銀行失敗預測模型的進一步探討

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摘要

銀行有效地運用從各種投資項目獲得的利潤是很重要的，資金的誤用可能造成銀行破產，影響投資者、顧客和員工，進而干擾經濟秩序。銀行破產也會波及別的產業和造成更廣範圍的財務問題。因此，銀行必須評估各自的作業風險和建立早期預警系統。本研究收集2002至2012年772家跨國銀行資料〈排除控股公司〉，採用邏輯模型去分析重要的變數。結果顯示資本比率、利息收入對利息費用、非利息收入對非利息費用、權益周轉率、貸款損失條款和財務困難呈負相關。另外，貸款比率、逾期放款率、固定資產和財務困難呈正相關。本研究的邏輯模型對預測G8銀行財務困難，效果最佳。
關鍵詞：銀行失敗、經濟合作發展組織、北美自由貿易協定、東南亞國協、歐盟

An Advanced Study of Bank Failure Prediction Models

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Abstract

Banks efficiently manage the capital that they obtain from profit in various investments. The mismanagement of capital causes collapse, which negatively affects investors, customers, and employees, and disrupts the economic order. This disruption can affect other industries and trigger large-scale financial distress. Therefore, banks must evaluate their operational risks and develop early warning systems. In the current study, data from 772 international banks (excluding holding companies) from 2002–2012 was analyzed, and a logistic model was applied to analyze critical factors. The results showed that capital ratios, interest income to interest expenses, non-interest income to non-interest expenses, return of equity, provisions for loan losses have significantly negative correlations with financial distress. In addition, loan ratios, non-performing loans, and fixed assets all have a significant positive correlation to financial distress. However, the accuracy of the logistic model for G8 banks provides the best prediction trends regarding financial distress.
Keywords: Bank Failure, OECD, NAFTA, ASEAN, EU

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I. Introduction

Banks efficiently manage their capital, loaning the capital received through deposits to create revenue. This process, which fosters industrial development and economic growth, separates banks from other businesses. When banks collapse because of mismanagement, it affects investors and employees, eliminating the rights of customers, negatively affecting other industries, and potentially leading to international financial distress and destabilized economies.

A liquidity crisis occurred in U.S. banks in August 2007, causing the most severe financial distress since 1929. Central banks injected astronomical amounts of capital into the financial markets, but failed to prevent this crisis. The capital markets lost control in September 2008, resulting in the U.S. government takeover of large financial institutions. This crisis forced regulators to seize numerous banks and other financial institutions in the United States and other countries worldwide, leading to a freeze in credit markets and a global recession.

Consequently, evaluating bank operations and establishing early warning systems became a top priority for global financial authorities. Early warning systems first appeared in the banking industry in the 1970s, when challenges arose in bank management. Banks operate normally before crises emerge and financial distress often erupts abruptly. Min et al. (2006) emphasized that installing an early warning system was critical because predictions can influence loans and profitability, thereby demonstrating the significance of early warning systems.

Previous studies have only analyzed early warning systems in a single country (Ravi and Pramodh 2008; Canbas et al. 2005; Chauhan et al. 2009; Cielen et al. 2004; Erdogan, 2008; Al-Saleh and Al-Kandari 2012; Zaki et al. 2011; Valahzaghard and Bahrami 2013;Boyacioglu et al. 2009; Lanine and Vander Vennet 2006; Sinha et al. 2010; Serrano-Cinca and Gutiérrez-Nieto 2013). It is widely believed that majority of existent studies of bank failures have relied too heavily on bank-level accounting data (Al-Saleh and Al-Kandari 2012；Valahzaghard and Bahrami 2013；Mannasoo and Mayes 2009；Boyacioglu et al. 2009；Ravi and Pramodh 2008；Zhao et al. 2009；Zaghdoudi 2013；Chauhan et al. 2009；Ravisankar and Rav 2010；Serrano-Cinca and Gutiérrez-Nieto 2013；Yildiz and Akkoc 2010). Therefore, using financial ratios to detect distress could be beneficial.

