statistics the 14 variables.

In addition, we ascertain whether adding a market-based variable, for the distance to default (DD), will improve the predictive performance of accounting-based MDA models. DD measures the effect of volatility in the firm's market asset values (σ_V) on the distance between the market value of the firm and its debt (Merton, 1974). We use the methodology detailed in Bharath and Shumway (2008) and Dinh et al. (2021) to calculate DD, expressed as follows.

$$\mathrm{DD} = \frac{\ln\left(\frac{V}{F}\right) + \left(\mu - 0.5\,\sigma_v^2\right)T}{\sigma_v\sqrt{T}}, \tag{1}$$

where V is the market value of the firm's assets, F is its debt, σ_V is the volatility of V, $V(\mu)$ is the mean annual change, and T is the forecasting horizon, which is 1 year.

The default is when the value of a firm's assets falls below that of its liabilities. In the model, DD is measured as the distance from firm value, in terms of the number of standard deviations, from the point of default. A lower value of DD indicates that the firm is closer to default—hence, it has a higher probability of default.

3.3 | Econometric techniques

Using the stepwise regression for each country in the ASEAN region, we select a subset of these accounting variables from the initial set of 14 accounting indicators. All indicators that are statistically significant in explaining the financial distress of firms in the ASEAN region will form the discriminant function that best predicts financial distress. This is a common procedure for reducing the number of variables used in MDA (Izan, 1984; Koh & Killough, 1990; Mselmi et al., 2017; Singh & Mishra, 2016; Taffler, 1983). The process enables us to rank the variables selected for the analysis based on their effects on the result. The indicator with the most significant effect that passes the eligibility test is then included in the analysis for predicting financial distress. At each stage, the accounting indicators that have been selected are tested against an exclusion criterion, and they may be excluded from the analysis if they fail to satisfy the criterion. The process continues until no further variables can be included or removed (Sirirattanaphonkun & Pattarathammas, 2012). The most important reason for using fewer indicators in the MDA model is to avoid reducing predictive power because of irrelevant and redundant variables (Todorov, 2007). This process involves several sequential steps. At each step, a variable is added or removed using the Wilks's lambda technique, which selects predictors that minimize the Wilks's lambda value (Huberty & Olejnik, 2006). Then, an F test is applied to Wilks's lambda for all indicators in the model to ensure its significance at an appropriate tolerance level. In line with common practice, the probabilities of the F test for inclusion and removal are 0.5 and 0.10, respectively.

The MDA model then measures the extent to which the explanatory variables can correctly classify (i.e., discriminate) between distressed and non-distressed firms. In Type 1 error, distressed firms are incorrectly classified as non-distressed. In Type 2 error, non-distressed firms are incorrectly classified as distressed. Finally, a chi-square statistic is applied to determine the significance (p) of the ability of the model to discriminate between the two groups used in our analysis at the 95% significance level ($p < 0.05$).

3.4 | Econometric strategies

Our analysis focuses on six different periods from 1997 to 2016. The period 1997–2000 covers the AFC period, characterized by large currency depreciation, economic downturns, and bearish stock markets. The period 2001–2003 encompasses the post-AFC period, when countries experienced a rebound in economic growth, and many firms in Asia engaged in restructuring and corporate governance

TABLE 1 The widely used accounting indicators used in the multiple discriminant analysis (MDA) analysis.

			Beaver (1966)	Deakin (1972)	Altman (1968)	Altman et al. (1977)	Ohlson (1980)	Taffler (1983)	Zmijewski (1984)	Izan (1984)	Koh and Killough (1990)	Shumway (2001)	Hillegeist et al. (2004)	Beaver et al. (2005)	Wu et al. (2004)	Tinoco and Wilson (2013)	Cultrera and Brédart (2016)	Total
Profitability	X_1	EBIT/TA			X	X				X		X	X		X		X	7
	X_2	S/TA			X							X	X					3
	X_3	NI/TA		X			X		X			X	X	X				6
	X_4	RE/TA			X	X					X	X	X					5
	X_5	EBITDA/TL												X				1
Liquidity	X_6	WC/TA		X	X	X	X					X	X		X			7
	X_7	CA/TL						X										1
	X_8	CA/CL					X		X	X		X	X		X		X	7
	X_9	CL/TA						X								X		2
	X_{10}	NOCREDINT						X								X		2
Leverage	X_{11}	TL/TA		X			X		X			X	X	X		X		7
	X_{12}	FU/TL	X	X			X						X			X	X	6
	X_{13}	MVE/TC				X												1
	X_{14}	MVE/TL			X					X		X	X					4

Note: The table lists financial ratios included as significant variables in previous studies. These indicators are used as a starting point for the accounting-based multiple discriminant analysis (MDA) model in this study. The total column sums the frequency of the ratio used in previous studies.

Abbreviations: CA/CL, current assets/current liabilities; CA/TL, current assets/total liabilities; CL/TA, current liabilities/total assets; EBIT/TA, earnings before interest and taxes/total assets; EBITDA/TL, earnings before interest, depreciation, and amortization/total liabilities; FU/TL, funds provided by operations/total liabilities; MVE/TC, market value of equity/total capital; MVE/TL, market value of equity/total liabilities; NI/TA, net income/ total assets; NOCREDINT, ratio of the no credit interval; RE/TA, retained earnings/total assets; S/TA, total sales/total assets; TL/TA, total liabilities/total assets; WC/TA, working capital/total assets.

TABLE 2 The descriptive statistics.

Panel A: Non-distressed			Mean	Median	Standard deviation
Profitability	X_1	EBIT/TA	0.086	0.068	0.163
	X_2	S/TA	0.789	0.580	0.873
	X_3	NI/TA	0.065	0.050	0.174
	X_4	RE/TA	0.164	0.183	0.578
	X_5	EBITDA/TL	0.000	0.000	0.000
Liquidity	X_6	WC/TA	0.121	0.113	0.328
	X_7	CA/TL	1.053	0.842	1.022
	X_8	CA/CL	1.929	1.469	1.608
	X_9	CL/TA	0.310	0.251	0.322
	X_{10}	NOCREDINT	−0.022	−0.020	1.660
Leverage	X_{11}	TL/TA	0.533	0.499	0.448
	X_{12}	FU/TL	0.225	0.132	0.691
	X_{13}	MVE/TC	2.192	1.276	2.522
	X_{14}	MVE/TL	1.712	1.152	2.029
		ICR	5.612	5.272	4.001
Panel B: Distressed			**Mean**	**Median**	**Standard deviation**
Profitability	X_1	EBIT/TA	−0.062	−0.006	0.485
	X_2	S/TA	0.443	0.293	0.795
	X_3	NI/TA	−0.004	−0.018	0.860
	X_4	RE/TA	−0.436	−0.049	1.654
	X_5	EBITDA/TL	−0.014	0.021	0.694
Liquidity	X_6	WC/TA	−0.272	−0.030	1.128
	X_7	CA/TL	0.799	0.474	1.305
	X_8	CA/CL	1.475	0.904	1.916
	X_9	CL/TA	0.615	0.355	1.115
	X_{10}	NOCREDINT	−1.324	−0.347	3.720
Leverage	X_{11}	TL/TA	0.865	0.654	1.111
	X_{12}	FU/TL	0.056	0.020	0.838
	X_{13}	MVE/TC	1.301	0.421	2.326
	X_{14}	MVE/TL	1.001	0.612	2.419
		ICR	−1.736	−0.250	3.357

Note: The table shows the mean, median, and standard deviation for each ratio in Table 1. The sample used in our study includes 720 firms for the 20 years from 1997 to 2016. Panel A shows the firms identified as non-distressed (ICR $\geq$ 1) or non-distressed (ICR $<$ 1).

reform (Joh & Jung, 2016). The period 2004–2006 is the pre-GFC period, defined by elevated economic growth and buoyant stock markets. The period 2007–2009 includes the GFC, with a high rate of global bank failure, market turmoil, and recessions. The period 2010–2012 represents the post-GFC period of recovery, but investors and regulators continued to exercise caution. Finally, the period 2013–2016 (our study period) is stable, with a slightly higher level of economic growth and stability.

