



How to cite this article:

Zainol Abidin, J., Abdullah, N. A. H., & Khaw, K. L. H. (2021). Bankruptcy prediction: SMEs in the hospitality industry. *International Journal of Banking and Finance*, 16(2), 51-80. <https://doi.org/10.32890/ijbf2021.16.2.3>

## **BANKRUPTCY PREDICTION: SMEs IN THE HOSPITALITY INDUSTRY**

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Received: 17/2/2021 Revised: 22/3/2021 Accepted: 22/3/2021 Published: 15/6/2021

### **ABSTRACT**

The objectives of this study are to predict bankruptcy risk among SMEs in the hospitality industry for a three-year horizon period and to investigate the factors that are significant in determining bankruptcy. The contribution of SMEs in the hospitality industry is essential as businesses in the hospitality industry are dominated by SME operators. However, the failure rate among SMEs is relatively high and almost 50 percent of hospitality establishments do not survive beyond five years of operation. The Stepwise logistic model was employed to determine significant predictors that could predict bankruptcy for the period of one year, two years and three

years before bankruptcy. Return on assets and firm age were found to be significant in all periods while other variables were identified to be important at a specific period prior to bankruptcy. In addition to return on assets and firm age, debt ratio and total assets turnover were found to be significant predictors of bankruptcy one-year prior to bankruptcy. However, in the two years prior to bankruptcy, debt ratio and total assets turnover were no longer important but current ratio, ownership concentration and gender diversity were found to be significant. As for the three years prior to bankruptcy, additional variables namely debt-to-equity ratio and board size were found to be significant, but ownership concentration and gender diversity ceased to be important. The findings of this study contribute to the limited literature in predicting the bankruptcy risk of small firms for a three-year horizon period by providing empirical evidence from SMEs in the hospitality industry of Malaysia.

**Keywords:** Bankruptcy, hospitality industry, logistic regression, prediction, SMEs.

JEL Classification: G30, G33.

## INTRODUCTION

Since the outbreak of the coronavirus disease 2019 (Covid-19) at the end of 2019, industries have encountered severe challenges, and this scenario is even more challenging for the hospitality industry (Hao et al., 2020). Malaysia is no exception as the outbreak of Covid-19 has adversely affected the hospitality industry and this industry continues to struggle with the impact of Covid-19 (Foo et al., 2020). As the hospitality industry is the backbone of tourism in Malaysia, the future of this industry is at risk of failure (Luk, 2020). The small and medium-sized enterprises (SMEs) operating in the hospitality industry seem to be more affected than their larger counterparts (Luk, 2020). This is significant because businesses in the tourism industry are dominated by SME operators (Set et al., 2012).

SMEs contribute significantly to Malaysia's economy in the short and long term (Yusoff et al., 2018). They represent the vast majority of the business population accounting for 98.5 percent of total enterprises

and providing 65.3 percent of total employment (Department of Statistics, 2017). The SMEs also contribute 38.9 percent to the national gross domestic product (GDP) and 17.9 percent to total exports in 2019 (Department of Statistics, 2020). In terms of distribution by sub-industry, there are 169,278 SMEs and 889,619 employees in the food and beverage (F&B), and accommodation business. In addition, the contribution of the tourism industry to Malaysia's GDP is significant, the third highest after manufacturing and commodities (Hirschmann, 2020). The Gross Value Added of Tourism Industries (GVATI) recorded a contribution of 15.9 percent to GDP, amounting to RM240.2 billion in 2019 (Department of Statistics, 2020). Both F&B and accommodation contributed 29.8 percent to the total GVATI, the second highest after retail trade (Department of Statistics, 2020).

Since SMEs are vital to the nation's economy, the government continues to support the SMEs with large budget allocations every year. Nonetheless, failure rates among SMEs are relatively high (Kalemli-Ozcan et al., 2020). For example, in Australia, an average of 64 percent of small businesses survived over a four-year period from 2014 to 2018 (Australian Small Business and Family Enterprise Ombudsman, 2019). Approximately 20 percent of U.S. small businesses fail within the first year, and around 50 percent of them fail within five years, and the rates are seen to be consistent over time (McIntyre, 2020). For the restaurant business, about 70 percent of them remain in business after two years in operation and 50 percent make it through their fifth year (McIntyre, 2020). Similarly in Malaysia, the SMEs are unable to sustain their businesses with approximately 60 percent of them failing (Chong, 2012), while almost 50 percent of hospitality establishments do not survive beyond five years of operation (Abod, 2017). Due to this, many studies have been conducted to examine the causes of business failure.

Since the work of Edmister (1972), numerous failure prediction models focusing on SMEs and utilizing financial, non-financial and governance indicators have been proposed (Altman et al., 2010; Donato & Nieddu, 2020; Keasey & Watson, 1987; Ma'aji et al., 2019). Nevertheless, there is a lack of studies focusing on SMEs in the hospitality industry (Pacheco, 2015; Zainol Abidin et al., 2020). Most of the published works on hospitality failure focused on public-listed firms (Barreda et al., 2017; Fernández-Gómez et al., 2016; Gemar et

al., 2019; Kim & Gu, 2006; Park & Hancer, 2012; Youn & Gu, 2010a; 2010b; Zhai et al., 2015). Similarly, in the context of Malaysian literature, the majority of research on corporate failures has focused on public-listed firms (Abdullah, 2020; Abdullah & Ahmad, 2005; Alifiah & Tahir, 2018; Low et al., 2001; Yasser & Mamun, 2015). However, there are relatively limited studies looking into the SMEs and most of the researches predict financially distressed SMEs in the manufacturing sector (Abdullah, Ahmad et al., 2016, Abdullah et al., 2016, Abdullah et al., 2019; Ma'aji et al., 2018, 2019).