However, these findings have caused some commentators to question the reliability and comparability of the emerging body of empirical evidence on banking. Huang et al. (2012) first analyzed regional groups' early warning systems for bank finances. However, the results presented only five financial ratios and did not include all of the countries in each regional group (excluding instances where no data was available). In addition, Huang et al. (2012) did not conduct an accuracy evaluation. Thus, we developed an optimal model, evaluated it for accuracy (Divsalar et al.2011), and compared the early warning indicators of bank failures in the Organization for Economic Co-operation and Development (OECD), North America Free Trade Area (NAFTA), Association of Southeast Asian Nations (ASEAN), European Union (EU), Newly industrialized country (NIC), G20, G8 based on the logistic model (i.e., the variables that were statistically significant in the model were based on each model).

The purpose of our study is to investigate the determinants of bank failure prediction and examine the predictive performance of the logistic model. This study proposed an early warning model for predicting commercial bank bankruptcy. We also investigated the usefulness of regional cooperation in designing models and monitoring certain sectors, based on a traditional bankruptcy prediction model. The remainder of the paper is organized as follows. Section 2 presents a brief review of the related literature. Section 3 provides details of the research design and sample selection procedure and develops our alternative model for estimating optimal earnings management. Section 4 presents our empirical findings. Section 5 contains a summary and conclusions.

II. Related Literature

Methods for predicting bankruptcy in financial firms, and especially banks, have been extensively researched since the late 1960s (Altman 1968) and several models can be used to predict bankruptcy. Classical statistical techniques influenced the formation of these models such as intelligent techniques (Kumar and Ravi 2007)、discriminant analysis (Swicegood and Clark 2001)、BPNN (Swicegood and Clark 2001; Bell 1997)、logistic regression (Bell 1997; Kolari et al. 2002； Zaghdoudi 2013；Olmeda and Fernandez 1997; Canbas et al. 2005；Al-Saleh and Al-Kandari 2012；Valahzaghard and Bahrami 2013)、feed forward neural networks (Olmeda and Fernandez 1997)、Principal Method (Canbas et al. 2005)、Linear Program (Cielen et al. 2004)、SOM network (Alam et al. 2000)、Genetic algorithm (Min et al. 2006；Martin et al.2011)、multivariate discriminant analysis (Cielen et al. 2004；Canbas et al.2005；Demyanyk and Hasan 2009)、neural network techniques (Boyacioglu et al. 2009)、support vector machines (Boyacioglu et al. 2009)、cox model(Brown and Dinc 2005; Mannasoo and Mayes 2009)、Multivariate Regression Analysis (Meyer and Pifer 1970)、Artificial Neural Network (Ravi and Pramodh 2008)、Data Envelopment Analysis(Cielen et al. 2004)、Fuzzy Model (Alam et al.2000；Tung et al. 2004；Yildiz and Akkoc 2010).