As previously discussed, the existing literature indicates that some MDA models developed for specific situations (e.g., particular periods or samples) do not perform well when applied to other situations. Thus, we develop specific models for each ASEAN country in the research sample. The predictive performance of these models for individual ASEAN countries is then compared to that of the single model developed for the entire ASEAN region.

TABLE 3 The discriminant functions for the entire Association of Southeast Asian Nations (ASEAN) region (Approach 1).

	Period	Discriminant functions
Total ASEAN	Entire period	$Z = -0.157 + 6.269\,X_1 + 0.226\,X_2 - 0.754\,X_3 + 0.335\,X_4 - 1.292\,X_9$
	AFC	$Z = 0.907 + 2.467\,X_1 + 1.095\,X_6 - 1.499\,X_{11}$
	Post-AFC	$Z = 0.043 + 4.618\,X_1 + 0.353\,X_2 - 1.421\,X_9$
	Pre-GFC	$Z = -0.205 - 6.969\,X_1 - 0.299\,X_2 + 2.471\,X_3 + 1.057\,X_7 + 0.778\,X_{11} + 0.007\,X_{13}$
	GFC	$Z = -0.452 + 7.127\,X_1 - 0.494\,X_3 + 1.018\,X_4 - 0.082\,X_8$
	Post-GFC	$Z = -0.316 + 7.905\,X_1 + 0.218\,X_2 + 0.629\,X_4 - 1.700\,X_9$
	Stable period	$Z = 0.017 + 8.258\,X_1 - 2.530\,X_3 + 0.635\,X_4 - 1.628\,X_9$

Note: The table presents the in-sample discriminant functions for the ASEAN region, including six major countries. The discriminant functions are reported for Approach 1 (in-sample testing for each period). X_1 denotes EBIT/TA. X_2 denotes S/TA. X_3 denotes NI/TA. X_4 denotes RE/TA. X_6 denotes WC/TA. X_7 denotes CA/CL. X_8 denotes CA/CL. X_9 denotes CL/TA. X_{11} denotes TL/TA. X_{13} denotes MVE/TC.

We first analyse how well the accounting-based MDA models predict financial distress in each ASEAN country and the entire region based on the financial distress indicator, the ICR. This approach is called Approach 1, the baseline model, to differentiate from Approaches 2 and 3, which use forward-testing and back-testing techniques. Approach 1 develops specific determinant functions for each year in the study (1997–2016) to see whether they can predict financial distress in the year ahead (per firm, per country). Because the MDA with one lag is used, the determinant model for each year is developed based on the prior year's data. For Vietnam, the entire sample covers only the period 2007–2016.

In addition, we examine the MDA models' predictive performance when applied to different scenarios using Approaches 2 and 3. Approach 1 is the in-sample analysis, the baseline approach for constructing the MDA models. Approaches 2 and 3 are used for out-of-sample analyses to evaluate the predictive performance of the MDA models. Approach 2 adopts a forward-looking approach by developing the accounting-based MDA models with the first half of the data sample (1997–2006) and applying them to the second half (2007–2016). In contrast, Approach 3 is a back-testing approach that develops models with the second half of the data sample (2007–2016) and back-tests them against the first half (1997–2006). Overall, the results confirm significant variations in the predictive accuracy of the financial distress models under different scenarios. In addition, we find that Approach 1 is likely to produce better financial distress prediction for most ASEAN countries than Approaches 2 and 3.

Our study also considers the effect of a market-based indicator, DD, in enhancing the predictive performance on financial distress of various MDA models. We aim to confirm whether incorporating both accounting-based- and market-based indicators into the model for predicting financial distress can considerably improve the predictive performance of these models.

4 | RESULTS

We initially constructed a single model for the entire ASEAN region across six different periods. This one-size-fits-all model covers the full sample of six ASEAN countries for the full period, 1997–2016. The single MDA model constructed after conducting a stepwise regression is as follows.

$$Z = -0.157 + 6.269X_1 + 0.226X_2 - 0.754X_3 + 0.335X_4 - 1.292X_9, \tag{2}$$

where X_1 is the ratio of earnings before interest and taxes to total assets, X_2 is the ratio of total sales to total assets. X_3 is the ratio of net income to total assets. X_4 is the ratio of retained earnings to total assets. Finally, X_9 is the ratio of current liabilities to total assets. Four of the five indicators used in the model come from the profitability group, suggesting that profitability is a critical indicator in the financial health of companies in the ASEAN region.

This single model using Approach 1 is used for in-sample testing. We also developed a single model for the entire ASEAN region for each subperiod (the AFC, post-AFC, pre-GFC, GFC, post-GFC periods, and a stable period). In addition, we constructed a single model for each individual ASEAN country for comparison purposes. The estimated intercepts included in the discriminant functions are used to facilitate interpretation of our empirical results, which are presented in Table 3 for the entire ASEAN region and Table 4 for each ASEAN country.

Our results with the MDA model for distress prediction for the entire ASEAN region indicate that the single model for the entire region (including all countries and periods) has accuracy of 61.1% in predicting which firms are distressed and 81.9% in predicting which firms are non-distressed. Hence, the combined accuracy across both distressed and non-distressed firms is 76.8%. Furthermore, the chi-square test results indicate that these results are significant at the 99% level.

The discriminant functions for each individual country and period with the MDA model for distress prediction vary from one another. As noted in several studies (Giesecke & Weber, 2006; Grice & Ingram, 2001; Oz & Simga-Mugan, 2018; Sayari & Mugan, 2016), these results highlight that discriminant functions vary based on the specific data set for which they were developed.

Some common variables are more prominent than others in predicting financial distress in the ASEAN region, as summarized in Table 5. Financial ratios in the profitability group are the most dominant financial indicators for predicting financial distress in the ASEAN region because they measure performance and are the main driver of a company's liquidity. Moreover, creditors often look at profitability ratios when determining credit terms with borrowers (Claessens et al., 2003). In particular, EBIT/TA is the most significant indicator in predicting financial distress, followed by RE/TA. These findings are in line with the existing literature (e.g., Altman, 1968; Altman et al., 1977; Hillegeist et al., 2004; Izan, 1984; Shumway, 2001; Wu et al., 2004). EBIT/TA appears most frequently because this important ratio reflects the earning power of the company's assets. Altman (1968) believes that the survival of a company's is based on its assets' earning power. The indicator that appears second most frequently is RE/TA, as it measures the companies' cumulative profitability over time. Routledge and Gadenne (2000) argue that past profitability is valuable for predicting a future capacity for self-financing.

As presented in Table 5, financial ratios in the profitability group are the most dominant financial indicators in predicting financial distress in the ASEAN region, followed by liquidity and leverage. However, these categories vary across periods and countries. Profitability is dominant in crisis periods, specifically during the AFC (1997–2000) and the GFC (1997–1999). Profitability is also prominent in Malaysia and Singapore. In contrast, liquidity ratios are the most prominent in predicting financial distress in post-crisis periods, such as the post-AFC (2001–2003), post-GFC (2010–2012), and stable periods (2013–2016). This group of financial indicators is particularly dominant in Indonesia. In contrast, financial ratios in the leverage group are more prevalent during the AFC (1997–2000) and the stable period (2013–2016). Leverage ratios do not appear to be dominant in Indonesia and Singapore. However, this group of financial ratios appears to be most prominent in Thailand and Vietnam.

Table 5 shows the most notable difference between the MDA models during the AFC. Fewer ratios are significant in the model in the other periods. ASEAN economies were hard hit during the AFC, commencing with the deep depreciation of the Thai Bhat and then rapidly spreading to the surrounding countries (Ito, 2007). The AFC was a period of high volatility in ASEAN currencies, stock markets, and company earnings. As a result, predicting financial distress using ICR is challenging. Following the AFC, conditions largely returned to normal. During the post-AFC period, some profitability ratios—such as NI/TA, RE/TA and EBITDA/TL—showed little or no significance as predictors of financial distress. However, following the AFC, countries in the region implemented several reforms, leading to more enhanced banking policies and capital flows. Over time, these changes stabilized the region, making it easier to predict company earnings from 1 year to the next, so the impact of the GFC on the region was mild compared to many countries elsewhere. This is evident from the ratios during the GFC, when the frequency was very similar to that of the entire period in Table 5.