In many studies, predictions of business failures were mainly based on short-term analyses, i.e. one year prior to failure. Nevertheless, preceding studies indicate that failure is a continuous process and the symptoms of a firm's failure emerge several years before the actual event (Hossari, 2007). This provides a basis that business failure can be predicted for a longer horizon. In light of the recent global pandemic and the uncertainty of doing business, it is of the utmost concern for a firm to predict the risk of business failure a few years ahead. Therefore, entrepreneurs can take proactive action to reduce the risk of failure if bankruptcy can be predicted with reasonable accuracy. Furthermore, the SMEs will have sufficient time to prepare for the crisis, so that strategic measures can be taken for a feasible recovery.

The purpose of this paper is to examine the factors that could predict the risk of bankruptcy among SMEs in the hospitality industry in the three years, two years and one year prior to bankruptcy. Financial, non-financial and governance variables are utilized as potential bankruptcy predictors and the model accuracy rate is examined using logistic regression (logistic). Thus, this study has several contributions to the research on bankruptcy prediction. Firstly, we contribute to a somewhat scarce research on bankruptcy prediction for SMEs in the hospitality industry. Secondly, we predict bankruptcy with a longer prediction period of up to three years prior to bankruptcy, and thirdly, we utilize financial, non-financial and governance variables to find predictors that best discriminate between bankrupt and healthy SMEs in the hospitality industry. This paper is structured as follows: Section 2 discusses the literature review, Section 3 describes the methodology, Section 4 presents the empirical results, and the conclusions are presented in Section 5.

## LITERATURE REVIEW

The first study to model small business failure was conducted by Edmister (1972). Using the Multiple Discriminant Analysis (MDA) technique, he examined a sample of 21 financially distressed and 21 healthy US small firms for the period between 1954 and 1969. Utilizing 19 financial ratios, the results revealed that quick ratio, inventory to sales, equity to sales, fund flow to current liabilities, current liabilities to equity and working capital to sales were the significant predictor variables with an overall classification rate of 93 percent.

Using a sample of UK small firms, Keasey and Watson (1987) analyzed a sample of 73 failed and 73 healthy firms from various industries for the period between 1970 and 1983. Employing a logistic model, they selected 28 financial indicators and non-financial indicators to predict small enterprise failure. For the financial variables, the logistic model selected pre-tax profit to total assets, profit before interest to total debt, quick ratio, total debt to total assets and fixed assets to total assets as significant determinants of failure. For the non-financial variables, the logistic model identified three-year average accounts submission lag, going concern qualification, audit to submission lag, bank floating charges and the number of directors as important indicators of failure. They reported that the model performed better when using both financial and non-financial information with a total classification rate of 82.2 percent in the testing sample.

Later, Cressy (1992) expanded the work of Edmister (1972), and Keasey and Watson (1987) by demonstrating that a five-year lag structure using financial ratios was able to generate better models. Using a logistic model and a sample of 636 small UK firms from different industries, results showed that net profits to total assets, current assets to total assets, net profit relative to total debts and current assets to current liabilities were significant determinants of bankruptcy. In addition, only net profits to total assets were found to be significant in every prior year samples. Hence, the author suggested that profitability should be regarded as the important determinant of small firm failure. Furthermore, he argued that it was necessary to utilize several years' data using financial ratios to generate a better classification rate on small firm solvency.

While Cressy (1992) suggested that profitability was an important determinant of failure for UK's small firms, Yazdanfar and Nilsson (2008) identified debt ratio as a significant bankruptcy predictor for Swedish SMEs. They constructed two bankruptcy prediction models for a three-year lag utilizing the MDA and logistic. Using a matched pair's sample of 1991 bankrupt and 1991 non-bankrupt firms in various industries, the MDA model identified quick ratio, debt ratio and profitability ratio as important predictor variables for all periods, while accounts receivable to total assets was found to be significant in the two years and three years before bankruptcy. The logistic model selected only one indicator, i.e. debt ratio as a significant bankruptcy indicator for all periods, while quick ratio, return on assets and accounts receivable to total assets were found significant either in one year, two years or three years before the actual bankruptcy event. The accuracy rates of both the MDA and logistic models decreased when the predictive horizon increased. The performance of the logistic model was slightly better than the MDA model with an accuracy rate for one year, two years and three years before bankruptcy, at 83.5 percent, 80.5 percent and 77.8 percent, respectively as compared to the MDA model at 82.8 percent, 78.1 percent and 75.4 percent, respectively.

In line with the above study, Altman et al. (2015) constructed a prediction model for a longer period, i.e. up to a 10-year horizon period. Using a sample of Finnish SMEs, three logistic models were constructed, i.e. financial model, non-financial model and a combined model (financial and non-financial). They reported that the performance of the combined model was better than the financial and non-financial models. Equity to total assets and firm size were the important predictors of bankruptcy in most of the prediction periods. This confirmed that both indicators were the core of the financial dimensions in the long run. The area under the Receiver Operating Characteristic (ROC) curve of the model decreased from 0.9482 in the first year to 0.7300 in 10th year in the testing sample.