Regulators monitor banks by conducting on-site examinations of their financial and operational conditions. They determine the safety and soundness of the institution using a five-part rating system, referred to as CAMEL (capital adequacy, asset quality, management expertise, earnings strength, and liquidity). The capital base of a bank is critical because it is the last line of defense against uninsured depositor losses and general creditors. Capital adequacy is a measure of the level and quality of a capital base. Asset quality measures the level of asset risks, which are influenced by the quality and diversity of borrowers and their abilities to repay loans. Management quality measures the quality of the bank officers and the efficiency of the management structure. Earnings ability measures performance and the stability of earning streams. Liquidity measures the ability of a bank to meet urgent, unforeseen deposit outflows. Each of these factors influences bank failure. Asset loss is a direct cause of bank failure; however, other factors indicate the ability of the bank to remain operational despite these losses. A comprehensive review of bank failure prediction models revealed that the financial ratios constructed to measure the CAMEL components (Cole and Gunther 1995; Sarkar and Sriram 2001; Tam and Kiang 1990; Whalen 1991) predict bank failures based on financial ratios. We proposed financial ratios based on publicly available balance and income data (in the call reports) that commercial banks must report to regulatory authorities. Several characteristics of these data reflect the soundness of a commercial bank. Zhao et al. (2009) suggested that financial ratios are effective variables for predicting and explaining bank failures. Several previous studies have investigated various financial ratios: (a) cash flow to loans (Ravi and Pramodh 2008; Chauhan et al. 2009); (b) interest expense to average assets (Canbas et al. 2005; Ravi and Pramodh 2008; Chauhan et al. 2009); (d) net income to equity (Olmeda and Fernandez 1997; Ravi and Pramodh 2008; Chauhan et al. 2009); (d) retained earnings to assets (Cielen et al. 2004; Chauhan et al. 2009), (e) current assets to assets (Olmeda and Fernandez 1997; Ravi and Pramodh 2008); and (f) the quick ratio (Cielen et al. 2004; Canbas et al. 2005).

III. Methodology

Financial ratios were used to predict financial distress in the banking industry, incorporating data from

2002–2012 from the Compustat database. The study comprised 772 banks[1] and 6773 samples (excluding financial holding companies). A logistic model was adopted to analyze the data. The variables and research model of the current study are presented in the following sections.

1. Dependent variables: bank failures

The definitions of financial distress are inconclusive, but are primarily based on financial statements. The current study modified the Whitaker (1999) model, in which a cash flow value lowers than the value of liabilities in the current year suggests financial distress. The value of the dummy variable was 1, and 0 was the contrary variable.

2. Independent variables: financial ratios

Previous studies have indicated that healthy banks had lower loan to asset ratios, higher net profit to average equity ratios, and higher fixed asset to long liability ratios (Boyacioglu et al. 2009). Yildiz and Akkoc (2010) stated that healthy banks had higher interest incomes compared to interest expenses, greater non-interest income compared to non-interest expenses, fewer non-performing loans compared to loans, and lower provisions for loan losses compared to loans. However, the empirical results of Serrano-Cinca and Gutiérrez-Nieto (2013) indicated that healthy banks had higher Tier 1 (core) capital compared to average assets.

3. Control variables: macroeconomic factors

We incorporated macroeconomic variables into the model, and identified the channels through which macroeconomic shocks contribute to bank failures. Macroeconomic indicators assist in explaining how the environment interacts with bank problems. Regarding macroeconomic developments, a sharp drop in actual GDP growth is an excellent indicator that banking problems might emerge (Hutchison and Mc-Dill 1999). A fall in stock prices is also associated with an increased likelihood of banking sector distress (Hutchison and Mc-Dill 1999). However, Männasoo and Mayes (2009) showed that increasing inflation is a crucial factor accompanying bank distress.

4. Empirical model

The study used the logistic method. The proxy variables are as follows: $CAPITAL_{j,t}$ is Tier 1 (core) capital compared to average assets in year t; $LOAN_{j,t}$ represents loans compared to assets in year t; $NPL_{j,t}$ is non-performing loans compared to all loans in year t; $PL_{j,t}$is the provision for loan losses compared to all loans in year t; $FA_{j,t}$ is fixed assets compared to long liabilities in year t; $ROE_{j,t}$ is net profit compared to average equity in year t; $IIIE_{j,t}$ is interest income compared to interest expenses in year t; $NIINIE_{j,t}$ is non-interest income compared to non-interest expenses in year t; variable $RGDP_{j,t}$ represents the change in gross domestic product divided by the consumer price index in year t; $STOCK_{j,t}$ denotes the average deviation of the stock index over

