Asian Economic and Financial Review, 2016, 6(9): 522-533

Asian Economic and Financial Review
ISSN(e): 2222-6737/ISSN(p): 2305-2147

URL: www.aessweb.com

BANK FAILURE PREDICTION MODELS FOR THE DEVELOPING AND DEVELOPED COUNTRIES: IDENTIFYING THE ECONOMIC VALUE ADDED FOR PREDICTING FAILURE

Yi-Shu Wang[1] --- **Xue Jiang**[2] --- **Zhen-Jia-Liu**[3†]
[1,2,3]*School of Business, Changzhou University, Changzhou City, Jiangsu Providence, China*

ABSTRACT

This study used data from 2003-2013, and used a logistic model to analyze the factors that influence financial early warning systems in developing and developed countries. We employed a bank capital adequacy ratio less than 8%, Tier I capital ratio less than 4%, and nonperforming loan ratio more than one third to measure bank failure and identify the financial ratio that most accurately predicts bank failure. The results indicate that the economic value added index is more effective than other indexes in predicting bank failure in NAFTA, ASEAN, EU, NIC, and G20 nations.

Keywords: Bank failure prediction, Business, Economic value added, Developing countries, Developed countries, Financial early warning.

Received: 10 December 2015/ **Revised:** 1 June 2016/ **Accepted:** 3 June 2016/ **Published:** 6 June 2016

Contribution/ Originality

The paper contributes the first logical analysis economic value added that influence financial early warning systems in developing and developed countries.

1. INTRODUCTION

Research on corporate failure prediction is expanding worldwide. From a practical perspective, corporate failure prediction influences the decisions of stakeholders (e.g., stockholders, creditors, managers, auditors, and employees). From an academic perspective, several studies have identified various determinants of corporate failure and have developed optimal models for predicting corporate failure. Banks differ from other industries because they receive deposits and provide loans for profit. Thus, the collapse of banks, often caused by mismanagement or the economic environment, negatively affects depositor rights and other industries, can induce international financial distress and destabilize economic development. Consequently, evaluating bank operations and establishing an early warning system are a top priority for global financial authority (Huang *et al.*, 2012).

Early warning systems first appeared in the banking industry in 1970s. The effectiveness of financial ratios, such as current (Jayadev, 2006) EBIT-to-assets (Jayadev, 2006) equity-to-debt (Jayadev, 2006; Distinguin *et al.*, 2011) equity-to-assets (Shkurti and Duraj, 2010; Maghyereh and Awartani, 2014) net income–to-assets (Li *et al.*, 2011) expenses-to-assets (Li *et al.*, 2011) working capital-to-assets (Ecer, 2013) ; and profit before taxes-to-equity ratios

† Corresponding author
DOI: 10.18488/journal.aefr/2016.6.9/102.9.522.533
ISSN(e): 2222-6737/ISSN(p): 2305-2147

(Shkurti and Duraj, 2010) for predicting and explaining bank failure has been investigated. However, these ratios follow generally accepted accounting principles, requiring conservatism in preparing financial statements that only reflect historic costs. Thus, traditional financial ratios do not reflect the actual bank value. The economic value added (EVA) index is calculated "after subtracting the cost of capital from the operating profits" (Stewart, 1991) and involves using adjustment items to reflect the true value of a firm. Furthermore, Teker *et al.* (2011) showed that EVA is useful in determining the true value of a bank. Conversely, numerous studies have adopted EVA to detect corporate failure (Timo and Virtanen, 2001; Pasaribu, 2008; Klecka and Scholleova, 2010; Anvarkhatibi *et al.*, 2013). However, these studies have adopted only the unadjusted EVA to predict corporate failure, which does not provide a comprehensive overview of a company's economic performance. Therefore, in this study, we employ the unadjusted EVA and adjusted EVA to predict bank failures and identify which index is superior in comparison to various financial ratios (accuracy). All the countries have different types of governments and cultures, laws, economic development. The operational system and environment of banks in nations are also substantially different and therefore cannot be considered equivalent. We developed an optimal model and compared the early warning indicators of bank failures in North America Free Trade

