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Prediction Models for Bank Failure: ASEAN Countries

(Model Jangkaan ke atas Kegagalan Bank: Negara-negara ASEAN)

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ABSTRACT

The paper analyses how global financial crisis effects the performance of banks. This study further estimate the determinants of banks failure on a sample of banks in ASEAN countries namely, Indonesia, Malaysia, Singapore, Cambodia, Thailand, Philippine, Singapore, and Vietnam. We define a bank as having failed when its profitability, equity, and loan quality are below a minimum standard. Besides bank-specific variables (microeconomic variables), some macroeconomic variables have been considered in this study. The findings reveal that during global finance crisis, the performance of the banks is at its weakest before its significant recovery. The findings show that the banking failure is positively linked to cost inefficiency, debt to equity ratio, an inflation rate, but negatively related to profitability. The findings suggest that cost inefficiency, can serve as a foundation for corrective action to be considered by banking authorities in the future.

Keywords: Bank performance; bank failure; logistic regression; ASEAN; early warning

ABSTRAK

Kertas ini menganalisis bagaimana krisis kewangan global mempengaruhi prestasi bank. Kajian ini selanjutnya menganggarkan penentu kegagalan sektor perbankan di negara-negara ASEAN iaitu Indonesia, Malaysia, Singapura, Kemboja, Thailand, Filipina, Singapura dan Vietnam. Kegagalan bank didefinisikan apabila keuntungan, ekuiti, dan kualiti pinjaman berada di bawah piawaian minimum. Selain daripada pemboleh ubah spesifik bank (pemboleh ubah mikroekonomi), beberapa pemboleh ubah makroekonomi juga dipertimbangkan dalam model kajian ini. Hasil kajian mendapati bahawa semasa permulaan krisis kewangan global, prestasi perbankan adalah yang paling teruk dan kemudian pulih dengan ketara selepas itu. Dapatan kajian menunjukkan bahawa kegagalan perbankan mempunyai hubungan yang positif dengan ketidakcekapan kos, nisbah hutang kepada ekuiti, kadar inflasi, tetapi berhubungan negatif dengan keuntungan. Dapatan kajian mencadangkan agar ketidakefisienan kos dapat berfungsi sebagai asas pertimbangan oleh pihak berkuasa perbankan dalam membuat tindakan pembetulan pada masa akan datang.

Kata kunci: Prestasi bank; kegagalan bank; regresi logistik; ASEAN; amaran awal

INTRODUCTION

In its publication on Sunday, 28 December 2008, the Guardian released an analysis on how the Global Financial Crisis (GFC) of the same year had changed the landscape of the banking industry in Europe and America. The global financial crisis also put ASEAN to the test on their ability to manage the economy. Mehmood and Hafeez (2017) noted that ASEAN initially experienced some difficultly. However, the group's performance improved in terms of asset growth and profitability since 2010. Rasiah et al. (2014) suggested that the impact of GFC on the ASEAN economy, especially Malaysia and Singapore, was largely felt through a decrease in aggregate demand caused by the collapse of the U.S and European economies. In Indonesia, the GFC also caused excessive capital outflow, thus causing exchange rate and liquidity shortages. The government subsequently introduced a massive bailout for Bank Century to prevent banking panic. Following the GFC, Zimmerman, and Stone (2018) noted that the positive development in ASEAN policy-making was attributed more to Asian-style solution than a Western one. The banking community focused on strengthening their collective resilience and commitment to ASEAN centrality. This explained why no austerity policy was launched to assist economic recovery in ASEAN.

The most noticeable impact of the GFC was in the declining commodity prices. Except for Singapore, the ASEAN economy is commodity-based. The price decline produced a negative impact and affected the export-oriented economies of the region. According to ADB, exports declined in 2009 by 25% in Indonesia, 13% in Malaysia, 18% in Thailand, and 32% in Viet Nam (Kawai 2009). The decline in commodity prices impacted the farmers as well as governments forcing the ASEAN economy into recession. In comparison, the impact of the GFC on the performance of banks in the MENA region showed positive contributions from asset size, capital, and liquidity in their performance (Mongid 2016). Unfortunately, innovation contributed negatively to performance.