[1] **OECD**(*Organization for Economic Co-operation and Development*): Austria, Belgium, Canada, Denmark, France, Germany, Greece, Iceland, Ireland, Italy, Luxembourg, Netherlands, Norway, Spain, Portugal, Sweden, Swiss, Turkey, United Kingdom, America, Japan, Finland, Austrlia, Mexico, Czech, Hungary, Korea, Poland, Slovak, Chile, Slovenia, Estonia, Israel. **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, Mexico, Brazil, China, India, Malaysia, Philippines, Thailand, Turkey. **G20**: Argentina,Austrlia, Brazil, Canada, China, European Union, India, Indonesia, Japan, Korea, Mexico, Russia, Saudi Arabia, South Africa, Turkey, America. **G8**: America, Japan, Canada, Russia, Italy, United Kingdom, France, Germany.

five years in year *t*; and $CPI_{j,t}$ denotes the consumer price index in year *t*.

5. Performance measures

A more detailed performance analysis was conducted regarding the proposed logistic methods, and their accuracy was obtained using Equation 1. Classification performance is typically presented using a confusion matrix as shown in Table 1, where TP is true positive, TN is true negative, FP is false positive, and FN is false negative. If a bankrupt firm is classified as bankrupt, then it is considered TP. By contrast, if a non-bankrupt firm is classified as non bankrupt, then it is considered TN. Any non-bankrupt firm that is classified as bankrupt produces a FP and any bankrupt firm that is classified as a non-bankrupt firm produces an FN (Divsalar et al. 2011).

Table 1 Confusion matrix

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

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

IV. Results

1. Descriptive statistics

Table 1 lists the OECD, NAFTA, ASEAN, EU, NIC, G20, and G8 banks. The capital ratios in these countries all exceed 6%, with OECD at 12% (highest) and NIC at 8.2% (lowest). Loans compared to assets ranged from 35% to 47%, non-performing loans compared to loans averaged approximately 40%, and provision for loan losses compared to loans averaged from 40% to 50%. These results indicated that credit policies were robust and stable, and appropriate loan losses are a suitable measure for risk management.

In addition, fixed assets compared to long liabilities were more than 50% in OECD and NAFTA, indicating that long liabilities were primarily used to purchase fixed assets, thereby adversely affecting capital movement. The return of equity had a positive value for all groups, with the EU at 15% (the highest), and the G8 at 7% (the lowest). The operating items (e.g., charging clients with interest on loans to pay interest on deposits) of banks had a positive value (interest income to interest expenses >100%), with the NIC at 168% (the highest) and the OECD at 125% (the lowest). In addition, the non-operating items (irrespective of the payment or collection of interest on deposits and loans) of banks also had a positive value (non-interest income to non-interest expenses >100%), with the OECD at 142% (the highest) and NAFTA at 119% (the lowest), indicating that these two items were bank profit sources.

Compared to these variables, the change in real gross domestic product had a positive value in the ASEAN and NIC, indicating that these two groups experienced economic growth; however, the OECD had a negative value (the lowest of the seven groups), indicating an economic recession. Furthermore, the fluctuation of the stock index was lower in the G20, thereby demonstrating a steady capital market. The NIC showed higher fluctuations in the stock index, indicating that economic growth in the group caused capital from various countries to flow into the stock market or that transaction and exchange systems were incomplete. The consumer price index in the NIC was high, indicating that the NIC experienced economic growth and product demand increased.

Table 2 Descriptive statistics: country samples (average values)

	OECD	NAFTA	ASEAN	EU	NIC	G20	G8
$CAPITAL_{j,,t}$	12%	11%	9.7%	9.9%	8.2%	9.5%	9.2%
$LOAN_{j,t}$	42%	39%	47%	40%	46%	35%	37%
$NPL_{j,t}$	41%	46%	42%	40%	45%	41%	43%
$PL_{j,t}$	44%	45%	51%	49%	52%	51%	47%
$FA_{j,t}$	52%	54%	47%	41%	39%	45%	47%
$ROE_{j,t}$	12%	10%	14%	15%	8%	9%	7%
$IIIE_{j,t}$	125%	146%	158%	138%	168%	147%	149%
$NIINIE_{j,t}$	142%	119%	122%	132%	127%	122%	126%
$RGDP_{j,t}$	-1.52%	-1.17%	2.89%	-1.12%	1.89%	-0.79%	-0.82%
$STOCK_{j,t}$	1.55	1.79	2.55	2.36	3.37	1.05	2.55
$CPI_{j,t}$	0.84%	0.58%	2.09%	0.91%	2.58%	0.45%	0.52%
Samples	1758	355	471	1572	858	936	823