Table 6 shows the percentage for being correctly predicted as distressed and non-distressed in the ASEAN countries. Across all MDA models, an average of 83% of the forecasts correctly predict non-distressed firms, whereas 61% correctly predict distressed firms. Overall 76.8% of the predictions are correct for distressed and non-distressed firms. The prediction rate is higher for distressed firms because they comprise a much smaller share of the sample than non-distressed firms. Therefore, swings in the percentage of distressed firms from one period to the next are much greater, making it harder to predict them than non-distressed firms. In our sample, 76% of the firms are non-distressed, and 24% are distressed firms; so, if in a sample of 100 loans, the loans of the distressed firms increase by 10% (24 + 10), then the distressed sample increases 42% (10/24), whereas a similar rise in the non-distressed sample (76 + 10) represents an increase of only 13% (10/76). Thus, in terms of percentage, the MDA model is more prone to Type 1 error (predicting distressed firms as non-distressed) than to Type 2 error (predicting non-distressed firms as distressed).

We now compare our prediction rates compare to those in other studies. Our results fall well within the range reported by Bellovary et al. (2007), who, in their review of distress prediction studies from 1930 to the 2000s, concluded that the forecast accuracy range of

TABLE 4 The discriminant functions for each Association of Southeast Asian Nations (ASEAN) country (Approach 1).

	Period	Discriminant functions
Indonesia	Full period	$Z = -0.603 + 3.310\ X_1 + 0.237\ X_2 + 1.426\ X_3 – 0.351\ X_4 + 1.655\ X_6 + 0.03\ X_{10}$
	AFC	$Z = -0.634 + 4.947\ X_1 + 0.891\ X_2 + 1.105\ X_6$
	Post-AFC	$Z = -0.051 + 3.593\ X_1 + 1.497\ X_6 + 0.04\ X_{10}$
	Pre-GFC	$Z = -0.405 + 6.337\ X_3 + 1.433\ X_6$
	GFC	$Z = -0.76 + 7.598\ X_1 – 0.183\ X_{10}$
	Post-GFC	$Z = -0.778 + 6.091\ X_1 + 1.087\ X_6 + 0.34\ X_{10}$
	Stable period	$Z = -0.321 + 3.11\ X_1 + 1.572\ X_6 + 0.044\ X1_0$
Malaysia	Full period	$Z = -0.869 + 6.315\ X_1 – 3.944\ X_3 + 2.698\ X_4 + 0.73\ X5 + 0.199\ X_{10}$
	AFC	$Z = 0.167 + 2.746\ X_5$
	Post-AFC	$Z = -1.558 + 7.052\ X_1 + 3.233\ X_4 + 2.458\ X_9$
	Pre-GFC	$Z = -0.754 + 0.639\ X_2 + 1.564\ X_5 + 0.467\ X_{10}$
	GFC	$Z = -1.147 + 4.168\ X_1 + 4.408\ X_4$
	Post-GFC	$Z = -0.678 + 9.148\ X_1 – 0.429\ X_2 + 3.377\ X_4 – 1.671\ X_5 + 0.609\ X_{10}$
	Stable period	$Z = -1.436 + 0.627\ X_8 + 3.21\ X_{12}$
The Philippines	Full period	$Z = -0.423 + 4.801\ X_1 + 0.647\ X_2 + 0.23\ X_4 – 1.787\ X_9 + 0.883\ X_{11}$
	AFC	$Z = -1.767 + 3.658\ X_{11}$
	Post-AFC	$Z = 0.122 + 3.539\ X_1 + 0.563\ X_2 – 2.753\ X_9 + 0.854\ X_{11}$
	Pre-GFC	$Z = -0.308 - 4.756\ X_1 – 0.826\ X_2 + 3.379\ X_3 + 2.403\ X_9 + 0.01\ X_{10} + 0.026\ X_{12}$
	GFC	$Z = -0.546 + 13.78\ X1 – 7.988\ X_3 + 1.476\ X_4 – 0.019\ X_{14}$
	Post-GFC	$Z = -0.330 - 7.183\ X_1 + 2.786\ X_9$
	Stable period	$Z = -1.836 + 10.340\ X_1 + 2.370\ X_6 – 0.116\ X_{10} + 2.128\ X_{11}$
Singapore	Full period	$Z = -0.774 + 4.076\ X_1 + 2.175\ X_4$
	AFC	No significant variables
	Post-AFC	$Z = 0.605 + 4.088\ X_1 – 2.814\ X_9$
	Pre-GFC	$Z = -0.784 + 4.08\ X_4 + 0.187\ X_{10}$
	GFC	$Z = -0.859 + 8.561\ X_1 + 1.865\ X_3 + 1.971\ X_4 – 0.968\ X_5$
	Post-GFC	$Z = -0.386 + 16.83\ X_1 – 13.249\ X_3$
	Stable period	$Z = -0.9 + 12.308\ X_1 – 4.223\ X_6$
Thailand	Full period	$Z = -0.112 + 8.038\ X_1 + 1.003\ X_6 – 0.219\ X_7 – 0.367\ X_{11} – 0.021\ X_{14}$
	AFC	$Z = -1.289 + 2.383\ X_5 + 0.372\ X_8 + 0.481\ X_{13}$
	Post-AFC	$Z = -0.703 - 9.768\ X_1 + 0.587\ X_7 + 1.435\ X_{11}$
	Pre-GFC	$Z = -0.289 - 6.838\ X_1 + 1.101\ X_3 – 0.647\ X_4 + 0.73\ X_5 + 0.945\ X_{11}$
	GFC	$Z = -0.057 + 10.305\ X_1 – 0.318\ X_3 + 0.075\ X_{10} – 0.326\ X_{11} – 1.332\ X_{12}$
	Post-GFC	$Z = -0.870 + 5.885\ X_1 + 3.445\ X_6 – 0.336\ X_8 + 0.715\ X_{11} + 2.451\ X_{12}$
	Stable period	$Z = 0.48 – 4.273\ X_5 + 0.109\ X_{14}$
Vietnam	Full period	$Z = -0.394 - 3.172\ X_5 + 0.373\ X_8 + 0.819\ X_{12} + 0.161\ X_{14}$
	GFC	$Z = -1.208 + 0.536\ X_2 – 1.735\ X_5 + 0.28\ _{X8} + 0.169\ X_{14}$
	Post-GFC	$Z = -1.567 + 2.994\ X_5 + 3.076\ X_9 – 0.297\ X_{14}$
	Stable period	$Z = -0.456 - 5.905\ X_5 + 0.46\ X_8 + 2.958\ X_{12} + 0.216\ X_{14}$

Note: The table presents the in-sample discriminant functions for each ASEAN country. In addition, the functions are reported for Approach 1 (in-sample testing for each country's periods). The entire ASEAN is developed from a dataset that includes six ASEAN countries. X_1 denotes EBIT/TA. X_2 denotes S/TA. X_3 denotes NI/TA. X_4 denotes RE/TA. X_5 denotes EBITDA/TL. X_6 denotes WC/TA. X_7 denotes CA/CL. X_8 denotes CA/CL. X_9 denotes CL/TA. X_{10} denotes NOCREDINT. X_{11} denotes TL/TA. X_{12} denotes FU/TL. X_{13} denotes MVE/TC. X_{14} denotes MVE/TA.

TABLE 5 The frequency of financial ratios appeared in the discriminant functions.

	X_1	X_2	X_3	X_4	X_5	X_6	X_7	X_8	X_9	X_{10}	X_{11}	X_{12}	X_{13}	X_{14}
Full period	6	3	3	5	1	2	1	0	2	2	2	0	0	1
AFC	2	1	0	0	2	2	0	1	0	0	2	0	1	0
Post-AFC	6	2	0	1	0	1	1	0	4	1	2	0	0	0
Pre-GFC	3	3	4	2	2	1	1	0	1	3	2	1	1	0
GFC	6	1	4	4	2	0	0	2	0	2	1	1	0	2
Post-GFC	6	2	1	2	2	2	0	2	3	2	1	1	0	1
Stable period	4	0	1	1	2	3	0	2	1	2	1	2	0	2
	33	12	13	15	11	11	3	7	11	12	11	5	2	6

Note: The table shows the frequency of each of the ratios in the discriminant functions using Approach 1 (in-sample testing for each period), as shown in Table A1. X_1 denotes EBIT/TA. X_2 denotes S/TA. X_3 denotes NI/TA. X_4 denotes RE/TA. X_5 denotes EBITDA/TL. X_6 denotes WC/TA. X_7 denotes CA/CL. X_8 denotes CA/CL. X_9 denotes CL/TA. X_{10} denotes NOCREDINT. X_{11} denotes TL/TA. X_{12} denotes FU/TL. X_{13} denotes MVE/TC. X_{14} denotes MVE/TA.