Similarly, Klepac and Hampel (2018) suggested that the model classification rate decreases with the shortened distance to bankruptcy. They developed a bankruptcy prediction model for a three-year period using a sample of manufacturing SMEs in 28 European Union countries. A sample of 170 SMEs that were declared bankrupt in 2014

and 830 active SMEs were utilized for the analysis. The decision tree model identified solvency ratio (net income + depreciation/liabilities) as a significant predictor of bankruptcy for all periods, while interest cover, liquidity ratio and return on assets were significant determinants of bankruptcy at a certain period prior to bankruptcy. The overall model classification rates for the one year, two years and three years prior to bankruptcy was 95.3 percent, 84.8 percent and 80.3 percent, respectively in the testing sample.

Consistent with findings by Yazdanfar and Nilsson (2008), Abdullah et al. (2019) found that debt ratio was an important indicator of failure for manufacturing SMEs in Malaysia. By employing a logistic model, they developed a four-year prediction model using financial and non-financial variables. The sample consisted of 278, 234, 162 and 58 matched pairs of distress and active SMEs over the period between 2000 and 2010. Debt ratio was found to have significant discriminating power for all periods, while some of the predictors, such as firm size, age, earnings before interest and tax to total assets, short-term liabilities to total liabilities, current ratio, net income to share capital and sales to total assets were found to be significant at a certain period prior to distress. The classification rates of the model for the one year, two years, three years and four years prior to distress was 90 percent, 87.5 percent, 75 percent and 66.5 percent, respectively in the holdout sample. Similar to Yazdanfar and Nilsson (2008), Altman et al. (2015), and Klepac and Hampel (2018), findings of their study revealed that the model prediction accuracy decreased as the period prior to the distress situation increased. Furthermore, they concluded that the sign of a firm in financial distress could be detected as early as four years before the actual event occurred.

Continuing with the same stream of research, Papan and Spyridou (2020) analyzed a sample of bankrupt and healthy SMEs in Greece for one year, two years and three years prior to bankruptcy. They developed four models, namely linear discriminant analysis (LDA), logistic, decision tree and neural network (NN) using financial ratios. Findings showed that all the four models identified either profitability or liquidity ratios as significant determinants of bankruptcy. Thus, the authors suggested that the SMEs in Greece should be cautious with their liquidity level and the productive use of assets to generate revenue. In terms of the models' performance, the LDA performed

slightly better than the rest of the models. The overall accuracy rates of the models for the respective one year, two years and three years before bankruptcy in the testing sample were (1) LDA – 70.8 percent, 63 percent, 70.5 percent, (2) Logistics – 65.8 percent, 62.5 percent, 68 percent, (3) decision tree – 62.5 percent, 62 percent, 61 percent, (4) NN – 70 percent, 65.7 percent, 65.5 percent.

Thus far, existing empirical studies on hospitality failure have focused on public-listed firms (Gemar et al., 2019; Gu, 2002; Kim, 2011, 2018; Kim & Upneja, 2014). A limited number of published works have analyzed the likelihood of SME failure in the hospitality industry. Pacheco (2015) employed a logistic model to predict bankruptcy using a sample of 25 failed and 460 active SMEs in the restaurant and accommodation business, and a set of financial ratios as input variables. The results indicated that debt to total assets and equity to total assets were related to the likelihood of failure among SMEs in Portugal. The model classification rate was only 67.8 percent. Similarly, Zainol Abidin et al. (2020) examined the probability of failure among Malaysian SMEs in the restaurant and accommodation business. Using financial, non-financial and governance information, they developed two models, i.e. logistic and artificial neural network (ANN). The logistic model identified return on assets and board size as significant indicators of failure, while the ANN model identified current ratio, debt-to-equity ratio, return on sales, return on assets and board size as significant. Since both models suggested board size as an important predictor of failure, this indicated that a firm's governance was also important for business survival. The overall classification rate of the logistic and ANN models in the holdout sample were 80 percent and 92 percent, respectively.

In the context of Malaysian literature, most of the studies model SME failure in the manufacturing sector (Abdullah, Ahmad et al., 2016, Abdullah et al., 2016, Abdullah et al., 2019; Ma'aji et al. 2018, 2019) and the only study that has conducted a failure prediction investigation of SMEs in the hospitality industry was for a single period only, i.e. two years prior to failure (Zainol Abidin et al., 2020). Therefore this study is intended to fill the gap by predicting the failure of SMEs in the hospitality industry for up to three years in advance. Moreover, this study utilized additional governance variables that have not been used in those studies, namely ownership concentration

related to SME that is 100 percent owned by a holding company and shareholders owned equal shares in the company. A model that can predict financially distressed SMEs for a period up to three years prior to distress is essential so that the model developed for SMEs in the hospitality industry can be useful to SMEs to help in sustaining their businesses. Additionally, earlier studies had suggested that ownership concentration was significant in predicting the failure of SMEs (Ciampi, 2015; Abdullah et al., 2016; Ma'aji et al. 2018). Since these additional variables are common in the SME ownership structure, these variables are expected to be significant predictors of failure for SMEs.