The role of banks in the economy is vital, although they are the first institution to suffer casualty when the economy recedes into crisis. The performance of the banking system influences and regulates most economic activities and vice versa. Pomerleano (2009) compiled the impacts of the GFC on ASEAN banking through studying Moody's average bank financial strength ratings. Rating agencies expect substantial pressure on loan quality to be the biggest threat for most banks. It produces some consequences such as credit impairment, lower profitability, and potential capital reduction. Credit risk deteriorates across the region as economic growth declines, and interest rate rises. The banking in Singapore was downgraded to B with a negative prospect. For Malaysia, the situation was similar. Thailand was also downgraded to D with a negative outlook. Indonesia and the Philippines were stable but were already at the D rating. This finding supports Sarifuddin et al. (2015) that investigated the cost efficiency of the thirty anchor banks from Malaysia, Thailand, and Indonesia. Most were found to have suffered under the Global Financial Crisis in 2008.

In cognizance of the impact of the GFC in the regional economy, deep concern was raised on the possibility of financial panics resulting from bank failures. This became the critical motivation in preventing disruption to the community. On this reasoning, a greater understanding of the root causes of bank failure is essential in helping to create a stable economic condition. A bank failure is furthermore costly to all its stakeholders. Accordingly, this study should potentially benefit the banking industry and assist relevant authorities in terms of identifying the variables that may be causal to the failure. The results may contribute to the establishment of an early warning system that can identify oncoming conditions for bank failure that is of interest to the banking authority. The objective of this study is to develop a model for investigating the bank's failure as a contribution to the overall efforts to increase resiliency in the bank industry and also provide for an early warning system. The model thus formulated may serve as a useful tool for this purpose. The model will help banking authority in its intensive oversight to high-risk institutions.

Given this background, the objective of this study is to evaluate the factors that determine the probability of commercial bank failure covering both conventional and Islamic banks in the ASEAN, between 2008 and 2014. The factors to be examined include the bank's capital strength (ETA), bank's efficiency (CIR), profitability (ROA), size (Total Asset) liquidity (LIQASSET), asset composition (LTA) and macro-economic condition (Inflation, GDP Growth).

This paper contributes to the field of early warning systems on the onset of bank failure using the case study on ASEAN banking. Since bank failure in ASEAN is mostly undetectable, the paper contributes to the existing literature on how bank failure can be defined. This was examined by using an artificial definition of bank failure that included zero or negative equity, losses, and excessive credit risk. As the banking crisis is very costly, an early warning system of oncoming failure conditions is crucial in sustaining banking stability and preventing banking panics. This paper provides an initial study for formulating such a system for the ASEAN banking industry.

LITERATURE REVIEW

Failure is inherent to the operation of banks or financial institutions due to the nature of their business, which involves both risk-taking and management of multiple risks. For that reason, bank failure has a long history. According to the literature, there are two main streams in the study of bank failures or crises. The first is the banking crisis at the country level and which is mainly examined at the macro scale. Such studies included Demirguc-Kunt and Detragiache (1998), Kaminsky and Reinhart (1999), Frankel and Rose (1996), Davis and Karim (2008), Reinhart and Rogoff, (2009), Alessi and Detken (2011), Levy-Yeyati and Panizza, (2011), Frankel and Saravelos(2012), Roseand Spiegel (2011), Dabrowski et al. (2016), Drehmann and Juselius (2014) and Tamadonejad et al. (2016). The second stream is the individual bank failure prediction model. This category is further sub-divided into two groups. One focuses only on bank-specific information, and the other includes macroeconomic variables. The studies by Coles and Gunther (1998), Beck, Jonghe, and Schepens (2013), Cole and White (2012), and Cleary and Hebb (2016) are in this category.

Most of the literature defines banking failure as the event when the bank receives external assistance, both mandatory and voluntary, or when its operation is directly closed. Gonzalez-Hermosillo et al. (1996)

defined bank failure as when the bank is recapitalized, taken over by another financial institution, has its license surrendered over or revoked, temporarily suspends operation or files for closure. Beaver (1967) introduced the concept of failure as the event of bankruptcy, bond default, an overdrawn bank account, or non-payment of a preferred stock dividend. The CAMEL rating has been used as a major tool by banking authority to assess a bank's financial soundness. Coles and Gunther (1998) developed an off-site monitoring model to predict bank failure from 1988 to 1990 in the USA. They concluded that only two CAMEL-type variables were found not significant. The CAMEL rating system, however, is less effective than the CAMEL-type logistic model, which only uses publicly available data. Cole and White (2012) confirmed that CAMEL data is effective in improving bank supervision since it can serve as an early warning system. These findings confirmed that the CAMEL rating variable could suitably be used to determine the event of bank failure.