MDA models is 32%–100%. Our literature review shows a much higher prediction rate when the data samples used are similar to those for which the models were developed. For example, the Altman (1968) study achieved high prediction rates when it used an equally weighted set of bankrupt and nonbankrupt US manufacturing companies. However, this accuracy fell by 26% when the sample used was in a different period (Grice & Ingram, 2001). However, our study uses a much more diverse sample of 720 companies in 10 different industries and countries in the ASEAN region, with no predetermined mix of distressed and non-distressed firms. The following examples compare the prediction rates with our MDA models for predicting financial distress to those in other ASEAN studies.

Ma'aji et al. (2018) used an MDA model and reported a predictive accuracy of distress of 64.7% for Malaysian SMEs in manufacturing for the 2000–2012 period. Our MDA model for Malaysia from 2000 onward (i.e., excluding the AFC) shows a similar accuracy rate (63.1%) but across a much more diverse range of sectors. Our correct overall prediction rates are over 80% for Indonesia and Thailand. This predictive accuracy compares favourably to that of Rahman et al. (2004), who applied a logit model to predict financial distress at banks for the period 1995 to 1997, correctly forecasting around 82% in Indonesia and 76% in Thailand. Our model for Thailand correctly predicted 67.5% of distressed firms across the full period. This result compares favourably to the rate in other studies on Thailand, such as Sirirattanaphonkun and Pattarathammas (2012), whose MDA model for SMEs correctly predicted 41.6% of distressed firms from 2000 to 2010, and Meeampol et al. (2014), whose model correctly predicted approximately 60% of the bankrupt firms in Thailand in the period 2010 to 2011.

In Tables 6 and 8, the 45 accuracy rates are below 50%, indicating that prediction is no better than chance. Six of them are in the crisis periods or a period coming out of a crisis, when large swings hamper the ability to predict distressed firms. Prediction performance for a country depends on its specific circumstances. Only during the AFC does the prediction of non-distressed firms fall below 60% for Thailand. We believe that the AFC originated in Thailand, so it is understandable that distress was more challenging to predict in this period than in prior years. The Philippines experienced the lowest rates of correct financial distress prediction in the post-GFC period, perhaps because it relies on remittance inflows from overseas workers. The GFC depressed demand for Filipino workers (Varga-Silva et al., 2009), slowing recovery of the economy. Therefore, in the post-GFC period, the impacts on businesses and the swings between the two periods would have been difficult to predict from the prior year. Indonesia went into the GFC with a steadily declining deficit, coupled with relatively low reliance on exports (Sangsubhan & Basri, 2012), and experienced very mild economic impacts during the crisis. This stability over time could explain Indonesia's high rate of correct predictions of distressed firms during the GFC.

Next, we compare the predictive performance of our MDA models for the entire ASEAN region and for each ASEAN country. The empirical results are presented in Table 7. Our results indicate that the MDA model for the entire ASEAN region correctly identifies 61.1% of distressed companies as distressed and 81.9% of non-distressed companies as non-distressed. In contrast, the accuracy rate of the country-specific models (except for Singapore) is well above 60% for "distressed" firms and well above 80% for those that are "non-distressed." Singapore has a low prediction rate of distressed

TABLE 6 Percentage correct prediction rates of in-sample results for individual periods (Approach 1).

		AFC	Post-AFC	Pre-GFC	GFC	Post-GFC	Stable period	Full period
Indonesia	Distressed	75.7%	61.2%	57.6%	84.4%	80.0%	50.0%	66.7%
	Non-distressed	77.2%	86.8%	88.8%	71.1%	91.6%	95.8%	86.1%
	χ^2	34.716***	44.880***	53.221***	25.398***	63.596***	84.890***	298.800***
Malaysia	Distressed	25.0%	56.0%	46.2%	63.2%	65.8%	76.3%	60.4%
	Non-distressed	91.9%	80.8%	86.5%	78.0%	85.9%	61.7%	80.8%
	χ^2	16.445***	34.820***	39.619***	48.164***	97.455***	23.573***	187.849***
The Philippines	Distressed	64.3%	55.0%	52.9%	77.8%	46.8%	68.1%	60.6%
	Non-distressed	66.2%	93.0%	89.6%	75.4%	83.8%	91.1%	85.8%
	χ^2	5.589**	69.551***	85.346***	56.193***	63.052***	90.313***	245.944***
Singapore	Distressed	–	32.0%	68.0%	45.8%	58.8%	76.2%	42.9%
	Non-distressed	–	89.4%	81.4%	96.0%	78.8%	70.7%	88.3%
	χ^2	–	26.155***	30.549***	81.299***	16.816***	13.128***	110.310***
Thailand	Distressed	84.7%	73.7%	55.1%	56.0%	82.5%	25.0%	67.5%
	Non-distressed	55.5%	82.0%	94.6%	90.6%	84.1%	95.7%	85.1%
	χ^2	21.310***	33.367***	91.495***	100.99***2	90.581***	45.612***	256.264***
Vietnam	Distressed				47.7%	68.1%	70.5%	61.6%
	Non-distressed				86.4%	75.2%	81.2%	82.2%
	χ^2				39.235***	52.501***	92.073***	119.811***
Total ASEAN	Distressed	59.7%	53.8%	54.7%	61.2%	64.0%	57.4%	61.1%
	Non-distressed	81.7%	90.5%	90.5%	82.2%	73.9%	78.0%	81.9%
	χ^2	60.771***	160.198***	250.166***	187.688***	184.599***	150.181***	781.549***

Note: The table presents the distressed/non-distressed predictive accuracy 1 year ahead of firm distress in Association of Southeast Asian Nations (ASEAN) countries over different periods using multiple discriminant analysis (MDA) models. Distressed and non-distressed are identified based on the interest coverage ratio (ICR). Total ASEAN is developed from a dataset that includes all six major ASEAN countries. For example, over the entire period, 66.7% of distressed firms in Indonesia were correctly identified as distressed, and 33.3% were incorrectly identified as non-distressed (Type I error). In addition, 86.1% of non-distressed firms were correctly identified as non-distressed, and 13.9% were incorrectly identified as distressed (Type II error). The table also presents the significant results determined by the chi-square test (χ^2) regarding the MDA model's ability to discriminate between distressed and non-distressed firms. ** and *** denote significance at the 95% and 99% level.

companies because it relies heavily on export markets. Thus, economic problems experienced by other countries caused swings in the earnings of Singaporean firms, making prediction difficult. However, as mentioned, the accuracy rate for each country aligns with the previous evidence and thereby suffices for predicting financial distress at firms.

We now evaluate the predictive performance of our MDA models using two approaches. First, we examine the models following Approach 1, with 1- and 2-year lags. Then, using Approaches 2 and 3, we conduct the out-of-sample analysis. Detailed results are provided in Appendices B and C (Tables C1, C2). Our results indicate that the predictive accuracy of financial distress is lower with our models using 2 lags than with the original MDA models using 1 lag. In addition, the results using Approaches 2 and 3 reveal variation in the distress prediction models when they are applied to samples other than the ones analysed. This result aligns with the existing empirical evidence. However, our results confirm that the MDA models for predicting financial distress in many ASEAN countries will likely perform better using Approach 1 than Approaches 2 and 3. Overall, the MDA models perform reasonably well at predicting financial distress 1 year ahead. However, the MDA models' predictive performance declines under three circumstances: (1) when the model is not developed for a specific country or period, (2) when the distressed rates have significant swings between the period in which the model is developed and the period being measured, and (3) when the percentage of distressed firms in the sample measured is small, leading to large swings in the percentage.

Finally, we determine whether including the market-based indicator, the DD, improves prediction of distress. The existing literature indicates that some studies prefer a mixed model incorporating both accounting-based

TABLE 7 A summary of the discriminant models and their accuracy rates in predicting financial distress for the entire period.

