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Visualising the Optimistic, Realistic, and Pessimistic Financial Distress Outlooks for Airport Operations in Malaysia

Mahayaudin M. Mansor, Universiti Teknologi MARA, Malaysia*
Nurain Ibrahim, Universiti Teknologi MARA, Malaysia
Siti Afiqah Muhamad Jamil, Universiti Teknologi MARA, Malaysia
https://orcid.org/0000-0002-9374-5559
Nur Amalina Shafie, Universiti Teknologi MARA, Malaysia
Siti Meriam Zahari, Universiti Teknologi MARA, Malaysia

ABSTRACT

This paper aims to visualise three financial distress outlooks using computer simulations. The financial distress exposure for airport operations in Malaysia between 1991 and 2021 is given by Altman Z''-score and modelled by the multivariate generalized linear model (MGLM). Seven determinants contributing to the financial distress from literature are examined. The determinant series are fitted individually by using linear model with time series components and autoregressive integrated moving average models to forecast values for the next 10 financial years. Future short- to long-term memory effects following COVID-19 are apparent in time series plots. In the simulations, the MGLM procedure utilised Gaussian, gamma, and Cauchy probability distributions associated with expectations and challenges of doing business as well as uncertainties in the economy. The underlying trends of realistic, optimistic, and pessimistic financial distress outlooks insinuate that the increasing risk of financial distress of airport operations in Malaysia is expected to continue for the next decade.

KEYWORDS

Airline Industry, Altman Z-Score, Data Analytics, Financial Distress Simulation, Multivariate Generalized Linear Model, Probability Distributions, R Computing, Time Series Forecasting

1. INTRODUCTION

As of 2022, the air transport industry in Malaysia consists of 40 airports providing services for 78 airlines from local destinations and around the globe. These 78 airlines comprise of 61 international airlines and 17 local airlines, including four cargo airlines. Since its establishment in 1992, the

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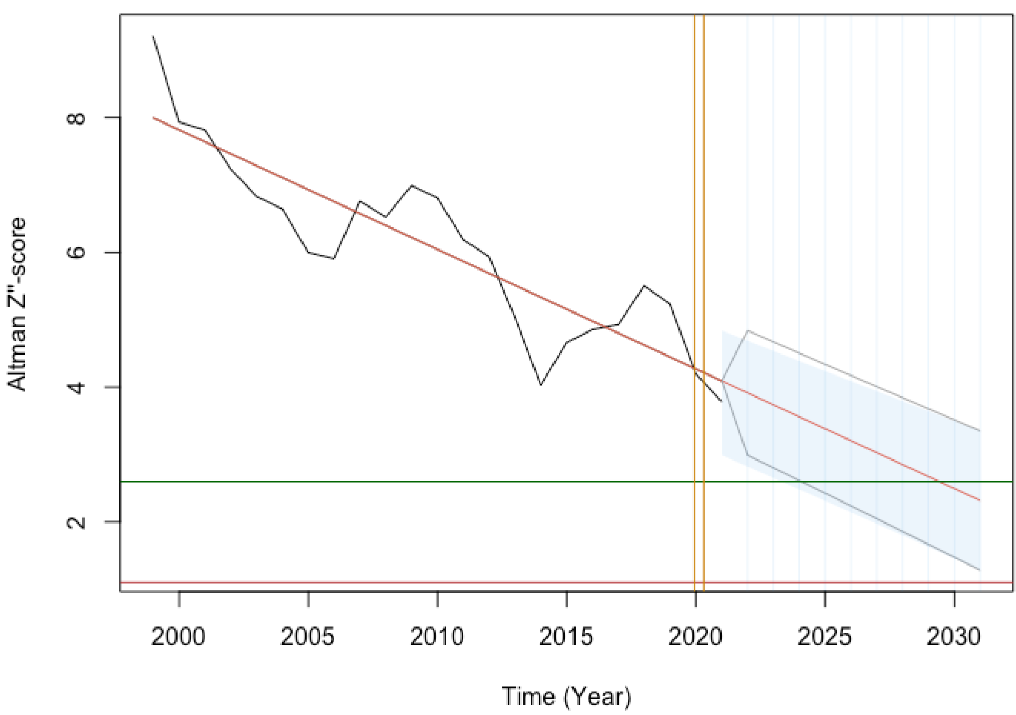
*Corresponding Author

Malaysia Airports Holdings Berhad (MAHB) has come to operate 39 airports, including 17 domestic, 5 international, and 17 short take-off and landing ports nationwide. Therefore, the majority of airport operations including flight passengers, cargo and mail in Malaysia are operated by MAHB. For MAHB, its highest revenue, RM 5.2 billion, and highest net profit, RM 748.5 million, were recorded in 2019 and 2014 respectively (Hao and Xuan, 2022). In this context, MAHB represents a substantial component of the Malaysian airport operations for this study.

Throughout the years, the financial performance for the airport operations in Malaysia has varied. Between 1999 and 2021, there were a series of challenges that contributed to a disruption in the air transport industry, such as the Great Recession in 2008, the 2014 incidents involving the disappearance of MH370 and the shooting down of MH17, and most recently the novel coronavirus (COVID-19) pandemic in 2020. The COVID-19 pandemic in particular has proven to leave a significant mark on the world's air transport industry. The period between the COVID-19 pandemic starting on March 11, 2020 (Cucinotta and Vanelli, 2020) and the COVID-19 being declared endemic in Malaysia on April 1, 2022 (Lee, 2022) is shown by the vertical lines on the time series plot of Altman Z"-score of MAHB in Figure 1.

Altman Z"-score measures the degree of financial distress of an organisation (Altman, 1968; Altman, 1983; Altman, 2013). The Altman Z"-score originates from the Altman Z-score (1968) and Altman Z"-score (1983) as a bankruptcy prediction model. The Z"-score is more practical when analysing airline operations than other measures as it is suitable for both public and private, manufacturing, and non-manufacturing firms (e.g. Subramaniam et al., 2019; Odibi et al., 2015; Mohammed et al., 2002). For example, the bankruptcy forecasting model that has shown to have high predictive accuracy when applied to United States (U.S.) and Indian airlines (Shi and Li, 2021).

Figure 1. Time series plot of Altman Z"-score for years 1999 to 2021 with a decreasing trend that continues linearly for years 2022 to 2031, including financial distress thresholds between financially stable and exposure to financial distress



In Figure 1, the calculated Altman Z”-score was the highest (9.20) in 1999 to 4.03 in 2014, and the recent score of 3.80 in 2021 which is at its worst position during the 23-year period.

The Z′′-score being more than 2.6 indicates that the financial situation of MAHB is safe from financial distress or any exposure of bankruptcy. If the Altman Z”-score is between 1.1 and 2.6, then the MAHB is being exposed to financial distress. MAHB is said to be having financial distress if the Z′′-score is less than 1.1. These financial distress threshold values of 1.1 and 2.6 are shown by the horizontal lines (green and firebrick respectively) in Figure 1. A univariate linear model with a trend is fitted to the observed Altman Z”-score from 1999 to 2021, and the declining linear trend (red) is concerning. Given the decline of the Altman Z′′-score in Figure 1, it is likely that this downward trend will continue. As shown in Figure 1, if the trend continues, into the future the forecasted trend line is expected to cross the green line by 2030, hence a reposition from being financially stable to exposing financial distress between year 2022 and 2031. Therefore, it is essential that the determinants of Altman Z′′-score for MAHB are examined.

The objective of this study is to implement multivariate procedure to model Altman Z′′-score and project three future scenarios for the increasing bankruptcy exposure of the largest airport operations in Malaysia via Gaussian, gamma and Cauchy probability distributions. The three scenarios are realistic, optimistic and pessimistic financial outlooks. It is noted that this study only focuses on the largest airport operations in Malaysia hence the results from this study may not be generalisable to other cases. However, the application of Gaussian, gamma and Cauchy probability distributions, as described in the following Section 4, to envision the realistic, optimistic and pessimistic financial outlooks could be universal.