2. LITERATURE REVIEW

Classical models for predicting bank bankruptcy have been extensively researched: multivariate adaptive regression spines (Martin *et al.*, 2011) logistic regression (Al-Saleh and Al-Kandari, 2012; Fungacova and Weill, 2013; Valahzaghard and Bahrami, 2013; Zaghdoudi, 2013; Canicio and Blessing, 2014) back propagation neural network (Pradhan *et al.*, 2013) hazard model (Kiefer, 2014; Maghyereh and Awartani, 2014) Principal Component Analysis (Adeyeye *et al.*, 2012) multiple discriminant analysis (Ioannidis *et al.*, 2010) fuzzy C-means clustering (Martin *et al.*, 2011) group method of data handling (Ravisankar and Rav, 2010) fuzzy adaptive resonance theory map (Ravisankar and Rav, 2010) artificial neural network (Ioannidis *et al.*, 2010) classification and regression trees (Ioannidis *et al.*, 2010) genetic algorithm (Martin *et al.*, 2011) partial least square discriminant analysis (Serrano-Cinca, 2013) k-Nearest neighbours (Ioannidis *et al.*, 2010) counter propagation neural network (Ravisankar and Rav, 2010) ordered logistic regression (Ioannidis *et al.*, 2010) neuro fuzzy (Yildiz and Akkoc, 2010) dynamic slacks based model (Wanke *et al.*, 2015) neural networks (Lopez and Pastor, 2015) geometric mean based boosting algorithm (Kim *et al.*, 2015) discriminant analysis (Cox and Wang, 2014). The Federal Deposit Insurance Corporation constructed financial ratios such as capital adequacy, asset quality, management quality, earnings strength, and liquidity (collectively referred to as CAMEL) to monitor banks and predict bank failure (Trussel and Johnson, 2012; Valahzaghard and Bahrami, 2013; Canicio and Blessing, 2014). The application of these traditional accounting tools for measuring corporate failures has been questioned, for various reasons. The tools are suitable for analyzing historical data, but not for future decision-making (Rappaport, 1995). Pasaribu (2008) showed that public companies that do not create EVA are at a high risk of distress. Timo and Virtanen (2001) indicated that EVA can warn about an approaching bankruptcy because economic bankruptcy occurs when the value of a firm becomes negative (i.e., when a firm is unable to earn profit in excess of the required return). Anvarkhatibi *et al.* (2013) asserted that the probability of bankruptcy decreases with increasing economic value. This is because higher company economic value results in positive EVA as a result of shareholder return and available opportunities for profitable investments and paying loan interest. Thus, Anvarkhatibi *et al.* (2013) indicated that EVA is a superior index for predicting bankruptcy and providing useful information for shareholders. Hence, the EVA measure could be dangerously susceptible as a distress warning device. Accordingly, we proposed Hypothesis 1 as follows:

H1**:** The corporate failure prediction accuracy of economic value added is higher than that of other financial ratios.

3. METHODOLOGY

Financial ratios were used to predict distress in the banking industry, incorporating data from 2003-2013 from the COMPUSTAT and AREMOS database.

The study comprised 775 banks[1] .

A logistic model was adopted to analyze the data. The variables and research model are presented in the following sections.

3.1. Dependent variables: Bank failures

Lin (2010) showed that a bank capital adequacy ratio less than 8%, Tier I capital ratio less than 4%, and nonperforming loan ratio more than one third is determined for the distressed bank. In addition, the capital adequacy ratio is calculated by dividing total capital by average assets; the elements of total capital are used as core capital combined with additional capital (i.e., Tier I capital plus Tier II capital).[2] Tier I capital (i.e., common stock and qualifying preferred stock) divided by risk-adjusted assets yields the Tier I capital ratio. The nonperforming loan ratio is measured as the nonperforming loans (i.e., past due loans, the principal and/or interest of which is unpaid for 30 days or more after the due date) divided by all loans (including interbank loans). This formula is based on the 1988 Basel Capital Accord standards for the definition of equity. Overall, the value of the dummy variable was 1 (distressed group), and the value of the contrary variable was 0.

3.2. Independent Variables: Financial Ratios

Jayadev (2006) stated that successful banks have high current ratios, earnings before interest, and taxes-to-assets ratios. Furthermore, Shkurti and Duraj (2010) stated that successful banks have high profit before taxes-to-equity ratios, and Li *et al.* (2011) showed that successful banks have low expenses-to-assets ratios. EVA also can be used to detect corporate failure (Timo and Virtanen, 2001; Pasaribu, 2008; Klecka and Scholleova, 2010; Anvarkhatibi *et al.*, 2013).

3.3. Control Variables: Bank Factors

Bank factors reflect bank operating environments, thus explaining how they affect bank failure. Shkurti and Duraj (2010) showed that successful banks have low interest expenses-to-deposits ratios. Moreover, Öğüt *et al.* (2012) asserted that successful banks have high interest revenue minus interest expenses-to-number of bank branches ratios. Canicio and Blessing (2014) showed that successful banks have high deposits-to-total assets ratios and that unsuccessful banks have high loans-to-assets ratios.

---

[1]NAFTA (*North America Free Trade Area*): America, Canada, Mexico. ASEAN *(Association of Southeast Asian Nations)*: Indonesia, Thailand, Malaysia, Philippines, Vietnam, Singapore. EU*(European Union)*: Denmark, Belgium, Lithuania, Hungarian, Spain, Greece, Poland, France, Finland, Bulgaria, Malta, Czech, Netherlands, Slovak, Slovenia, Cyprus, Austria, Ireland, Sweden, Italy, Portugal, Germany, Romania, United Kingdom, Luxembourg, Latvia, Estonia).NIC *(Newly industrialized country)*:South- Africa, Brazil, China, India, Turkey. G**20**: Argentina, Austrlia, Japan, Korea, Russia, Saudi Arabia

[2]Tier II capital includes preferred stock, subordinated debt, and loan loss reserves.

