“Failure threats of insurance companies: A case study of financial environments of Jordan”

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FAILURE THREATS OF INSURANCE COMPANIES: A CASE STUDY OF FINANCIAL ENVIRONMENTS OF JORDAN

Abstract

Insurance firms are known to have unique financial failure characteristics that affect the financial environment of the countries. Therefore, the purpose of this study is to assess the validity of the model used in predicting the financial failures of insurance companies. The model is believed to help in stabilizing the financial environment of the countries by predicting any collapses in the insurance sector. A discriminate regression technique was used to test 28 indicators chosen from 11 financial failure model parameters. 11 parameters of the model are the following: solvency, profitability, operational capabilities, structural soundness, capital expansion capacity, capital adequacy, reinsurance and actuarial issues, management soundness, capital expansion capacity, earnings and profitability, and liquidity. The results of the study proved that 22 variables from 11 parameters were significant; the study also validated the use of the financial failure model as a stable predictor of the financial failure of ASE insurance firms. The stability of the insurance industry is interpreted through the minimum deviation between the real and measured performances. The deviation was present in 3 out of 95 observations, and it affected only 3 firms out of 19, 1 firm out of 3 turned out to be affected by the risker deviation which is the type II error distorted observation. To conclude, the study by mentioning that insurance firms are not threatened by failure or distress and the financial failure model is a valid prediction model.

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JEL Classification G22, G17, N25, C10

INTRODUCTION

It was reported in the 1930s that a few public Jordanian firms were listed in the counter market and were able to trade shares. The first corporate bond was issued in the 1960s, which was then followed up by the Amman Financial Market (AFM) launch in January 1978. It is an organized exchange that includes 66 listed firms. A major development then occurred in the Jordanian Capital Market on March 11, 1999, where three new institutions named Jordan Securities Commission (JSC), Amman Stock Exchange (ASE), and Securities Depository Center (SDC) replaced the AFM. The establishment of the Jordan Insurance Association for insurance companies boosted the Kingdom's economy. The Jordan Insurance Federation (JIF) was then established in 1989 following a Royal Decree, which comprises licensed 24-member insurance companies; they consist of one foreign insurance company, two 'takaful' operators, and 22 conventional insurers, 20 out of 24 companies are listed in the Amman Stock Exchange, which gives a clear indication that the market lacks the services of reinsurance companies. Consequently, the operations of the Jordanian insurers were reinsured by preserving a portion of the risk, which was ceded through the reminder of the Arab and foreign reinsurance companies.

Thus, the problem that the study is trying to address is the effect of the insurance industry and other financial industries on the stability of the country's financial environment. Economies could suffer from recessions due to the failure of a single financial firm. All the financial firms in the financial sector will be affected if a single financial firm experienced a failure, and as a result, the whole financial sector will collapse.

1. LITERATURE REVIEW

In the last seven decays, scholars and researchers heavily discoursed the topic of the financial failure of companies that belongs to different exchanges sectors around the globe. In this literature review section, high-ranking journals are listed and summarized chronologically.

To begin with, Altman (1968) developed Z-Score model and Altman et al. (1977) developed ZETA credit risk model for assessing financial distress. Moreover, effective indicators and predictors variables of the corporate distress were specified and quantified. Altman et al. (2007) classified distress firms into original samples; it was shown that the discriminant-ratio model provided an early warning capacity up to four years before the financial distress. Both statistical analysis, artificial intelligence, and neural networks can be used to assess the financial distress probability. Bose and Pal (2006), Jardin and Severin (2012), Gestel et al. (2006), Lin et al. (2014), Carlos (1996), Chen and Du (2009), Gepp and Kumar (2015), Bae (2012), Wilson and Sharda (1994), Jo et al. (1997), and Li and Sun (2009) showed that the artificial intelligence and neural networks outperformed the traditional statistical techniques in predicting the financial distress around the globe. Kumar and Ghimire (2013) indicated that qualitative factors play a vital role in the financial soundness of insurance firms. However, they do not grasp the big picture of the insurer's financial health. It was also shown that the financial performance of each company and their aggregated overview fall under the following dimensions: capital adequacy, assets quality, reinsurance, and actuarial issues, management soundness, earnings and profitability, and liquidity.

Halpern et al. (2009) observed that the firms that avoided financial distress or bankruptcy have a more critical influence on debt composition than the governance proposed changes. Tinoco and Wilson (2013) showed the utility of combining accounting, market, and macro-economic data for listed companies in financial distress prediction models. Dairui and Jia (2009) proved that there is a relationship between 13 variables (corporate governance variables, agency costs, and ownership structure, etc.) and the probability of financial distress. Zmijewski (1984) showed that the slack-based measure (SBM) data envelopment analysis (DEA) model has obvious advantages in predicting corporate financial stress, and categorized firms into safe, grey, and distress zones by proposing cut-off points. Das et al. (2003) proposed the compilations and usages of the key indicators in the surveillance of the insurance sector firms' financial soundness. Furthermore, there is other qualitative information that could be also used in the surveillance process such as the ownership arrangements.

Christidis and Gregory (2010) developed a new "dynamic logit" model (micro and macro variables) for prediction failures in the UK. Manzaneque et al. (2016) confirmed a negative relationship between board size and financial distress, while the ownership concentration does not have any significant impact on the Spanish financial distress. Amendola et al. (2015) found that micro-economic indicators and firm-specific factors influence the exit of Italian firms through bankruptcy, liquidation, and inactivity routes. Smajla (2014) showed that composite companies in Croatia have the best capital adequacy, retention ratio (due to reinsurance services), management, and profitability. Nonetheless, their liquidity still needs some improvements.

Jahur and Quadir (2012) identified that rate adequacy, sales trends, indebtedness, management capability, financial planning, etc. of the Bangladesh SMEs are the cause of financial distress problems. It was also illustrated that fund management and resource crunch, poor accounting system, poor financial control, poor productivity and profitability, and management succession are the causes of financial distress. Geng et al. (2015) observed that financial performance and profitability indicators

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play an important role in the prediction of the profitability deterioration in China. Sevim et al. (2014) showed that Turkey's economy uses macroeconomic indicators to predict crises a year before it actually happens.

