Bank Failure Prediction: Empirical Evidence from Asian Banks- Impact of Derivatives and Other Balance Sheet Items

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Abstract

This research contributes to the literature on bank failure prediction by augmenting the set of traditional CAMEL bank-specific financial distress indicators incorporated in econometric bank failure forecasting models, with a range of indicators that capture information relating to a bank's business structure, off-balance sheet items, derivative investments and credit risk.

To evaluate both classification accuracy and to estimate probable time to failure, we use a Cox proportional hazards model incorporating an expanded vector of explanatory variables in the hazard function. Our data set comprises both publicly-listed banks and private banks, engaged in commercial banking or investment banking, from nine Central and East Asian countries, over the period 2000-2009. We also estimate a Probit model incorporating the same explanatory variables to provide a benchmark for evaluation of the classification accuracy of the Cox model. We find that while variables relating to a bank's derivative investments and credit risk have predictive power, variables relating to business structure and off-balance sheet items do not have a role in bank failure prediction in our sample.

1. Introduction

The Asian economic and financial crisis of 1997-98 had a devastating impact on the Asian region, leading to the near-collapse of a number of East Asian economies and the onset of economic recession and turbulence in financial markets. Intervention by the International Monetary Fund was required to support the economies of Thailand, Indonesia and South Korea.

It is widely agreed that the dominant cause of the crisis was financial sector vulnerability. The decade leading up to the crisis was characterized by liberalisation of financial markets and capital flows, and rapid credit expansion flowing from easy monetary policy. This resulted in increased levels of non-performing loans and increased volatility in asset prices. These factors, coupled with high debt-equity ratios in both financial and non-financial corporations, and inadequate financial sector supervision and regulation, combined to create an environment of financial sector vulnerability.

The crisis reached its nadir in mid-1998 and, although the recovery had begun in 1999, between 2000 and 2009 many Asian banks become inactive as they struggled through insolvency, bankruptcy and distress. As noted by Hutchison & McDill (1999), banks are sensitive to economic shocks and sudden changes in economic activity that makes them prone to failure, not only during periods of crisis, but for some years after that.

Given that bank failures typically have much greater and more far reaching adverse effects on economic activity than other corporate failures, it is not surprisingly that most countries subject the banking industry to greater regulation and closer supervision than other industries. This supervision normally involves periodic on-site examination of bank activities and records, as well as ongoing off-site surveillance to provide regulators with an early warning of potential problems. As noted by Gilbert, Mayer and Vaughan (2000), off-site surveillance involves the employment of both supervisory screens, which use financial ratios indicative of financial soundness to identify deviations from what regulators deem to be acceptable norms, and econometric models, which provide forecasts of the future financial health of the banks.

However, it is not only knowledge of the factors causing banks to struggle which is of importance to authorities and regulatory bodies. It would also be highly desirable to know *when* a financially troubled bank might fail. Being able to estimate survival time would enable a regulator to make a more informed decision about the timing and nature of any intervention that might be required.

This research contributes to the literature on bank failure prediction by augmenting the set of traditional bank-specific financial distress indicators incorporated in econometric bank failure forecasting models, with a range of indicators that capture information relating to a bank's business structure, off-balance sheet items, derivative investments and credit risk. As well as evaluating classification accuracy, we employ both the probit model and the Cox proportional hazard models to estimate the likelihood of failure and the probable time to failure, respectively.

Our paper is organized as follows. Section 2 contains a brief literature review, Section 3 discusses the additional explanatory variables we use, Section 4 explains the theory and methodology, in Section 5 we have outlined our data, in Section 6, we have presented and discussed our results and in Section, 7 we have summarized our conclusions.

2. Brief Literature Review

There is an extensive literature investigating which variables are most relevant for explaining and predicting bank financial distress[1] . Financial ratios have been used as bank-specific variables in many studies because they can assess an institution's probability of becoming distressed, insolvent or bankrupt (Rahman et al,2004).

The most widely adopted approach is the CAMEL principle which entails calculating and analyzing financial ratios covering five main areas: Capital, Assets, Management, Earnings and Liquidity[2]. It is widely agreed these five factors, also referred to as the "traditional CAMEL", allow a bank's distressed state of fragility to be identified and addressed before the bank actually closes down.

[1] See, for example, Altman (1981), Caprio and Klingebiel (1996), Demirguc-Kunt and Detragiache (1999) and Hardy and Pazarbasioglu (1998) for general surveys of the literature, and Rojas-Suarez (2001) for a survey of Asian and South American research.
[2] See Appendix for a description of CAMEL variables

Recently, Mannasoo and Mayes (2009), applying survival analysis through the use of a hazard function and a complementary log-log model (clog log), examined the joint role of macroeconomic, structural and bank-specific factors in explaining banking failure in Eastern Europe, and found that each of these factors played a role in explaining bank failure.

Molina (2002) used CAMEL variables and the Cox proportional hazard model with time-varying covariates to investigate which financial indicators could predict banking failure during the Venezuelan banking crisis.. The study concluded that the banks which failed were not only less profitable but had lower investments in liquid and sounder assets (government bonds). He also found that failed banks had lower operational costs and higher financial expenses, suggesting that banks in trouble had embarked on cost cutting as well as offering higher interest rates to try and attract depositors.

There have been few studies on banking failure prediction in Asian countries. Two of the most recent studies are by Bongini et al (2000) and Rahman et al (2004), both of which attempt to explain the factors which caused banks and financial institutions to become distressed. The period of these studies were between 1995 and 1997 and covered several East Asian countries including Indonesia, South Korea, Thailand, Malaysia and Philippines. All of these countries, except Philippines, have also been captured within our study.