3.4. Empirical model[3]

The study used the logistic method. The proxy variables are as follows: $CR_{j,t}$ represents current assets compared with current liabilities. $EBITTA_{j,t}$ represents earnings before interest and taxes compared with assets. $EBTE_{j,t}$ represents earnings before taxes compared with equity. $ETA_{j,t}$ represents expenses compared with assets. $IED_{j,t}$ represents interest expenses compared with deposits. $NETI_{j,t}$ represents interest revenue minus interest expenses compared with number of bank branches. $DTA_{j,t}$ represents deposits compared with total assets. $LTA_{j,t}$ represents loans compared with assets. $UAEVA_j$ is the unadjusted EVA[4] compared with the outstanding shares; $AEVA_j$ is the adjusted EVA[5] (join accounting adjusted items) compared with the outstanding shares ; $EDAEVA_j$ represents the adjusted EVA[6] (join accounting adjusted items and economic depreciation adjusted items) compared with the outstanding shares.

3.4. Performance Measures

Fungacova and Weill (2013) proposed an early warning model for the quarters (1Q, 2Q, 3Q, and 4Q) prior to the event of bank distress that used financial ratios. Banks with cut-off points above 0.5 were classified as bankrupt banks and banks under 0.5 were classified as successful banks. The overall predictive power is the ratio between the sum of all safe and failed banks accurately identified and the total number of banks. A more detailed performance analysis was conducted regarding the proposed logistic methods, and their accuracy was obtained using Equation 1.

Table-1. Confusion matrix

		Predicted class	
		Bankrupt	Non-bankrupt
Actual Class	Bankrupt	TP	FN
	Non-bankrupt	FP	TN

$$\text{Accuracy (\%)} = \frac{TP + TN}{TP + FP + FN + TN} \times 100 \qquad (1)$$

Source: Authors investigation

[3]To shorten the tables, we omitted the solution because this paper has 420 empirical models. One financial ratio is the independent variable (ranging from failure prior to Q-1 to Q-4), and one failure prediction models is the dependent variable; three control variables are used in each logistical model. The empirical results showed that the relationship between the financial ratios and failures prediction was supported by Jayadev (2006); Ecer (2013); Li, Sanning and Shaffer (2011); Shkurti and Duraj (2010).

[4]Huang and Liu (2010).

[5]Ibid.

[6]Ibid.

3.5. Robustness Test[7]

We also repeat the same analyses out-of-sample to tackle a possible sample specific issue and get more robust and general results

4. RESULTS

4.1. Descriptive Statistics

Table 2 shows that the mean of all financial ratios (including EVA). The current ratios all exceed 100%, with NAFTA at 172.52% (highest) and EU at 117.85% (lowest). Earnings before interest, taxes compared with assets, and earnings before taxes compared with equity had a positive value for all groups. Expenses compared with assets were less than 30%, indicating that operating policies were robust. Conversely, the mean of the interest revenue minus interest expenses compared with the number of bank branches exceeded 0[8], showing that public banks in these countries have a large capacity for measuring and managing risk.

Interest expenses compared with deposits ranged from 11.25% to 20.11%, deposits compared with total assets averaged approximately 50%, and loans compared with assets averaged approximately 45%. These results indicated that credit policies were robust and stable, and appropriate loan losses are a suitable measure for risk management. In addition, the mean of the EVA is positive[9], showing that the public banks in these countries have a considerable ability to be profitable or to manage funds efficiently.

4.2. Empirical Test

The comparisons of predicted and actual bankruptcy classifications are shown in Tables 3-6. As indicated in Table 3 (one quarter before a failure), NAFTA banks had the highest value (the accuracy of the logistic model was 39.57%) when unadjusted EVA was employed to predict bank failure (the proxy variable is the bank capital adequacy ratio below 8%) and the lowest value (the accuracy of the logistic model was 27.23%) when the expenses compared with assets were employed to predict bank failure (the proxy variable is bank Tier I capital ratio below 4%)；ASEAN banks had the highest value (the accuracy of the logistic model was 35.08%) when adjusted EVA (join accounting adjusted items) was employed to predict bank failure (the proxy variable is bank capital adequacy ratio below 8%), and the lowest value (the accuracy of the logistic model was 26.58%) when adjusted EVA (join accounting adjusted items) was employed to predict bank failure (the proxy variable is bank Tier I capital ratio below 4%)；EU banks had the highest value (the accuracy of the logistic model was 37.52%) when unadjusted EVA was employed to predict bank failure (the proxy variable is bank capital adequacy ratio below 8%) and the lowest value (the accuracy of the logistic model was 28.16%) when the earnings before interest and taxes compared with assets were employed to predict bank failure (the proxy variable is bank Tier I capital ratio below 4%)；NIC banks had the highest value (the accuracy of the logistic model was 39.98%) when adjusted EVA (join accounting adjusted items and economic deprecation adjusted items) was employed to predict bank failure (the proxy variable is bank capital adequacy ratio below 8%), and the lowest value (the accuracy of the logistic model was 27.61%) when adjusted EVA (join accounting adjusted items) was employed to predict bank failure (the proxy variable is bank Tier I capital ratio below 4%. G20 banks had the highest value (the accuracy of the logistic model was 36.94%) when adjusted EVA (join accounting adjusted items and economic deprecation adjusted items) was employed to predict bank failure (the proxy

[7]We adopted 1 (in sample) to 1 (out of sample) and showed that this method is consistent with “performance measures”.