Ntoiti (2013) indicated that financial management practices, human resource management practices, and corporate governance practices have a significantly negative relationship with financial distress, while government regulations have a positive relationship with the financial distress in Kenya. Simpson and Damaoh (2008) found that in Ghana, the CARMEL model was the most comprehensive compared to the other evaluation models and tools.

Following the literature review, this study develops a financial failure model that helps in achieving the purpose of the paper by evaluating the emerging markets' financial distress, testing the significance of the indicators, and examining the applicability of the model. The study is considered to be unique as there is little availability of similar research in this area of knowledge and it also contributes to the decision-making processes of ASE and Jordan Insurance Federation (JIF).

2. HYPOTHESES DEVELOPMENT

Since 28 indicators are being tested, the hypotheses apply for each one of the indicators

H1: There is no significant effect of the independent variable on the financial failure score (solvency margin as a dummy variable (1 if solvency ratio > = 150%; 0, otherwise)).

H2: There is a significant effect of the independent variable on the financial failure score (solvency margin as a dummy variable (1 if solvency ratio > = 150%; 0, otherwise)).

3. METHODOLOGY

The sample used in this study is the annual data, which includes 19 financial statements of the listed companies. One company out of the 20 listed companies was excluded due to one year of missing data. The data covers a period of 5 years from 2014 to 2018. Moreover, the statistical analysis used 95 panel data observations.

The parameters (indicators) of the financial failure model are solvency (total liabilities/total assets, total liabilities/total shareholders' equity, net operating cash flow/total liabilities); profitability (operating profit margin, earnings before income tax/total assets, earnings before income tax/shareholder equity); structural soundness (fixed assets/total assets, current assets/total assets, shareholders' equity/fixed assets); business development capacity (total assets of this year/total assets of last year, net profit of this year/net profit of last year); capital expansion capacity (net profit/number of ordinary shares at the end of year, net assets (total assets-total liabilities)/number of ordinary shares at the end of year, capital reserves/number of ordinary shares at the end of year, net increase in cash and cash equivalents/number of ordinary shares at the end of year); earnings and profitability (loss ratio, expense ratio, return on asset, return on equity); operational capabilities (sales revenue/total assets, sales revenue/fixed assets); reinsurance and actuarial issues (retention ratio, net technical reserves/net claims paid at the end of the year, net technical reserves to net realized premiums); management soundness (asset per employee (total assets/number of employees)); capital adequacy (surplus/technical reserves ratio, solvency ratio (net written premium/total equity)); liquidity (Graham rating = (2* equity)/total liabilities). In addition, Table 1 also shows the measurements of 28 indicators and their references. This model is also used by other industries to deal with financial distress; it combines the parameters and indicators from the CARMEL model.

3.1. Financial failure model

Financial failure score (solvency margin is a dummy variable (1,0)) = $\alpha + \beta_1$ L/A $+\beta_2$ L/E $+\beta_3$ OCF/L$+\beta_4$ OPM $+\beta_5$ EBT/A $+\beta_6$ EBT/E $+\beta_7$ R/A $+\beta_8$ R/FA $+\beta_9$ A_1/A_0 $+\beta_{10}$ P_1/P_0 $+ \beta_{11}$ FA/TA $+\beta_{12}$ CA/TA $+\beta_{13}$ E/FA $+\beta_{14}$ EPS $+\beta_{15}$ NA/OS $+\beta_{16}$ CR/OS $+\beta_{17}$ NIC/OS $+\beta_{18}$ SR/TR $+\beta_{19}$ SOL $+\beta_{20}$ RET. $+\beta_{21}$ TR/C $+\beta_{22}$ TR/RP $+\beta_{23}$ A/NEM $+\beta_{24}$ LOSR $+\beta_{25}$ EXPR $+\beta_{26}$ ROA $+\beta_{27}$ ROE $+\beta_{28}$ GRAH. (definition of each variable is illustrated further).

The dependent variable for the financial failure model is a dummy variable, which takes value 0 when a company is in financial distress and 1, otherwise, a company is considered as "distressed" when its solvency margin is less than 150% in each year according to Internationally Active Insurance Groups & Reinsurance Standards Instructions and Amendments.

Solvency: a performance indicator variable that indicates the insufficient funds of fulfilling stakeholders' debts in the long and short run (Geng et al., 2015).

1) L/A: total liabilities/total assets (since all the firms are exposed to the same market conditions the ratio should be kept within the industry levels; there is the tradeoff between the tax shield of debt and the equity of shareholders, which should be kept at a safety margin). (Geng et al. 2015)

2) L/E: total liabilities/total shareholders' equity (Geng et al., 2015).

3) OCF/L: net operating cash flow/total liabilities (operation cash reserves are used as a health indicator of the operation management and as a protection against technical distresses) (Geng et al., 2015).

Profitability: solvency problems could be caused by low profitability (Geng et al., 2015).

4) OPM: operating profit margin (Geng et al., 2015).

5) EBT/A: earnings before income tax/total assets (Geng et al., 2015).

6) EBT/E: earnings before income tax/shareholder equity (Geng et al., 2015).

Operational capabilities: it shows the contribution in ROE and ROA, and the degree of controlling firm activities (Geng et al., 2015).

7) R/A: sales revenue/total assets (Geng et al., 2015).

8) R/FA: sales revenue/fixed assets (Geng et al., 2015).

Business development capacity: short and long run sustainability is achieved through assets and profit growths (Geng et al., 2015).

9) A_1/A_0: total assets of this year/total assets of last year (Geng et al., 2015).

10) P_1/P_0: net profit of this year/net profit of last year (Geng et al., 2015).

Structural soundness: it shows the tradeoff between liquidity and profitability in the investment structure level (Geng et al., 2015).

11) FA/TA: fixed assets/total assets (Geng et al., 2015).

12) CA/TA: current assets/total asset (Geng et al., 2015).

13) E/FA: shareholders' equity/fixed assets (Geng et al., 2015).