In Indonesia, the CAMEL-type model of bank failure is usually used. Mongid (2000), and Hadad et al. (2004) studied the early warning system for commercial bank failure using CAMEL-type data. They applied ten ratios for capital, eleven ratios for financial conditions, and a dummy for the type of banking firm. Their model thus formulated could predict accurately within three months of oncoming failure. Santoso et al. (2005), who conducted a similar study also produced similar results. Raz (2018) studied the risk of failure for large banks in Indonesia and concluded that the risk was lower when the capital position was stronger. Pekkaya and Figen (2019) support the use of CAMEL-type data for bank failure as an effective and superior.

Hermosillo (1997) concluded that both macroeconomic and microeconomic factors at bank-level data were important in determining a bank's failure and distress. Models based on bank-specific variables, which included a measure of credit risk, liquidity risk as well as moral hazard, performed well in predicting the probability of failure. He also noted that macroeconomic or regional economic variables could improve the predictive power of bank failure models. Recent studies on the bank failure prediction model included a macro-economic indicator to enhance the predictive power of the CAMEL-type data. Studies by Curry et al. (2007), Bharath and Shumway (2008), Campbell et al. (2008), and Arena (2010) showed that additional information improved the model substantially, especially when data on asset prices were included. They were mostly using the dichotomous model. Hsu and Liu (2019) applied a parametric survival time regressions model to study Asian bank failures. They concluded that individual bank indicators, such as earning asset quality, liquidity position, stable earnings, and bank size, were significant variables. For macroeconomic variables, however, only inflation and money supply were found relevant.

Another study by Beck et al. (2013) has examined the risk of failure due to the impact of competition primarily where related to risk-taking and profitability, using large cross-country variations in the relationship between bank competition, profitability, and bank stability. They also explored the market, regulatory and institutional features that can explain variation in the risk of failure. They concluded that excessive competition increased banking's fragility due to lower profitability. Deposit insurance increases fragility with the increase in bank risk-taking. The employment of an effective credit biro system increases information sharing and inhibits higher risk-taking.

The newer application of CAMEL-type data for predicting bank failure is widely popular. Jin et al. (2011) extended the use of CAMEL-type data with auditor quality and governance. They used auditor type, Tier 1 capital ratio, the proportion of securitized loans, growth in loans, and loan mix as predictors. All showed significant results. De Young and Toma (2013) studied a bank failure incidence in the U.S by extending the earning to cover income from nontraditional banking activities contributing to the failures of hundreds of U.S. commercial banks during the financial crisis. They concluded that fee-for-service income was mainly from non-traditional activities such as insurance sales, loan servicing, and securities brokerage. These activities reduced the probability of bank failure during the crisis.

In contrast, noninterest income from stakeholder activities, such as investment banking, insurance underwriting, and venture capital, increased the probability of failure. Le and Viviani (2018) suggested the use of a new method to study bank failure. They found that loan quality, capital quality, operations efficiency, profitability, and liquidity were still very accurate variables if new techniques such as the artificial neural network and k-nearest neighbor methods were applied. Khokher and Alhabsyi (2019) however, indicated that only capital was found significant as failure predictor. Carmona et al. (2019) apply extreme gradient boosting to predict bank failure in the U.S. They inferred that lower values for retained earnings to average equity, pre-tax return on assets, and total risk-based capital ratio are associated with a higher risk of bank failure. Bank generated a higher yield on earning assets indicated high risk-taking and inhibited the chance of bank failure.

In general, Cole and White (2012) concluded that bank failure during GFC was not different from that of the 1990s and that they were recognizable. The CAMELS approach to judging the safety and soundness of commercial banks is still valid, especially for capital adequacy, asset quality, earnings, and liquidity that can serve as powerful predictors of bank failure during the 2008–2010 crises. Calice (2014) noted that the early warning system of bank failure using CAMEL-type data was still accurate and useful for banking supervision. Cleary and Hebb (2016) applied CAMEL-type data and could successfully distinguish between failed banks and those that survived. Bank capital (C) and loan quality (A) were the most important determinants. Additionally, Almanidis and Sickles (2010) found that inefficiency increased risk of failure, whereas, Mongid et al. (2012) found that capital, efficiency, and risk were interrelated.

The above review indicates that some studies were made in examining bank failure in the ASEAN region during the recent global financial crisis. To gauge its impact at the macroeconomic level, the researchers have included the variables of inflation and economic growth in the model.