This contribution is outlined in the following manner. Section 2 highlights the determinants, from literature, contributing to the response variable of Altman Z′′-score together with their measurement and descriptive statistics. Future values for each of the determinants are, given by using suitable time series models, illustrated also in Section 2. Multivariate procedure is employed to fit the observed Altman Z′′-score in Section 3. In Section 4, the fitted multivariate model is used to forecast financial stability of airport operations in Malaysia for years 2022 to 2031, and project future exposures to financial distress using Gaussian, gamma and Cauchy probability distributions in the simulations. Concluding remarks are given in Section 5.

2. FORECASTING THE DETERMINANTS

2.1. Determinants of Financial Distress

There is a considerable literature on the application of Altman Z-score models to describe financial stability for air transport industry; studies include the U.S. (e.g. Gritta et al., 2011), India (e.g. Mahtani and Garg, 2020) and Europe (e.g. Shi and Li, 2021). In this study, the variables and its measurement are detailed in Table 1 together with corresponding literature.

In Table 1, there are seven determinants grouped as financial and non-financial explanatory variables and one response variable of Altman Z”-score. The four financial determinants are the financial ratios of leverage (LE), liquidity (LI), net operating margin (NM) and asset turnover (AT). We also include the role of three determinants of non-financial variables that are total passenger (TP), total cargo (TC) and total mail (TM) movements, which are measured by the natural logarithms of total movement of passengers, aircraft, cargo, and mail. Natural log is applied to the non-financial determinants to deflate the big positive observations and potentially reduce heteroscedasticity. As for the response variable, Altman Z”-score is calculated as the weighted average combination of financial ratios as outlined in Table 1 (third column, first row).

The data for this study is acquired from the MAHB financial annual reports. All descriptive statistics of the variables are given in Table 2. In addition, the series of each determinant from 1999 to 2021 is plotted in time order in Figure 2 for the non-financial determinants and in Figure 3 for the financial determinants.

Table 1. Summary of variables and measurement

Variable Type	Name (Abbreviation)	Measurement
Response (Financial distress)	Altman Z”-score (AZ)	6.56(Working capital/Total assets + 3.26(Retained earnings/Total assets) + 6.72(Earnings before interest and taxation/Total assets) + 1.05(Book value of equity/Book value of total liabilities) + 3.25 (Shi and Li, 2021; Mahtani and Garg, 2020; Subramaniam et al., 2019; Nazar et al., 2022; Odibi et al., 2015; Gritta et al., 2011; Mohammed et al., 2002)
Determinant (Non-financial)	Total passenger movement (*TP*)	Log of total passenger movement (Dana and Greenfield, 2019; Nazar et al., 2022; Jenatabadi and Ismail, 2007)
	Total cargo movement (*TC*)	Log of total cargo movement (Hong and Zhang, 2010; Nazar et al., 2022)
	Total mail movement (*TM*)	Log of total mail movement (Baltazar et al.,2018; Nazar et al., 2022)
Determinant (Financial)	Leverage (*LE*)	Total liabilities/Total assets (Shi and Li, 2021; Lee and Kang, 2011; Mahtani and Garg, 2020; Nazar et al., 2022; Lee and Jang, 2007)
	Liquidity (*LI*)	Current assets/Current liabilities (Shi and Li, 2021; Nazar et al., 2022; Lee and Jang, 2007)
	Net operating margin (*NM*)	Net profit/Revenue (Shi and Li, 2021; Nazar et al., 2022; Rosly and Bakar, 2003)
	Asset turnover (AT)	Revenue/Total assets (Sunjoko and Arilyn, 2016; Nazar et al., 2022)

Table 2. Summary of descriptive statistics of financial distress determinants

Determinant	Min	Median	Mean	Max	Sd	Skewness
Altman Z”-score	3.784	5.999	6.044	9.209	1.3571	0.2743
Total passenger movement (*TP*)	16.19	17.68	17.72	18.47	0.5467	-0.7280
Total cargo movement (*TC*)	20.31	20.65	20.62	20.77	0.1220	-0.9892
Total mail movement (*TM*)	16.63	17.09	17.11	17.56	0.2751	-0.1550
Leverage (*LE*)	0.1970	0.5069	0.4511	0.6695	0.1505	-0.2048
Liquidity (*LI*)	0.7806	1.3529	1.4460	3.1562	0.5606	1.1545
Net operating margin (*NM*)	-0.5981	0.1439	0.0854	0.3362	0.2071	-2.3728
Asset turnover (*AT*)	0.0830	0.2754	0.2621	0.4014	0.0849	-0.4550

The mean of Altman Z”-score is 6.044 which is within the safe zone (greater than 2.6), so on average MAHB is experiencing a favourable condition of stable financials. The mean and the median values are approximately the same, and the skewness value between -0.50 and 0.50 suggests that the Altman Z”-score distribution is fairly symmetrical with 50% of the observations are greater than 5.999 and another 50% are smaller than 5.999; similarly and accordingly to *TM*, *LE*, and *AT*. The mean and median for *TP* and *TC* is also similar but the skewness between –0.50 and –1.00 indicates that the distributions are moderately skewed to the left whereas observations are concentrated more towards the right side of the distributions.

Leverage (*LE*) associates with the outstanding debt of the company. Leverage below one indicates higher solvency of the company because of either increased total assets or decreased total liabilities. It is also common for the ratio to be 0.5 as it means only 50% of a company's assets are in the form of liabilities. In Table 1 (row 5), the leverage varies from 0.1970 to 0.6695 with a mean of 0.451, implying that MAHB has relatively good financial standing. While leverage is negatively affecting the financial stability, liquidity is positively affecting the financial stability. Liquidity (*LI*) indicates how the company can easily alleviate the burden of its current liabilities from its current assets. The ratio for liquidity is deemed to be good when the ratio is more than 1.0. The average *LI* is 1.4460 but the median is 1.3529 and the *LI* distribution is highly skewed to the right (skewness>$\pm$1), with the minimum observation of 0.7806 suggesting that more *LI* values are smaller than the mean. In fact, there are 12 years *LI* values that are lesser than 1.0 which means MAHB's current liabilities most of time was exceeded its current assets.

Like liquidity, net operating margin and asset turnover also positively affect the financial stability of the company. Net operating margin (*NM*) is defined as the ratio of net profit to revenue, and measures the degree of effectiveness in keeping the growth of revenue ahead of rising costs. For *NM*, the mean value is 0.0854 with a range from -0.5981 to 0.3362 and standard deviation (sd) of 0.2071, showing that MAHB generates relatively good revenue but simultaneously has stalled in its growth of revenue for some years. It is noted that the distribution of *NM* is highly skewed to the left as majority of the observations are more than 0.0854. However, *NM* can take negative value whenever the costs are more than the income. Lastly, asset turnover (*AT*) shows how effectively the company uses its resources (e.g. fixed assets such as machinery, buildings, planes and land) to generate profit, with a higher value of the asset turnover ratio suggesting that the company can manage their fixed assets well. The average *AT* is 0.2621 with a range of 0.083 to 0.401 illustrating that asset turnover in MAHB is relatively well-accommodated, and a low standard deviation indicates that the observations fluctuated relatively close to the mean value.

2.2. Time Series Forecasting

In this section, each time series of the non-financial and financial determinants from years 1999 to 2021 is plotted in Figures 2 and 3 respectively. Each of the observed series (black line) is fitted by using both a linear model with time series components and autoregressive integrated moving average (ARIMA) models, to estimate future values for the next ten financial years from 2022 to 2031.