Bongini et al (2000), found that the traditional CAMEL variables were still an accurate predictor of banking failure. Additionally, foreign ownership was found to make the bank less likely to close compared to privately owned institutions. The study also found that institutions which had strong relationships with "industrial groups" or "influential families" had greater probability of becoming distressed. This was because the connections allowed the institutions to enjoy exemptions from certain regulations, thus making them more fragile during times of crisis.

Rahman et al (2004) only focused on CAMEL ratios as explanatory variables. Using logistic regression, the study found that the only ratios which were commonly significant across all the countries within its study (Indonesia, South Korea and Thailand) were capital adequacy, loan management and operating efficiency.

3. Additional Explanatory Variables

In addition to CAMEL ratios, this study applies non-CAMEL ratios to assess bank performance. By combining CAMEL ratios with non-traditional indicators to assess the bank's business structure, exposure to credit risk, usage of derivative instruments and off -balance sheet items, we are applying a more comprehensive approach and can assess a bank's position more accurately.

To analyze the banks' business structure we have included two growth rates; loan growth rate and asset growth rate. The loan growth rate is important because it captures information regarding a bank's solvency, loan and risk position. Moreover, and as noted by Foos et al, (2007), it reflects the bank's dependency on interest income and thus indirectly, the bank's profitability.

The asset growth rate is used for its forecasting ability because past performance is often assumed to be a predictor for future returns (Cooper et al, 2008). Although the asset growth rate has been proven to be significant in the assessment of a bank's performance, its scope remains limited because it does not capture the value of potential growth or future opportunities that a bank may have, therefore must be interpreted together with other growth rates and ratios (Cooper et al, 2008). Our growth rates are calculated by comparing one year's performance against the previous year, to show if the bank has improved year-on-year and the degree of change it has undergone.

Balance-sheet figures can fail to capture the new business activities banks engage in. As off-balance-sheet activities are becoming more popular, especially in Asian countries, this poses questions on Asian banks actual liability and debt position However, a culture of non-transparency has prevented these questions from being considered seriously (Neftci, 1998). The prevalence of off-balance-sheet items hinders transparent reporting and skews the perception of external stakeholders who are unaware of the bank's overall exposure (Neftci, 1998).

The impact of off-balance-sheet portfolios on banks should be included in assessment of a financial institution's performance. Failure of which would exclude important information representing the institution's level of productivity and output. More importantly, ratios related to off-balance-sheet figures can provide useful indication of a bank's technological advancement and level of efficiency.

The most popular off-balance-sheet item is derivatives, which we have also included as an indicator to assess banking performance. Derivative instruments have become increasingly popular amongst banks and financial institutions. Derivatives are used for hedging, trading and , as noted by Kimball (2000), they allow a bank to diversify its capital portfolio, by altering proportions of debt and equity.

Derivatives were attractive because banks did not need to disclose derivative related activities or contracts. According to Mayer (1998), the Basel Committee's decision to give bank's the freedom to decide their own approach to disclosure meant that external stakeholders, including investors, could be easily mislead and reduced the central banks' monitoring abilities. However, following the global financial crisis, many accounting boards have updated their policies to push for greater transparency and fairer reporting for derivatives[3].

[3] Previously, for example, the Financial Accounting Standards Board (FASB)'s policy for derivatives and hedging was covered by FAS 133, *"Accounting for Derivative Instruments and Hedging Activities"* issued in June 1998. Recently, ASC 815 has been introduced as an Accounting Standards Update in March 2010 to overcome ambiguities related to credit derivative features (Shah and Bolton, 2010). As for the International Accounting Standards Board (IASB), which sets guidelines applied by more than 100 countries across the globe, it is planning to introduce reforms by 2013 to improve fair value reporting (Jones, 2010).

The final component we have used to assess banking performance is credit risk. This encompasses default rates, non-performing loans and debt. If previously credit risk was managed through the use of simpler insurance mechanisms, this process has become more complicated with the introduction of new instruments which allow risks to be transferred and migrated between different counterparties (Altman, 2001). Because of this, it is important we capture credit risk as a measure of banking performance. Although there is no consensus amongst central banks, regulatory authorities and financial institutions on the method in which credit risk should be measured, we have applied four ratios which should be able to capture key information related to loans, loan loss provision and deposits.

4. Theory and Methodology

We begin our research by using a Probit model to gauge the significance of each of our 16 explanatory factors and estimate the probability of an Active bank becoming Inactive. We will combine both data sets (inactive and active banks) and assign the value of 1 if the bank is inactive and assign the value of 0 if the bank is active. By doing this, the regression will be assessed based on the interaction of the two types of data. This will provide a better explanation of the significance and magnitude of each independent variable.

The probit function, based on the standard normal probability distribution, will give us the following equation as the density function,

$$? \; ??? = \frac{?}{???} \, ?^{??G?^{?}} \qquad (1)$$

In the function above, Z is a standard normal random variable (Hill et al, 2008).

Our probit function will be as follows,

? ???? ? ?? ? ??? ? ? ? ?????? ?? ? ? ??? (2)

Here ? ??? is the cumulative distribution function (CDF) that we have used to calculate normal probabilities.

The relationship between our dependent variable, Y, and the 16 independent variables can be estimated using the following model,

????? ? ??? ? ??? ? ? ?????? ? ?????? ? ????? ? ????? ? ?????? ? ?????? ? ??????? ??????? ? ????????? ? ?????? ? ?????? ? ??????? ? ?????? ? ?????? ? ?????? ? ?????? ? ?????? (3)

This probit model is non-linear and after estimating each ß value, we will be able to forecast the probability of a bank becoming inactive. The probit statistical model for this will be,

? ? ? ?? ? ?? ? ? ????? ? ?????? ? ????? ? ????? ? ?????? ? ????? ? ??????? ??????? ? ????????? ? ?????? ? ?????? ? ??????? ? ?????? ? ?????? ? ?????? ? ?????? ? ?????? (4)

? ? ? ??? ? ? ?????? ? ????? ? ????? ? ????? ? ????? ? ?????? ? ??????? ? ??????? ??????? ? ?????? ? ?????? ? ?????? ? ??????? ? ?????? ? ?????? ? ?????? ? ?????? (5)

Here ? ? ??? is the Probit function.