[8]US ten thousand dollars

[9]US dollars

variable is bank capital adequacy ratio below 8%), and the lowest value (the accuracy of the logistic model was 19.25%) when unadjusted EVA was employed to predict bank failure (the proxy variable is bank capital adequacy ratio below 8%).

As indicated in Table 4 (two quarters before a failure), NAFTA banks had the highest value (the accuracy of the logistic model was 60.91%) when unadjusted EVA was employed to predict bank failure (the proxy variable is bank capital adequacy ratio below 8%), and the lowest value (the accuracy of the logistic model was 38.57%) when the expenses compared with assets were employed to predict bank failure (the proxy variable is bank Tier I capital ratio below 4%)；ASEAN banks had the highest value (the accuracy of the logistic model was 54.09%) when adjusted EVA (join accounting adjusted items) was employed to predict bank failure (the proxy variable is bank capital adequacy ratio below 8%), and the lowest value (the accuracy of the logistic model was 37.67%) when adjusted EVA (join accounting adjusted items) was employed to predict bank failure (the proxy variable is bank’s Tier I capital ratio below 4%)；EU banks had the highest value (the accuracy of the logistic model was 57.79%) when adjusted EVA (join accounting adjusted items and economic deprecation adjusted items) was employed to predict bank failure (the proxy variable is bank capital adequacy ratio below 8%), and the lowest value (the accuracy of the logistic model was 39.85%) when the earnings before interest and taxes compared with assets was employed to predict bank failure (the proxy variable is bank Tier I capital ratio below 4%)；NIC banks had the highest value (the accuracy of the logistic model was 57.91%) when adjusted EVA (join accounting adjusted items and economic deprecation adjusted items) was employed to predict bank failure (the proxy variable is bank capital adequacy ratio below 8%), and the lowest value (the accuracy of the logistic model was 38.34%) when the earnings before interest and taxes compared with assets was employed to predict bank failure (the proxy variable is bank Tier I capital ratio below 4%)；G20 banks had the highest value (the accuracy of the logistic model was 56.92%) when adjusted EVA (join accounting adjusted items and economic deprecation adjusted items) was employed to predict bank failure (the proxy variable is bank capital adequacy ratio below 8%), and the lowest value (the accuracy of the logistic model was 27.53%) when adjusted EVA was employed to predict bank failure (the proxy variable is bank Tier I capital ratio below 4%).

Compared to Table 3 and Table 4, as indicated in Table 5 (three quarters before a failure), NAFTA banks had the highest value (the accuracy of the logistic model was 58.72%) when unadjusted EVA was employed to predict bank failure (the proxy variable is bank capital adequacy ratio below 8%), and the lowest value (the accuracy of the logistic model was 36.24%) when adjusted EVA (join accounting adjusted items and economic deprecation adjusted items) was employed to predict bank failure (the proxy variable is bank non-performing loan ratio above one third or more)；ASEAN banks had the highest value (the accuracy of the logistic model was 52.12%) when adjusted EVA (join accounting adjusted items) was employed to predict bank failure (the proxy variable is bank capital adequacy ratio below 8%), and the lowest value (the accuracy of the logistic model was 36.18%) when unadjusted EVA was employed to predict bank failure (the proxy variable is bank’s non-performing loan ratio above one third or more)；EU banks had the highest value (the accuracy of the logistic model was 55.79%) when unadjusted EVA was employed to predict bank failure (the proxy variable is bank capital adequacy ratio below 8%), and the lowest value (the accuracy of the logistic model was 38.15%) when the current assets compared with current liabilities was employed to predict bank failure (the proxy variable is bank non-performing loan ratio above one third or more)；NIC banks had the highest value (the accuracy of the logistic model was 55.81%) when adjusted EVA (join accounting adjusted items and economic deprecation adjusted items) was employed to predict bank failure (the proxy variable is bank capital adequacy ratio below 8%), and the lowest value (the accuracy of the logistic model was 36.73%) when the current assets compared with current liabilities was employed to predict bank failure (the proxy variable is bank non-performing loan ratio above one third or more)；G20 banks had the highest value (the accuracy of the logistic model was 54.86%) when adjusted EVA (join accounting adjusted items and economic deprecation adjusted items) was employed to predict bank failure (the proxy variable is bank capital adequacy ratio below 8%), and the lowest value (the accuracy of the logistic model was 26.57%) when unadjusted EVA was employed to predict bank failure (the proxy variable is bank non-performing loan ratio above one third or more).