All determinant series are observed annually and none of the plots show a seasonality component, hence seasonal terms do not exist. A realisation of time series (X_t) with a trend is given by:

$$X_t = \beta_0 + \beta_1 t + \varepsilon_t \tag{1}$$

where β_0 is the estimated trend at time zero, β_1 is the increase or decrease in the trend per unit of time t, and ε_t is the error term. The other univariate time series model used in this section is ARIMA(p,d,q) written in terms of backshift operator $\mathbf{B}$:

$$(1-\phi_1\mathbf{B}^1-\ldots-\phi_p\mathbf{B}^p)(1-\mathbf{B})^d X_t = (1-{}^{\theta}{}_1\mathbf{B}^1-\ldots-{}^{\theta}{}_q\mathbf{B}^q)\ (1-\mathbf{B})^q\varepsilon_t \tag{2}$$

where *ϕ's* are the autoregressive (AR) coefficients to be estimated, *θ's* are the estimated moving average (MA) coefficients, p is the order of AR process, q is the order of MA process, d is the order of differencing to meet stationarity assumption which is usually achieve after first order differencing, B is one-time period shift backward (e.g. $\mathbf{B}X_t = X_{t-1}$), and ε_t is the error term. The error terms are assumed to be independently and identically distributed (*iid*) with mean zero and constant variance, $\varepsilon_t \sim N(0, \sigma_\varepsilon^2)$.

The fitting details of models (1) and (2) for the seven determinant series are given in Table 3, together with six error measures used to estimate fitting discrepancies between the observed and fitted values. The six error measures are mean squared error (ME), root mean squared error (RMSE), mean absolute error (MAE), mean percentage error (MPE), mean absolute percentage error (MAPE), and mean absolute scaled error (MASE). For each determinant series, the fitted model that has a greater number of error measurements with a smaller value (underlined in Table 3) compared to the other model is determined to be the better model. The red lines in Figures 2 and 3 are the fitted values from the better model, and the blue lines are the forecast series of 10-step ahead estimated by the better model.

In Figure 2(a), the total passenger movement (*TP*) increased year after year from 1999 to 2019 and plummeted in 2020 following the worldwide travel bans due to COVID-19, and dropped further to its lowest level in 2021. In case of *TP* series, model (1) is fitted to the series and the fitted model is given in Table 3 as (3), and model (2) as (4). Between models (3) and (4), model (4) has the smallest RMSE, MAE, MPE, MAPE and MASE values (underlined) compared to model (3), hence the observed *TP* is best modelled by model (4) that is an ARIMA(2,0,0) model with non-zero mean. The red line is the fitted values from (4) and was used to predict future values for years 2022 to 2031 (blue line). As many governments around the globe have lifted their COVID-19 quarantine requirements and travel-border restrictions, it makes sense that the forecasted series (in blue) increases quite logarithmically to return to its initial level during COVID-19 period by 2027. In time series analysis, this effect refers to short-medium term memory effect after a random shock. A similar effect is seen in the forecasted series for total cargo movement (*TC*), given by model (6), in Figure 2(b) but it expected to return to its initial level faster than the forecasted *TP* series. The forecasted total mail movement (*TM*) series, modelled by (8), on the other hand exhibiting a long-memory effect which may take more than a decade before returning to its initial level. Another common feature in the time series plots in Figure 2 is the *TP*, *TC* and *TM* is declined sharply before 2020.

For all series, models (1) and (2) are implemented in *R* using *tslm* and *auto.arima* respectively (*R* Core Team, 2018). The ARIMA models listed in Table 3 are based on Box-Cox transformation and are the best ARIMA model selected for each determinant series is according to either the smallest Akaike information criteria (AIC), AIC corrected for small sample sizes (AICc) or Bayesian information criteria (BIC) value (Hyndman and Khandakar, 2008).

The leverage (*LE*) series in Figure 3(a) shows an upward trend with some variability between 1999 to 2021, and was fitted best by a random walk model with a drift (10) in Table 3. The forecasted *LE* series suggests that the trend of outstanding debts of MAHB will continue to increase into the future. Trends in the observed series of the other financial determinants are not in a good shape as well.

Although the net operating margin (*NM*) and asset turnover (*AT*) series in Figures 3(c) and 3(d) respectively were declining sharply before 2020, a small rise can be detected after 2020. However, in general, liquidity (*LI*), *NM* and *AT* series show declining trends. A very low decreasing trend of LI series in Figure 3(b) was traced by model (11). The downward trends are projected to continue during the next decade for *LI*, *NM* and *AT* but at much faster rate for *NM* and *AT*. This would be unfortunate as *LI*, *NM* and *AT* are positively affecting the financial stability of the company.

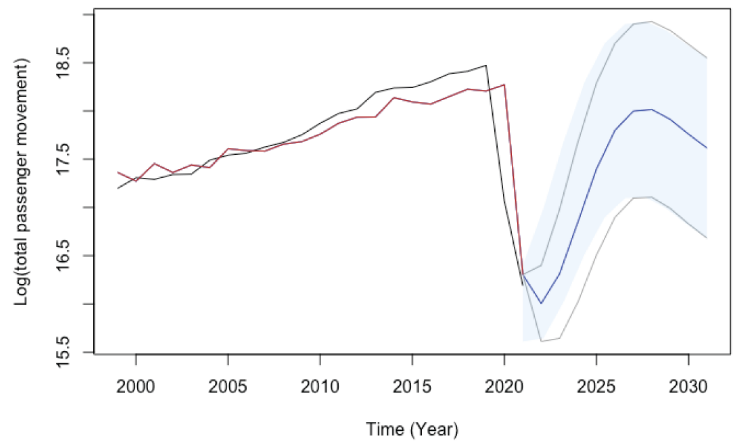
The forecast values of 10-step ahead predictions for years 2021 to 2031 for non-financial and financial determinants given by the best model in Table 3 are detailed in Table 4. These values will be used in the Section 4 to forecast the degree of financial distress for airport operations in Malaysia.

3. MODELLING FINANCIAL DISTRESS

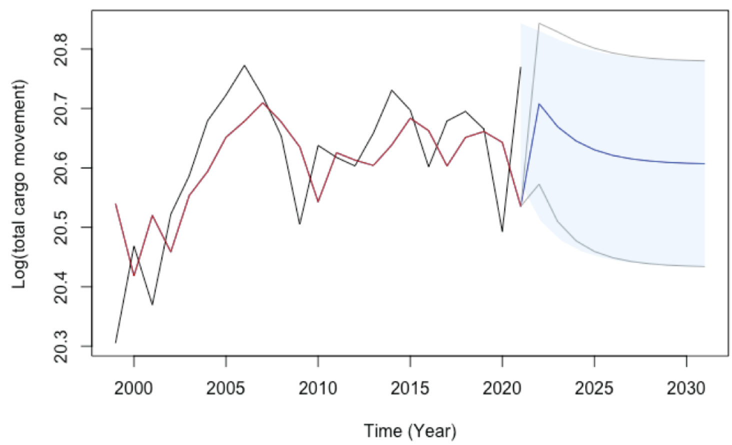
The main objective of this section is to use the seven non-financial and financial determinants described in Sections 2 and 3 as the predictor variables to model the response variable of Altman Z”-score. Prior to that, linear relationship between the predictors and the response variables is examined qualitatively (Figure 4, first column) and quantitatively (Figure 4, first row).

All predictor variables have a degree of linear relationship with the Altman Z”-score (*AZ*). The strongest negative relationship was given by *LE*, followed by *TC*, *TP* and *TM*. The *NM* and *AT*

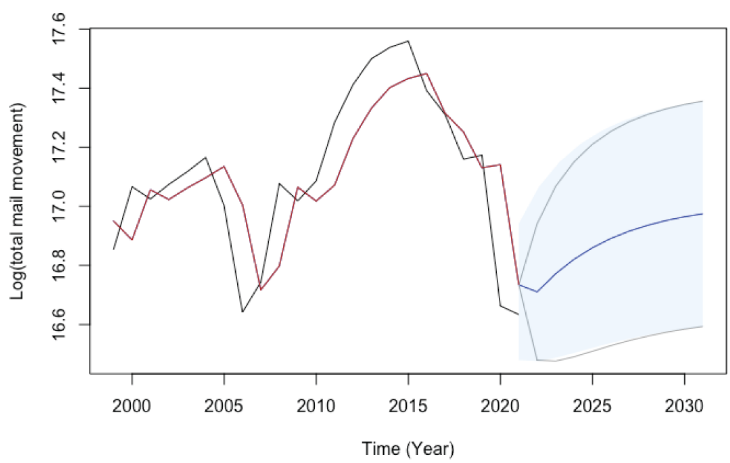
Figure 2. Time series plot of the observed non-financial determinants from 1999 to 2021 (black line), in-sample fitted values (red) by a chosen time series model, and points forecast (blue) bounded within 80% upper and lower limits for 2022 to 2031