METHODOLOGY AND DATA

SAMPLE AND DATA

Samples for the study included all commercial banks operating between 2008 to 2014 in the ASEAN region, whether successful or otherwise. This was, however, subjected to data availability. The total samples were 1545 banks that included conventional and Islamic banks. Of these, 133 banks were classified as failed bank as they experienced zero or negative equity, losses, and excessive loan losses as indicated by exceeding loan loss provision above their capitals.

Across-sectional analysis was conducted using the end year 2008 to 2014 financial bank report generated from Bankscope Database and pooled it into one group.

The samples were classified into two groups; namely the banks that failed during the 2008-2014 period and those that survived. Bank failure should first be determined here. The concept of failure varies between official failure, market failure or economic failure. These provide options for the research with the final choice largely depending on data availability. In this study, we follow Calice (2014) who studied an early warning system for banking in the MENA, using accounting data to define bank failure. The Early Warning System (EWS) used was quite successful in predicting the occurrence of insolvency events but failed with problems that originate from the liability side. We adopted this approach since regulatory action such as a forced merger, closure, or liquidity support were less likely to be announced during the crisisto prevent banking panic. Further, the incidence of bank's closure in ASEAN was relatively rare especially among conventional commercial and Islamic banks.

Three concepts of bank failure were applied here. If a bank thus assessed is included in this definition, the bank will be classified as a failed bank. The first concept is based on an equity position. A company that has zero or negative capital is classified as Zombie Company and economically it is bankrupt. In this study, a bank that owns zero or negative equity is defined as a failed bank. The second concept is based on profitability. The banking business is in the business of generating profit. When a bank fails to generate profits, its function as a business unit also fails, irrespective of the reasons. The third is the loan loss reserve (LLR). Since data on problem loans were not available for all ASEAN countries, we used a simple approach for higher credit risk using loan loss reserves (LLR). A high LLR is indicative of the bank experiencing high credit risk. In this study, we defined a bank as failed when its LLR exceedsits equity.

We adopted this definition since bank closure was relatively rare in ASEAN after the Asian crisis, especially among commercial and Islamic banks. The definition of bank failure followed that of Calice (2014) who studied an early warning system for banking in the MENA. In this paper, a bank was classified as failed when it experienced one of these: zero or negative equity, losses and excessive loan losses. The Early Warning System (EWS) is quite successful in predicting the occurrence of insolvency in samples. But it, however, failed with problems that originate from liability.

The Empirical Model and Variables

The model for the early warning system in lieu of bank failure is derived from the corporate bankruptcy literature as shown in Table 1.

$$\text{Failure}(P_i) = \alpha + \beta_1 \text{LIQASSET} + \beta_2 \text{CIR} + \beta_3 \text{ROA} + \beta_4 \text{LASSET} + \beta_5 \text{DER} + \beta_6 \text{LTA} + \beta_7 \text{ETA} + \beta_8 \text{INFL} + \beta_9 \text{EGRW} + \acute{\varepsilon} \qquad (1)$$

Since the dependent variable is dichotomous (1 represents a failed bank and 0 for one that survived), the appropriate estimation model to use in this study is the Logistic model. The model estimates the probability of failure from 0 to 1. The use of a Logistic model makes it possible to assess the results using standard regression procedures to determine the level of significance. At the same time, the probability of bank failure can be assessed. The estimation was carried out by using Stata and limited dependent variables by applying logistic regression.

From the variables mentioned above, we expect that all variables are capable of explaining bank failure in the ASEAN. This indicates that the variables can discriminate and predict that a certain bank will fail given financial information obtained one or two years before the event. Liquidity position can prevent and generate failure. Over investing in liquid assets reduces income and lowers profitability. Simultaneously, a stronger liquidity position enhances the bank's reputation and attracts cheaper fundsfor a profitable investment such as lending or interbank placement. The higher the liquid assets, the better the bank can fulfill its obligations to reduce the probability of failure.