As indicated in Table 6 (four quarters before a failure), NAFTA banks had the highest value (the accuracy of the logistic model was 56.59%) when unadjusted EVA was employed to predict bank failure (the proxy variable is bank capital adequacy ratio below 8%), and the lowest value (the accuracy of the logistic model was 33.72%) when adjusted EVA (join accounting adjusted items and economic deprecation adjusted items) was employed to predict bank failure (the proxy variable is bank Tier I capital ratio below 4%)；ASEAN banks had the highest value (the accuracy of the logistic model was 50.36%) when adjusted EVA (join accounting adjusted items) was employed to predict bank failure (the proxy variable is bank capital adequacy ratio below 8%), and the lowest value (the accuracy of the logistic model was 33.14%) when unadjusted EVA was employed to predict bank failure (the proxy variable is bank Tier I capital ratio below 4%)；EU banks had the highest value (the accuracy of the logistic model was 53.74%) when unadjusted EVA was employed to predict bank failure (the proxy variable is bank capital adequacy ratio below 8%), and the lowest value (the accuracy of the logistic model was 35.01%) when the earnings before interest and taxes compared to assets was employed to predict bank failure (the proxy variable is bank Tier I capital ratio below 4%)；NIC banks had the highest value (the accuracy of the logistic model was 53.84%) when adjusted EVA (join accounting adjusted items and economic deprecation adjusted items) was employed to predict bank failure (the proxy variable is bank capital adequacy ratio below 8%), and the lowest value (the accuracy of the logistic model was 33.72%) when the earnings before interest and taxes compared to assets was employed to predict bank failure (the proxy variable is bank Tier I capital ratio below 4%)；G20 banks had the highest value (the accuracy of the logistic model was 52.94%) when adjusted EVA (join accounting adjusted items and economic deprecation adjusted items) was employed to predict bank failure (the proxy variable is bank capital adequacy ratio below 8%), and the lowest value (the accuracy of the logistic model was 24.48%) when adjusted EVA was employed to predict bank failure (the proxy variable is bank Tier I capital ratio below 4%).

Overall, compared with the other traditional financial ratios for all of the tested models, the empirical solutions show that EVA is superior in predicting bank failure. These findings support Hypothesis 1. The EVA likely reflects an enterprise's real economic value and can be employed to prevent the inefficient management of funds (i.e., income excess capital cost) to ensure that corporations do not waste resources. Thus, the accuracy of bank failure prediction has been increased. Moreover, the EVA could be the optimal index for predicting bank failure in these countries. In addition, a bank capital adequacy ratio less than 8%, Tier I capital ratio less than 4%, and nonperforming loan ratio more than one third can be the optimal index for predicting bank failure in these countries.

Results from variance inflation factors to explain variables for correlation; the result lies between 1.425 and 1.847 (Variance Inflation Factors<10).There is no correlation problem. We repeat the same analyses out-of-sample to tackle a possible sample specific issue and get general robust results[10],[11]. Overall, the analysis of the prediction model show that all measures of predictive ability, there are differences between eight models.

[10]In order to shorten the tables, we omit the solution

[11]We adopted 1 (in sample) to 1 (out of sample)

Table-2. Descriptive statistics (% ; Average Values)

	NAFTA	ASEAN	EU	NIC	G20
$CR_{j,t}$	172.52	148.55	117.85	123.68	124.17
$EBITTA_{j,t}$	89.21	77.42	93.48	112.08	113.52
$EBTE_{j,t}$	66.84	56.58	77.18	103.55	128.41
$ETA_{j,t}$	25.36	18.25	21.54	19.23	20.12
$IED_{j,t}$	17.35	19.21	11.25	19.63	20.11
$NETI_{j,t}$	102.58	99.31	85.26	91.15	103.25
$DTA_{j,t}$	52.38	50.05	52.38	55.12	54.31
$LTA_{j,t}$	44.21	43.34	47.31	43.12	47.31
$UAEVA_j$	0.88	1.73	0.99	1.12	0.79
$AEVA_j$	0.72	0.99	0.78	0.97	0.66
$EDAEVA_j$	0.62	0.98	0.64	0.86	0.56
Samples	205	162	1135	132	245