Although the Probit model allows us to forecast the probability of an active bank becoming inactive, the model is not multivariate, and thus, is unable to control the correlation between the different factors and variables. As pointed out by several researchers, for example Molina (2001) and Shumway (2001), it fails to consider the duration of the bank's survival and its results have higher likelihood of being biased and inconsistent because it is static.

Given the shortcomings of the probit model, we conduct a Survival analysis by applying a hazard model to investigate banking failure in more depth. A main advantage of using this analysis compared to probit and logitfunctions is that it is able to capture time variations in assessing the probability of a bank becoming inactive.

In survival analysis, the model will focus on the event occurring within a specific timeframe. In this case, our timeframe is between 2000 and 2010, whereby data is captured over the most recent four-years (t= 0, 1, 2, 3) of Accounting Reports published. For the purpose of predicting the probability of the active banks becoming inactive, the year that this is deemed to occur (when t=3) is the year in which the Last Accounting Report was published on Bankscope.

We apply the Cox proportional hazard model (Cox ,1972), where we model the time-to-failure as a function of our 16 variables. This model emphasizes the conditional probability rather than the unconditional probability that the event will occur. A bank, for example, will not be analyzed merely in terms of the probability of it closing down. Instead, we will analyze the probability of the bank closing down, given that it has been in distress for a specified period.

The survival analysis that we apply is built on two main concepts; the survivor function and the hazard function (Kiefer, 1988). In our sample of Asian banks, each bank is either “inactive” which includes an observable time component or “active” which are censored. The observations in our dataset are discrete whereby the figures are captured on an annual basis. We track each bank, i, in year t=0, 1, 2, 3 with t=3 being the most recent year. The banks that remained active until year of t=3, are treated as censored observations in the model. To consider this censoring, we apply Molina’s approach (2002), and include a dummy variable, d_i. This dummy variable is equal to 1 if the bank is inactive before t=3 and equal to 0 if the bank is still active at t=3.

Following Kiefer’s approach (1988), we denote T as duration and requires a distribution function to be specified.

? ??? ? ??? ? ?? (6)

This equation specifies the probability that T, which is a random variable, is less than the value of t. The corresponding density function is

? ??? ? ? ? ??? / ? ? (7)

Because we are studying data over a fixed duration, we need to define our Survivor function

? ??? ? ? ? ? ???

? ? ?? ? ?? (8)

We also need to define the Hazard rate.

? ??? ? ???? / ???? (9)

Another definition to clearly indicate probability is,

$$????\ ?\ \ ??\bullet_{???}\frac{??\,???\ 7\ \ ?\,WK\ 7\ ?\ W}{?}?\ \ \frac{????}{????}\ ?\ \ \frac{?????????}{??} \tag{10}$$

The hazard rate represents the continuous probability of a bank becoming inactive. This is the probability of inactiveness in a short period of time h, under the condition that the bank remained active until time t.

The proportional hazard model was suggested by Cox (1972, 1975). Since then, there have been various studies to adjust, extend and transform the Cox model. Cox's time-varying covariates were combined with time-independent parameters to allow for greater flexibility in a band-width selection in a study conduc ted by Tian et al (2005). As for Kraus (2007), in his study, the Cox model was combined with a smooth test based on Schwarz's model dimension rules.

We will be applying the Cox model in its original form, to model the Asian banks time-to-inactiveness as a function of different bank-specific financial ratios. This model is a partial-likelihood approach which is semi-parametric because ? (in the equation below) can be estimated without requiring a baseline hazard function to be specified. Assuming the durations follows a sequence of $t_1 < t_2 < \ldots < t_n$ then we will have,

$$\frac{???_{??}?_{??}??}{s^{?}_{???}\,???_{??}?_{??}??} \tag{11}$$

This represents a conditional probability for an observation 1 which has reached a conclusion at time of t_1. This is based on the assumption that any observation (n) could have also reached the conclusion at time t_1. Banks that are assigned a 1, for example, indicates it has reached its conclusion which is that it has closed down or become inactive.

The relationship between the time to event with the covariates is represented by the following equation,

(12)

??_???? ? ??_????? ?????????? g ???????

Here ?_??? is the baseline hazard and ?_??? is the hazard rate at time ???. Z represents the number of covariates.

This Cox model allows us to assess the probability of a bank failing and because we apply time-specific covariates, the model will simultaneously capture the banks' time to failure . The model also assesses the significance of each independent variable, therefore allowing us to understand better the main factors which cause banking failure as well as the way in which the variables interact with each other and the resulting event outcome.

5. Data

As explained above, the CAMEL ratios we have calculated are based on figures published in the balance sheets of the banks. The figures we have used for our data set are obtained mainly from Bankscope, a service provided by Bureau Van Dijk. We have included both publicly-listed banks as well as private banks. We include two types of banks: commercial banks and investment banks[4].

We have extracted data from nine countries from Central and East Asia: China, Hong Kong, India, Indonesia, Korea, Malaysia, Singapore, Taiwan and Thailand. These countries have either a developed, advanced economy or a developing, emerging economy.

We have two types of datasets; one for Active banks and one for Inactive banks. This depends on Bankscope's categorization of the bank. Active banks are banks which are still in existence and operating. For the category of Inactive banks, it will include banks which have gone through bankruptcy, insolvency or in liquidation.