2. Empirical test

Table 3 shows that the capital ratio was significantly and negatively correlated to financial distress in ASEAN, NIC, G20, and G8 banks. These results are consistent with those of Serrano-Cinca and Gutiérrez-Nieto (2013) and demonstrate that healthy finances do not occur when banks are experiencing financial distress. The loan ratio was significantly positively correlated to financial distress in NAFTA, ASEAN, EU, and NIC banks, which is consistent with the results derived by Boyacioglu et al.(2009). Non-performing loans were significantly and positively correlated to financial distress in OECD, NAFTA, ASEAN, EU, and NIC banks, and these results were consistent with the results of Yildiz and Akkoc (2010). Overall, greater flexibility in loan policies increases the risk of finance in banking. Conversely, loan loss provisions were significantly and negatively correlated to financial distress in OECD, EU, NIC, G20, and G8 banks. These results were not consistent with those presented by Yildiz and Akkoc (2010), indicating that loan losses can be included in the expected lending risks of banks and can serve as a measure for risk management to reduce the possibility of financial crises. Fixed assets[2] had a significantly positive correlation with financial distress in the ASEAN, NIC, and G8 banks. These results were not consistent with those of Boyacioglu et al.(2009), suggesting that long liabilities were limited by fixed assets, and thereby detrimental for capital movement, resulting in financial crises. Return of equity had a significantly negative correlation to financial distress in OECD banks, and these results were consistent with those of Boyacioglu et al. (2009). Interest income to interest expense ratios and non-interest income to non-interest expense ratios were significantly and negatively correlated to financial distress in the OECD, G20, and G8 banks, and these results were consistent with those of Yildiz and Akkoc (2010). The results show that when banks focus on primary operating items or non-primary operating items financial distress does not occur.

Regarding macroeconomic factors, the changes in real gross domestic product, the volatility of the stock index, and the consumer product index all had different relationships in the seven regional nationals banking sectors. For example, changes in real gross domestic product showed a significant positive correlation with financial distress in the OECD, G20, and G8 banks, changes in real gross domestic product showed a significant negative correlation with financial distress in the ASEAN bank and a non-significant relationship with financial distress in the NAFTA, EU, and NIC banks. Conversely, the volatility of the stock index had a significant

[2] Fixed assets to long liability.

positive correlation to financial distress in OECD, NAFTA, ASEAN, and EU banks, a significant negative correlation to financial distress in NIC and G8 banks, and a non-significant relationship with financial distress in G20 banks. In addition, the consumer product index was significantly and positively correlated to financial distress in OECD and EU banks, significantly and negatively correlated to financial distress in G20 banks, and had a non-significant relationship with financial distress in NAFTA, ASEAN, NIC, and G8 banks. These results demonstrated the differences in cultures, laws and regulations, and economic systems under which various groups and differing countries operate.