Source: Authors investigation

Table-3. Performance Measures (Accuracy %)-One quarter before a failure

	Bank failure: bank capital adequacy ratio less than 8%				
Panel A	NAFTA	ASEAN	EU	NIC	G20
$CR_{j,t}$	37.59	33.63	29.30	28.13	19.98
$EBITTA_{j,t}$	33.66	34.28	32.57	30.19	20.09
$EBTE_{j,t}$	28.31	28.93	31.69	29.92	25.66
$ETA_{j,t}$	29.78	30.54	34.45	33.38	29.26
$UAEVA_j$	39.57	27.62	37.52	28.72	19.25
$AEVA_j$	28.31	35.08	29.59	35.56	36.58
$EDAEVA_j$	27.73	34.58	30.11	39.98	36.94
Panel B	Bank failure: bank Tier I capital ratio less than 4%				
$CR_{j,t}$	NAFTA	ASEAN	EU	NIC	G20
$EBITTA_{j,t}$	35.94	32.96	28.16	27.68	19.49
$EBTE_{j,t}$	32.25	32.16	31.23	29.25	19.51
$ETA_{j,t}$	27.23	27.81	30.68	28.74	24.74
$UAEVA_j$	28.81	29.29	33.15	31.67	28.83
$AEVA_j$	37.96	26.58	35.88	27.61	19.75
$EDAEVA_j$	27.55	33.59	28.43	34.43	34.74
Panel C	Bank failure: bank nonperforming loan ratio more than one third				
$CR_{j,t}$	36.75	32.95	28.25	27.68	19.85
$EBITTA_{j,t}$	32.98	33.34	31.93	29.65	19.96
$EBTE_{j,t}$	27.85	28.44	31.92	29.39	25.65
$ETA_{j,t}$	29.46	29.95	33.74	32.84	28.76
$UAEVA_j$	38.65	27.18	36.68	28.24	19.68
$AEVA_j$	27.85	34.35	29.78	34.65	35.59
$EDAEVA_j$	27.29	33.86	29.58	36.75	36.13

Source: Authors investigation

Table-4. Performance Measures (Accuracy %)-Two quarters before a failure

	Bank failure: bank capital adequacy ratio less than 8%				
Panel A	NAFTA	ASEAN	EU	NIC	G20
$CR_{j,t}$	57.91	51.88	45.35	43.53	31.13
$EBITTA_{j,t}$	51.92	52.48	50.27	46.66	31.48
$EBTE_{j,t}$	43.81	44.73	48.93	46.23	39.76
$ETA_{j,t}$	46.35	47.12	53.13	50.97	45.24
$UAEVA_{j}$	60.91	42.74	57.79	44.48	30.85
$AEVA_{j}$	43.62	54.09	45.74	54.81	55.94
$EDAEVA_{j}$	42.91	53.32	46.53	57.91	56.92
Panel B	Bank failure: bank Tier I capital ratio less than 4%				
$CR_{j,t}$	NAFTA	ASEAN	EU	NIC	G20
$EBITTA_{j,t}$	50.64	45.46	39.85	38.34	27.76
$EBTE_{j,t}$	45.55	45.98	44.09	41.01	27.92
$ETA_{j,t}$	38.57	39.37	42.95	40.65	35.13
$UAEVA_{j}$	40.75	41.41	46.53	44.69	39.87
$AEVA_{j}$	53.16	37.67	50.51	39.11	27.53
$EDAEVA_{j}$	38.57	47.35	40.23	47.96	48.93
Panel C	Bank failure: bank nonperforming loan ratio more than one third				
$CR_{j,t}$	53.78	48.38	42.48	40.89	29.78
$EBITTA_{j,t}$	48.42	48.92	46.94	43.73	29.94
$EBTE_{j,t}$	41.14	41.97	45.74	43.32	37.52
$ETA_{j,t}$	43.43	44.12	49.54	47.57	42.43
$UAEVA_{j}$	56.47	40.19	53.68	41.69	29.53
$AEVA_{j}$	41.14	50.36	42.88	51.15	52.26
$EDAEVA_{j}$	40.34	49.67	43.59	53.78	52.93

Source: Authors investigation

Table-5. Performance Measures (Accuracy %)-Three quarters before a failure

	Bank failure: bank capital adequacy ratio less than 8%				
Panel A	NAFTA	ASEAN	EU	NIC	G20
$CR_{j,t}$	55.81	49.99	43.63	41.91	29.92
$EBITTA_{j,t}$	50.33	50.57	48.43	44.94	30.96
$EBTE_{j,t}$	42.76	43.77	47.13	44.53	38.27
$ETA_{j,t}$	44.64	45.39	51.19	49.11	43.57
$UAEVA_{j}$	58.72	41.15	55.79	42.77	29.65
$AEVA_{j}$	42.35	52.12	44.05	52.82	53.91
$EDAEVA_{j}$	41.31	51.38	44.82	55.81	54.86
Panel B	Bank failure: bank Tier I capital ratio less than 4%				
$CR_{j,t}$	NAFTA	ASEAN	EU	NIC	G20
$EBITTA_{j,t}$	50.74	45.57	39.93	38.44	27.75
$EBTE_{j,t}$	45.61	46.09	44.19	41.09	27.97
$ETA_{j,t}$	38.63	39.43	43.45	40.73	35.17
					Continue

$UAEVA_j$	40.83	41.49	46.65	44.83	39.87
$AEVA_j$	53.33	37.73	50.65	39.16	27.52
$EDAEVA_j$	38.63	47.47	40.34	48.09	49.06
Panel C	Bank failure: bank nonperforming loan ratio more than one third				
$CR_{j,t}$	48.25	43.43	38.15	36.73	26.79
$EBITTA_{j,t}$	43.46	43.91	42.14	39.24	26.93
$EBTE_{j,t}$	36.95	37.77	41.06	38.97	33.71
$ETA_{j,t}$	39.37	39.61	44.43	42.77	38.11
$UAEVA_j$	50.67	36.18	48.17	37.44	26.57
$AEVA_j$	36.47	45.25	38.59	45.78	46.68
$EDAEVA_j$	36.24	44.58	39.14	48.25	47.47