Although Bankscope listed 105 inactive banks and 693 active banks for these nine countries, the total number of banks which had the relevant data was only 78 for inactive banks and 527 for active banks. This gives a combined total of 605 banks for our data sample.

The number of banks per country is summarized in Table 1.

[4] Whether a bank is labeled as a commercial bank or investment bank depends on Bankscope's categorization of the financial institutions

Table I: Summary of Banks per Country

Country	Active banks	Inactive banks	Country Total
China	63	11	74
Hong Kong	51	12	63
India	69	11	80
Indonesia	61	11	72
Korea	50	5	55
Malaysia	75	10	85
Singapore	32	5	37
Taiwan	96	10	106
Thailand	30	3	33
Total	527	78	**605**

We have chosen the period after the 1997 Asian financial crisis, which is year 2000 until year 2009. This means that we only capture data from banks that published their Last Accounting Report within this time period. Banks that published their Last Accounting Report prior to 2000 (for example 1999 or 1998) were excluded from the sample.

The figures extracted are from the most recent Report, up to the third year prior to it. This ensures that we capture data in the final year that an Inactive bank was able to produce an Accounting Report. In total, we capture four years worth of data. Banks which did not provide four years of data were excluded from the sample.

We have decided on 16 financial ratios to be our variables. Our first four ratios are based on the traditional CAMEL concept. Although we have selected indicators for Capital, Assets, Earnings and Liability, the "M" component was excluded[5] The other 12 ratios are non-CAMEL, non-traditional ratios which have only recently been applied to assess each bank's performance. Our non-traditional ratios cover four key areas: Growth Rate, Off Balance Sheet Items, Derivatives

[5] As noted by Mannasoo and Mayes (2009), management quality is often difficult to measure (Furthermore, other indicators already serve as an indirect assessment of management's performance, for example, cost efficiency, which is usually captured under Earnings quality (Molina, 2002).

and Credit Risk. All 16 ratios will be used as the independent variables in both the Probit and Cox models. These variables are defined and explained below.

Table II: Bank Financial Indicators

Independent Variables

	Variable	Formula	Symbol
1	Capital Ratio	Equity/Total Assets	Cap
2	Return on Average Assets	Net Income/Total Average Assets	ROA
3	Earnings Ratio	Cost/ Income	Eng
4	Liquidity Ratio	Deposits & Short Term Funds/Total Assets	Liq
5	Loan Growth Rate	Total Loans in t(1) / Total Loans in t(0)	GR1
6	Asset Growth Rate	Total Assets in t(1)/Total Assets in t(0)	GR2
7	Off Balance Sheet Ratio 1	Off Balance Sheet Items/Liabilities	Off1
8	Off Balance Sheet Ratio 2	Off Balance Sheet Items/Total Assets	Off2
9	Derivatives Ratio 1	Total Notional Derivative/Equity	Dvt1
10	Derivatives Ratio 2	Derivative Assets / Total Assets	Dvt2
11	Derivatives Ratio 3	Derivative Liabilities/ Total Liabilities	Dvt3
12	Derivatives Ratio 4	Total Notional Derivative/Off Balance Sheet Items	Dvt4
13	Credit Risk Ratio 1	Loan Loss Provision/Loans	CR1
14	Credit Risk Ratio 2	Loans/ Total Assets	CR2
15	Credit Risk Ratio 3	Loan Loss Provision/Total Assets	CR3
16	Credit Risk Ratio 4	Deposits & Short Term Funds/ Liabilities	CR4

6. Empirical results

6.1 Means Test

We calculate the mean and standard deviation of the 16 variables over the period of four years and compare our predicted outcome with the actual results. The results are summarized in Table III below and discrepancies have been highlighted in bold.

Table III: Analysis of All Variables
via Means Test

		Active Banks		Inactive Banks		Difference (Active - Inactive)	
	Variable	**Mean**	**Std Dev**	**Mean**	**Std Dev**	**Expected Result**	**Actual Result**
							(t-stat)
1	**Cap**	0.17995	0.20027	0.09272	0.10719	+	0.08723 (5.8359)
2	**ROA**	1.36375	5.02069	-0.01341	7.72189	+	1.37716 (1.5280)
3	**Eng**	58.55406	49.87307	60.15179	39.68738	-	-1.59773 (-0.3201)
4	**Liq**	0.69690	0.26245	0.81917	0.15599	-	-0.12227 (-5.8114)
5	**GR1**	1.54946	5.07743	1.07820	0.32604	+	0.47125 (2.1016)
6	**GR2**	1.27342	2.04022	1.07655	0.27486	+	0.19687 (2.0907)
7	**Off1**	0.56720	9.81837	0.33188	0.41338	-	**0.23532 (0.5469)**
8	**Off2**	0.89814	18.17228	0.41340	1.55151	-	**0.48473 (0.5978)**
9	**Dvt1**	0.43293	1.60152	0.68809	1.50758	-	-0.25515 (-1.3837)
10	**Dvt2**	0.00653	0.04235	0.00108	0.01038	+	0.00544 (2.4918)
11	**Dvt3**	0.00637	0.03780	0.00036	0.00340	+	0.00601 (3.5541)
12	**Dvt4**	0.91290	24.81894	0.00774	0.05687	+	0.90516 (0.8372)
13	**CR1**	0.05506	1.23643	0.02398	0.11150	-	**0.03109 (0.5618)**
14	**CR2**	0.46547	0.27555	0.67708	1.07777	-	-0.21162 (-1.7257)
15	**CR3**	0.00573	0.04952	0.01397	0.06635	-	-0.00824 (-1.0542)
16	**CR4**	0.57824	4.11751	0.88336	0.18053	-	-0.30512 (-1.6902)

For the CAMEL ratios, all four are consistent with our predictions. The Cap and ROA are higher for active banks compared to inactive banks due to better capital and asset portfolios, thus resulting in a positive mean when compared. Eng and Liq were negative as predicted because inactive banks are assumed to waste more on daily costs and expenses and would have more deposits than assets thus resulting in a negative means test result. However, the difference between means is not statistically significant for ROA and Eng.