## **METHODOLOGY**

### **Sample and Data**

The sample firms consisted of bankrupt and non-bankrupt SMEs in the hospitality industry. The list of SMEs with Malaysia Standard Industrial Classification (MSIC) codes of 5510 (short-term accommodation activities) and 5610 (food and beverage activities) was retrieved from the Companies Commission of Malaysia (CCM) database for the period between 2000 and 2016. The CCM database provides information such as company profile, balance sheets and income statements. The samples were chosen based on the SME's definition endorsed by the National SME Development Council. SMEs are defined as having annual sales of up to RM20 million (SME Corporation, 2013), while bankrupt SMEs are defined as those being wound up by a court order or creditor's request under Section 218 (1) (e) and (2) of the Companies Act 1965.

Subsequently, after going through the SMEs' financial data and other relevant information, subject to data availability, 634 bankrupt SMEs were identified. The bankrupt SMEs were matched with non-bankrupt SMEs on the basis of same firm size (total assets within the range of 10 percent) and same sub-industry. Matching sample was required as there could be significant differences between two groups if healthy firms were to be selected at random (Jones, 1987).

The total SMEs sampled were 1,268, representing 350 companies (40 accommodation and 310 F&B) one year prior to bankruptcy, 444 firms

(60 accommodation and 384 F&B) two years prior to bankruptcy and 474 firms (54 accommodation and 420 F&B) three years prior to bankruptcy. As observed, the more we moved closer to the bankruptcy date, the less number of samples of bankrupt companies as most of them were unable to submit financial reports, which resulted in a smaller sample for the year closer to bankruptcy. In line with previous studies, 70 percent of the total sample was utilized as the training sample and the remaining 30 percent was retained as the holdout sample to test the models' performance (Cultrera & Brédart, 2016; Ptak-Chmielewska, 2019).

## **Variables**

The logistic model employed a dichotomous dependent variable for bankruptcy prediction. The dependent variable took the value of one if the SME was bankrupt and zero if the SME was not bankrupt. As there is a lack of established theory that discusses the appropriate predictors of business failure, the independent variables in this study were selected based on previous empirical studies on SME failure and on the availability of the data (Balcaen & Ooghe, 2006; Chancharat, 2011). The analysis considered three categories of input variables namely financial, non-financial and governance as potential indicators of business failure. Table 1 presents the list of variables and their descriptions.

The selected variables included eight financial variables that were grouped into five categories namely liquidity, leverage, profitability, efficiency and firm size. (1) Liquidity measures the ability of a company to meet its short-term debt obligations as they fall due. It is measured using the current ratio (Abdullah et al., 2019; Cultrera & Brédart, 2016; Klepac & Hampel, 2018; Zainol Abidin et al., 2020). The higher the ratio, the more liquid the company as it has enough resources to pay off its debt commitments, hence the possibility of failure is low. (2) Leverage was represented by debt ratio and debt-to-equity ratio. A higher leverage ratio indicates a higher level of indebtedness that can lead to the risk of default and bankruptcy (Abdullah et al., 2019; Pacheco, 2015; Yazdanfar & Nilsson, 2008). (3) Profitability measures the ability of a company to generate profit relative to revenue, assets and shareholders' equity. It is measured using return on assets, return on equity and return on sales (Abdullah

**Table 1**

*Description of Financial, Non-financial and Governance Variables*

Variable	Category	Description
Current ratio	Financial	Current assets to current liabilities
Debt ratio	Financial	Total liabilities to total assets
Debt-to-equity ratio	Financial	Total liabilities to total equity
Return on assets	Financial	Net income to total assets
Return on equity	Financial	Net income to total equity
Return on sales	Financial	Net income to sales
Total assets turnover	Financial	Sales to total assets
Size	Financial	Natural logarithm of total assets
Age	Non-financial	Natural logarithm of firm age in years
OwnerC1	Governance	A dummy variable with a value of 1 if a company is 100 percent owned by a holding company, otherwise 0.
OwnerC2	Governance	A dummy variable with a value of 1 if shareholders own equal shares, otherwise 0.
OwnerC3	Governance	A dummy variable with a value of 1 if one or more shareholders hold more than 25 percent of the company's outstanding shares, otherwise 0.
OwnerC4	Governance	A dummy variable with a value of 1 if one shareholder holds more than 50 percent of the company's outstanding shares, otherwise 0.
Board size	Governance	Number of directors
Gender diversity	Governance	A dummy variable with a value of 1 if there is at least a female director in the boardroom, otherwise 0.

et al., 2019; Klepac & Hampel, 2018; Zainol Abidin et al., 2020). A higher ratio means the business is performing well by generating revenue and profits hence signifying lower bankruptcy probabilities. (4) Efficiency was represented by the total assets turnover. A higher ratio implies the ability of a firm to employ its assets effectively to generate sales (Abdullah et al., 2019; Terdpaopong & Mihret, 2011). Hence, a negative relationship between efficiency and business failure. (5) *Size* refers to the company size and is measured by the natural logarithm of total assets (Abdullah et al., 2019; Altman et al., 2010, 2015; Back, 2005; Ma'aji et al., 2019). As for non-financial variables, *age* is the company age and is measured by the natural logarithm of company age in years (Altman et al., 2010, 2015; Ma'aji et al., 2019).