	Prediction rate		Discriminant functions
Total ASEAN	Distressed	61.1%	$Z = -0.157 + 6.269\,X_1 + 0.226\,X_2 - 0.754\,X_3 + 0.335\,X_4 \_ 1.292\,X_9$
	Non-distressed	81.9%	
Indonesia	Distressed	66.7%	$Z = -0.603 + 3.310\,X_1 + 0.237\,X_2 + 1.426\,X_3 - 0.351\,X_4 + 1.655\,X_6 + 0.03\,X_{10}$
	Non-distressed	86.1%	
Malaysia	Distressed	60.4%	$Z = -0.869 + 6.315\,X_1 - 3.944\,X_3 + 2.698\,X_4 + 0.73\,X_5 + 0.199\,X_{10}$
	Non-distressed	80.8%	
The Philippines	Distressed	60.6%	$Z = -0.423 + 4.801\,X_1 + 0.647\,X_2 + 0.23\,X_4 - 1.787\,X_9 + 0.883\,X_{11}$
	Non-distressed	85.8%	
Singapore	Distressed	42.9%	$Z = -0.774 + 4.076\,X_1 + 2.175\,X_4$
	Non-distressed	88.3%	
Thailand	Distressed	67.5%	$Z = -0.112 + 8.038\,X_1 + 1.003\,X_6 - 0.219\,X_7 - 0.367\,X_{11} - 0.021\,X_{14}$
	Non-distressed	85.1%	
Vietnam	Distressed	61.6%	$Z = -0.394 - 3.172\,X_5 + 0.373\,X_8 + 0.819\,X_{12} + 0.161\,X_{14}$
	Non-distressed	82.2%	

Note: The table compares the in-sample discriminant functions for the entire Association of Southeast Asian Nations (ASEAN) region and each ASEAN country. The functions are reported for Approach 1 (in-sample testing for each country for the entire 20-year period). Total ASEAN is developed from a dataset that includes all six major ASEAN countries. X_1 denotes EBIT/TA. X_2 denotes S/TA. X_3 denotes NI/TA. X_4 denotes RE/TA. X_5 denotes EBITDA/TL. X_6 denotes WC/TA. X_8 denotes CA/CL. X_9 denotes CL/TA. X_9 denotes CL/TA. X_{10} denotes NOCREDINT. X_{11} denotes TL/TA. X_{12} denotes FU/TL. X_{14} denotes MVE/TL.

indicators and market-based factors (Beaver et al., 2005; Hillegeist et al., 2004; Pham et al., 2018; Shumway, 2001; Singh & Mishra, 2016; Tinoco & Wilson, 2013; Wu et al., 2004). To avoid repetition of the results in this paper, we do not report all the discriminant functions and distress prediction results for every country and period. Empirical results are reported only for the models in which DD was significant and led to an improvement in distress prediction. In addition, we limit the analysis to models using Approach 1 to develop specific discriminant models for each country and each of the six periods.

First, we use DD as a single explanatory indicator for distress prediction, in what we call the DD model. In most cases DD was significant in correctly predicting distressed firms (60% average accuracy compared with 61% for the accounting-based model). These results support the conclusions by Agarwal and Taffler (2008), who compared accounting-based models with market-based models for nonfinancial UK firms. They found little difference in predictive performance between these accounting-based and market-based models. However, the DD model has a much lower correct percentage in predicting non-distressed firms than our accounting-based model (56% for the DD model compared with 84% for the accounting-based model). Thus, the DD model was more prone to Type 2 errors.

Second, we incorporate DD as an extra variable into the accounting-based MDA model, called the MDA-DD model. We conducted a stepwise analysis to eliminate the DD variable if it was not significant. Our empirical results indicate that the DD variable was significant and led to predictive improvement only in a small number of cases in the combined MDA-DD model, as shown in Table 8. Unlike in the results for the original accounting-based MDA model (shown in Table 6), those for the MDA-DD model (shown in Table 8) have average improvement of 4.74% (distressed) and 3.80% (non-distressed) in periods when DD is significant in predicting financial distress. However, given that when DD is not significant in other periods, there is 0% improvement, the MDA-DD model improves predictive performance by an overall average of only 0.90% for distressed firms and 0.63% for non-distressed firms across all periods and all six ASEAN countries.

These findings imply that many accounting-based MDA models already include a simplistic market-cap variable (or variables), such as the ratio of the market value of equity to total liabilities or assets (MVE/TL; MVE/TA) in their group of financial leverage indicators (Altman, 1968; Altman et al., 1977; Hillegeist et al., 2004; Shumway, 2001; Zmijewski, 1984). Our MDA models, developed using key variables from prominent studies, also include these leverage indicators. Some studies (Agarwal & Taffler, 2008; Doumpos et al., 2015) have shown that any improvement from adding a sophisticated market-based variable such as DD is substantially diminished when a primary market-cap variable has already been included as an accounting variable.

TABLE 8 The predictive performance of financial distress improves when the distance to default (DD) is incorporated into the MDA models: The MDA-DD models.

		AFC (1997–2000)	Post-AFC (2001–2003)	Pre-GFC (2004–2006)	GFC (2007–2009)	Post-GFC (2010–2012)	Stable period (2013–2016)	The entire period (1997–2016)
Malaysia	Distressed						+2.6%	+6.3%
	Non-distressed						+2.7%	
The Philippines	Distressed				+3.7%			
	Non-distressed		+0.4%				+0.7%	
Singapore	Distressed						+4.8%	
	Non-distressed						+1.4%	
Thailand	Distressed						+16.7%	
	Non-distressed	+14.8%	+6.4%					
Vietnam	Distressed					+0.9%		
	Non-distressed							
Total ASEAN	Distressed			+2.0%				+0.9%
	Non-distressed						+0.2%	

Note: The table shows the percentage to which the distressed/non-distressed predictive accuracy, as shown in Table 6 (using Approach 1), is improved by adding a distance to default (DD) variable to the accounting-based MDA models. The table only shows results for the countries and periods where the addition of DD improved the predictive performance of the MDA model. For example, the addition of DD did not result in significant improvement in Indonesia. As such, the results are excluded from the table.

5 | CONCLUSIONS

This study uses accounting-based indicators to examine the performance of the MDA in predicting corporate financial distress in six ASEAN countries. First, the study identifies common accounting-based indicators in predicting financial distress, although individual models are developed for different countries and periods. Profitability ratios are found to perform best in predicting financial distress in the ASEAN countries, followed by liquidity ratios and then leverage ratios. These findings enable regulators to compare and predict financial distress commonly found in an increasingly integrated area, such as the ASEAN region. Second, the uniform MDA model for the entire ASEAN region and period generally performs well in predicting financial distress. A lower rate of predictive accuracy is evident when volatility is high, such as the beginning and end of crisis and noncrisis periods. Moreover, the single MDA model can be used to predict financial distress 1 year ahead for companies in the ASEAN region. Finally, our empirical findings indicate that including a market-based variable, the distance to default, does not significantly improve the predictive performance of the accounting-based MDA models in predicting financial distress. Thus, the MDA model can be used to predict corporate financial distress at companies in ASEAN countries before a default occurs, helping investors and managers to make appropriate decisions.

The study has important policy implications. It is essential to understand the difference in credit risk across countries if regulators and policy makers achieve greater banking integration, a goal desired within the region. The Basel III accord, in response to the financial problems during the GFC, was created by the Basel Committee on Banking Supervision to fill a range of gaps in the pre-crisis regulatory framework and provide the basis for a robust banking system that will help to prevent greater structural vulnerabilities. However, modelling credit risk is a key challenge for banks in developing countries. Each ASEAN country has its own banking system and risk models. The common indicators identified, and the specific MDA models developed for predicting financial distress can be used as benchmarks in developing credit risk models. In addition, although MDA models are generally less accurate when applied to samples other than the one developed, significant result can be obtained when a single model is used. Thus, our study recommends a single model for the entire ASEAN region that would support the achievement of an integrated banking system going forward.