(a) Total passenger movement series modelled by ARIMA(2,0,0) model with non-zero mean in (4)



(b) Total cargo movement series modelled by ARIMA(1,0,0) model with non-zero mean in (6)

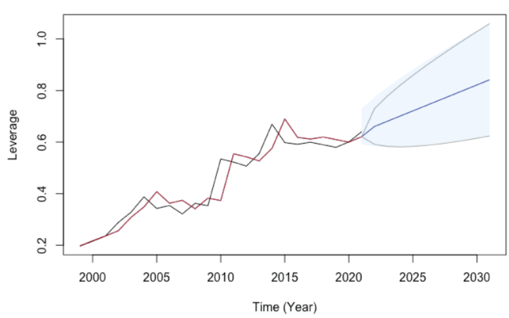


(c) Total mail movement series modelled by ARIMA(1,0,0) model with non-zero mean in (8)

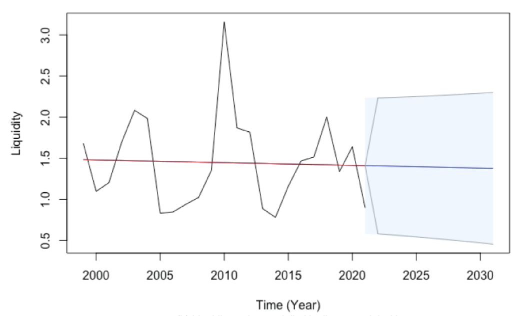
Table 3. Fitting detailed: Estimated coefficients and resubstitution errors for each of the financial distress determinants (see Eq. (3) – (16))

Series	Fitted Model	Accuracy					
		ME	RMSE	MAE	MPE	MAPE	MASE
TP	$TP_t=17.40+0.0263t$ (3)	0.0000	0.5054	0.3329	-0.0845	1.9079	2.0407
	$TP_t=17.59+1.3714TP_{t-1}-0.6405TP_{t-2}$ (4)	0.0049	0.2874	0.1664	-0.0017	0.9438	1.0198
TC	$TC_t=20.51+0.0090t$ (5)	1.55e-16	0.1032	0.0786	-0.0025	0.3818	0.8964
	$TC_t=20.61+0.6233TC_{t-1}$ (6)	0.0110	0.1009	0.0778	0.0511	0.3781	0.8876
TM	$TM_t=17.02+0.0078t$ (7)	1.55e-16	0.2641	0.1954	-0.0239	1.1453	1.4794
	$TM_t=17.02+0.7986TM_{t-1}$ (8)	0.0084	0.1721	0.1304	0.0385	0.7657	0.9874
LE	$LE_t=0.2014+0.0208t$ (9)	-1.21e-18	0.0513	0.0413	-1.6883	9.5302	1.0453
	$LE_t=0.0201+LE_{t-1}$ (10)	7.69e-06	0.0514	0.0362	-0.2872	7.7460	0.9172
LI	$LI_t=1.485-0.0033t$ (11)	-1.45e-17	0.5478	0.4351	-13.559	33.549	0.9167
	$LI_t=1.4460$ (12)	1.94e-13	0.5483	0.4346	-13.579	33.489	0.9155
NM	$NM_t=0.3138-0.0190t$ (13)	-1.13e-17	0.1584	0.1150	52.254	85.268	1.2708
	$NM_t=NM_{t-1}$ (14)	-0.0345	0.1659	0.0866	-77.659	118.03	0.9567
AT	$AT_t=0.3443-0.0068t$ (15)	-1.81e-18	0.0695	0.0546	-11.001	26.449	1.5345
	$AT_t=AT_{t-1}$ (16)	-0.0098	0.0618	0.0340	-11.469	20.257	0.9569

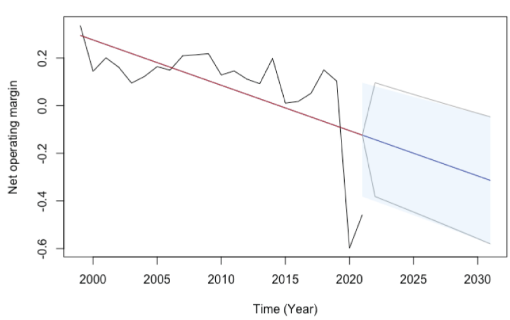
Figure 3. Time series plot of the observed financial determinants from 1999 to 2021 (black line), in-sample fitted values (red) by a chosen time series model, and points forecast (blue) bounded within 80% upper and lower limits for 2022 to 2031



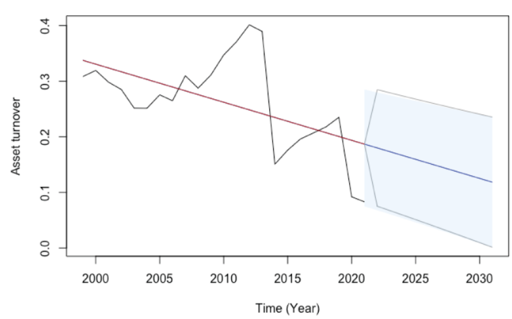
(a) Leverage series modelled by ARIMA(0,1,0) with an upward drift in (10)



(b) Liquidity series modelled by linear model with a decreasing trend in (11)



(c) Net operating margin series modelled by linear model with a declining trend in (13)



(d) Asset turnover series modelled by linear model with a downward trend in (15)

Table 4. The values of 10-step ahead predictions plotted as blue line in Figures 2 and 3

Year	Series						
	TP	TC	TM	LE	LI	NM	AT
2022	16.0057	20.7080	16.7105	0.6604	1.4066	-0.1429	0.1799
2023	16.3144	20.6695	16.7719	0.6806	1.4034	-0.1619	0.1731
2024	16.8553	20.6454	16.8209	0.7007	1.4001	-0.1809	0.1662
2025	17.3995	20.6304	16.8600	0.7209	1.3968	-0.2000	0.1594
2026	17.7992	20.6211	16.8912	0.7410	1.3935	-0.2190	0.1525
2027	17.9989	20.6153	16.9162	0.7612	1.3903	-0.2380	0.1457
2028	18.0168	20.6116	16.9361	0.7813	1.3870	-0.2571	0.1388
2029	17.9133	20.6094	16.9520	0.8015	1.3837	-0.2761	0.1320
2030	17.7601	20.6080	16.9647	0.8216	1.3804	-0.2951	0.1252
2031	17.6161	20.6071	16.9748	0.8418	1.3772	-0.3141	0.1183

show a moderate linear association while *LI* has the lowest positive relationship with Altman Z”-score. Therefore, all the seven determinants would be useful if none of the predictor variable carries similar information. Correlation for each pair of the predictor variables shows only low to moderate association which would not be contributing to multicollinearity, a typical problem in multivariate modelling. Variance inflation factor (VIF) will be used to confirm multicollinearity. Nazar et al. (2022) investigated nine determinants affecting the Altman Z”-score and their reduced models excluded variables of firm size and total aircraft movement due to multicollinearity.

In this study, multivariate generalized linear model (MGLM) is employed to link the dependencies between the response variable and all seven determinants illustrated in Figure 4. Generalized linear model uses the iteratively reweighted least squares method for maximum likelihood estimation of the model parameters (Nelder and Wedderburnm, 1972). The MGLM is a versatile generalisation of linear models as the fitting procedure allows all predictors despite their underlying association not being linear. This feature is important as shocks or extreme irregularities such as financial turmoil and pandemic outbreak can induce non-linearity or non-Gaussian input to the system (e.g. Soubeyrand et al. 2014; Mansor at el. 2016).