Capital expansion capacity: market ratio could be used as a comparison factor among the industry firms and also could affect the ability of an investor to buy the firm's stock, firm financial resource, and the share of each stock in each firm from its investment (operation, cash, and capital reserves) (Geng et al., 2015).

14) EPS: net profit/number of ordinary shares at the end of the year (Geng et al., 2015).

15) NA/OS: net assets (total assets-total liabilities)/number of ordinary shares at the end of the year (Geng et al., 2015).

16) CR/OS: capital reserves/number of ordinary shares at the end of the year (Geng et al., 2015).

17) NIC/OS: net increase in cash and cash equivalents/number of ordinary shares at the end of the year (Geng et al., 2015).

Capital adequacy: it is considered as an ultimate risk to the financial stability of an insurer stems, because of writing business that is intense in volume, volatile or undetermined result (Das et al., 2003).

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18) SR/TR: surplus[1]/technical reserves[2]ratio (Das et al., 2003).

19) SOL: solvency ratio (net written premium[2]/total equity1) (Das et al., 2003).

Reinsurance and actuarial issues: probable serve risk scenarios, which are usually covered by the insurer's capital and reinsurance (Das et al., 2003).

20) RET.: retention ratio (reflects the portion of risk that is covered by the reinsurers and the overall underwriting strategy) (Das et al., 2003).

21) TR/C: net technical reserves/net claims paid at the end of the year (survival ratio: shows the company value, estimates the accuracy of the reported and outstanding claims). (Das et al., 2003)

22) TR/RP: net technical reserves/net realized premiums (it is an indication for life insurers that the reserves increase in step with the volume of long-term business) (Das et al., 2003).

Management efficiency (Soundness): it is an operational efficiency indicator that is correlated with the management soundness; and it is affected by the exchange efficiency between different distributions channels in selling its products such as brokers, agents, and internet and call centers. (Das et al., 2003).

23) A/NEM: asset per employee (total assets/number of employees) (Das et al., 2003).

Earnings and profitability: low profitability may lead to solvency problems.

24) LOSR: loss ratio (indicator for pricing policy) (Das et al., 2003).

25) EXPR: expense ratio (indicator for operating cost) (Das et al., 2003).

26) ROA: return on asset (indicator for pricing policy) (Das et al., 2003).

27) ROE: return on equity (Das et al., 2003; Geng et al., 2015).

Liquidity: it is a term that refers to the loss of confidence in an insurer, usually results in a cancel over, return of unexpired premium, or seeking insurance elsewhere.

28) GRAH.: Graham rating = (2* equity)/total liabilities) (Graham, 2003).

3.2. Statistical techniques

The technique used in this study is the discriminant analysis; it is an analysis that constructs predictive models for group memberships. Based on the linear combinations of the predictor variables, groups are discriminated at their best, and discriminant functions are composed (or, for more than two groups, a set of discriminant functions). The known sample of cases for the group memberships is used at the beginning to generate the functions. Later on, the functions could be used for new cases that have unknown group memberships and known measurement of the predictor variables.

4. RESULTS

The testing results of the financial distress model showed that there are 95 valid cases without missing or out-of-range group codes and/or at least one missing discriminating variable.

Table 1 includes 76 cases at a good level and 19 cases at a poor level. It also reveals that the mean of the successful level is higher than the mean of the distress level for the following parameters: OCF/L, OPM, EBT/A, EBT/E, A1/A0, P1/P0, CA/TA, E/FA, EPS, NA/OS, NIC/OS, SR/TR, TR/C, A/NEM, ROA, ROE, and GRAH. On the other hand, the rest of the parameters (L/A, L/E, R/A, R/FA, FA/TA, CR/OS, SOL, RET., TR/RP, LOSR, and EXPR) had a higher mean for the distress level than the successful level. Regarding the standard deviation, the parameters L/A, L/E, R/A, NA/OS, NIC/OS, SR/TR, SOL, RET., TR/C, TR/RP, LOSR, EXPR, and GRAH. had a higher successful level devia-

1 Total equity is illustrated as capital for simplicity, but the quality of capital (Tiers) should be examined in further analysis.

2 It is important to note that Ratio of capital/technical reserves (life insurance) and Ratio of net premium/capital (non-life insurers) may lead to distorted results because of insufficient reserving (life) and underpricing (non-life).

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tion than a distress level deviation, while it is the total opposite for OPM, EBT/A, EBT/E, R/FA, A1/A0, P1/P0, FA/TA, CA/TA, E/FA, EPS, ROA, and ROE. Finally, a couple of parameters (OCF/L, CR/OS, and A/NEM) had almost the same standard deviation for both levels.

According to Table 2 the main null hypothesis can be rejected; there is no significant effect for the following variables: L/A, L/E, OCF/L, EBT/A, EBT/E, FA/TA, CA/TA, EPS, NA/OS, CR/OS, SR/TR, SOL, RET, A/NEM, and GRAH (Significant Wilks' Lambda at 1% (*P*-value < 1%)), R/A , ROA (Significant Wilks' Lambda at 5% (*P*-value < 5%)) and OPM, TR/C, E/FA, LOSR, and ROE (Significant Wilks' Lambda at 10% (*P*-value < 10%)). Thus, alternative hypothesis can be accepted. On the other hand, in regards of the other variables: R/FA, A1/A0, P1/P0, NIC/OS, TR/RP, and EXPR (insignificant Wilks' Lambda (*P*-value > 10%)), we cannot reject the null hypothesis. Therefore, there is no significant effect on financial failure score.

Table 3 shows that there is no correlation between 28 variables. Only 44 correlations coefficients between the variables were either above + 0.5 or below – 0.5, and the rest of 378 correlation coefficients aren't highly correlated with one another.