Source: Authors investigation

Table-6. Performance Measures (Accuracy %) - Fourth quarters before a failure

	Bank failure: bank capital adequacy ratio less than 8%				
Panel A	NAFTA	ASEAN	EU	NIC	G20
$CR_{j,t}$	53.84	48.33	42.32	40.72	29.36
$EBITTA_{j,t}$	48.38	48.89	46.86	43.56	29.52
$EBTE_{j,t}$	40.72	41.83	45.64	43.17	37.26
$ETA_{j,t}$	43.28	43.99	49.48	47.51	42.27
$UAEVA_j$	56.59	39.98	53.74	41.51	29.11
$AEVA_j$	40.62	50.36	42.72	51.02	52.05
$EDAEVA_j$	40.13	49.66	43.45	53.84	52.94
Panel B	Bank failure: bank Tier I capital ratio less than 4%				
$CR_{j,t}$	NAFTA	ASEAN	EU	NIC	G20
$EBITTA_{j,t}$	44.25	39.81	35.01	33.72	24.67
$EBTE_{j,t}$	39.84	40.24	38.63	36.29	24.89
$ETA_{j,t}$	33.91	34.59	37.66	35.69	30.97
$UAEVA_j$	35.78	36.34	40.72	39.15	34.97
$AEVA_j$	46.39	33.14	44.12	34.36	24.48
$EDAEVA_j$	33.72	41.42	35.33	41.95	42.77
Panel C	Bank failure: bank nonperforming loan ratio more than one third				
$CR_{j,t}$	51.57	46.32	40.59	39.05	28.24
$EBITTA_{j,t}$	46.36	46.85	44.92	41.77	28.45
$EBTE_{j,t}$	40.32	40.09	43.75	41.41	35.77
$ETA_{j,t}$	41.55	42.18	47.41	45.53	40.54
$UAEVA_j$	54.19	38.36	51.47	39.82	28.11
$AEVA_j$	39.28	48.25	40.97	48.88	49.86
$EDAEVA_j$	38.51	47.58	41.67	51.57	50.71

Source: Authors investigation

5. CONCLUSION

This study used data from 2003-2013, and used a logistic model to analyze the factors that influence financial early warning systems in developing and developed countries. The results indicate that EVA is superior in predicting bank failure in NAFTA, ASEAN, EU, NIC, and G20 nations. The EVA likely reflects an enterprise's real economic value and can be employed to prevent the inefficient management of funds (i.e., income excess capital cost) to ensure that corporations do not waste resources. Thus, the accuracy of bank failure prediction has been increased. Moreover, the EVA could be the optimal index for predicting bank failure in these countries.

In this study, we adopted cut off points greater 0.5 to classify companies as bankrupt, and points below than 0.5 indicated successful companies. However, this value is frequently used and subjective and optimal cut off points should be determined in future. This study demonstrated the determinants of bank failure in terms of various financial factors. Therefore, future studies should examine all relevant factors or devise new theories that predict bank crises.

Funding: This work has been supported by a grant from the Jiangsu Provincial Department of Education Philosophy and Social Science Foundation (Project Number 2014SJB474).

Competing Interests: The authors declare that they have no competing interests.

Contributors/Acknowledgement: All authors contributed equally to the conception and design of the study.

REFERENCES

Adeyeye, P.O., O.D. Fajembola, M.O. Olopete and D.B. Adedeji, 2012. Predicting bank failure in Nigeria using principal component analysis and D-score model. Research Journal of Finance and Accounting, 3(8): 159-170.

Al-Saleh, M.A. and A.M. Al-Kandari, 2012. Prediction of financial distress for commercial banks in Kuwait. World Review of Business Research, 2(6): 26-45.

Anvarkhatibi, S., R. Mohammadi and J. Mohammadi, 2013. Investigation of the effect of the value added, earning quality and leverage ratio on bankruptcy in organizations accepted in Tehran's stock market. Journal of Natural and Social Sciences, 2(2): 223-229.

Canicio, D. and K. Blessing, 2014. Determinants of bank failures in multiple-currency regime in Zimbabwe (2009–2012). International Journal of Economics and Finance, 6(8): 229-246.

Cox, R.A.K. and G.W.Y. Wang, 2014. Predicting the US bank failure: A discriminant analysis. Economic Analysis and Policy, 44(2): 202-211.

Distinguin, I., A. Tarazi and J. Trinidad, 2011. The use of accounting and stock market data to predict bank financial distress: The case of East Asian banks. Philippine Management Review, 18: 1-18.

Ecer, F., 2013. Comparing the bank failure prediction performance of neural networks and support vector machines: The Turkish case. Ekonomska Istrazivanja-Economic Research, 26(3): 81-98.