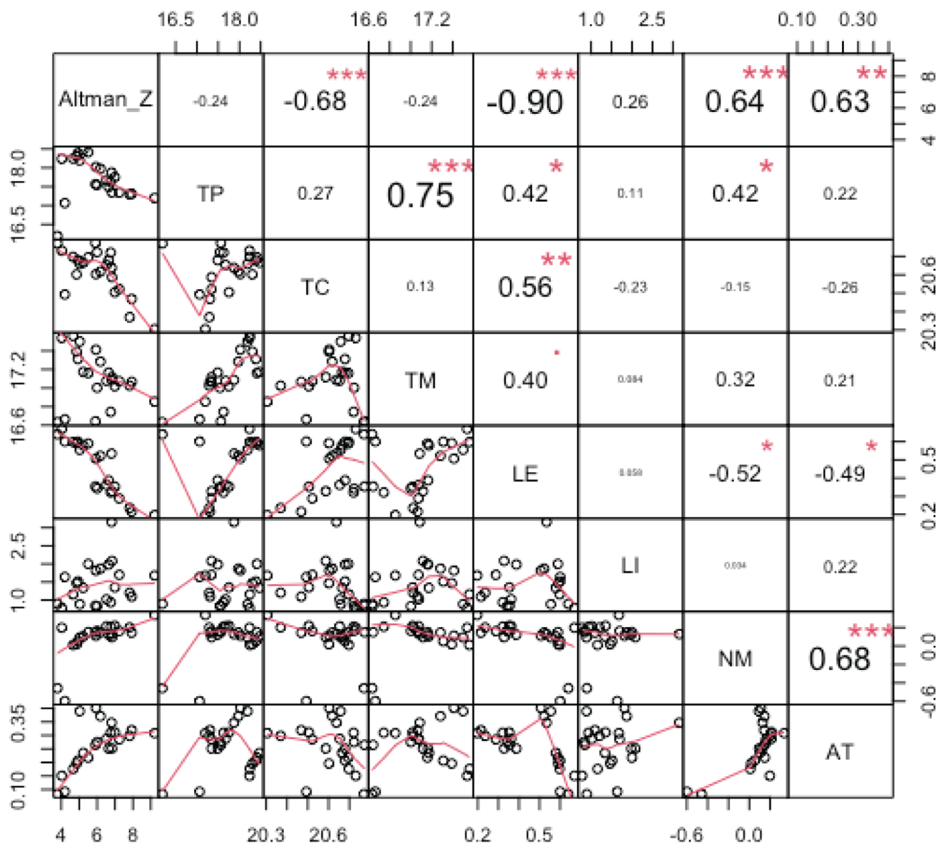
It is also noted that some of the paired observations in the scatter plots in Figure 4 (first column) do not follow straight lines, but all predictor variables have a degree of linear dependency with response variable. So, the fitted model is:

$$AZ_i = 77.66 - 3.95\, LE_i + 0.54\, LI_i + 2.55\, NM_i + 1.43\, AT_i - 0.30\, TP_i - 2.77\, TC_i - 0.50\, TM_i \tag{17}$$

where the direction of contributions towards response variable given by the symbol of estimated coefficients is similar to Figure 4 (first row). All estimated coefficients are statistically significant (p-value$\leq$0.10). The mean and sd of the model residuals are approximately zero and 0.17 respectively; the Breusch-Pagan test (p-value=0.22) failed to reject the assumption of homoskedasticity in the model residuals; and normality tests (i.e. Shapiro-Wilk, Jerque-Bera and Anderson-Darling) confirmed normality, hence the $\varepsilon_i \sim N(0, \sigma\varepsilon 2)$ assumption is met. In addition, none of the VIF values being higher than 10 suggests there is no multicollinearity problem in (17).

Summary statistics of the observed Altman Z”-score and the estimated *AZ* distribution by the fitted model (17) are compared in Table 5. The estimated minimum, median, maximum, interquartile range (IQR) and sd values are approximately similar to the observed Altman Z”-score. The mean value

Figure 4. Pearson's correlation matrix and scatter plot between variables



*** means p < 0.001, ** p < 0.01, and * p < 0.05

Table 5. Comparison of descriptive statistics of the observed and estimated Altman Z"-score series from 1999 to 2021

Altman Z''-Score	Min	Median	Mean	Max	IQR	sd	Skewness
Observed	3.784	5.999	6.044	9.209	1.8384	1.3571	0.2743
Estimated	3.635	6.125	6.044	9.025	1.9062	1.3460	0.1633

of both distributions is the same to three decimal places, and skewness of the estimated distribution is slightly closer to normal distribution than for the observed. In conclusion, the fitted model (17) has successfully captured most of the statistical characteristics of the observed Altman Z"-score. The fitted and observed time series plots are given in Figure 5.

4. FINANCIAL DISTRESS BEYOND 2021

4.1. Probability Distribution for Financial Distress Outlook

Gaussian distribution is an ideal representation of realism in this study as the distribution of negative and positive random numbers is approximately balanced (or symmetrical). Realistically, there are unexpected ups and downs in business over any period of time, so business operators should expect the financial results of their businesses to be around the expected outcome. These unexpected ups and the downs may be well represented by the positive and negative random numbers from Gaussian distribution. Most of the values are clustered at the centre of the distribution around the mean, mode and median where approximately 95% of the values lie within normal limits defined as two standard deviations below and above the mean (e.g. Smith, 2000). Furthermore, Gaussian distribution fits many processes, both natural and anthropogenic, such as modelling laser heat source (Liu et al., 2016), estimating fluorescence microscope spreads in flow cytometric DNA histograms (Lampariello et al., 1991) and interpreting the noise that corrupts a signal (Al-Nahhal et al., 2019).

Despite the arguments and limitations of Gaussian distribution (e.g. McKelvey et al., 2005), Gaussian distribution is still a useful first approximation in modelling that facilitates researchers and practitioners to advance their studies (e.g. Maliani et al., 2012; Wen and Liu, 2013; Guo and Zhai, 2022). Approximately 99.7% of the random values in Gaussian distribution fluctuate up to 3 standard deviations from the centre of the distribution, so it is not highly likely to draw some extreme values from either left or right tails of Gaussian distribution. In this study, extreme values associated to extreme events are also essential. In the case of finance, the world economy has at times experienced severe financial and economic crises. For example, the subprime mortgage crisis in 2007 that lead to a severe financial crisis from 2008 to 2009 globally which affected financial performance of many businesses and financial institutions (e.g., Allen and Christa, 2013). Other examples include the 2001 dotcom crash and the 9/11 attack on the World Trade Centre in the same year, and the slump in the U.S. stock market in 2011 (e.g. Mansor et al., 2018). In terms of pandemic, the outbreak of severe acute respiratory syndrome (SARS) in 2003 (Cherry and Krogstad, 2004) and the most recent example of extreme event is the COVID-19 pandemic outbreak which started on March 11, 2020 (Cucinotta and Vanelli, 2020). Therefore, to avoid underrepresentation of extreme values in this study, gamma and Cauchy probability distributions were utilised.

Cauchy distribution has a taller peak and thicker tails (kurtosis) than Gaussian distribution. A probability distribution with kurtosis in general contains extreme values. Therefore, it is possible to draw some extreme values from Cauchy distribution. The applications of Cauchy distribution in research resulting from this feature cover many disciplines, including physics (e.g. Wan and Achim, 2011; Wang et al., 2019; Xu et al., 2021), measurement problems, risk analysis and financial analysis (Alzaatreh et al., 2016). Finance literature has also used kurtosis to interpret the investment risk given by dramatic changes in stock prices and cryptocurrency distributions (e.g. Basher and Sadorsky, 2006; Conlon and McGee, 2020). In addition, Cauchy distribution is approximately symmetrical, meaning that the proportion between the large negative random numbers (losses) associated with extreme events, and large positives (gains) associated with the rapid recoveries following extreme events, is approximately balanced. However, for many occasionally occurring extreme events, businesses may experience more negative impacts such as significant losses, rather than gains. For instance, the subprime mortgage crisis that was first widely reported on July 1, 2007 is believed to have led to the collapse of financial services firm Lehman Brothers in 2008 (e.g. Mansor et al., 2018). So, this study employs Cauchy distribution to represent a pessimistic financial outlook where business operators expect the worst financial results despite some substantial recoveries, if any, following extreme events.