Table 1. Group statistics

Status		Mean	SD	Valid N (Stat.)		Status		Mean	SD	Valid N (Stat.)	
				Unw.	W.					Unw.	W.
Distress	L/A	0.733	0.035	19	19	Successful	L/A	0.583	0.109	76	76
	L/E	2.815	0.514	19	19		L/E	1.543	0.612	76	76
	OCF/L	–0.013	0.107	19	19		OCF/L	0.065	0.102	76	76
	OPM	0.019	0.067	19	19		OPM	0.042	0.039	76	76
	EBT/A	0.003	0.041	19	19		EBT/A	0.037	0.026	76	76
	EBT/E	–0.012	0.148	19	19		EBT/E	0.092	0.072	76	76
	R/A	0.553	0.104	19	19		R/A	0.452	0.178	76	76
	R/FA	13.304	29.074	19	19		R/FA	10.507	9.960	76	76
	A1/A0	1.025	0.089	19	19		A1/A0	1.051	0.076	76	76
	P1/P0	0.526	3.363	19	19		P1/P0	1.011	1.885	76	76
	FA/TA	0.158	0.093	19	19		FA/TA	0.077	0.054	76	76
	CA/TA	0.787	0.088	19	19		CA/TA	0.901	0.063	76	76
	E/FA	5.401	10.819	19	19		E/FA	9.474	8.259	76	76
	EPS	–0.007	0.092	19	19		EPS	0.097	0.075	76	76
	NA/OS	0.589	0.121	19	19		NA/OS	1.346	0.362	76	76
	CR/OS	0.044	0.243	19	19		CR/OS	0.021	0.245	76	76
	NIC/OS	0.095	0.053	19	19		NIC/OS	0.215	0.107	76	76
	SR/TR	0.497	0.096	19	19		SR/TR	1.318	1.246	76	76
	SOL	2.098	0.458	19	19		SOL	1.158	0.557	76	76
	RET.	0.839	0.053	19	19		RET.	0.674	0.162	76	76
	TR/C	1.137	0.310	19	19		TR/C	1.441	0.738	76	76
	TR/RP	1.040	0.294	19	19		TR/RP	1.012	0.315	76	76
	A/NEM	12.467	0.288	19	19		A/NEM	12.713	0.290	76	76
	LOSR	0.826	0.097	19	19		LOSR	0.778	0.107	76	76
	EXPR	1.108	0.264	19	19		EXPR	0.954	0.409	76	76
	ROA	0.014	0.041	19	19		ROA	0.029	0.020	76	76
	ROE	0.032	0.153	19	19		ROE	0.073	0.056	76	76
	GRAH.	0.734	0.132	19	19		GRAH.	1.599	0.937	76	76

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Table 2. Equality of group means

Variables	Wilks' Lambda	F	Df1	Df2	*P*-Val.	Variables	Wilks' Lambda	F	Df1	Df2	*P*-Val.
L/A	0.726***	35.150	1	93	0.000	NA/OS	0.536***	80.424	1	93	0.000
L/E	0.572***	69.574	1	93	0.000	NIC/OS	0.999	0.132	1	93	0.717
OCF/L	0.915***	8.607	1	93	0.004	CR/OS	0.806***	22.338	1	93	0.000
OPM	0.963*	3.526	1	93	0.064	SR/TR	0.919***	8.172	1	93	0.005
EBT/A	0.825***	19.704	1	93	0.000	SOL	0.668***	46.266	1	93	0.000
EBT/E	0.826***	19.532	1	93	0.000	RET.	0.830***	19.053	1	93	0.000
R/A	0.943**	5.603	1	93	0.020	TR/C	0.968*	3.060	1	93	0.084
R/FA	0.995	0.488	1	93	0.487	TR/RP	0.999	0.122	1	93	0.728
A1/A0	0.982	1.720	1	93	0.193	A/NEM	0.894***	10.992	1	93	0.001
P1/P0	0.992	0.705	1	93	0.403	LOSR	0.967*	3.198	1	93	0.077
FA/TA	0.790***	24.717	1	93	0.000	EXPR	0.975	2.417	1	93	0.123
CA/TA	0.689***	41.933	1	93	0.000	ROA	0.947**	5.256	1	93	0.024
E/FA	0.966*	3,246	1	93	0.075	ROE	0.962*	3.649	1	93	0.059
EPS	0.776***	26.844	1	93	0.000	GRAH.	0.853***	15.988	1	93	0.000

Note: *** Significance at 1%; ** Significance at 5%; * Significance at 10%.