At the government or regulatory level, knowledge of credit risk is essential for maintaining quality lending practices and sufficient capital. Policy makers can use our findings to estimate corporate financial distress and portfolio credit risk in the banking system. As a result, regulators can make timely regulatory adjustments to minimize negative impacts on the financial system and the economy. At the bank level, lenders need to measure the credit risk or financial distress of firms because lenders need to be aware of borrowers' potential bad debts in order to make provisions, evaluate risk, determine a credit policy, and allocate capital. By helping to detect banks with weak assets at an early stage so that they can minimize losses, the models developed in this study can facilitate these actions by banks.

ACKNOWLEDGEMENTS

We would like to thank the editor-in-chief and the anonymous referees for their time and effort in reading the paper and providing insightful and valuable comments and suggestions. The paper has greatly benefited from their comments and suggestions. Open access publishing facilitated by The University of Western Australia, as part of the Wiley - The University of Western Australia agreement via the Council of Australian University Librarians.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available from the corresponding author upon reasonable request.

ORCID

Dung V. Dinh https://orcid.org/0000-0003-3233-6273
Nam Thanh Vu https://orcid.org/0000-0002-9956-6658
Duc Hong Vo https://orcid.org/0000-0001-7823-0349

REFERENCES

Adusei, M., & Obeng, E. Y. T. (2019). Board gender diversity and the capital structure of microfinance institutions: A global analysis. *The Quarterly Review of Economics and Finance*, *71*, 258–269.

Agarwal, V., & Taffler, R. (2008). Comparing the performance of market-based and accounting-based bankruptcy prediction models. *Journal of Banking & Finance*, *32*(8), 1541–1551.

Al-Dhamari, R., Al-Wesabi, H., Farooque, O. A., Tabash, M. I., & El Refae, G. A. (2023). Does the investment committee mitigate the risk of financial distress in GCC? The role of investment inefficiency. *International Journal of Accounting and Information Management*, *31*, 321–354.

Allen, D. E., Powell, R., & Singh, A. K. (2015). Quantitative financial risk management. In *A critique of credit risk models with evidence from mid-cap firms* (pp. 296–311). John Wiley & Sons.

Altman, E. I. (1968). Financial ratios, discriminant analysis and the prediction of corporate bankruptcy. *Journal of Finance*, *23*(4), 589–609.

Altman, E. I., Haldeman, R. G., & Narayanan, P. (1977). ZETA analysis: A new model to identify bankruptcy risk of corporations. *Journal of Banking and Finance*, *1*(1), 29–54.

Altman, E. I., Iwanicz-Drozdowska, M., Laitinen, E. K., & Suvas, A. (2017). Financial distress prediction in an international context: A review and empirical analysis of Altman's Z-score model. *Journal of International Financial Management & Accounting*, *28*(2), 131–171.

Asquith, P., Gertner, R., & Scharfstein, D. (1994). Anatomy of financial distress: An examination of junk-bond issuers. *Quarterly Journal of Economics*, *109*(3), 625–658.

Beaver, W. H. (1966). Financial ratios as predictors of failure. *Journal of Accounting Research*, *4*, 71–111.

Beaver, W. H., McNichols, M. F., & Rhie, J. (2005). Have financial statements become less informative? Evidence from the ability of financial ratios to predict bankruptcy. *Review of Accounting Studies*, *10*(1), 93–122.

Bellovary, J., Giacomino, D., & Akers, M. (2007). A review of bankruptcy prediction studies: 1930 to present. *Journal of Financial Education*, *33*, 1–42.

Bharath, S. T., & Shumway, T. (2008). Forecasting default with the Merton distance to default model. *Review of Financial Studies*, *21*(3), 1339–1369.

Bonsall, S. B., Bozanic, Z., & Fischer, P. E. (2013). What do management earnings forecasts convey about the macroeconomy? *Journal of Accounting Research*, *51*, 225–266.

Boubaker, S., Cellier, A., Manita, R., & Saeed, A. (2020). Does corporate social responsibility reduce financial distress risk? *Economic Modelling*, *91*, 835–851.

Cao, Y., Liu, X., Zhai, J., & Hua, S. (2020). A two-stage Bayesian network model for corporate bankruptcy prediction. *International Journal of Finance and Economics*, *20200810*, 455–472. https://doi.org/10.1002/ijfe.2162

Chen, C. C., Chen, C. D., & Lien, D. (2020). Financial distress prediction model: The effects of corporate governance indicators. *Journal of Forecasting*, *39*(8), 1238–1252.

Chijoriga, M. M. (2008). Application of multiple discriminant analysis (MDA) as a credit scoring and risk assessment model. *International Journal of Emerging Markets*, *6*(2), 132–147.

Claessens, S., Djankov, S., & Klapper, L. (2003). Resolution of corporate distress in East Asia. *Journal of Empirical Finance*, *10*(1–2), 199–216.

Crespí-Cladera, R., Martín-Oliver, A., & Pascual-Fuster, B. (2021). Financial distress in the hospitality industry during the Covid-19 disaster. *Tourism Management*, *85*, 104301.

Cultrera, L., & Brédart, X. (2016). Bankruptcy prediction: The case of Belgian SMEs. *Review of Accounting and Finance*, *15*(1), 101–119. https://doi.org/10.1108/raf-06-2014-0059

Dang, V. C., & Tran, X. H. (2021). The impact of financial distress on tax avoidance: An empirical analysis of the Vietnamese listed companies. *Cogent Business & Management*, *8*(1), 1953678.

Datastream. (2016) *Thomson reuters datastream*. Available at: Subscription Service.

Deakin, E. (1972). A discriminant analysis of predictors of business failure. *Journal of Accounting Research*, *10*(1), 167–179.

Dinh, D. V., Powell, R. J., & Vo, D. H. (2021). Forecasting corporate financial distress in the southeast Asian countries: A market-based approach. *Journal of Asian Economics*, *74*, 101293.

Doumpos, M., Niklis, D., Zopounidis, C., & Andriosopoulos, K. (2015). Combining accounting data and a structural model for predicting credit ratings: Empirical evidence from European listed firms. *Journal of Banking & Finance*, *50*, 599–607.

du Jardin, P. (2009). Bankruptcy prediction models: How to choose the most relevant variables? *Bankers, Markets & Investors*, *98*, 39–46.

Faelten, A., & Vitkova, V. (2014). Who gains from corporate rescues? Distressed M&A during four financial crises. http://citeseerx.ist.psu.edu/viewdoc/summary?doi=10.1.1.637.7773

Farooq, M., & Noor, A. (2021). The impact of corporate social responsibility on financial distress: Evidence from developing economy. *Pacific Accounting Review*, *33*(3), 376–396.

Farooq, M., Noor, A., & Qureshi, S. F. (2022). The impact of corporate social responsibility on financial distress: Empirical evidence. *Social Responsibility Journal*, *18*(5), 1050–1067.

García, C. J., & Herrero, B. (2021). Female directors, capital structure, and financial distress. *Journal of Business Research*, *136*, 592–601.

Gharghori, P., Chan, H., & Faff, R. (2006). Investigating the performance of alternative default-risk models: Option-based versus accounting-based approaches. *Australian Journal of Management*, *31*(2), 207–234.

Giesecke, K., & Weber, S. (2006). Credit contagion and aggregate losses. *Journal of Economic Dynamics and Control*, *30*(5), 741–767.

Grice, J. S., & Ingram, R. W. (2001). Tests of generalizability of Altman's bankruptcy prediction models. *Journal of Business Research*, *54*(1), 53–61.

Hillegeist, S., Keating, E., Cram, D., & Lundstedt, K. (2004). Assessing the probability of bankruptcy. *Review of Accounting Studies*, *9*(1), 5–34.

Huberty, C. J., & Olejnik, S. (2006). *Applied MANOVA and discriminant analysis*. John Wiley & Sons.

Ito, T. (2007). Asian currency crisis and the international monetary fund, ten years later: Overview. *Asian Economic Policy Review*, *2*(1), 16–49.

Izan, H. (1984). Corporate distress in Australia. *Journal of Banking & Finance*, *8*(2), 303–320.

Joh, S. W., & Jung, J. (2016). Top managers' academic credentials and firm value. *Asia-Pacific Journal of Financial Studies*, *45*(2), 185–221.

Johnson, S., Boone, P., Breach, A., & Friedman, E. (2000). Corporate governance in the Asian financial crisis. *Journal of Financial Economics*, *58*, 141–186.