With regard to the governance variables, *OwnerC1* was represented by a dummy variable that took the value of one if a company is 100 percent owned by a holding company, otherwise zero. *OwnerC2* was a dummy variable that took the value of one if shareholders owned equal shares, otherwise zero. *OwnerC3* was a dummy variable that took the value of one if one or more shareholders owned more than 25 percent of the firm's outstanding shares, otherwise zero (Abdullah et al., 2016; Ma'aji et al., 2019). *OwnerC4* was a dummy variable that took the value of one if a shareholder owned more than 50 percent of the firm's outstanding shares; otherwise zero (Ciampi, 2015). Board size indicated the number of directors in the company (Abdullah et al., 2016 Ciampi, 2015; Ma'aji et al., 2019) and gender diversity constituted a dummy variable that took the value of one if there was at least a woman director on board, otherwise zero (Abdullah et al., 2016; Ma'aji et al., 2019).

## **Method**

Various techniques are available to construct models that can predict business failure. Among the most popular statistical methods that are widely used in the corporate failure studies is logistic (Shi & Li, 2019). Shi and Li's (2019) review of 321 papers found that the most frequently used model is logistic, which represented 38.3 percent of the total sample. The logistic model does not require the independent variables to be multivariate normal or groups to have equal covariance matrixes (Balcaen & Ooghe, 2006). It fits well into the failure

prediction problem characteristics, where the dependent variable is binary (bankrupt/non-bankrupt), the groups are discrete, identifiable and non-overlapping (Ohlson, 1980). The logistic model yields a score between zero and one, which conveniently gives the probability of failure. Furthermore, the estimated coefficients were interpreted separately and provided the importance of each of the independent variables in explaining the estimated probability of failure. The coefficient was estimated using the maximum likelihood approach. A cut-off value of 0.5 was utilized to differentiate between bankrupt and non-bankrupt SMEs in this study. A company was classified as bankrupt if the calculated probability was more than 0.5, otherwise as non-bankrupt. To examine which variables influence the occurrence of bankruptcy, a logistic model is estimated as follows:

$$P(Y = 1) = \frac{1}{1 + e^{-(\alpha + \beta_1 X_1 + \beta_2 X_2 + \dots + \beta_n X_n)}} = \frac{1}{1 + e^{-y}} \quad (1)$$

where  $P$  represents the bankruptcy probability,  $\beta_n$  represents the model parameter estimates, and  $X_n$  represents the input variables. The logistic model was estimated using a forward stepwise method to identify the most significant factors that could predict bankrupt and non-bankrupt SMEs in the hospitality industry.

## RESULTS

### Descriptive Statistics and Correlations

The descriptive statistics of the independent variables mean difference used to estimate the logistic model is presented in Table 2. The results of the financial variables revealed that current ratio, debt ratio, return on assets, return on sales and total assets turnover had a significant mean difference between the bankrupt and non-bankrupt SMEs throughout one year, two years and three years prior to bankruptcy. However, debt-to-equity ratio was found to be significant one year and two years prior to bankruptcy. As for non-financial variables, the bankrupt SMEs were significantly younger than the healthy SMEs throughout the one year, two years and three years prior to bankruptcy. The average age of bankrupt SMEs was seven to nine

years while the non-bankrupt SMEs was 12 to 16 years. Overall, the findings showed that bankrupt SMEs were significantly younger, highly leveraged, less liquid, less profitable and less efficient.

With regard to governance variables, the non-bankrupt SMEs had significantly more members in the boardroom compared to the bankrupt SMEs, two years and three years prior to bankruptcy. It appeared that the non-bankrupt SMEs had three directors sitting on the board, whereas the bankrupt SMEs had only two directors sitting on the board. Ownership concentration and gender diversity were found to be statistically insignificant for all periods except for gender diversity in the one year prior to bankruptcy, the non-bankrupt SMEs had more female directors in the boardroom compared to the bankrupt SMEs. On average, 39 percent of non-bankrupt SMEs and 32 percent of bankrupt SMEs had female directors in the boardroom.

**Table 2**

*Descriptive Statistics and Mean Difference Test*

No.	Variable	Sample Size	Year Prior to Bankruptcy	Bankrupt		Non-Bankrupt		Bankrupt - Non-Bankrupt
				Mean	SD	Mean	SD	
1	Current ratio	350	1	0.5145	0.8090	4.4635	4.7141	-3.9491***
		444	2	0.4981	0.4576	4.9656	9.3740	-4.4675***
		474	3	1.1898	1.9228	2.5336	3.3145	-1.3438***
2	Debt ratio	350	1	2.3210	3.6002	0.3033	0.1731	2.0176***
		444	2	1.6772	2.8302	0.5277	1.0050	1.1496***
		474	3	1.2560	1.2537	0.6856	0.9159	0.5704***
3	Debt-to-equity ratio	350	1	-0.7437	8.0683	0.5464	0.4862	-1.2900**
		444	2	-3.0672	11.7251	0.7078	1.7739	-3.7750***
		474	3	-0.8301	14.5717	0.7963	4.3061	-1.6264
4	Return on assets	350	1	-0.5715	1.7564	0.1558	0.2313	-0.7273***
		444	2	-0.3786	0.8150	0.1671	0.2694	-0.5457***
		474	3	-0.1741	0.8352	0.1550	0.1485	-0.3292***
5	Return on equity	350	1	0.2524	2.0217	0.2341	0.3686	0.0183
		444	2	0.3650	2.1834	0.2279	0.3161	0.1370
		474	3	0.3588	2.0109	0.2374	0.7765	0.1214

(continued)