Table 3. Correlation pooled within group matrices

Variables Variables	L/A	L/E	OCF/L	OPM	EBT/A	EBT/E	R/A	R/FA	A_1/A_0	P_1/P_0	FA/TA	CA/TA	E/FA	EPS	NA/OS	NIC/OS	CR/OS	SR/TR	SOL	RET.	TR/C	TR/RP	A/NEM	LOSR	EXPR	ROA	ROE	GRAH
L/A	1.00	0.92	–0.08	0.19	–0.07	0.13	0.21	0.11	0.14	–0.13	–0.01	–0.02	–0.08	0.14	–0.03	0.08	0.19	–0.86	0.76	0.67	0.23	0.26	–0.28	0.02	0.08	–0.10	0.10	–0.95
L/E	0.92	1.00	–0.08	0.06	–0.17	0.02	0.12	0.14	0.14	–0.15	–0.08	0.01	–0.06	0.08	–0.02	0.09	0.15	–0.67	0.75	0.58	0.24	0.29	–0.21	0.13	0.07	–0.15	0.02	–0.79
OCF/L	–0.08	–0.08	1.00	0.24	0.38	0.37	0.11	–0.03	0.61	0.09	0.03	–0.01	–0.03	0.44	0.29	0.34	0.13	–0.02	–0.01	–0.02	0.35	–0.02	0.06	–0.23	–0.31	0.34	0.33	0.06
OPM	0.19	0.06	0.24	1.00	0.74	0.80	–0.05	–0.15	0.26	0.20	0.11	–0.01	–0.13	0.73	0.06	0.05	0.14	–0.19	0.14	0.19	0.24	0.04	–0.28	–0.57	–0.12	0.60	0.67	–0.20
EBT/A	–0.07	–0.17	0.38	0.74	1.00	0.94	0.24	–0.09	0.40	0.33	0.11	–0.06	–0.10	0.86	0.04	0.05	0.00	–0.05	0.07	0.09	0.06	–0.19	–0.17	–0.51	–0.39	0.84	0.78	0.02
EBT/E	0.13	0.02	0.37	0.80	0.94	1.00	0.22	–0.06	0.42	0.25	0.07	–0.03	–0.10	0.87	0.03	0.09	0.03	–0.17	0.24	0.18	0.10	–0.14	–0.24	–0.41	–0.34	0.80	0.85	–0.15
R/A	0.21	0.12	0.11	–0.05	0.24	0.22	1.00	0.23	0.12	–0.05	0.04	–0.10	0.02	0.00	–0.43	0.00	–0.29	–0.39	0.57	0.45	–0.46	–0.60	–0.37	–0.08	–0.60	0.20	0.21	–0.29
R/FA	0.11	0.14	–0.03	–0.15	–0.09	–0.06	0.23	1.00	–0.04	–0.06	–0.61	–0.04	0.88	–0.09	–0.05	0.06	0.03	–0.13	0.21	0.06	–0.13	–0.17	0.15	0.03	–0.05	0.18	0.17	–0.12
A_1/A_0	0.14	0.14	0.61	0.26	0.40	0.42	0.12	–0.04	1.00	0.07	0.12	–0.12	–0.08	0.39	0.05	0.28	–0.01	–0.11	0.26	0.08	0.22	–0.12	–0.10	–0.12	–0.26	0.29	0.31	–0.11
P_1/P_0	–0.13	–0.15	0.09	0.20	0.33	0.25	–0.05	–0.06	0.07	1.00	–0.02	0.08	0.06	0.30	0.19	–0.03	0.10	0.03	–0.12	–0.19	0.03	–0.05	0.04	–0.49	–0.14	0.23	0.15	0.09
FA/TA	–0.01	–0.08	0.03	0.11	0.11	0.07	0.04	–0.61	0.12	–0.02	1.00	–0.69	–0.67	0.01	–0.20	–0.12	–0.37	–0.02	0.02	0.04	–0.01	–0.05	–0.04	0.04	–0.01	0.03	0.03	–0.01
CA/TA	–0.02	0.01	–0.01	–0.01	–0.06	–0.03	–0.10	–0.04	–0.12	0.08	–0.69	1.00	0.11	0.06	0.28	0.07	0.48	0.01	–0.13	0.01	0.16	0.19	–0.19	–0.18	0.00	–0.22	–0.20	0.02
E/FA	–0.08	–0.06	–0.03	–0.13	–0.10	–0.10	0.02	0.88	–0.08	0.06	–0.67	0.11	1.00	–0.11	0.04	0.10	0.18	0.04	–0.04	–0.12	–0.09	–0.13	0.18	–0.09	0.09	0.08	0.05	0.06
EPS	0.14	0.08	0.44	0.73	0.86	0.87	0.00	–0.09	0.39	0.30	0.01	0.06	–0.11	1.00	0.40	0.12	0.31	–0.18	0.05	0.16	0.44	0.21	–0.04	–0.47	–0.25	0.75	0.76	–0.15
NA/OS	–0.03	–0.02	0.29	0.06	0.04	0.03	–0.43	–0.05	0.05	0.19	–0.20	0.28	0.04	0.40	1.00	0.18	0.74	–0.01	–0.41	–0.11	0.75	0.67	0.43	–0.18	0.14	0.00	–0.01	0.01
NIC/OS	0.08	0.09	0.34	0.05	0.05	0.09	0.00	0.06	0.28	–0.03	–0.12	0.07	0.10	0.12	0.18	1.00	0.18	–0.04	0.14	0.07	0.10	–0.04	0.05	0.03	0.00	0.00	0.07	–0.05
CR/OS	0.19	0.15	0.13	0.14	0.00	0.03	–0.29	0.03	–0.01	0.10	–0.37	0.48	0.18	0.31	0.74	0.18	1.00	–0.22	–0.17	0.16	0.57	0.53	0.05	–0.22	0.17	–0.11	–0.06	–0.22
SR/TR	–0.86	–0.67	–0.02	–0.19	–0.05	–0.17	–0.39	–0.13	–0.11	0.03	–0.02	0.01	0.04	–0.18	–0.01	–0.04	–0.22	1.00	–0.60	–0.68	–0.24	–0.23	0.24	0.19	0.10	0.01	–0.13	0.95
SOL	0.76	0.75	–0.01	0.14	0.07	0.24	0.57	0.21	0.26	–0.12	0.02	–0.13	–0.04	0.05	–0.41	0.14	–0.17	–0.60	1.00	0.66	–0.25	–0.33	–0.49	0.14	–0.14	0.07	0.23	–0.68
RET.	0.67	0.58	–0.02	0.19	0.09	0.18	0.45	0.06	0.08	–0.19	0.04	0.01	–0.12	0.16	–0.11	0.07	0.16	–0.68	0.66	1.00	0.06	0.03	–0.51	–0.03	0.01	0.03	0.16	–0.66
TR/C	0.23	0.24	0.35	0.24	0.06	0.10	–0.46	–0.13	0.22	0.03	–0.01	0.16	–0.09	0.44	0.75	0.10	0.57	–0.24	–0.25	0.06	1.00	0.84	0.24	–0.32	0.18	0.04	0.08	–0.22
TR/RP	0.26	0.29	–0.02	0.04	–0.19	–0.14	–0.60	–0.17	–0.12	–0.05	–0.05	0.19	–0.13	0.21	0.67	–0.04	0.53	–0.23	–0.33	0.03	0.84	1.00	0.33	–0.11	0.34	–0.17	–0.12	–0.23
A/NEM	–0.28	–0.21	0.06	–0.28	–0.17	–0.24	–0.37	0.15	–0.10	0.04	–0.04	–0.19	0.18	–0.04	0.43	0.05	0.05	0.24	–0.49	–0.51	0.24	0.33	1.00	0.13	0.16	–0.01	–0.13	0.27
LOSR	0.02	0.13	–0.23	–0.57	–0.51	–0.41	–0.08	0.03	–0.12	–0.49	0.04	–0.18	–0.09	–0.47	–0.18	0.03	–0.22	0.19	0.14	–0.03	–0.32	–0.11	0.13	1.00	0.27	–0.35	–0.30	0.06
EXPR	0.08	0.07	–0.31	–0.12	–0.39	–0.34	–0.60	–0.05	–0.26	–0.14	–0.01	0.00	0.09	–0.25	0.14	0.00	0.17	0.10	–0.14	0.01	0.18	0.34	0.16	0.27	1.00	–0.31	–0.28	–0.01
ROA	–0.10	–0.15	0.34	0.60	0.84	0.80	0.20	0.18	0.29	0.23	0.03	–0.22	0.08	0.75	0.00	0.00	–0.11	0.01	0.07	0.03	0.04	–0.17	–0.01	–0.35	–0.31	1.00	0.93	0.07
ROE	0.10	0.02	0.33	0.67	0.78	0.85	0.21	0.17	0.31	0.15	0.03	–0.20	0.05	0.76	–0.01	0.07	–0.06	–0.13	0.23	0.16	0.08	–0.12	–0.13	–0.30	–0.28	0.93	1.00	–0.11
GRAH	–0.95	–0.79	0.06	–0.20	0.02	–0.15	–0.29	–0.12	–0.11	0.09	–0.01	0.02	0.06	–0.15	0.01	–0.05	–0.22	0.95	–0.68	–0.66	–0.22	–0.23	0.27	0.06	–0.01	0.07	–0.11	1.00