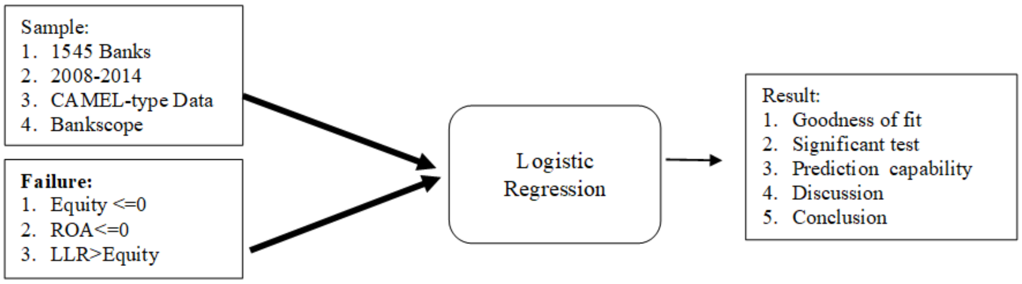

FIGURE 1. The Block Diagram of the Sample, Data and Model

TABLE 1. Variable, Definition and Expected Results

No	Variable		Dependent Variable	The expectation of Failure
1.	FAILURE	P_i	Dummy for failed = 1, 0 = Survived Failed is when zero or negative equity, losses and excessive loan losses	
			Independent Variable	
1.	LIQASSET	X1	Liquid asset / total asset	Positive / Negative
2.	CIR	X2	Cost to Income Ratio	Positive
3.	ROA	X3	Profit before tax / Total asset	Negative
4.	LASSET	X4	Log total asset	Negative / Positive
5.	DER	X5	Total debt / total equity	Positive
6.	LTA	X6	Loan / Total Asset	Negative/Negative
7.	ETA	X7	Equity to Total Deposit Ratio	Negative
8.	INFL	X8	Consumer price index	Negative/Positive
9.	EGRW	X9	Annual GDP growth	Negative

The higher the proportion of the cost to income (CIR) increases the probability of failure. Podpiera and Podpiera (2005) concluded that efficiency is a good indicator of bank failure. Liquidity is the ability of the bank to pay short term liabilities.

Bank profitability is negative to failure as the bank can generate more income relative to its spending. The profitable bank can also indicate the quality of management. Asset size can have positive as well as negative consequences. It can increase the risk of failure when the bank enters speculative business such as foreign exchange dealership or lending in speculative sectors such as oil and gas companies or risky commercial property lending. Big banks on the other hand can operate more efficiently due to economies of scale and scope.

Capital is the bank's defense against the probability of failure and it can provide a cushion against bankruptcy. The higher the amount of capital, the lower is the probability of a bank to fail. The capital strength variables, measured by equity to total assets ratio (ETA) are expected to give negative signs. Capital is measured using the debt to equity ratio (DER). Higher ratios will increase the risk of failures.

Loan to asset ratio (LTA) measures the risky asset of the bank. The higher the proportion of loans, the higher the probability of bank failure in the future if the loan defaults. It may indicate the aggressiveness with which managers handle risk. The more aggressive approach increases the probability of failure. In contrast, the loan is a profitable business if it is managed prudently and generates income for both depositors and investors.

The inflation rate may impact on bank failure. The rate is positive when inflation generates an economic problem for consumers and the economy in general then it increases problem loans, and fosters interest rate hikes. The inflation rate can also be favorable as it indicates a strong consumer demand that escalates spending. Economic growth is negative to failure as it signifies that the economy is growing and business activities are running well.

The Model Valuation

The early warning models were assessed for their ability to predict bank failure at one or two years before the event. The t-tests were used to examine the coefficients of parameters individually based on the null hypothesis that the coefficient of an individual parameter from the estimated model is zero. The t-value was derived from t-value (β_i-0/se) where 'se' is the standard error of estimates. With this analysis, we can reject or accept the hypothesis with a certain level of confidence.

The model applies pseudo R^2 to verify its capability in explaining the relationship between the response variable and predictors. According to Hosmer et al. (2013), the traditional R^2 carries bias when it is applied to a limited dependent variable model which employs the criterion of maximum likelihood. For predictive ability, the goodness of fit measure, such as the Chi-squared distribution, was employed since it is more appropriate for binary models.

To be effective, the early warning system model formulated should be able to discriminate between sound banks and those likely to fail. To assess this ability, we examined the correct classification of samples and the misclassification rate. This study covers type I and type II errors. A superior early warning model should have its type I error lower than its type II error.

RESULTS

In this study, a total of 1545 banks were sampled. Of these, 133 banks (9 % of samples) were classified as failed banks and the remainder (91%) survived the GFC. In the ASEAN, banks of Laos predominantly failed (58%) during the crisis, followed successively by banks of Cambodia (30%) and Thailand (15%). The remaining countries recorded less than a 10% failure rate. Surprisingly, all Brunei banks survived. The details are presented in Table 2.