No.	Variable	Sample Size	Year Prior to Bankruptcy	Bankrupt	Non-Bankrupt	Bankrupt - Non-Bankrupt		
6	Return on sales	350	1	-0.2743	0.5111	0.0595	0.1027	-0.3337***
		444	2	-0.2501	0.4144	0.0972	0.5230	-0.3472***
		474	3	-0.2642	1.2488	0.0886	0.5037	-0.3527***
7	Total assets turnover	350	1	2.9180	2.5807	4.5193	3.5653	-1.6013***
		444	2	2.4920	2.6575	4.0796	3.9298	-1.5876***
		474	3	2.2908	2.3938	4.0682	3.6267	-1.7774***
8	Size	350	1	12.5180	1.1682	12.5239	1.1559	-0.0059
		444	2	12.7718	1.1349	12.7671	1.1365	0.0048
		474	3	12.8632	1.1768	12.8640	1.1832	-0.0008
9	Age	350	1	1.8797	0.5450	2.3951	0.6071	-0.5154***
		444	2	1.8833	0.5944	2.4791	0.5704	-0.5958***
		474	3	1.9918	0.5603	2.6210	0.4524	-0.6292***
10	OwnerC	350	1	0.5748	0.2213	0.6022	0.2251	-0.0274
		444	2	0.5742	0.2329	0.5879	0.2352	-0.0136
		474	3	0.5931	0.2266	0.6009	0.2377	-0.0078
11	Board size	350	1	2.63	1.007	2.58	0.853	0.0514
		444	2	2.68	1.007	2.89	1.005	-0.2072**
		474	3	2.65	0.995	3.08	1.319	-0.4219***
12	Gender diversity	350	1	0.3247	0.2779	0.3866	0.2701	-0.0619**
		444	2	0.3223	0.2962	0.3480	0.2911	-0.0258
		474	3	0.3402	0.2932	0.3749	0.2766	-0.0347

Note: \*, \*\* and \*\*\* significant at 10%, 5% and 1%, respectively.

Pearson correlation matrix<sup>1</sup> between the independent variables were implemented for one year, two years and three years prior to bankruptcy. The findings revealed that the correlations among the variables were relatively low except for *debt ratio* and *return on assets*, and *OwnerC1* and *OwnerC3*, one year prior to bankruptcy and *debt-to-equity ratio* and *return on equity*, two years prior to bankruptcy. Although the low correlations indicated that the dataset did not suffer from multicollinearity problems, variance inflation factor (VIF) test was conducted to cross-check the findings. Table 3 presents the VIF values of each variable for one year, two years and three years prior to bankruptcy, and the findings suggested that multicollinearity was not a problem in this study.

**Table 3**

*Variance Inflation Factor*

No.	Independent Variable	VIF		
		1 year prior	2 years prior	3 years prior
1	Current ratio	1.137	1.078	1.198
2	Debt ratio	3.251	1.448	1.277
3	Debt-to-equity ratio	1.400	1.702	1.172
4	Return on assets	3.089	1.674	1.539
5	Return on equity	1.442	1.695	1.223
6	Return on sales	1.249	1.286	1.481
7	Total assets turnover	1.345	1.403	1.385
8	Size	1.512	1.417	1.573
9	Age	1.177	1.169	1.141
10	OwnerC1	1.116	1.089	1.179
11	OwnerC2	1.707	1.626	1.427
12	OwnerC3	1.301	1.296	1.367
13	OwnerC4	1.702	1.639	1.576
14	Board size	1.193	1.293	1.384
15	Gender diversity	1.124	1.029	1.086

**Logistic Regression Model**

Table 4 presents the results of the three estimated logistic models one year, two years and three years prior to bankruptcy. The Hosmer and Lemeshow test for all the three models showed that the p-value was insignificant at the 0.05 level suggesting that the models adequately fitted the data. The logistic models identified return on assets and firm age as significant predictors throughout the one year, two years and three years prior to bankruptcy indicating that these were the most influential variables in predicting bankruptcy among SMEs in the hospitality industry. A significant negative coefficient for return on assets indicated that achieving a high level of profit lowered the likelihood of bankruptcy. When firms recorded sufficient profits, they were able to retain part of the profits and reinvest it for future growth.

The findings was consistent with Cressy's (1992) as he found return on assets to be an important determinant of bankruptcy throughout a five-year horizon period among small firms in the UK. This also corresponded with findings in previous studies (Abdullah et al., 2019; Altman et al., 2010; Cultrera & Brédart, 2016; Klepac & Hampel, 2018; Ma'aji et al., 2019; Williams, 2014).

The results also yielded a significant negative coefficient between firm age and bankruptcy suggesting that the longer a firm existed, the higher the chances of survival. The resource-based view of the firm argued that older firms had larger resources than younger firms, hence the probability of failure among older firms were lower (Williams, 2014). Due to this, it was much easier for older firms to deal with unforeseen expenses and operational problems (Williams, 2014). Furthermore, older firms had a better understanding of their business environment which would enable them to effectively manage highly competitive business environment (Ucbasaran et al., 2013). In addition, Altman et al. (2015) explained that a young firm had a high risk of failure which diminished over time as the firm aged. This could be seen as the firm progressed from micro, small, medium to being a large, established firm which may take place over a period of years. Therefore, an increase in the firm's years of business operations decreases the probability of bankruptcy. Altman et al. (2010), Cultrera and Brédart (2016), Ma'aji et al. (2019) reported similar findings using SME samples.