Table 4 shows the log determinate values, it was calculated for the successful and total but not for distress because it had only 19 observations, which also lead to undetermined equality of population covariance matrices values for distress, successful and total. Unfortunately, that comes at a disadvantage to the result claims. Moreover, the values of the successful and total were almost the same. Therefore, there is not clear evidence that the results will not be affected.

Table 4. Equality of covariance matrices

Log determinate		
Status	**Rank**	**Log determinate**
Distress	.[a]	N / A
Successful	28	–132.416
Total	28	–122.773

Table 5 is divided into multiple parts. To begin with, in Part A, an Eigenvalue of 3.804 was calculated, which is an indication that the function explains only 3.804 of the variances of the company's performance (dependent variable). It is also a good indication of the fitness of the model (high Eigenvalue is associated with better fitness). Furthermore, it was also tabulated that the canonical correlation has a value of 0.89, which is a great value since it has a high effect size ($0.89^{\wedge 2} = 0.796$). In Part B, it is proved that the prediction model is statistically significant since the *P*-value is < 1%. In Part C, the predictors are ranked from the best to the according to the standardized canonical discriminant function coefficients (TR/RP, SR/TR, L/E, R/A, CR/OS, P1/P0, OPM, EBT/A, R/FA, NIC/OS, ROA, OCF/L, EXPR, FA/TA, LOSR, TR/C, SOL, A/NEM, A1/A0, RET., ROE, E/FA, CA/TA, EPS, EBT/E, GRAH., L/A, and NA/OS). However, the claims shown in part D are not consistent with Part C. In Part D, the values of the variables (L/E, SOL, and L/A) in the structural matrix are more than 0.3, which is against the result claims since it is required that all the variables have a factor of 0.3. Moreover, the unstandardized coefficients of the discriminant equation are tabulated in Part E:

Performance score = +5.246 +1.077*** x SR/TR +1.677*** x L/E +5.399** x R/A +6.316*** x CR/OS +9.754* x OPM +13.254*** x EBT/A +9.581** x ROA +2.430*** x OCF/L+2.468*** x FA/TA +1.490* x LOSR +0.135* x TR/C +0.057*** x SOL –0.027*** x A/NEM –0.624*** x RET. –2.303* x ROE –0.027* x E/FA –4.032*** x CA/TA –3.939*** x EPS –7.084*** x EBT/E –1.358*** x GRAH. –12.331*** x L/A –4.302*** x NA/OS (*** means significance at 1%, ** means significance at 5%, * means significance at 10%). Significant variables are ranked from best predictor to the worst one.

To further elaborate, 22 significant indicators in predicting the financial failure, which are shown in the formula above, are the following: profitability (operating profit margin, earnings before income tax/total assets, earnings before income tax/shareholder equity); operational capabilities (sales revenue/total assets, sales revenue/fixed assets); solvency (total liabilities/total assets, total liabilities/total shareholders' equity, net operating cash flow/total liabilities); structural soundness (fixed assets/total assets, current assets/total assets); and capital expansion capacity (net assets (total assets-total liabilities)/number of ordinary shares at the end of year, capital reserves/number of ordinary shares at the end of year). While the significant CARMEL parameters were: reinsurance and actuarial issues (RET. ratio, net technical reserves/net claims paid); management soundness (asset per employee); earnings and profitability (loss ratio, ROA and ROE); capital adequacy (surplus/technical reserves ratio and solvency ratio (net written premium/total equity); capital expansion capacity (EPS); and liquidity (Graham rating).

Finally, in part F it is shown that the mean for distress performance score is –0.965, and the mean for successful performance score is 3.859.

Table 6 includes 76 weights of successful performance and 19 weights of distress performance with no missing values of distress performance with no missing values. The sensitivity of the original cells was calculated to be 97.4% and that leaves 2.6% as false-negative results. 97.4% of the prediction attempts of the successful performance companies were successful, while 2.6% were distress. On the other hand, the specificity was calculated to be 94.7%, leaving 5.3% of false-positive results. In other words, 94.7% of the prediction attempts of the distress performance companies are distress, while 5.3% are successful. Therefore, this model has high sensitivity and specificity. Furthermore, the cross-validated cells result shows a calculated sensitivity of 92.1%, which means 7.9% are false

Table 5. Summary of canonical discriminant functions

Part A: Eigenvalue

Function	Eigenvalue	# of variance	Cumulative%	Canonical correlation
1	3.804	100	100	0.890

Part B: Wilks' Lambda

Test of function	Wilks' Lambda	Chi-square	df	*P*-value
1	0.208***	123.985	28	0.000