The two growth rate ratios and the two off balance sheet ratios are all higher for active banks compared to inactive banks. We expected positive signs in the mean difference for the loan growth and asset growth because active banks should be stronger and have more consistent year-on-year performance. While we did not expect positive signs for the off-balance-sheet ratios, it should be noted the difference between the means for these variables is not statistically significant

We might speculate that active banks are more prudent and more transparent, thus they should maintain lower proportions of off-balance-sheet items relative to the size of their asset base and total liabilities. The means test result suggests that active banks are perhaps using off balance sheet items excessively. If inactive banks maintained lower ratios than active banks, this shows that they used less off balance sheet items, thus, the off balance sheet ratios might not be a significant factor leading to their failure.

For the derivative ratios, all variables had the expected sign, although the results for Dvt1 and Dvt4 were not significant.

Surprisingly, for the credit risk ratios, none of the differences in means were statistically significant. We had assumed that distressed banks would be facing higher numbers for bad loans which should have resulted in higher loan loss provision. However, CR1 produced a positive means test result which is different to our expectation as we had estimated that the ratio figures for inactive banks would be higher. As for the other three credit risk ratios, they all produced positive results which were consistent with our preliminary expectations, based on the assumption active banks would maintain stronger credit and loan portfolios relative to their assets and liabilities, but the differences were not significant.

6.2. Probit Model Results

We have examined the relationship between CAMEL and non-CAMEL variables by conducting four different regressions on variations of the Probit model. We expect the CAMEL variables to be the most statistically significant as they represent the key elements of a bank's performance; Capital Assets, Earnings and Liquidity. As for the Derivative and Credit Risk variables, we expect the outcome to be less significant because these are still relatively new areas of assessing banks within Asia and less data is available to conduct the testing.

We then identify which of the variables are able to maintain statistical significance across the different models and compare which of its coefficient had the greatest significance. We will use these selected coefficients to assess the type of relationship that the key variables have with banking failure.

In our first Probit model, we test the relationship between all 16 variables. This includes the 4 CAMEL variables, 2 Growth rate variables, 2 Off Balance sheet variables, 4 Derivative related variables and 4 Credit Risk variables. The results appear in Table IV below:

Table IV: Factors Determining Banking Failure

	Model 1		Model 2		Model 3		Model 4	
Intercept	-0.416539		-1.363971	***	-2.066201	***	-1.353729	***
	(-0.818623)		(-4.176091)		(-7.526579)		(-3.718166)	
					CAMEL Variables			
Cap	-3.229739	***	-0.849562		-1.006467		-3.063206	***
	(-3.671937)		(-1.563498)		(-1.626109)		(-4.360703)	
ROA	-0.051999		-0.029081	**	-0.041205	*	- 0.061080	**
	(-1.625462)		(-1.984425)		(-2.775575)		(-2.241365)	
Eng	0.003832	**	0.004181	***	0.000981		0.003551	**
	(-2.380984)		-3.334153		(1.174208)		(2.498981)	
Liq	-2.684657	***	0.310023		0.026648		-2.834870	***
	(-3.436109)		-0.906724		(0.041982)		(-4.370219)	
					Growth Rate Variables			
GR1	-0.2278621		-		-		-	
	(-1.215771)							
GR2	-0.386107		-		-		-	
	(-1.391287)							
					Off Balance Sheet Variables			
Off1	0.208893		-		-		-	
	-0.900922							
Off2	-0.328121		-		-		-	
	(-1.322933)							
					Derivative Variables			
Dvt1	0.501481	**	0.126496		-		0.533627	***
	(-3.126072)		(-1.114966)				(-3.718166)	
Dvt2	43.39615	***	-2.381812		-		45.14943	***
	(-3.962349)		(-0.831853)				(-4.360703)	
Dvt3	-184.6248	***	-21.9338	**	-		-189.0846	***
	(-5.196203)		(-3.002699)				(-5.952174)	
Dvt4	-0.167134	*	-1.278235		-		-0.182252	
	(-0.383933)		(-1.489210)				(-0.388325)	
					Credit Risk Variables			
CR1	-0.555603		-		-0.503203		-0.762813	
	(-0.661447)				(-0.990373)		(-0.957158)	
CR2	1.109292	***	-		0.476868	***	0.989143	***
	-4.134205				(3.267296)		(4.704850)	
CR3	-1.297429		-		0.593008		-0.857334	
	(-0.390947)				(0.567161)		(-0.282522)	
CR4	2.246385	***	-		0.919435	*	2.605656	***
	-3.934966				(1.881950)		(5.283963)	
Observations	1216		1674		2160		1624	
Pseudo R^2	0.147532		0.058448		0.062986		0.118191	

**, **, * Significance at 1%, 5% and 10% levels respectively. Z- statistics are in parentheses

The results of the regression show that none of the growth rate or off-balance sheet variables are statistically significant. From the CAMEL variables, the Cap, Eng and Liq were statistically significant and ROA was not. From credit risk variables, the only ones which were significant were CR2 and CR4. The derivative variables were the strongest factors with all four variables showing statistical significance.

In the second model, we only focus on the relationship between CAMEL and Derivative variables. Unlike in Model 1 which showed all derivative variables as significant, in Model 2, only Dvt3 was significant. CAMEL also deteriorated slightly with only two variables being significant. Surprisingly, one of these variables is the ROA which had not shown significance in Model 1.