The optimal results for the explicit equation of the logistic model regarding banking financial distress in regional groups can be expressed using the following financial variables. OECD bank variables are ranked from non-performing loan to loan ratios, provisions for loan losses to loan ratios, ROE, interest income to interest expense ratios, and finally non-interest income to non-interest expense ratios. NAFTA bank variables are ranked from loan to asset ratios to non-performing loan to loan ratios. ASEAN bank variables are ranked from Tier 1 (core) capital to average asset ratios, loan to asset ratios, non-performing loan to loan ratios, and finally, fixed asset to long liability ratios. EU bank variables are ranked from loan to asset ratios, non-performing loan to loan ratios, and finally, provisions for loan losses to loan ratios. NIC bank variables are ranked from Tier 1 (core) capital to average asset ratios, loan to asset ratios, non-performing loan to loan ratios, provisions for loan losses to loan ratios, and fixed asset to long liability ratios. G20 bank variables are ranked from Tier 1 (core) capital to average asset ratios, provisions for loan losses to loan ratios, interest income to interest expense ratios, and non-interest income to non-interest expense ratios；in which G8 banks are ranked from Tier 1 (core) capital to average asset ratios, provisions for loan losses to loan ratios, fixed asset to long liability ratios, interest income to interest expense ratios, and finally, non-interest income to non-interest expense ratios. In addition, the variance inflation factors[3] of variables were smaller than 10 in our logistic model, indicating that the related variables were not collinear. According to the Cox & Snell R^2 and the Nagelkerke R^2 , the NIC banks have a higher ability to explain the bank failure model proposed in this study, whereas EU banks have a lower ability to explain the model.

Erdogan (2008) indicated that logistic regression can be used as a part of an early warning system, establishing a cut-off point or level of probability (typically, 0.5) that categorizes a bank as failed. In this study, bankrupt banks were classified as 1 and successful banks were classified as 0. Banks with cut-off points under 0.5 were classified as 1 (bankrupt banks) and banks above 0.5 were classified as 0 (successful banks). Regarding a more detailed performance analysis of the proposed logistic methods, accuracy was obtained using Equation 1. The comparisons of predicted and actual bankruptcy classifications are shown in Tables 4 to 11. Because the financial crisis of 2008 might have restructured the global financial market, we separated data from before 2008 and after 2008 to obtain the accuracy of the logistic model.

As indicated in Table 4 (all samples), the accuracy of the logistic model is 48.12% (prior to 2008) and 48.10% (following 2008). Thus, regarding the overall data, these percentages indicate that no significant differences were found in the results from before or after 2008. In addition, the values were lower than 50%, implying lower accuracy in the model. However, Table 5 (OECD banks) shows that the accuracy of the logistic model was 47.84% (before 2008) and 50.76% (after 2008); thus, our study improved the accuracy of the logistic model for bank failure prediction in OECD banks after the financial crisis. In addition, Table 6 (NAFTA banks) shows that the accuracy of the logistic model was 45.27% (before 2008) and 49.27% (after 2008); thus, we improved the accuracy of the logistic model for bank failure prediction in NAFTA banks after the financial crisis. Table 11 (G8 banks) shows that the accuracy of the logistic model was 50.51% (before 2008) and 65.33%

[3] The results were omitted to save space.

(after 2008); thus, we also improved the accuracy of the logistic model for bank failure prediction in G8 banks after the financial crisis.

Compared to OECD, NAFTA, and G8; Table 7 (ASEAN banks) shows that the accuracy of the logistic model was 60.39% (before 2008) and 48.61% (after 2008); Table 8 (EU banks) shows that the accuracy of the logistic model was 42.21% (before 2008) and 39.65% (after 2008) ; Table 9 (NIC banks) shows that the accuracy of the logistic model was 54.32% (before 2008) and 40.77% (after 2008); Table 10 (G20 banks) shows that the accuracy of the logistic model was 47.32% (before 2008) and 46.56% (after 2008). Overall, we improved the accuracy of the logistic model for bank failure prediction in OECD, NAFTA, and G8 banks after the financial crisis.

Furthermore, based on regional groups and regarding the accuracy of the logistic model, G8 banks performed better (the results for both before and after 2008 were above 50%) than other groups. By contrast, EU banks performed worse (the results for both before and after 2008 were below 50%) compared to the other groups. According to the time line (before or after 2008), before 2008, ASEAN banks had the highest value (the accuracy of the logistic model was 60.39%) and EU banks possessed the lowest value (the accuracy of the logistic model was 42.21%). Moreover, after 2008, G8 banks had the highest value (the accuracy of the logistic model was 65.33%) and EU banks possessed the lowest value (the accuracy of the logistic model was 39.65%).