However, some business operators could potentially expect only positive financial results every year despite the challenges of doing business and uncertainties in the economy. While Gaussian and Cauchy distributions are symmetrical in shape, the gamma distribution is positively skewed and contains only positive random numbers. A positively skewed distribution has a thicker and long tail on the right-hand side of the distribution, which means the random values in the right tail are within a wider range of values compared to the left-hand side of the distribution. It is noted that the similarity between Cauchy and gamma distributions is non-normality, while for this study the similarity between gamma and Gaussian distributions in this study is that they are not intended for extreme events. Although random values from a gamma distribution might not be able to represent some double-digit profits, a gamma distribution consisting of only positive random values (gains) is used in this study to satisfy an optimistic financial outlook. Gamma distribution has also been applied in other studies, such as to model insurance claims and pricing (e.g., Cummins, 1991), volatility (e.g., Xie and Wu, 2017), loan defaults (e.g., Tong et al., 2013), telecommunication services (Bogachev and Bunde, 2009), and rainfall (Aksoy, 2000; Husak et al., 2007; Kumar, 2017).

4.2. Predicting Altman Z”-Score for the Next Decade

In this section, the fitted MGLM model (17) in Section 3 is used to estimate Altman Z”-score for years 2022 to 2031 based on the given determinants’ future values in Table 4 of Section 2. For the error terms, Gaussian, gamma and Cauchy probability distributions were fitted to demonstrate realistic, optimistic and pessimistic financial outlooks. The selection of values for the error terms in this procedure is completely random using *R* functions of *rnorm* for Gaussian (GE), *rgamma* for gamma (ME) and *rcauchy* for Cauchy distributions (*R* Core Team, 2018). The estimated values of Altman Z”-score for 2022 to 2031 using MGLM model with Gaussian errors (MGLM+GE), gamma (MGLM+ME) and Cauchy (MGLM+CE) are given in Table 6. The realisation of MGLM+GE represents a realistic financial outlook while realisations of MGLM+ME and MGLM+CE represent optimistic and pessimistic financial outlooks respectively, and are plotted in Figure 5.

The lowest predicted Altman Z”-score from a realistic financial outlook (Table 6, first row) is 2.99 for the year 2027 which is the closest value to the financial distress exposure threshold of 2.60. The thresholds of 2.60 and 1.10 for financial distress exposure and having financial distress are shown in Figure 5 as horizontal lines in green and firebrick respectively. It is noted that none of the predicted values under optimistic financial outlook is closer to the threshold of 2.60. On the other hand, there are three values below the thresholds (Table 6, underlined), of which the lowest is 0.2481, that pessimistically project MAHB will be in a financial distress situation in 2024.

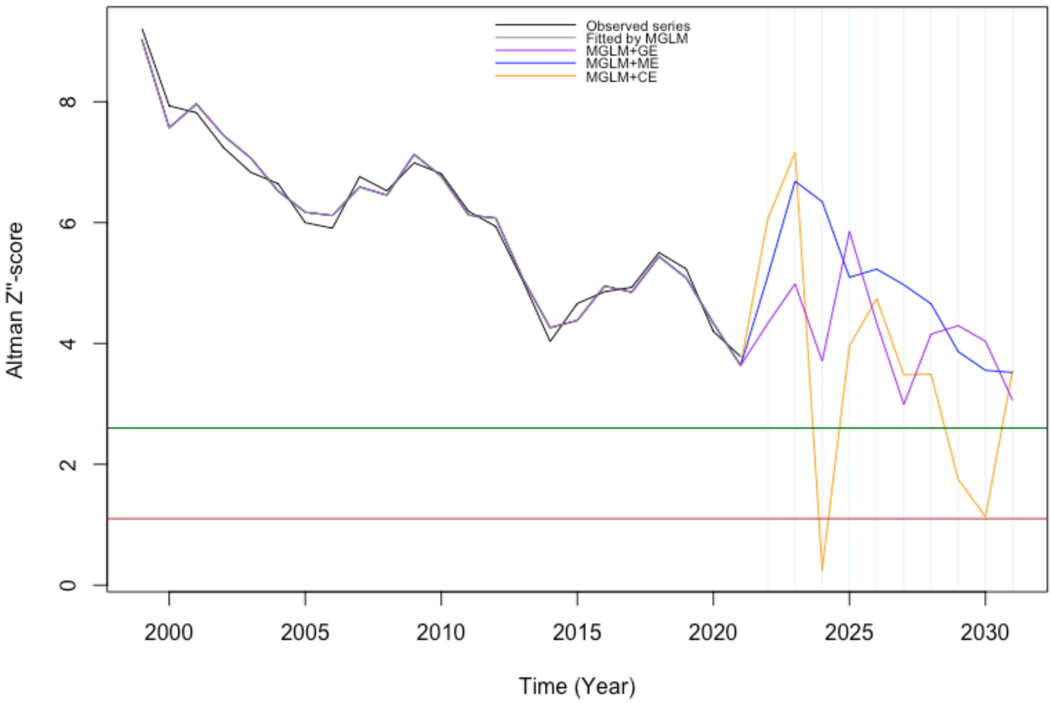
In Figure 5, the observed Altman Z”-score series from 1999 to 2021 (line in black) is plotted in tandem with the fitted MGLM model to show the lack of discrepancies between the observed and the fitted Altman Z”-score values. The error measurements of ME, RMSE, MAE, MPE and MASE, of –4.71e-15, 0.17, 0.15, –0.05 and 0.14 accordingly, are relatively small. The realisations plotted between 2022 and 2031 are the future values of Altman Z”-score from Table 6. The realistic financial outlook given by the realisation made by MGLM+GE (in purple) while optimistic (blue) and pessimistic (orange) financial outlooks are given by MGLM+ME and MGLM+CE respectively.

As expected, the realistic financial outlook series fluctuates between optimistic and pessimistic financial outlooks. However, it is difficult to comment on the general underlying trends for the three financial outlooks based on only one set of random GE, CE and ME. The forecast values may be different when different sets of random GE, CE and ME are utilised. Hence, a simulation procedure is carried out in Section 4. The summary statistics of the realisations of realistic, optimistic and pessimistic financial outlooks are given in Tables 7.

Table 6. The 10-step ahead predictions of Altman Z”-score using MGLM with Gaussian, gamma and Cauchy errors for realistic, optimistic, and pessimistic financial outlooks respectively

Outlook	Year									
	2022	2023	2024	2025	2026	2027	2028	2029	2030	2031
Realistic (MGLM+GE)	4.3327	4.9858	3.7051	5.8534	4.3371	2.9905	4.1534	4.2942	4.0360	3.0561
Optimistic (MGLM+ME)	5.1143	6.6845	6.3452	5.0943	5.2301	4.9694	4.6560	3.8633	3.5548	3.5187
Pessimistic (MGLM+CE)	6.0617	7.1560	<u>0.2481</u>	3.9615	4.7422	3.4805	3.4904	<u>1.7477</u>	<u>1.1316</u>	3.5581

Figure 5. Time series plot of the observed Altman Z"-scores and the fitted MGLM for years 1999 to 2021, and 10-step ahead prediction values for years 2022 to 2031



4.3. Financial Distress Outlook Simulation

1000 time series of length 10 years, the length of forecast series for the Altman Z"-score from 2022 to 2031, are simulated using MGLM (17) where the probability distributions of GE, ME, and CE were fitted to the residuals. In each simulation, the 10 forecast values were obtained and summary statistics for each forecast series were estimated and stored. The summary statistics are minimum, median, mean, maximum, sd, skewness and kurtosis. For 1000 simulations (N=10^3), there were 1000 forecast series hence 1000 values of summary statistics; so, their averages were calculated and stored. The replications of the simulation using MGLM+GE, MGLM+ME and MGLM+CE are also done for N=10 and 10^2, independently. The averages of the summary statistics for realistic, optimistic and pessimistic financial outlooks replicated 10, 10^2 and 10^3 are presented in Table 7.