In addition to return on assets and firm age, the logistic model identified debt ratio and total assets turnover as important predictors of bankruptcy, one year before bankruptcy. A significant positive coefficient for debt ratio suggests that the higher the debt level, the higher the chances of a firm going into bankruptcy. Too much debt increases the firm's financial risks, thus increasing its bankruptcy risk and offsetting the tax savings benefit of debt interest (Hirshleifer, 1966). The findings of this study concurred with studies by Abdullah et al. (2019), Altman (1968), Pacheco (2015), Yazdanfar and Nilsson (2008) and Youn and Gu (2010a). Shane (1996) further explained that younger firms tended to borrow more because their owners had limited resources and this could result in large amounts of debt outstanding. Consequently, the inability of owners to fulfil their debt commitments could drive firms to financial distress.

The negative coefficient of total assets turnover indicated that SMEs with lower efficiency were more likely to fail. It seemed to suggest that bankrupt SMEs failed to use their assets efficiently and to manage their operations effectively. This inefficiency would make them suffer from negative earnings and in turn would affect their operating cash flow. As a result, they could face difficulties meeting their financial commitments. The failure to meet these commitments could drive the company to financial distress and ultimately to bankruptcy. The results of this study was consistent with Terdpaopong and Mihret's (2011) which recorded a negative relationship; despite this, it contradicted the findings of Abdullah et al. (2019), four years prior to failure which indicated a positive sign. A possible explanation for a positive sign could be that a company with high total assets turnover but recorded lower profits could indicate high sales volume without good control over its costs, thus increasing the probability of failure.

Two years prior to bankruptcy, debt ratio and total assets turnover were no longer important and the logistic model identified current ratio, OwnerC1 and gender diversity as significant indicators of bankruptcy. The negative coefficient of current ratio suggested that less liquid SMEs were more likely to fail (Altman & Sabato 2007; Brédart, 2014; Klepac & Hampel, 2018; Lugovskaya, 2010; Terdpaopong & Mihret, 2011, Wellalage & Locke, 2012). SMEs that had low levels of liquidity may have limited cash flows for meeting their working capital requirements and debt obligations. Hence, there was a higher probability that these SMEs could default their financial commitments and eventually be forced into bankruptcy.

As for the OwnerC1, a positive coefficient revealed that SMEs that were 100 percent owned by a holding company were more likely to fail. The possible reason was that the decision-making process could be slow due to multiple management levels. Major decisions must often go through various chains of command within the parent company bureaucracy before any action can be taken. Hence, in a competitive business environment, the ability of a company to make speedy decisions is critical for business survival.

The negative coefficient of gender diversity indicated that more female directors in the boardroom were more likely related to survival among SMEs in the hospitality industry. Abdullah et al. (2016) found

**Table 4**  
*Stepwise Logistic Regression Model*

Variable	Category	1 year prior		2 years prior		3 years prior	
		Coefficient	Change in -2Log Likelihood	Coefficient	Change in -2Log Likelihood	Coefficient	Change in -2Log Likelihood
Current ratio	Financial			-4.829	80.805 (0.000)***	-0.212	8.081 (0.004)***
Debt ratio	Financial	6.941	72.282 (0.000)***			1.022	33.453 (0.000)***
Debt-to-equity Ratio	Financial					-0.023	2.954 (0.086)*
Return on assets	Financial	-14.080	39.048 (0.000)***	-39.121	76.680 (0.000)***	-0.378	3.494 (0.062)*
Total assets turnover	Financial	-0.567	14.303 (0.000)***			-0.436	54.924 (0.000)***
Age	Non-financial	-0.867	4.088 (0.043)**	-1.156	3.193 (0.074)*	-2.638	86.250 (0.000)***

(continued)

Variable	Category	1 year prior		2 years prior		3 years prior	
		Coefficient	Change in -2Log Likelihood	Coefficient	Change in -2Log Likelihood	Coefficient	Change in -2Log Likelihood
Subsidiary	Governance			8.473	10.411 (0.001)***		
Gender diversity	Governance			-3.984	13.121 (0.000)***	-0.918	6.626 (0.010)***
Board size	Governance					-0.342	6.113 (0.013)**
Hosmer & Lemeshow Test		12.558 (0.128)		1.040 (0.998)		14.160 (0.078)	
Constant		0.033 (0.978)		12.645 (0.000)		8.535 (0.000)	

Note: \*, \*\* and \*\*\* significant at 10%, 5% and 1%, respectively.

that manufacturing SMEs with female managing directors were less likely to fail than those having male counterparts. Previous studies suggested that firm performance improved with the presence of female directors in the boardroom (Campbell & Minguez-Vera, 2008; Julizaerma & Mohamad Sori, 2012; Post & Byron, 2015). The possible explanation could be that more diverse board members could bring their own personal background to their board position as their experience is more extensive and comprehensive. Bassett-Jones (2005) argued that diverse perspectives could influence board members to critically analyse complex problems and develop creative and innovative solutions. Robinson and Dechant (1997) further suggested that female directors performed better than their male counterparts in group problem solving and decision-making that required discussion and consensus, thus this could lead to board effectiveness.

Three years prior to bankruptcy, additional variables namely debt-to-equity ratio and board size were established as significant, but OwnerC1 and gender diversity were no longer important. The positive coefficient of debt-to-equity ratio implied that highly leveraged SMEs were more likely to fail. Generally, SMEs rely heavily on debt to finance their business operations (Altman, 2010). Hence, a firm has to carry a bigger burden when interest payment takes a significant portion of the firm's profit and this may affect its operating profits. A highly leveraged firm would be generating insufficient profit and cash flows to cover its debt obligations, thus was more likely to face bankruptcy risk. The findings concurred with those of Back et al. (1996), Ciampi (2015), Kim (2011), and Terdpaopong and Mihret (2011).