Jung, K., & Kim, B. (2008). Corporate cash holdings and tax-induced debt financing. *Asia-Pacific Journal of Financial Studies*, *37*(6), 983–1023.

Koh, H., & Killough, L. (1990). The use of multiple discriminant analysis in the assessment of the going-concern status of an audit client. *Journal of Business Finance & Accounting*, *17*(2), 179–192.

Li, Z., Crook, J., Andreeva, G., & Tang, Y. (2021). Predicting the risk of financial distress using corporate governance measures. *Pacific-Basin Finance Journal*, *68*, 101334.

Liang, D., Tsai, C. F., Lu, H. Y. R., & Chang, L. S. (2020). Combining corporate governance indicators with stacking ensembles for financial distress prediction. *Journal of Business Research*, *120*, 137–146.

Liou, D. K., & Smith, M. (2007). Macroeconomic variables and financial distress. *Journal of Accounting, Business and Management*, *14*, 17–31.

Lopez, J. A., & Saidenberg, M. R. (1999). Evaluating credit risk models. *Journal of Banking & Finance*, *24*(1–2), 151–165.

Ma'aji, M. M., Abdullah, N. A. H., & Khaw, K. L. (2018). Predicting financial distress among SMEs in Malaysia. *European Scientific Journal*, *14*(7), 91–102.

Magee, S. (2013). The effect of foreign currency hedging on the probability of financial distress. *Accounting and Finance*, *53*, 1107–1127.

Mangena, M., Priego, A. M., & Manzaneque, M. (2020). Bank power, block ownership, boards, and financial distress likelihood: An investigation of Spanish listed firms. *Journal of Corporate Finance*, *64*, 101636.

Männasoo, K., Maripuu, P., & Hazak, A. (2018). Investments, credit, and corporate financial distress: Evidence from central and Eastern Europe. *Emerging Markets Finance and Trade*, *54*(3), 677–689.

Mariano, S. S. G., Izadi, J., & Pratt, M. (2021). Can we predict the likelihood of financial distress in companies from their corporate governance and borrowing? *International Journal of Accounting and Information Management*, *29*(2), 305–323.

Meeampol, S., Lerskullawat, P., Wongsomtham, A., Srinammuang, P., Rodpetch, V., & Noomoi, R. (2014). Applying emerging market Z-score model to predict bankruptcy: A case study of listed companies in the stock exchange of Thailand (set). In *Management, knowledge and learning international conference* (pp. 25–27). ToKnowPress.

Merton, R. C. (1974). On the pricing of corporate debt: The risk structure of interest rates. *The Journal of Finance*, *29*(2), 449–470.

Mselmi, N., Lahiani, A., & Hamza, T. (2017). Financial distress prediction: The case of French small and medium-sized firms. *International Review of Financial Analysis*, *50*, 67–80.

Nguyen, L. T. M., Le, D., Vu, K. T., & Tran, T. K. (2023). The role of capital structure management in maintaining the financial stability of hotel firms during the pandemic—A global investigation. *International Journal of Hospitality Management*, *109*, 103366.

Noga, T. J., & Schnader, A. L. (2013). Book-tax differences as an indicator of financial distress. *Accounting Horizons*, *27*, 469–489.

Ohlson, J. (1980). Financial ratios and the probabilistic prediction of bankruptcy. *Journal of Accounting Research*, *18*(1), 109–131.

Oz, I., & Simga-Mugan, C. (2018). Bankruptcy prediction models' generalizability: Evidence from emerging market economies. *Advances in Accounting*, *41*, 114–125.

Pham, N. B. V., Do, T. T., & Vo, H. D. (2018). Financial distress and bankruptcy prediction: An appropriate model for listed firms in Vietnam. *Economic Systems*, *42*(4), 616–624.

Pindado, J., Rodrigues, L., & de la Torre, C. (2008). Estimating financial distress likelihood. *Journal of Business Research*, *61*(9), 995–1003.

Platt, H. D., & Platt, M. B. (2002). Predicting corporate financial distress: Reflections on choice-based sample bias. *Journal of Economics and Finance*, *26*(2), 184–199.

Pongsata, S., Ramage, J., & Lawrence, H. (2004). Bankruptcy prediction for large and small firms in Asia: A comparison of Ohlson and Altman. *Journal of Accounting and Corporate Governance*, *1*(2), 1–13.

Rahman, S., Tan, L., & Hew, O. (2004). Identifying financial distress indicators of selected banks in Asia. *Asian Economic Journal*, *18*(1), 45–58.

Routledge, J., & Gadenne, D. (2000). Financial distress, reorganization and corporate performance. *Accounting and Finance*, *40*(3), 233–259.

Salmi, T., & Martikainen, T. (1994). A review of the theoretical and empirical basis of financial ratio analysis. *Finnish Journal of Business Economics*, *4*(94), 426–448.

Sangsubhan, K., & Basri, M. C. (2012). The global financial crisis and ASEAN: Fiscal policy response in the case of Thailand and Indonesia. *Asian Economic Policy Review*, *7*(2), 248–269.

Sayari, N., & Mugan, C. S. (2016). Industry-specific financial distress modelling. *Business Research Quarterly*, *20*(1), 45–62.

Shahwan, T. M., & Habib, A. M. (2020). Do the efficiency of corporate governance and intellectual capital affect a firm's financial distress? Evidence from Egypt. *Journal of Intellectual Capital*, *21*(3), 403–430.

Shi, Y., & Li, X. (2019). An overview of bankruptcy prediction models for corporate firms: A systematic literature review. *Intangible Capital*, *15*(2), 114–127.

Shleifer, A., & Vishny, R. W. (1997). A survey of corporate governance. *Journal of Finance*, *52*, 737–783.

Shumway, T. (2001). Forecasting bankruptcy more accurately: A simple hazard model. *Journal of Business*, *74*(1), 101–124.

Singh, B. P., & Mishra, A. K. (2016). Re-estimation and comparisons of alternative accounting-based bankruptcy prediction models for Indian companies. *Financial Innovation*, *2*(6), 1–28.

Sirirattanaphonkun, W., & Pattarathammas, S. (2012). Default prediction for small-medium enterprises in an emerging market: Evidence from Thailand. *Seoul Journal of Business*, *18*(2), 25–54.

Taffler, R. J. (1983). The assessment of company solvency and performance using a statistical model. *Accounting and Business Research*, *13*(52), 295–308.

Thai, S. B., Goh, H. H., Teh, B. H., Wong, J. C., & Ong, T. S. (2014). A revisit of the Altman Z-score model for companies listed in Bursa Malaysia. *International Journal of Business and Social Science*, *5*(12), 197–207.

Tinoco, M. H., & Wilson, N. (2013). Financial distress and bankruptcy prediction among listed companies using accounting, market, and macroeconomic variables. *International Review of Financial Analysis*, *30*, 394–419.

Todorov, V. (2007). Robust selection of variables in linear discriminant analysis. *Statistical Methods and Applications*, *15*(3), 395–407.

Vargas-Silva, C., Jha, S., & Sugiyarto, G. (2009). Remittances in Asia: Implications for the fight against poverty and the pursuit of economic growth. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.1618025

Vassalou, M., & Xing, Y. (2004). Default risk in equity returns. *Journal of Finance*, *59*(2), 831–868.

Vu, N. T., Nguyen, N. H., Tran, T., Le, B. T., & Vo, D. H. (2023). A LASSO-based model for financial distress of the Vietnamese listed firms: Does the covid-19 pandemic matter? *Cogent Economics & Finance*, *11*(1), 2210361.

World Bank. (2019). GDP (current US$). http://data.worldbank.org/indicator/NY.GDP.MKTP.CD

Wu, Y., Gaunt, C., & Gray, S. (2004). A comparison of alternative bankruptcy prediction models. *Journal of Contemporary Accounting and Economics*, *6*(1), 34–45.

Zhang, W. (2015). R&D investment and distress risk. *Journal of Empirical Finance*, *32*, 94–114.

Zmijewski, M. E. (1984). Methodological issues related to the estimation of financial distress prediction models. *Journal of Accounting Research*, *22*(2), 59–82.

How to cite this article: Powell, R. J., Dinh, D. V., Vu, N. T., & Vo, D. H. (2023). Accounting-based variables as an early warning indicator of financial distress in crisis and non-crisis periods. *International Journal of Finance & Economics*, 1–20. https://doi.org/10.1002/ijfe.2864

APPENDIX A

TABLE A1 Number of companies in the research population.