Part C: Standardized canonical discriminant function coefficients

	L/A	L/E	OCF/L	OPM	EBT/A	EBT/E	R/A	R/FA	A1/A0	P1/P0	FA/TA	CA/TA	E/FA	EPS	NA/OS	NIC/OS	CR/OS	SR/TR	SOL	RET.	TR/C	TR/RP	A/NEM	LOSR	EXPR	ROA	ROE	GRAH.
Function 1	–1.216	0.997	0.251	0.448	0.395	–0.650	0.899	0.333	–0.079	0.473	0.157	–0.276	–0.241	–0.309	–1.415	0.262	0.627	1.205	0.031	–0.092	0.091	1.255	–0.008	0.156	0.226	0.252	–0.194	–1.146

Part D: Structural matrix

	NA/OS	L/E	SOL	CA/TA	L/A	EPS	FA/TA	CR/OS	EBT/A	EBT/E	RET.	GRAH.	A/NEM	OCF/L	SR/TR	R/A	ROA	ROE	OPM	E/FA	LOSR	TR/C	EXPR	A1/A0	P1/P0	R/FA	NIC/OS	TR/RP
Function 1	–0.477	0.443	0.362	–0.344	0.315	–0.275	0.264	–0.251	–0.236	–0.235	0.232	–0.213	–0.176	–0.156	–0.152	0.126	–0.122	–0.102	–0.100	–0.096	0.095	–0.093	0.083	–0.070	–0.045	0.037	0.019	0.019

Part E: Canonical discriminant function coefficients

	L/A	L/E	OCF/L	OPM	EBT/A	EBT/E	R/A	R/FA	A1/A0	P1/P0	FA/TA	CA/TA	E/FA	EPS	NA/OS	NIC/OS	CR/OS	SR/TR	SOL	RET.	TR/C	TR/RP	A/NEM	LOSR	EXPR	ROA	ROE	GRAH.	Const
Function 1	–12.331	1.677	2.430	9.754	13.254	–7.084	5.399	0.021	–0.999	0.210	2.468	–4.032	–0.027	–3.939	–4.302	1.073	6.316	1.077	0.057	–0.624	0.135	4.032	–0.027	1.490	0.588	9.851	–2.303	–1.358	5.246

Part F: Functions of group centroids

Status	Distress	Successful
Function 1	3.859	– 0.965

Note: *** Significance at 1%; ** Significance at 5%; * Significance at 10%.

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Table 6. Classification statistics

Classification results					
Cases	Count or Percentage	Status	Predicated group membership		Total
			Distress	Successful	
Original	Count	Distress	18	1	19
		Successful	2	74	76
	%	Distress	94.7	5.3	100
		Successful	2.6	97.4	100
Cross-validated	Count	Distress	17	2	19
		Successful	6	70	76
	%	Distress	89.5	10.5	100
		Successful	7.9	92.1	100

positive (92.1% of the prediction attempts of the successful performance companies are successful and 7.9% are distress). In addition, it also shows specificity of 89.5%, which means that 10.5% are false-positive (89.5% of the prediction attempts of the distress performance companies are distress and 10.5% are successful). This is also an indication that the model has high sensitivity and specificity. Finally, the original group cases were 96.8% correctly classified, and 91.6% were correctly classified in the cross-validated group cases.

Table 7 reveals that 3 observations have type I and II errors (difference between real performance and predicted performance). Specifically, 2 observations had type I error where the firms' performance turned out to be successful although their prediction was distress (Arab Jordanian Group in 2018, and the Mediterranean & Gulf in 2014). Moreover, 1 observation had a type II error where the firms' performance turned out to be distress although their prediction was successful (the Arab Assurers in 2015). The rest of the 95 observations were consistent and error-free, which means the model matches between real performance and predicted performance (successful performance is predicted when the real performance is successful, and distress performance is predicted when the real performance is distress). Finally, the probability of determination for good is 95% for the Arab Assurers in 2015, and for distress is 57% for Arab Jordanian Group in 2018, and 99.6% for the Mediterranean & Gulf in 2014.

Table 7. Comparison of real performance vs. predicted performance

Firm	Year	Perf.	Pred. P.	Type I error	Type II error	Firm	Year	Perf.	Pred. P.	Type I error	Type II error
Arabia	2014	Good	Good	0%	100%	Arab Union International	2014	Poor	Poor	100%	0%
Arabia	2015	Good	Good	0%	100%	Arab Union International	2015	Poor	Poor	100%	0%
Arabia	2016	Good	Good	0%	100%	Arab Union International	2016	Poor	Poor	100%	0%
Arabia	2017	Good	Good	0%	100%	Arab Union International	2017	Good	Good	0%	100%
Arabia	2018	Good	Good	0%	100%	Arab Union International	2018	Good	Good	0%	100%
Al-Nisr Al-Arabi	2014	Good	Good	0%	100%	National	2014	Good	Good	0%	100%
Al-Nisr Al-Arabi	2015	Good	Good	0%	100%	National	2015	Good	Good	0%	100%
Al-Nisr Al-Arabi	2016	Good	Good	0%	100%	National	2016	Good	Good	0%	100%
Al-Nisr Al-Arabi	2017	Good	Good	0%	100%	National	2017	Good	Good	0%	100%
Al-Nisr Al-Arabi	2018	Good	Good	0%	100%	National	2018	Good	Good	0%	100%
Middle East	2014	Good	Good	0%	100%	Jordan International	2014	Good	Good	0%	100%
Middle East	2015	Good	Good	0%	100%	Jordan International	2015	Good	Good	0%	100%
Middle East	2016	Good	Good	0%	100%	Jordan International	2016	Good	Good	0%	100%
Middle East	2017	Good	Good	0%	100%	Jordan International	2017	Good	Good	0%	100%
Middle East	2018	Good	Good	0%	100%	Jordan International	2018	Good	Good	0%	100%
Jordan	2014	Good	Good	0%	100%	Euro Arab Group	2014	Good	Good	0%	100%
Jordan	2015	Good	Good	0%	100%	Euro Arab Group	2015	Good	Good	0%	100%