Table 3 shows the descriptive statistics of the variables in this study. The failure rate of 9% represents the number of samples classified as failed banks. LIQASSET indicates the role of liquidity position on the bank's survival. The mean for LIQASSET is 11.88 which indicates that on average ASEAN banking holds 11.88% of its assets in liquid instruments such as cash, central bank securities, and short-term financial instrument. The lowest is less than 1% and the highest is 83% of bank assets.

TABLE 2. Failing rate of the ASEAN Banking

Country	FAILURE	SURVIVE	Failure Rate
BN	0	13	0%
ID	27	428	6%
KH	21	70	30%
LA	7	12	58%
MY	18	193	9%
PH	20	202	10%
SG	6	66	9%
TH	27	178	15%
VN	7	250	3%
Total	133	1412	9%

Note: Failure when equity negative, losses or loan provision exceed its capital.

Sources: Authors' Calculation

TABLE 3. Descriptive Statistics of Variables

Variables	Obs.	Mean	Std. Dev.	Min	Max
FAILURE	1545	0,09	0,28	0,00	1,00
LIQASSET	1545	11,88	12,07	0,21	82,29
CIR	1545	59,16	36,02	4,91	892,06
ROA	1545	1,30	1,77	-20,10	13,37
LASSET	1545	14,51	19,39	7,35	19,62
DER	1545	7,38	8,44	-83,41	178,83
LTA	1545	55,64	18,43	-0,90	95,37
ETA	1545	16,14	14,16	-1,2	97,27
INFLATION	1032	4,93	3,38	0,36	18,68
GDPGRW	1032	5,79	1,83	-1,75	15,24

Cost to income ratio (CIR) is the indicator of the operation efficiency of the bank. The higher ratio indicates correspondingly lower efficiency. The mean CIR here is 59% and standard deviation 36.02. It indicates that the distribution is very good since the means is larger than its standard deviation. The size of a bank's asset designates its ability to benefit from economies of scale and also implies its relatively larger size than those in less developed ASEAN countries such as Cambodia and Laos.

For the capital position, we used Debt to Equity ratio (DER) and Equity to Total Asset (ETA). On average, the DER is around 7.38 times, meaning that the average bank's debt is almost 7.5 times its equity. A bank that experiences negative equity also shows negative DER. However, a negative DER does not necessarily indicate good performance since it could be to the contrary. From Equity to Total Assets (ETA), we found that the mean is 16.14%. This shows that around 84% of bank assets are being financed by debt. For asset composition, we used Loan to Total Asset (LTA). In ASEAN banking, LTA is usually high since lending is the main business. The mean is 55.64 indicating that more than half of bank assets are loan or financing.

For macroeconomic variables, we employed inflation rate and GDP growth, with the former being the consumer price index. On average, inflation was 4.93%. The lowest inflation was recorded for Brunei and the highest Vietnam. The mean GDP growth was 5.7 with the lowest at 1.75% and the highest, 15.24%.

The predictive model was estimated using logistic regression from the Stata Software. Two models were employed for this study. Model 1 was the combination of bank-level data and macroeconomic data and used to determine bank failure or survival. Model 2 only applied bank-specific variables for estimation. The Chi-Square for model 1 was 25 and for Model 2, 38. Both were significant at 1% thus permitting their eligibility for further analysis. For Model 1 the total number of samples used was 1032 banks and for Model 2, 1545 banks. The difference was mainly due to the availability of macroeconomic data. Based on the Akaike Information Criterion (AIC) and Bayesian Information Criteria (BIC), Model 1 showed the lower value and thus assumed more superior. The panel variance between models was significant at 1%, which suggested that the predictive estimates using panel data were accurate. The regression output is presented below in Table 4.

The regression results presented in Table 4 showed that the liquid asset is positive but not significant. This suggests that the bank that holds more liquid asset is prone to failure as its income generation is lower. Such banks have a trade-off with investment opportunities such as loans. This result is interesting since previous findings were negative; i.e., liquidity position is beneficial during the crisis period. Both models have produced a similar result. The CIR for Model 1 was 0.09 and for Model 2, 0.08. Banks with a higher CIR ratio are not efficient and prone to difficulty in general and failure due to lack of efficiency. Both models produced

TABLE 4. Regression output for bank failure

No.	Variable	Model 1 (With Macroeconomic Variables)	Model 2 (Without macroeconomic Variables)
1	LIQASSET	0.0098	0.01
2	CIR	0.087***	0.081***
3	ROAA	-1.10***	-1.1***
4	LASSET	-0.19	-0.36
5	DER	0.12**	0.034**
6	LTA	1.9	-0.051
7	ETA	3.7	-2.3
8	INFLATION	-0.37*	
9	GDPGRW	-0.15	
	_Cons	-6.91	-3.60
	Lnsig2u		
	_Cons	1.91***	2.11***
	Pseudo R2	0.59	0.56
	Chi-Sq	329	485
	N	1032	1545
	Log Likelihood Chi-Sqrd	329	308
	Akaike (AIC)	245	399
	Bayesian (BIC)	389	437

Note: *. **, *** denotes level of significant at 5%,1% and less than 1%

similar results and were significant at 1%. Results from this study are expected to contribute to banks' efficiency which is critical to their survival.