Country	Number of listed companies	Number of delisted companies
Indonesia	539	372
Malaysia	797	363
The Philippines	271	63
Singapore	143	650
Thailand	563	750
Vietnam	699	88

Source: DataStream (2016).

APPENDIX B

B.1 | The accounting-based MDA model using lag-2

To determine whether using lag-2 has a material impact on predictive performance, we ran a lag-2 MDA model with the entire dataset (all countries) using Approach 1. We found that the longer lag reduces overall accuracy by 4.2% (76.8% accuracy falls to 72.6% across the two groups: distressed versus non-distressed). However, the result is still significant at a 99% level. We also examined how predictive performance changes if we use a cash flow-related variable rather than the interest coverage ratio (ICR) as the distress variable. Two alternatives are used, EBITDA to interest expenses and operating cash flows to interest expenses, using Approach 1. Using EBITDA to interest expenses showed no significant change (lowering the overall predictive accuracy by 0.7%–76.1%). Using the operating cash flows to interest expenses as a substitute for ICR had a more substantial change, reducing overall predictive accuracy by 9.2%–67.6%.

APPENDIX C

C.1 | Results from Approaches 2 and 3

TABLE C1 The discriminant functions from out-of-sample modelling.

	Period	Discriminant functions
Total ASEAN	AFC–Pre-GFC	$Z = -0.167 + 4.647\,X_1 + 0.306\,X_2 - 0.754\,X_3 - 0.818\,X_6 - 1.017\,X_9$
	GFC–Current	$Z = -0.518 + 6.470\,X_1 + 0.174\,X_2 - 0.641\,X_3 + 0.776\,X_4 + 0.495\,X_6 - 0.818\,X_9$
Indonesia	AFC–Pre-GFC	$Z = -0.059 + 3.447\,X_1 + 0.525\,X_2 + 2.015\,X_3 – 0.349\,X_4 – 1.564\,X_9 + 0.036\,X_{10}$
	GFC–Current	$Z = -0.602 + 5.060\,X_1 + 1.377\,X_6 + 0.052\,X_{10}$
Malaysia	AFC–Pre-GFC	$Z = -0.952 + 7.239\,X_1 + 0.535\,X_2 – 4.041\,X_3 + 2.454\,X_4 + 0.169\,X_{10}$
	GFC–Current	$Z = -0.672 + 4.522\,X_1 + 2.951X_4 + 0.239\,X_{10} – 0.465\,X_{11}$
The Philippines	AFC–Pre-GFC	$Z = -0.209 - 3.698\,X_1 – 0.688\,X_2 + 0.189\,X_4 + 2.052\,X_9$
	GFC–Current	$Z = -1.523 + 8.473\,X_1 + 0.58\,X_2 – 3.488\,X_3 + 1.246X_4 + 1.018\,X_6 – 1.926\,X_9 + 2.425\,X_{11}$
Singapore	AFC–Pre-GFC	$Z = 1.037 + 2.31\,X_1 + 2.03\,X_3 – 2.949\,X_{11}$
	GFC–Current	$Z = -0.957 + 11.992\,X_1 + 1.771\,X_4 – 1.204\,X_5$
Thailand	AFC–Pre-GFC	$Z = -0.414 - 8.415\,X_1 + 0.594\,X_5 + 1.219\,X_{11} + 0.024\,X_{14}$
	GFC–Current	$Z = -0.160 + 8.200\,X_1 + 1.682\,X_6 – 0.249\,X_8 + 0.07\,X_{10} – 0.017\,X_{14}$

	Profitability					Liquidity				Leverage	
	X_1	X_2	X_3	X_4	X_5	X_6	X_8	X_9	X_{10}	X_{11}	X_{14}
AFC—Pre-GFC (Approach 2)	6	4	4	3	1	1	0	3	2	2	1
GFC–Current (Approach 3)	6	2	2	3	0	4	1	2	3	2	1

Note: The table presents the out-of-sample discriminant functions for each of the Association of Southeast Asian Nations (ASEAN) countries. The functions are reported for Approach 2 (a forward-testing out-of-sample discriminant function developed from the first half of the data sample, from the Asian financial crisis to pre-global financial crisis [GFC], which is then applied to the second half of the data sample); and Approach 3 (a backward-testing out-of-sample discriminant function developed from the second half of the data sample, from the GFC to the stable period, which is then applied to the first half of the data sample). The data for all of ASEAN (total ASEAN) is developed from a dataset that includes all six ASEAN countries. The bottom section of the table summarizes the frequency at which each ratio appears in the discriminant functions. X_1 denotes EBIT/TA. X_2 denotes S/TA. X_3 denotes NI/TA. X_4 denotes RE/TA. X_5 denotes EBITDA/TL. X_6 denotes WC/TA. X_8 denotes CA/CL. X_9 denotes CL/TA. X_{10} denotes NOCREDINT. X_{11} denotes TL/TA. X_{14} denotes MVE/TA.

TABLE C2 Percentage of correct prediction rates from out-of-sample testing in multiple discriminant analysis models.

		AFC Approach 3 Back-testing	Post-AFC	Pre-GFC	GFC Approach 2 Forward-testing	Post-GFC	Stable period
Indonesia	Distressed	70.1%	63.3%	63.6%	75.0%	80.0%	50.0%
	Non-distressed	78.5%	88.5%	84.6%	79.8%	92.3%	98.9%
	χ^2	119.663***	63.820***	54.455***	28.933***	63.710***	86.883***
Malaysia	Distressed	31.7%	56.0%	46.2%	60.5%	73.7%	65.8%
	Non-distressed	94.8%	85.4%	88.4%	80.8%	84.1%	68.2%
	χ^2	14.303***	34.215***	30.636***	49.480***	90.695***	15.192***
The Philippines	Distressed	50.0%	51.7%	47.1%	85.2%	44.7%	46.8%
	Non-distressed	60.2%	91.6%	87.4%	67.5%	87.3%	92.9%
	χ^2	15.311**	54.820***	33.146***	38.190***	65.561***	77.822***
Singapore	Distressed	46.4%	52.0%	80.0%	75.0%	52.9%	61.9%
	Non-distressed	91.0%	91.8%	78.7%	87.9%	78.4%	65.7%
	χ^2	2.155	21.013***	29.602***	42.125***	18.569***	7.005
Thailand	Distressed	68.6%	55.3%	67.3%	62.0%	87.5%	25.0%
	Non-distressed	81.2%	82.7%	93.9%	91.0%	82.3%	94.0%
	χ^2	82.333***	32.030***	72.472***	85.226***	52.855***	45.946***
Total ASEAN	Distressed	53.5%	45.2%	38.9%	68.4%	67.6%	60.1%
	Non-distressed	87.7%	91.7%	92.4%	71.0%	71.6%	75.2%
	χ^2	68.709***	144.343***	13.938-	135.048***	169.720***	146.255***

Note: The table presents the distressed/non-distressed predictive accuracy 1 year ahead of the distress of firms for Association of Southeast Asian Nations (ASEAN) countries over different periods. The firms are identified as distressed or non-distressed based on the interest coverage ratio (ICR). Total ASEAN is developed from a dataset that includes six ASEAN countries. The results are reported for Approach 2 (a forward-testing out-of-sample discriminant function developed from the first half of the data sample, 1997–2006, and then applied to the second half, 2007–2016); and Approach 3 (a backward-testing out-of-sample discriminant function developed from the second half of the data sample, 2007–2016, and then applied to the first half, 1997–2006). For example, where Approach 2 is applied to the global financial crisis (GFC), Indonesia had 75.0% of distressed firms that were correctly classified as distressed and 25.0% that were incorrectly classified as non-distressed (Type I error), whereas 79.8% of non-distressed firms were correctly classified as non-distressed and 20.2% incorrectly classified as distressed (Type II error). Vietnam is excluded from the analysis because insufficient data was available to build a model from Asian financial crisis (AFC) to Pre-GFC. The table also presents the significance results determined by the chi-square test (χ^2) concerning the multiple discriminant analysis (MDA) model's ability to discriminate between distressed and non-distressed firms. ** and *** denote significance at the 95% and 99% levels.