Table 7 (cont.). Comparison of real performance vs. predicted performance

Firm	Year	Perf.	Pred. P.	Type I error	Type II error	Firm	Year	Perf.	Pred. P.	Type I error	Type II error
Jordan	2016	Good	Good	0%	100%	Euro Arab Group	2016	Good	Good	0%	100%
Jordan	2017	Good	Good	0%	100%	Euro Arab Group	2017	Good	Good	0%	100%
Jordan	2018	Good	Good	0%	100%	Euro Arab Group	2018	Good	Good	0%	100%
Delta	2014	Good	Good	0%	100%	The Islamic	2014	Good	Good	0%	100%
Delta	2015	Good	Good	0%	100%	The Islamic	2015	Good	Good	0%	100%
Delta	2016	Good	Good	0%	100%	The Islamic	2016	Good	Good	0%	100%
Delta	2017	Good	Good	0%	100%	The Islamic	2017	Good	Good	0%	100%
Delta	2018	Good	Good	0%	100%	The Islamic	2018	Good	Good	0%	100%
Jerusalem	2014	Good	Good	0%	100%	The Arab Assurers	2014	Poor	Poor	100%	0%
Jerusalem	2015	Good	Good	0%	100%	The Arab Assurers	2015	Poor	Good	5%	95%
Jerusalem	2016	Good	Good	0%	100%	The Arab Assurers	2016	Poor	Poor	99%	1%
Jerusalem	2017	Good	Good	0%	100%	The Arab Assurers	2017	Good	Good	1%	99%
Jerusalem	2018	Good	Good	0%	100%	The Arab Assurers	2018	Good	Good	6%	94%
The United	2014	Good	Good	0%	100%	Arab Jordanian Group	2014	Poor	Poor	100%	0%
The United	2015	Good	Good	0%	100%	Arab Jordanian Group	2015	Poor	Poor	100%	0%
The United	2016	Good	Good	0%	100%	Arab Jordanian Group	2016	Poor	Poor	100%	0%
The United	2017	Good	Good	0%	100%	Arab Jordanian Group	2017	Poor	Poor	100%	0%
The United	2018	Good	Good	0%	100%	Arab Jordanian Group	2018	Good	Poor	57%	43%
Jordan French	2014	Poor	Poor	100%	0%	The Mediterranean & Gulf	2014	Good	Poor	100%	0%
Jordan French	2015	Good	Good	0%	100%	The Mediterranean & Gulf	2015	Poor	Poor	100%	0%
Jordan French	2016	Good	Good	0%	100%	The Mediterranean & Gulf	2016	Poor	Poor	100%	0%
Jordan French	2017	Good	Good	0%	100%	The Mediterranean & Gulf	2017	Poor	Poor	100%	0%
Jordan French	2018	Good	Good	0%	100%	The Mediterranean & Gulf	2018	Poor	Poor	100%	0%
Al-Manara	2014	Poor	Poor	100%	0%	First	2014	Good	Good	0%	100%
Al-Manara	2015	Poor	Poor	100%	0%	First	2015	Good	Good	0%	100%
Al-Manara	2016	Good	Good	2%	98%	First	2016	Good	Good	0%	100%
Al-Manara	2017	Poor	Poor	100%	0%	First	2017	Good	Good	0%	100%
Al-Manara	2018	Poor	Poor	100%	0%	First	2018	Good	Good	0%	100%

Note: Perf. = Performance, Pred. P. = Predicted performance.

5. DISCUSSION

The results presented in this study are consistent and contradicting to a certain degree with Altman et al. (1997), Kumar and Ghimire (2013), Dairui and Jia (2009), Zmijewski (1984), Das et al. (2003), Manzaneque et al. (2016), Amendola et al. (2015), Smajla (2014), Geng et al. (2015), and Simpson and Damaoh (2008). The findings are consistent in predicting the financial distress of the firms and the significant variables that affect the financial soundness. However, they are contradicting in determining the significant coefficients and their sign. The strong point of this paper is the usage of more variables and parameters to check the soundness and failure of the insurance companies that is in comparison to the other articles that used CARMEL model variables and parameters like Simpson and Damaoh (2008), Smajla (2014), and Kumar and Ghimire (2013). Moreover, the weakness of this paper is concentration on the micro approach variables, unlike Tinoco and Wilson (2013), Christidis and Gregory (2010), Sevim et al. (2014), and Ntoiti (2013) that used micro and macro variables in predicting the financial failure of the firms. Another weakness to point out is the usage of traditional statistical techniques, which was avoided by Bose and Pal (2006), Jardin and Severin (2012), Gestel et al. (2006), Lin et al. (2014), Carlos (1996), Chen and Du (2009), Gepp and Kumar (2015), Bae (2012), Wilson and Sharda (1994), Jo et al. (1997), and Li and Sun (2009). Instead, artificial intelligence and neural networks approaches were used in predicting financial distress around the globe.

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CONCLUSION

The financial failure of insurance firms in any exchange of the sector services is tremendously important due to the vital role it plays in stabilizing the country's financial environment accompanied with the other financial industries. Herein, the novelty in the development of the financial failure model is the key factor that differentiates this paper. The model consisted of 28 indicators selected from 11 parameters; it was derived from the other financial failure models regardless of the sector services that were mentioned in the literature review.

The results showed that the financial failure model is a good fit and statistically significant. The model even did a better job explaining the variances of the company's performance. There were a few contradictions between some results, which did not support the fitness of the model. Nevertheless, the model had high sensitivity and specificity in the original and cross-validated group cases. Moreover, the minimum deviation between the real and predicted performance is an indication of the insurance industry stability, 22 indicators out of 28 were found to be significant.

In conclusion, this paper summarizes a couple of important outcomes. To begin with, few deviations between the real and predicted performance are an indication that none of the insurance firms are threatened by failure or distress. This statement also supports the fact that the financial failure model is sustainable in predicting the financial failure of the insurance firms in ASE. It also reinforces the stability of ASE exchange and the entire financial environment in Jordan. Finally, it is recommended for future studies to assess the model by adding macro approach indicators and using artificial intelligence and neural networks as an analysis technique.

AUTHOR CONTRIBUTIONS

Conceptualization: Hussein Mohammad Salameh.
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Investigation: Hussein Mohammad Salameh.
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Validation: Hussein Mohammad Salameh.
Visualization: Hussein Mohammad Salameh.
Writing – original draft: Hussein Mohammad Salameh.

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