The negative coefficient of board size suggested that more directors in the boardroom increased the likelihood of SME survival (Abdullah et al., 2016; Zainol Abidin et al., 2020; Keasey & Watson, 1987). The result was consistent with that of Ma'aji et al. (2019), who concluded that the probability of failure among SMEs was lower when the board size was larger due to increased oversight and expertise. Drawing from the expertise of its many members, the firm was expected to achieve better performance. Further, larger boardroom members would provide better perspectives and ideas that could lead to more in-depth and thorough consideration of issues. Farag and Mallin (2017) suggested that the quality of decisions made by firms with larger boards were more superior.

Table 5 presents the classification results of the logistic models one year, two years and three years before bankruptcy. One year prior to bankruptcy, the model correctly classified 93.5 percent of the bankrupt SMEs and 99.1 percent of the non-bankrupt SMEs in the estimation sample and 94.2 percent of the bankrupt SMEs and 93.1 percent of the non-bankrupt SMEs in the holdout sample. This resulted in an overall classification rate of 96.3 percent and 93.6 percent in the estimation and holdout samples, respectively. The model seemed to perform better in predicting the bankrupt SMEs than the non-bankrupt SMEs in the holdout sample. Furthermore, the model performed well in predicting bankruptcy two years prior with an overall classification rate of 98.1 percent in the estimation sample and 95.5 percent in the holdout sample. However, the accuracy rate of the model decreased when predicting bankruptcy three years before the bankruptcy event. The overall accuracy rate was 85.0 percent and 76.4 percent in the estimation and holdout samples, respectively. The results showed that an increase in the bankruptcy prediction period resulted in a decrease in the prediction model accuracy rate. Similar results were reported by Abdullah et al. (2019), Klepac and Hampel (2018), and Yazdanfar and Nilsson (2008).

**Table 5**

*Classification Accuracy Rate*

Percentage Correctly Classified	1 year prior		2 years prior		3 years prior	
	Estimation Sample	Holdout Sample	Estimation Sample	Holdout Sample	Estimation Sample	Holdout Sample
Bankrupt	93.5	94.2	98.1	95.5	83.3	76.8
Non-Bankrupt	99.1	93.1	98.1	95.6	86.7	76.1
Overall	96.3	93.6	98.1	95.5	85.0	76.4
Observation	240	110	310	134	334	140

**CONCLUSION**

The study used empirical data of SMEs in the hospitality industry and assessed the prediction accuracy of logistic models using a set

of financial, non-financial and governance variables on a three-year horizon period. The findings revealed that return on assets and firm age was consistently significant throughout the one year, two years and three years prior to bankruptcy. SMEs that recorded sufficient profits were able to retain part of their profits and over the years they would have larger resources that would enable them to handle financial crisis more easily, hence increasing their chances of survival. As for other indicators, they were only found to be significant at a certain period before bankruptcy. For the one year prior to bankruptcy, debt ratio and total assets turnover were found to be significant predictors of bankruptcy, while current ratio, OwnerC1 and gender diversity were found to be significant in the two years prior to bankruptcy. Other variables were found to be significant in three years prior to bankruptcy namely current ratio, debt ratio, debt-to-equity ratio, total assets turnover, gender diversity and board size. In addition, governance variables seemed to be significant during the early periods of bankruptcy. The results showed that having female directors and more members in the boardroom during the early periods could contribute to the success of a business. Furthermore, as SMEs moved closer to bankruptcy, the classification accuracy rate of the model increased with a less number but significant variables which were identified to predict bankruptcy. The findings of this study also showed that the bankruptcy risk of SMEs could be detected as early as three years in advance.

The logistic model emphasized the importance of return on assets and firm age to predict bankruptcy risk of SMEs in the hospitality industry as these variables have always been significant in discriminating between bankrupt and non-bankrupt SMEs for all periods. Achieving a sufficiently high level of profit is crucial in sustaining long run business growth. Furthermore, younger companies have a lower chance of survival as they have limited cash reserves for their business operations.

Therefore, an effective failure prediction model could reduce economic losses for the affected parties by providing signals that would enable them to take preventive measures in possible adverse situations. Lenders could use the model to assess the risk of loan defaulters, while creditors could use the results of this study as a tool to evaluate the creditworthiness of their potential debtors. Investors could use the

model to assess the financial health of a company before investing, thus minimizing their investment risks. For the regulators and government agencies that are managing the SMEs, improved policies are required such as providing special funds for young companies, debt limit, profit margin, total assets turnover and setting the minimum number of board of directors. As in other industries, there must be a guideline for loan disbursement to SMEs in order for the government not to lose its investments and to improve the hospitality industry. A limitation of this study is that other variables which could impact the SMEs such as business location and external factors were not considered as these could also contribute in analyzing the bankruptcy risk of SMEs in the hospitality industry.

### **ACKNOWLEDGMENT**

This research received no specific grant from any funding agency in the public.

### **ENDNOTE**

- <sup>1</sup> The results of Pearson correlation matrix for one year, two years and three years prior to bankruptcy are available upon request.

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