Fungacova, Z. and L. Weill, 2013. Does competition influence bank failures? Evidence from Russia. Economics of Transition, 21(2): 301-322.

Huang, D.T., B. Chang and Z.C. Liu, 2012. Bank failure prediction models: For the developing and developed countries. Quality and Quantity, 46(2): 553-558.

Huang, D.T. and Z.C. Liu, 2010. Board composition and corporate value in Taiwan high technology firms. International Journal of Organizational Innovation, 2(4): 126-138.

Ioannidis, C., F. Pasiouras and C. Zopounidis, 2010. Assessing bank soundness with classification techniques. Omega, 38(5): 345-357.

Jayadev, M., 2006. Predictive power of financial risk factors: An empirical analysis of default companies. Vikalpa, 31(3): 45-56.

Kiefer, M.V., 2014. Bank failures and mergers in Turkey: 1992-2014. International Journal of Finance and Banking, 1(3): 45-64.

Kim, M.J., D.K. Kang and H.B. Kim, 2015. Geometric mean based boosting algorithm with over-sampling to resolve data imbalance problem for bankruptcy prediction. Expert Systems with Applications, 42(3): 1074-1082.

Klecka, J. and H. Scholleova, 2010. Bankruptcy models enuntiation for Czech glass making firms. Economics and Management, 15: 954-959.

Li, G., L.W. Sanning and S. Shaffer, 2011. Forecasting bank failures: Timeliness versus number of failures. Applied Economics Letters, 18(16): 1549-1552.

Lin, S.L., 2010. A two-stage logistic regression-ANN model for the prediction of distress banks: Evidence from 11 emerging countries. African Journal of Business Management, 4(14): 3149-3168.

Lopez, I.F.J. and S.I. Pastor, 2015. Bankruptcy visualization and prediction using neural networks: A study of U.S. commercial banks. Expert Systems with Applications, 42(6): 2857-2869.

Maghyereh, A.I. and B. Awartani, 2014. Bank distress prediction: Empirical evidence from the gulf cooperation council countries. Research in International Business and Finance, 30(1): 126-147.

Martin, A., V. Gayathri, G. Saranya and P.V. Gayathri, 2011. A hybrid model for bankruptcy prediction using genetic algorithm, fuzzy c-means and mars. International Journal on Soft Computing, 2(1): 12-24.

Öğüt, H., M.M. Doğanay, N.B. Ceylan and R. Aktaş, 2012. Prediction of bank financial strength ratings: The case of Turkey. Economic Modelling, 29(3): 632-640.

Pasaribu, R.B., 2008. Financial distress prediction in indonesia stock exchange case study of trade industry public company. Journal of Economics Business and Accounting, 11(2): 153-172.

Pradhan, R., K.K. Pathak and V.P. Singh, 2013. Bankruptcy prediction and neural networks clubbed for Z score analysis of oriental bank of commerce. International Journal of Research in Computer Engineering and Electronics, 2(1): 1-6.

Rappaport, A., 1995. Creating shareholder value: The new standard for business n performance. New York: The Free Press.

Ravisankar, P. and V. Rav, 2010. Financial distress prediction in banks using group method of data handling neural network, counter propagation neural network and fuzzy artmap. Knowledge Based Systems, 23(8): 823-831.

Serrano-Cinca, C., 2013. Gutiérrez-Nieto, B. Partial least square discriminant analysis for bankruptcy prediction. Decision Support Systems, 54(3): 1245-1255.

Shkurti, R. and B. Duraj, 2010. The assessment of the financial soundness of the banking sectors in Balkan countries using early warning indicators- a comparative study with policy implications. CEA Journal of Economics, 5(1): 33-48.

Stewart, G.B., 1991. The quest for value. New York: Harper Business.

Teker, D., S. Teker and M. Sönmez, 2011. Economic value added performances of publicly owned banks: Evidence from Turkey. International Research Journal of Finance and Economics, 75: 132-138.

Timo, S. and I. Virtanen, 2001. Economic value added: A simulation analysis of the trendy, owner-oriented management tool. Acta Wasaensia(90).

Trussel, J. and L. Johnson, 2012. A parsimonious and predictive model of the recent bank failures. Academy of Banking Studies Journal, 11(1): 15-31.

Valahzaghard, M.K. and M. Bahrami, 2013. Prediction of default probability in banking industry using camels index: A case study of Iranian banks. Management Science Letters, 3(4): 1113-1118.

Wanke, P., C.P. Barros and J.R. Faria, 2015. Financial distress drivers in Brazilian banks: A dynamic slacks approach. European Journal of Operational Research, 240(1): 258-268.

Yildiz, B. and S. Akkoc, 2010. Bankruptcy prediction using Neuro fuzzy: An application in Turkish banks. International Research Journal of Finance and Economics, 60: 114-126.

Zaghdoudi, T., 2013. Bank failure prediction with logistic regression. International Journal of Economics and Financial Issues, 3(2): 537-543.