The profitability coefficient for Model 1 was 1.10, and significant at 1%. This suggests that high profitability banks are less prone to fail. Model 2 showed a similar result at a coefficient of 1.12 and significant at 1%. The result generally supports the hypothesis that profitability is an important pillar for bank survival. The logarithmic form was used for asset size since the value can vary very much. Asset size is related to economies of scale. Both of the models showed negative values which suggest that large banks are stronger than smaller ones in managing the crisis. Large banks can distribute their business activities into various segments thus increasing the effect of diversification. The coefficient for Model 1 was -0.19 which means 19% less probability in experiencing a crisis. Model 2 produced a substantially greater negative value of -0.36. The results strongly confirmed that larger banks are more reliable than smaller ones in weathering out the GFC. This directly corroborates the implicit government support for such banks on the basis of too big to fail (TBTF) when they experienced difficulty.

In assessing the contribution of capital in preventing bank failure, the study applied debt to equity ratio (DER) and equity to the asset (ETA). DER was positive indicating when the leverage is too high, it is prone to failure. Large DER also suggested a high probability of failure. The coefficient for Model 1 was 0.12 which means a 12 % increase in the probability for failure when the DER is increased by 100%. Interestingly, when the estimation excludes the macroeconomic variables, the coefficient value was lower. In general, the result supports the findings of Mongid (2000), Hadad et al. (2004), and Montgomery et al. (2005) in that the bank-specific variables are the ultimate variable for bank's performance and indicative of the risk of failure. The finding (DER) confirms the need to limit the capital adequacy regulation not only to be based on asset risk but also liability risk.

The effects of other variables, such as equity to the total asset (ETA) and asset composition (LTA) were not significant. We expect that loan, as a liquid asset; will contribute significantly to the probability of bank failure during the GFC. However, the result varied with the findings of some contemporary workers. According to Antoniades (2015), the main characteristic of failed banks during the GFC was the excessive position in an illiquid asset such as a loan on the property sector. This finding was consistent with the subsequent conclusion by Lin and Yang (2016) who confirmed the role of profit in reducing the risk of failure in Asian banking. The finding also supported those by Jin and Kanageratnam (2011), Cole and White (2012), Beck et al. (2013) and Cleary and Hebb (2016).

The inflation rate is negative and significant at 5%. The rate reflects the ability of banking to benefit from the macroeconomic instability since it is indicative of the price bubble which reduces the effective cost of borrowing. It also reflects on strong consumers' demand in ASEAN. The inflation rate in the region tends to be higher than elsewhere. The study supports the findings of previous studies such as Hermosillo (1997) and Lin and Yang (2016). However, it differs from that by Demirguc-Kunt and Detragiache (1998). Other variables appeared no significant in influencing the risk of bank failure.

To assess the capability of models formulated to predict bank failure accurately, we developed and computed two types of error known as Type I Error and Type II Error and their combination. We preferred to present failure prediction error (failed banks predicted as survived) rather than an overall performance for banking supervision interest. The cost of predicting successful banks (i.e, those that survived the GFC) as failed banks is less costly than the reverse. When a bank is failed but predicted as survived, the resolution is more complicated because the problem recognition is too late. In general, Model 1, which included macroeconomic variables, correctly predicted 62% of the sample banks while Model 2, which excluded the variables, predicted 59%.

In summary, the results showed that the variables employed in the study are statistically significant. These comprised Cost Efficiency (CIR), Profitability (ROA), Capital Position (DER), and Inflation Rate. Findings on CIR supported those in previous studies such as Podpiera and Podpiera (2005), Almanidis and Sickles (2010), Sarifuddin et al. (2015) and Le and Viviani (2018). Findings on ROA agreed with those by Cole and White (2012), Jin et al. (2011) and Calice (2014). DER findings were also consistent with those by Cole and White (2012), Cleary and Hebb (2016), Hsu and Liu (2019), and Khokher and Alhabsy (2019). Finally, results on inflation were aligned with those by Hermoslillio (1997) and Lin and Yang (2016).