We then examine the interaction between CAMEL variables and Credit Risk variables in Model 3. In this model, the CAMEL variables were less influential and three failed to reach statistical significance. Only the ROA maintained significance, but only at 10% level. Similarly, only two of the four Credit Risk variables produced statistically significant outcomes. CR2 was significant at 1% level but CR4 was only at 10% level.

For the final probit regression, model 4, we combine the CAMEL variables with the Derivative and the Credit Risk variables. By doing this, all four CAMEL variables and three of the Derivative variables showed outcomes which were statistically significant. As for the Credit Risk variables, CR2 and CR4 were statistically significance at a 1% level.

Overall, the only variables which were able to maintain significance for at least three of the four models are RoA, Eng, Dvt3, CR2 and CR4. From the results, we compare these variables across the four models to identify which of the coefficients had the greatest significance because these coefficients will show us the type of relationship the variables have when influencing the banks to become inactive. Table V below summarizes the significance level of the coefficients for the different models. The coefficient with the highest statistical significance is in bold.

Table V:
Comparison of Coefficients of the Most Significant Variables

Key variables	Coefficients	Prob.	Model
ROA	-0.029081	0.0472	Model 2
	-0.041205	**0.0055**	**Model 3**
	-0.06108	0.0250	Model 4
Eng	0.003832	0.0173	Model 1
	0.004181	**0.0009**	**Model 2**
	0.003551	0.0125	Model 4
Dvt3	**-184.6248**	**0.0000**	**Model 1**
	-21.9338	0.0027	Model 2
	-189.0846	**0.0000**	**Model 4**
CR2	**1.109292**	**0.0000**	**Model 1**
	0.476868	0.0011	Model 3
	0.989143	**0.0000**	**Model 4**
CR4	2.246385	0.0001	Model 1
	0.919435	0.5706	Model 3
	2.605656	**0.0000**	**Model 4**

For RoA, the most statistically significant is the coefficient in Model 3 which is a negative figure. This indicates that as the RoA increases, the probability of a bank becoming inactive will decrease. This is consistent with our preliminary assumption because an increase in RoA indicates the bank has strong income levels relative to a strong asset base. If these two elements continued to be positive, then this could help a bank to become stronger.

The second key variable is Eng, which represents the bank's earnings. This has been calculated as cost divide by income. The most significant coefficient for this variable is from Model 2 and is positive implying that as the cost to income ratio increases, the probability of the bank becoming inactive will also increase. This is realistic because a consistent increase in the ratio indicates that a bank's costs are increasing at a greater rate than its income. This demonstrates efficiency and if income levels cannot increase at the same rate or higher than cost, the bank's performance will continue to deteriorate.

From the derivative variables, Dvt3 was consistently significant. Dvt3 was calculated as Derivatives for Liabilities divided by Total Liabilities of the bank. The coefficients from Model 1 and Model 4 are equally significant and both have negative signs. This shows that as the Derivative Liabilities ratio decreases, the probability of a bank becoming inactive will increase. The ratio can decrease due to an increase in the bank's liabilities or due to reduction in the value of the derivative instruments. As the instruments become more out-of-the-money, the value of the derivatives used for hedging will deteriorate and will create greater losses upon mark-to-market assessment of the bank's position.

The two Credit risk variables which were significant were CR2 and CR4, both of which had positive signs. CR2 was computed as Loans divided by Total Assets, and CR4 was its counterpart, computed as Deposits & Short Term funds divided by Total Liabilities. The positive signs indicate that as these two ratios increase, so will the probability of a bank becoming inactive. These results are consistent with the general perception that a bank should not be too focused and too dependent on single components within its business activities to generate growth and profit for the bank.

CR2 would increase if loans increased at a greater rate than total assets, indicating that its expansion is not supported by an equally expanding asset base. This implies that although the bank is able to improve its figures for loans, it is unable to grow the rest of its assets which can place the bank in a vulnerable position. This principle also applies to CR4, whereby Deposits should always be within a reasonable proportion of the bank's total liabilities. If CR4 continues to increase, then the bank could eventually become insolvent and this could result in it closing down.

6.3. Results of Cox Model

While the Probit model provides insight into the main factors which determine the probability of a bank becoming inactive, it does not capture a time element because it is static in nature. Consequently, it is unable to identify the precise point in time when an ailing bank is expected to actually become inactive. To overcome this, we run further regression using the Cox proportional hazard model. The 16 independent variables and the dependent variable will remain unchanged for the four models, but we have added a time covariate as an additional variable which will enable us to understand banking failure patterns more accurately.

Our first Cox proportional hazard model, Model 1, captures the relationship between all 16 variables. The following variables were statistically significant; all 4 CAMEL variables (Cap, ROA, Eng and Liq), 1 Derivative variables (Dvt3), and 2 Credit risk variables (CR2 and CR3). None of the Off Balance sheet or Growth rate variables was statistically significant, which was the same as the Probit model 1. However, there was a distinction in the results of the Derivative variables of the Probit model, whereby all four were statistically significant. As for the CAMEL variables, only three from four were significant, excluding the ROA

.

From these 16 variables, 6 were selected for the Forward Stepwise (Likelihood Ratio) regression of the Cox regression for the Survival Analysis. The order in which the variables were entered into the model is as follows: CR2, ROA, Eng, Dvt3, CR4, and lastly, Dvt1. When we compare the Beta coefficients of these 6 variables against those from the Probit model, we can see that the results are similar, although not equal. For the ROA, the Cox model was -0.043 and for the Probit model was -0.05. The numerical difference is only 0.007 and the signs are both negative.