Table 3 Relationships between financial ratios and bank failure

	OECD	NAFTA	ASEAN	EU	NIC	G20	G8
Intercept	-1.758***	4.677	-2.276***	0.289	-1.697***	1.107***	-1.626***
$CAPITAL_{j,,t}$	-0.028	0.680	-1.571**	-0.397	-1.956**	-1.571**	-1.995**
$LOAN_{j,t}$	0.083	2.725***	2.825***	1.168***	1.673*	0.054	1.66
$NPL_{j,t}$	9.719***	2.016***	1.581***	1.405***	1.694*	-0.644	-1.038
$PL_{j,t}$	-0.231*	-0.104	0.097	-1.239***	-0.826**	-1.233**	-1.724***
$FA_{j,t}$	0.015	0.027	0.135*	0.032	0.936**	0.107	0.917*
$ROE_{j,t}$	-1.187**	-1.004	0.407	-0.132	0.384	-1.281	0.585
$IIIE_{j,t}$	-1.672***	-0.021	0.084	0.422	-3.219	-2.207**	-1.881***
$NIINIE_{j,t}$	-4.650**	0.694	0.076	-0.697	0.059	-2.177***	-2.081***
$RGDP_{j,t}$	2.902***	0.314	-2.056***	0.467	0.128	1.057**	0.497**
$STOCK_{j,t}$	2.126***	1.757***	1.453***	0.881*	-1.907**	-0.0492	-1.861***
$CPI_{j,t}$	1.127****	-0.035	0.053	1.184**	-0.049	-1.758**	-0.133
x^2	80.155***	59.047***	82.709***	57.573***	57.214***	60.726***	62.527***
Cox and Snell R^2	0.438	0.346	0.448	0.339	0.474	0.397	0.452
Nagelkerke R^2	0.584	0.470	0.632	0.465	0.633	0.536	0.605
Sample	1758	355	471	1572	858	936	823

Table 4 Confusion matrix: all samples

Panel A	*Before 2008*	Predicted class	
		Bankrupt	Non-bankrupt
Actual Class	Bankrupt	983	884
	Non-bankrupt	932	702
Panel B	*After 2008*	Predicted class	
		Bankrupt	Non-bankrupt
Actual Class	Bankrupt	894	805
	Non-bankrupt	893	680

Table 5 Confusion matrix: OECD

Panel A	*Before 2008*	Predicted class	
		Bankrupt	Non-bankrupt
Actual Class	Bankrupt	326	257
	Non-bankrupt	214	106
Panel B	*after 2008*	Predicted class	
		Bankrupt	Non-bankrupt
Actual Class	Bankrupt	258	236
	Non-bankrupt	185	176

Table 6 Confusion matrix: NAFTA

Panel A	*Before 2008*	Predicted class	
		Bankrupt	Non-bankrupt
Actual Class	Bankrupt	35	42
	Non-bankrupt	39	32
Panel B	*after 2008*	Predicted class	
		Bankrupt	Non-bankrupt
Actual Class	Bankrupt	47	56
	Non-bankrupt	49	55

Table 7 Confusion matrix: ASEAN

Panel A	*Before 2008*	Predicted class	
		Bankrupt	Non-bankrupt
Actual Class	Bankrupt	49	59
	Non-bankrupt	42	105
Panel B	*after 2008*	Predicted class	
		Bankrupt	Non-bankrupt
Actual Class	Bankrupt	39	60
	Non-bankrupt	51	66