From the results shown in Table 5, we can infer that the models are not accurate enough in predicting failed banks. Model 1 performed better with an overall success rate of 62%. In comparison Model 2 scored marginally lower at 59%. Further investigations showed that the success rate in predicting bank failure using the models varies between countries in ASEAN with the Thai economy recording lowest accuracy.

To test the validity of the model we conducted some robust tests. The first test was the specification error. We used the link test for this purpose and recorded contradictory results that the predicted value (-hat) was found significant whereas simultaneously the variable-Squared (_hats) was also significant. Future research on bank failure should consider including other variables, together with their interactions. Our modeling however failed to consider the use of loan loss provision to total

TABLE 5. Model performance

Country	Model 1(With Macroeconomic Variables)			Model 2(Without Macroeconomic Variables)		
	Failure	Prediction	Performance	Failure	Prediction	Performance
BN	0	0	100%	0	0	100%
ID	13	9	69%	27	23	84%
KH	15	11	73%	21	15	74%
LA	2	2	100%	7	3	42%
MY	15	8	53%	18	8	44%
PH	13	8	62%	20	14	68%
SG	2	2	100%	6	45	74%
TH	16	6	38%	27	6	22%
VN	6	4	67%	7	6	81%
Total	82	51	62%	133	79	59%

Notes: Model 1 applies macroeconomic variables and owns fewer observations

loan ratio (LLR) as a potentially good predictor, since we were too focused on using the loan to asset ratio variable. The reason for not using the former variable (LLR) was to prevent multi collinearity as we define failure when loan loss provision exceeds the equity capital.

To support the Pseudo R-Squared, we apply the test of model fit known as the Hosmer and Lemeshow's goodness-of-fit test. It is to evaluate if the predicted and observed frequency in the same direction or not. A good model should produce a close relationship. The Hosmer–Lemeshow test showed that from the 10 groups, with 1032 observations, the Chi-Squared (8) value was 30.98 and Probability of 0.0001. It means the predicted and observed significantly differ.This suggests that the models failed to consistently predict the probability of bank failure. In addition, modeling using Probit regression and Skewed logistic regression produced less accurate results than those derived from traditional logistic regression.

CONCLUSIONS

This paper investigated the impact of the GFC on bank failure in the ASEAN banking market. Three conditions must be fulfilled to classify a bank as having failed based on equity position, credit risk, and profitability. On this basis,133 banks were classified as failed from a total of 1 545 sample banks. To provide further evidence on the validity of the models used to predict bank failure, we presented results on their capability to identify failed banks from successful ones. In general, the models showed low accuracy in predicting failure with a success rate of 62% for Model 1 and 59% for Model 2. The incorporation of other economic variables in the models appears to improve their predictive capability.

From our logistic regression, we can infer that the failure of the ASEAN banking is linked positively to cost inefficiency which suggests that the probability of failure is higher if the bank is not efficient. The debt to equity ratio (DER) is positive which implies that if a bank borrows excessively relative to its equity, the probability to fail increases. A bank with high profitability and a large size will have a lesser probability to fail. Interestingly, the inflation rate is negative indicating that a bank operating in a condition of relatively high inflation has greater chances to survive. Future studies should focus on the linkage between the micro aspects of banking firms and the macro-environment within which the bank is operating. On the definition of failure, further elucidation is necessary since the current one is insufficiently clear.

In general, there is a quality gap in the banking industry among members of the ASEAN. Fifty-eight percent of banks in Laos is considered failed, as compared to 30% in Cambodia, 15% in Thailand, and 9% for both Malaysia and Singapore. Failure rates in Brunei, Indonesia, and Vietnam are below average. The result revealed that banking in the more developed markets in ASEAN, such as in Thailand, Malaysia, and Singapore, are very sensitive to global economic disturbance. This wide region-wide variation in banking quality between member economies may pose constraints in the effort to realize the ASEAN Banking Integration Framework (ABIF). Theoretically, ABIF will benefit ASEAN as a whole but it may also create unequal competition. Since cost inefficiency is positive and significant, the Framework can be used as a foundation for corrective action by respective banking authorities in the future. To ensure the effectivenes of capital regulation, the banking authorities in ASEAN should complement it with limiting the debt to equity ratio as an additional tool for capital supervision.

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