Table VI: Forward Stepwise

Bank Survival: Cox Model 1

		ß	Sig.	Exp(ß)	-2 Log Likelihood	Chi-Square	Sig.
Step 1	CR2	.254	.000	1.289	2336.386	24.934	.000
Step 2	ROA	-.051	.000	.950	2322.560	43.635	.000
	CR2	.253	.000	1.288			
Step 3	ROA	-.048	.000	.953	2312.764	57.210	.000
	Eng	.006	.000	1.006			
	CR2	.257	.000	1.292			
Step 4	ROA	-.047	.000	.954	2292.599	64.478	.000
	Eng	.005	.001	1.005			
	Dvt3	-26.845	.000	.000			
	CR2	.250	.000	1.284			
Step 5	ROA	-.044	.000	.957	2266.366	65.348	.000
	Eng	.005	.002	1.005			
	Dvt3	-144.390	.000	.000			
	CR2	.265	.000	1.304			
	CR4	.396	.127	1.486			
Step 6	ROA	-.043	.000	.958	2260.390	65.373	.000
	Eng	.005	.002	1.005			
	Dvt1	.639	.000	1.894			
	Dvt3	-181.783	.000	.000			
	CR2	.300	.000	1.349			
	CR4	.768	.001	2.155			

The numerical difference is also small for Eng (0.005 against 0.0038), Dvt 1 (0.639 and 0.501) and Dvt 3 (-181.783 and -184.62) and all three of these variables had coefficients with the same sign. Greater differences only became apparent when comparing the coefficients for CR2 (0.300 and 1.109) and CR4 (0.7680 and 2.246).

It is interesting to note that although ROA and Eng were also statistically significant at 1% level, the model chose CR2 as the first variable for the Stepwise. And although Dvt1 and CR4 were not statistically significant, when included in the model, the statistical significance of the model remains at 1% significance level overall. This indicates that both of these variables are able to explain variation in the time to the banks' failure, which cannot be explained by the other variables. The chi-square also continues to improve as these variables are included in the model.

In Model 2, we only examine the relationship between the 4 CAMEL variables with the 4 Derivative variables. We discover that the most statistically significant variables are still the same as in model 1. The variables include; Cap, ROA, Eng, Liq and Dvt3.

However, there was a difference in the order that the model entered the variables and removed them. The first variable, ROA, is followed by Dvt3 instead of Eng. And unlike in the previous model, Cap is also entered into this model. ROA however, is subsequently removed from the model just after Cap was added.

This is not surprising though because ROA is measured based on total average assets, and Eng and Cap are also ratios which incorporate total asset figures as their denominator. Because of this, ROA would not add variation in the time to a banks' failure that would be different to the variation already provided by Cap and Eng.

Table VII: Forward Stepwise
Bank Survival: Cox Model 2

		ß	**Sig.**	**Exp(ß)**	**-2 Log Likelihood**	**Chi-Square**	**Sig.**
Step 1	ROA	-.047	.000	.954	3246.865	21.682	.000
Step 2	ROA	-.045	.000	.956	3218.429	34.606	.000
	Dvt3	-27.381	.000	.000			
Step 3	ROA	-.042	.000	.959	3212.202	43.183	.000
	Eng	.004	.005	1.004			
	Dvt3	-26.402	.000	.000			
Step 4	Cap	-2.058	.005	.128	3202.244	50.745	.000

	ROA	-.017	.185	.983			
	Eng	.005	.001	1.005			
	Dvt3	-24.901	.000	.000			
Step 5	Cap	-2.651	.000	.071	3203.847	42.628	.000
	Eng	.006	.000	1.006			
	Dvt3	-24.531	.000	.000			

Table VIII: Forward Stepwise
Bank Survival: Cox Model 3

		ß	Sig.	Exp(ß)	-2 Log Likelihood	Chi-Square	Sig.
Step 1	Liq	2.510	.000	12.304	4091.329	44.585	.000
Step 2	Liq	2.399	.000	11.015	4080.494	71.515	.000
	CR2	.218	.000	1.243			
Step 3	ROA	-.022	.022	.979	4076.363	83.215	.000
	Liq	2.083	.000	8.030			
	CR2	.221	.000	1.248			

In Model 3, we only examine the relationship between the 4 CAMEL variables with the 4 Credit Risk variables. Compared to model 1 and model 2, Eng has deteriorated and is no longer statistically significant which also happened to Eng in the Probit model 3. The other 3 CAMEL variables (Cap, ROA & Liq) maintain their significance. From the 4 Credit Risk variables, 2 are statistically significant (CR2 & CR3), as they had been in model 1 also. In the Probit model, although the 2 Credit Risk variables were also significant, the other CAMEL variables were not as only the ROA was able to maintain significance, and only at a 10% level.

Liq was the first variable to be entered into the Stepwise, followed by CR2 and ROA. Unlike model 1, CR4 was not entered. Also, Cap and Eng were not included although they had been in model 2. This indicates that the CAMEL variables were more significant compared to the Derivative variables, but not as significant when compared to the Credit risk variables.

Table IX: Forward Stepwise.
Bank Survival: Cox Model 4

		B	Sig.	Exp(B)	-2 Log Likelihood	Chi-Square	Sig.
Step 1	CR2	.249	.000	1.283	3206.640	34.511	.000
Step 2	ROA	-.046	.000	.955	3192.521	53.740	.000
	CR2	.249	.000	1.282			
Step 3	ROA	-.045	.000	.956	3163.872	64.172	.000
	Dvt3	-28.331	.000	.000			
	CR2	.243	.000	1.275			
Step 4	ROA	-.041	.000	.959	3124.230	65.112	.000
	Dvt3	-173.599	.000	.000			
	CR2	.264	.000	1.302			
	CR4	.461	.052	1.586			
Step 5	ROA	-.041	.000	.960	3116.939	65.194	.000
	Dvt1	.706	.000	2.027			
	Dvt3	-212.448	.000	.000			
	CR2	.301	.000	1.351			
	CR4	.870	.000	2.386			
Step 6	ROA	-.038	.000	.963	3110.714	75.790	.000
	Eng	.004	.006	1.004			
	Dvt1	.698	.000	2.011			
	Dvt3	-208.279	.000	.000			
	CR2	.302	.000	1.352			
	CR4	.860	.000	2.364			

In Model 4, we examine the relationship between the 4 CAMEL variables, the 4 Derivative variables as well as the 4 Credit risk variables. We still excluded the 2 Growth Rate variables and 2 Off Balance Sheet variables as none of these variables were statistically significant in either the Cox Model 1 or the Probit Model 1.