Table 8 Confusion matrix: EU

Panel A	*Before 2008*	Predicted class	
		Bankrupt	Non-bankrupt
Actual Class	Bankrupt	255	233
	Non-bankrupt	279	119
Panel B	*after 2008*	Predicted class	
		Bankrupt	Non-bankrupt
Actual Class	Bankrupt	214	155
	Non-bankrupt	259	58

Table 9 Confusion matrix: NIC

Panel A	*Before 2008*	Predicted class	
		Bankrupt	Non-bankrupt
Actual Class	Bankrupt	61	90
	Non-bankrupt	79	140
Panel B	*after 2008*	Predicted class	
		Bankrupt	Non-bankrupt
Actual Class	Bankrupt	127	141
	Non-bankrupt	148	72

Table 10 Confusion matrix: G20

Panel A	*Before 2008*	Predicted class	
		Bankrupt	Non-bankrupt
Actual Class	Bankrupt	155	124
	Non-bankrupt	162	102
Panel B	*after 2008*	Predicted class	
		Bankrupt	Non-bankrupt
Actual Class	Bankrupt	85	108
	Non-bankrupt	102	98

Table 11 Confusion matrix: G8

Panel A	*Before 2008*	Predicted class	
		Bankrupt	Non-bankrupt
Actual Class	Bankrupt	102	79
	Non-bankrupt	117	98
Panel B	*after 2008*	Predicted class	
		Bankrupt	Non-bankrupt
Actual Class	Bankrupt	124	49
	Non-bankrupt	99	155

V.Conclusion

This study comprised 772 international banks (excluding financial holding companies) and used data from 2002–2012, employing a logistic model to analyze the factors that influence financial early warning systems. The results suggested that capital ratio has a significant negative correlation to financial distress in ASEAN, NIC, G20, and G8 banks. The loan ratio has a significant positive correlation to financial distress in NAFTA, ASEAN, EU, and NIC banks. Non-performing loans have a significant positive correlation to financial distress in OECD, NAFTA, ASEAN, EU, and NIC banks. Provisions for loan losses have a significant negative correlation to financial distress in OECD, EU, NIC, G20, and G8 banks. Fixed assets have a significant positive correlation to financial distress in ASEAN, NIC, and G8 banks. The return of equity only had a significant negative correlation to financial distress in OECD banks. Ratios of interest income to interest expenses and non-interest income to non-interest expenses have significant negative correlations to financial distress in OECD, G20, and G8 banks. Thus the empirical results show that OECD (Organization for Economic Co-operation and Development)、NAFTA (North America Free Trade Area)、ASEAN (Association of Southeast Asian Nations)、EU(European Union)、NIC (Newly industrialized country)、G20、G8 have different bank-sector environments. In addition, the logistic model for bank failure prediction in this study predicted the financial distress of global banks and explained most of the banking trends in NIC banks (Cox & Snell R^2 and Nagelkerke R^2). Moreover, the accuracy of the logistic model for G8 banks was higher than that of other regions, and the accuracy for EU banks was lower than that for other regions.

Most international banks are protected by deposit insurance. In times of financial distress, government interventions can prevent the collapse of banks. The risk of operating a bank grows with the internationalization of the capital market. The growing role is a financial intermediary, which stabilizes economic order. Forecasting financial distress has three benefits: (a) depositors can diversify their assets to reduce risks; (b) governments can institute regulations and examine insurance to manage the operational risks of banks; and (c) international cooperation can reduce potential financial distress, mitigating the domino effect.

In addition, Erdogan (2008) indicated that logistic Regression can be used as a part of an early warning system, establishing a cut off-point or level of probability (typically, 0.5) that categorizes a bank as failed. In this study, we adopted cut-off points under 0.5 to classify bankrupt banks and points greater than 0.5 to classify successful banks; however, this value is frequently used and is subjective, and optimal cut off points should be analyzed in the future. In addition, numerous factors affect financial crisis prediction, and differences exist between cultures, laws and regulations, and economic development. Therefore, future studies can be conducted to research all relevant factors.

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