The summary statistics for N=1 describing the distribution for the 10-step ahead predictions of Altman Z"-score in Table 6. The minimum value from the realistic outlook is 2.99, which is above the financial distress exposure threshold of 2.60. The skewness of 0.41 being between -0.50 and 0.50 suggests that realistic Altman Z"-score distribution is fairly symmetrical with 50% of the observations being smaller than 4.22 and the other half being bigger than 4.22. The mean and median are approximately the same, the sd is nearly 1.00 and the kurtosis is close to a normal distribution, as expected. As the N increases from 10, 10^2 to 10^3, all values converge to approximately the same leading or rounded integer of 2, 4, 4, 6, 1, 0 and 2 for minimum, median, mean, maximum, sd, skewness and kurtosis respectively – particularly the skewness.

The minimum values from the optimistic financial outlooks for N=1, 10, 10^2 and 10^3 are approximately 4.0, which is well above the financial distress exposure threshold of 2.60. It is noted that the random numbers from gamma distribution are all positives. In the simulations, it is observed that the average of means is larger than the average of medians for optimistic financial outlook as the

ME distribution in theory is positively skewed. In addition, the shape of the optimistic distribution leans towards being moderately skewed to the right as the N increases. In other words, forecast values in the right tail are within a wider range of values compared to the left-hand side of the distribution. Hence, more large positive future values of Altman Z"-score can be found in the optimistic outlook distribution compared to the realistic outlook distribution. On average, the maximum future values of Altman Z"-score is 7.0 and spreading about 1.0 around the mean of 5.0.

The distribution of pessimistic financial outlook for N=1 is not asymmetrical as described by the skewness 0.09, and skewness from the simulations is approximately 0.03. However, the average kurtosis is high (more than 3.0), suggesting that some Altman Z"-score future values are extrema, as designed. The minimum of Altman Z"-score future values for N=1 is 0.25, which is well below the financial distress threshold of 1.10. When the N increases from 10, 10^2 to 10^3, the average of minima increases in value more consistently than the average of maxima and means. The average of sd values increases, reflecting the increasing average in the deviation of Altman Z"-score future values from its mean as more extrema are introduced as the N increases.

It is understood that the pattern disclosed in the averages of minimum, median, mean, maximum and sd for both MGLM+GE and MGLM+ME simulations is not seen in MGLM+CE except in the averages of medians as they are consistently approaching 4.00. Hence, supporting the fact that median is robust against extreme values while mean depends on all observations, including extrema. For example, product moment skewness of differences of absolute values about the mean that was designed to detect directionality in time series, is highly sensitive to extreme outliers (Mansor et al., 2020). Subsequently, median is chosen to describe the underlying trends for realistic, optimistic and pessimistic financial outlooks.

In each simulation, 10-step ahead values for years 2022 to 2031 were estimated and stored according to year. For 1000 simulations (N=10^3), there were 1000 forecast values for year 2022, 1000 forecast values for 2023, up to year 2031 accordingly. Therefore, yearly medians of 1000 forecast values were obtained and stored. The simulation using MGLM+GE, MGLM+ME and MGLM+CE are also replicated for N=10 and 10^2, independently.

Table 7. Summary of descriptive statistics of 10-step ahead predictions (2022-2031), and the average of the statistics from N randomised realistic, optimistic and pessimistic outlooks series

Outlook	Statistic							
	N	Min	Median	Mean	Max	sd	Skewness	Kurtosis
Realistic (MGLM+GE)	1	2.9905	4.2238	4.1744	5.8534	0.8456	0.4093	2.8877
	10	2.4950	4.1398	4.1511	6.0074	1.0877	0.1673	2.3949
	10^2	2.1893	4.0074	4.0306	5.9299	1.1776	0.0642	2.4239
	10^3	2.2641	4.0287	4.0357	5.8489	1.1349	0.0332	2.4211
Optimistic (MGLM+ME)	1	3.5187	5.0318	4.9031	6.6845	1.0709	0.2347	2.1175
	10	3.7333	4.8387	4.9341	6.8753	0.9763	0.4499	2.8896
	10^2	3.6817	4.8327	5.0288	7.1754	1.1165	0.5769	2.6934
	10^3	3.7262	4.8768	5.0534	7.1737	1.1007	0.5915	2.7414
Pessimistic (MGLM+CE)	1	0.2481	3.5242	3.5578	7.1560	2.1320	0.0912	2.2365
	10	-0.5676	4.1876	6.6306	30.271	9.2181	1.0454	4.4725
	10^2	-20.703	4.1637	3.4004	20.828	12.561	0.1672	4.9524
	10^3	-22.545	4.0740	5.2629	42.389	19.773	0.0279	4.7700

Table 8 consists of the median of Altman Z”-score future values for realistic, optimistic and pessimistic financial outlooks replicated 10, 10^2 and 10^3 times for years 2022 to 2031. Forecast values for N=1 are related to the 10-step ahead predictions in Table 6 as described in Section 4.1. The forecast values from 2022 through 2031 for realistic financial outlook from the simulations (N=10, 10^2 and 10^3) converged to approximately the same rounded integer. This is similar to the optimistic financial outlook for years 2022 to 2032 for all accounts, except for one median of minima in 2022 when N=10. The yearly medians of Altman Z”-score future values for a pessimistic financial outlook subtly prescribe similar effect but are stabilised at N=10^2 to 10^3. Therefore, the medians of Altman Z”-score future values for realistic, optimistic and pessimistic financial outlooks at N=10^3 for years 2022 to 2031 are plotted in Section 5 to summarise the underlying trends for the three financial outlooks.

5. CONCLUSION

Three probability distributions were utilised in the simulations using *R* computing to postulate three financial distress outlooks for the increasing risk of financial distress of the largest airport operations in Malaysia. The degree of financial distress described by Altman Z”-score was modelled by the multivariate generalized linear model (MGLM) using four financial and three non-financial determinants from literature. The fitted MGLM met all the modelling assumptions and obtained the coefficient of determinant R^2 of 98.36%, indicating that only 1.64% of the total variation in the observed Altman Z”-score is unable to be explained by the combined variation of the seven determinants. Gaussian distribution was fitted to the residuals to obtain a realistic financial distress outlook, while gamma and Cauchy distributions were fitted for optimistic and pessimistic financial outlooks accordingly. All distributions of the simulated series (N=10, 10^2 and 10^3) successfully captured the statistical characteristics of Gaussian, gamma and Cauchy distributions.

The financial distress outlooks are visualised in Figure 6. Figure 6 features the underlying trends (dashed lines) for realistic (in purple), optimistic (blue) and pessimistic (orange) financial distress outlooks during the ten financial years from 2022 to 2031, in addition to the initial forecast

Table 8. The 10-step ahead prediction values, and its median from N of randomised realistic, optimistic and pessimistic outlooks for 2022 to 2031

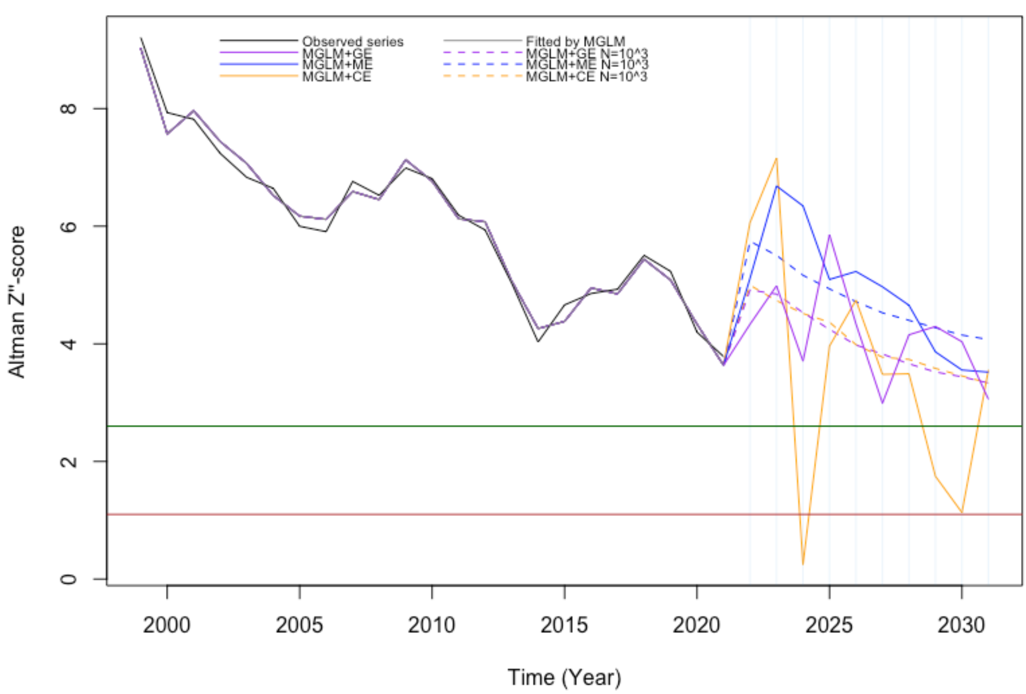
Outlook	Year										
	N	2022	2023	2024	2025	2026	2027	2028	2029	2030	2031
Realistic (MGLM+GE)	1	4.3327	4.9858	3.7051	5.8534	4.3371	2.9905	4.1534	4.2942	4.0360	3.0561
	10	5.3960	4.7311	5.0399	3.7642	4.4693	3.8829	3.4045	3.5268	3.7218	3.7040
	10^2	4.7947	5.0383	4.5688	4.0036	3.9920	3.7605	3.5214	3.5436	3.4282	3.3503
	10^3	4.9160	4.8454	4.5312	4.2450	3.9799	3.8263	3.6604	3.5212	3.4393	3.3337
Optimistic (MGLM+ME)	1	5.1143	6.6845	6.3452	5.0943	5.2301	4.9694	4.6560	3.8633	3.5548	3.5187
	10	5.2686	5.5117	4.8753	4.7743	5.0792	4.9877	4.5167	4.3194	4.2614	3.7814
	10^2	5.7383	5.4397	5.0323	4.7176	4.7405	4.6766	4.3790	4.2624	4.1583	3.8902
	10^3	5.7437	5.5040	5.1656	4.9342	4.7165	4.5276	4.3997	4.2734	4.1493	4.0741
Pessimistic (MGLM+CE)	1	6.0617	7.1560	0.2481	3.9615	4.7422	3.4805	3.4904	1.7477	1.1316	3.5581
	10	5.9789	4.6628	5.0913	5.0732	3.2898	3.8073	3.5992	3.9333	2.7016	3.3976
	10^2	4.9380	4.9878	4.4660	4.3684	4.2441	4.1785	3.9020	3.6883	3.4454	3.1746
	10^3	4.9964	4.7355	4.5158	4.3671	3.9859	3.7729	3.7350	3.5822	3.4541	3.3335

approximation N=1 (solid lines). The underlying trends are described by median of Altman Z"-score future values from simulations $N=10^3$ for having converged values following consistent approximations and median for being robust against extrema.

In Figure 6, the Altman Z"-score is predicted to increase in 2022 and 2023 for all three financial distress outlooks (solid lines), hence reducing the risk of MAHB in experiencing financial distress in the future. A similar pattern is noticeable in the underlying trends. In particular, the future short-term memory effect demonstrated in the optimistic financial outlook. This suggests that MAHB optimistically could recover financially from COVID-19, because Altman Z"-score is expected to return to its initial level before COVID-19, by 2023. However, the apparent growth in the future short-term memory effect for all three financial outlooks would be retarded by a slow downward trend in 2023 through 2031. A prior assessment to examine the individual determinant revealed future short to long-term memory effects as well between years 2022 and 2031 due to COVID-19 for all non-financial determinants. It is noted that the underlying trend for optimistic financial outlook outperformed the underlying trends for realistic and pessimistic financial outlooks during the forecast period, as expected. However, the underlying trend for the pessimistic financial outlook is depicted almost in tandem with the underlying trend of the realistic financial outlook. This could be due to the similar symmetric properties between Gaussian and Cauchy distributions.

In conclusion, the underlying trends for all three financial distress outlooks suggest that the downward trend in Altman Z"-score in general is likely to continue. As the Altman Z"-score decreases, the risk of financial distress increases. It is also noted that the outstanding debts of MAHB are expected to grow during the next decade and liquidity is predicted to continue to decrease, meaning MAHB's current liabilities could exceed its current assets. In addition, the degree of effectiveness of MAHB in keeping the growth of revenue ahead of rising costs of airport operations and in managing their

Figure 6. Time series plot of the observed Altman Z"-scores and the fitted MGLM for years 1999 to 2021, and 10-step ahead prediction values and the median of randomised realistic, optimistic and pessimistic financial outlooks from simulations for years 2022 to 2031



fixed assets to generate profit is fluctuated around downward trends. Therefore, any strategy that reduces the financial leverage and increases liquidity, net operating margin, and asset turnover of MAHB should take place, at least cost-effectively, in managing increasing future total movements of passenger, cargo, and mail. This should happen while maintaining the MAHB's business values, high quality practices and reputation. However, it is also noted that the underlying trends modelled by the MGLM in Figure 6 are not expected to cross the financial distress exposure threshold of 2.60 by 2030 as projected by the univariate model in Figure 1. Assuming the realistic financial distress outlook fits the MAHB's risk appetite, the Altman Z"-score is projected to decrease to 3.33 in 2031, just 0.73 above the financial distress exposure threshold.

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Mahayaudin M. Mansor obtained a B.Sc.App. (Hons) (Mathematical Modelling) from Universiti Sains Malaysia in 2005, a M.Sc. (Quantitative Science) from Universiti Teknologi MARA in 2011, and a Ph.D. in Statistics from The University of Adelaide, Australia in 2018. He worked in banking and insurance before teaching Statistics and Business Mathematics at the Universiti Tun Abdul Razak Malaysia. After completing his PhD studies, he worked as a researcher specialising in data management and quantitative research at the Australian Centre for Precision Health, University of South Australia. He is currently a senior lecturer in Statistics at the School of Mathematical Sciences, Universiti Teknologi MARA and an external supervisor register at the School of Mathematical Sciences, The University of Adelaide. His research interest focuses on data analytics, time series, R computing, quantitative finance and vulnerable populations.

Nurain Ibrahim received the Bachelor of Science (Hons) (Statistics), Master of Science Applied Statistics from Universiti Teknologi MARA in 2013 and 2014, and PhD in Biostatistics from University of Liverpool, United Kingdom in 2020. She is currently a senior lecturer with the School of Mathematical Sciences, College of Computing, Informatics and Media, Universiti Teknologi MARA, Malaysia. Her research interest includes biostatistics, data mining with multivariate data analysis, and applied statistics. She has experienced in teaching A-level students for UK, US and Germany bounds at INTEC Education College in 2013 to 2014.

Siti Afiqah Muhamad Jamil received her first degree in Bachelor of Science (Hons) (Statistics) from Universiti Teknologi MARA (UiTM) in 2016 and a PhD degree from Universiti Tun Hussein One Malaysia in 2020. She is currently a senior lecturer in School of Mathematical Sciences, College of Computing, Informatics and Media, UiTM, Malaysia. Her research interest include survival analysis, statistical modelling, regression analysis, biostatistics and applied statistics.

Nur Amalina Shafie received a Bachelor of Applied Science (Hons) with a major in Statistics and minor in Management, and a Master of Science (Statistics) from Universiti Sains Malaysia in 2009 and 2012, respectively. She received a Ph.D. degree from Universiti Kebangsaan Malaysia in 2019. She is currently a senior lecturer at the School of Mathematical Sciences, Universiti Teknologi MARA. Her current research interest includes forecasting, financial time series, and applied statistics.

Siti Meriam Zahari received her first degree in Bachelor of Applied Science, with a specialization in Mathematics and Economics, and her second degree in Master of Economic Management from Universiti Sains Malaysia in 2003 and 2004, respectively. She received a PhD degree from Universiti Teknologi MARA in 2009. Since 2009, she has been with the School of Mathematical Sciences, Universiti Teknologi MARA as a senior lecturer. Her current research interest includes time series econometrics, statistical outliers, decision analysis and forecasting.