All four CAMEL variables are significant but only one Derivative variable (Dvt3) was significant also. Nonetheless, in the Stepwise, Dvt3 as well as Dvt1 were entered. Only Dvt2 was excluded. This indicates the model was able to derive some value in Dvt1's figures and recognized its contribution in explaining the banks' survival. Despite the variable not being statistically significant on its own, when entered into the Stepwise, the overall model improved its Chi-square and the statistical significance did not reduce.

One Credit risk variable (CR2) was significant and was captured in the Stepwise. All the same variables are entered into the Stepwise as in model 1, but in a different order. Eng was the 3rd variable entered in model 1, but in model 4, it was the 6th and final variable entered.

Although model 1 and model 4 captured the same variables, the Chi-square of model 4 is higher than in model 1. Nonetheless, the significance levels are still the same, confirming that the combination of these 6 variables in the Cox proportional hazard model is the most effective way to predict a bank becoming inactive.

7. Conclusion

By applying two different empirical models and using data for Asian banks from the Bankscope database, it is possible to identify bank-specific variables which determine an Asian bank's probability of becoming inactive. The two models applied were the Probit model and the Cox proportional hazard model.

We discovered that for the independent variables, all four CAMEL ratios were influential factors in at least two from the four Probit models and corresponding Cox models. But for the non-traditional, non-CAMEL variables, only ratios for derivatives and credit risk were found to be significant. The off-balance sheet ratios and growth rates were not significant in either the Probit or Cox model.

For the Probit models, the first model which included all 16 variables had the highest Pseudo R^2, indicating it had the highest log-likelihood and was the best fit. For the Cox model, we assess the model's suitability based on the Chi-square. We identified model 3 and model 4 as having the best fit between the data and our hypothesis.

Although both models provided similar significance levels for the independent variables, the Cox model was able to construct a more inclusive and in-depth picture about Asian banks' performance and the probability of their failure.

We conclude that the Cox model is superior to the Probit model for two main reasons. The Cox model was able to identify the contribution and value of a variable to the overall model, regardless of their preliminary level of statistical significance. Secondly, in forecasting the probability of a bank becoming inactive, the Cox model is able to identify a specific point in time that this will occur. This is because it includes in its regression time varying covariates as a third type of variable to interact with dependent and independent variables.

We recommend that further studies be conducted to examine banks from the Asian countries which we were not able to include in ours due to data limitations. As our study has established that the non-traditional ratios for derivatives and credit risk are significant, further studies should also test the interaction between these ratios with macroeconomic and structural factors. Such tests would have the potential to explain more comprehensively banking performance and probability of failure within the Asian region.

Appendix 1

Traditional CAMEL Variables

Capital Ratio (Cap): The capital ratio is formulated as Equity/Total Assets. It is very widely applied because Capital is a fundamental component of a bank's structure and Equity provides protection against asset malfunction. It is viewed as a buffer which can support a bank 's losses and reduce its risk (Mannasoo & Mayes, 2009; Shen & Hsieh, 2004; Arena, 2005). The Capital Adequacy Ratio for inactive banks should be lower than for active banks.

Assets (ROA): We measure the quality of Assets through the Return on Average Assets which is very similar to the Return on (Total) Assets ratio. Our ratios is calculated as Net Income/Average of Total Assets (Derviz & Podpiera, 2004; Rahman et al, 2004; Arena, 2005;). This ratio gives us an indication of the bank's ability to use its assets to generate income which subsequently translates into profit. Because of this, it is applied as a profitability index (Molina, 2002). The ROAA for inactive banks should also be lower than for active banks.

Earnings Ratio (Eng): Our indicator for earnings is the Cost to Income ratio. It compares the changes in costing against the changes in income whereby the former should not be increasing at a faster rate than the latter. This ratio also reflects on the management's efficiency. The formula is Overheads/ (Net Interest Revenue + Other Operating Income). The Cost to Income ratio for inactive banks should be higher than for active banks as an indication of poorer earnings performance.

Liquidity (Liq): The liquidity ratio is defined as Deposits & Short Term Funding/ Total Assets (Cole & Gunther, 1998; Bou-Said & Saucier, 2003; Rahman et al, 2004). The Numerator of the formula includes customer deposits, deposits from other banks as well as short-term borrowings. Banks have to monitor liquidity closely because it must be able to daily withdrawals and obligations to its customers. It must be prepared to face sudden deposit shocks which may require emergency borrowing at higher costs (Rahman et al, 2004). The Liquidity Ratio for inactive banks should also be higher than for active banks.

Additional Variables

Loans Growth (GR1): The Loan growth rate is calculated by dividing the current year's total loans over the previous year's total loans. Growth rates are important to assess a bank's business structure and to evaluate if the year-on-year performance is improving or deteriorating. The Loans growth rate for inactive banks should be lower than for active banks.

Assets Growth (GR2): This variable is similar to the Loans growth rate and is calculated by dividing the current year's total assets over the previous year's total assets. In addition to assessing the bank's current performance, compared to previous years, the Assets growth rate can also be used as an indicator of future performance and can be a powerful forecasting tool for the bank (Cooper et al, 2008). The Assets growth rate for inactive banks should be lower than for active banks.

Off Balance Sheet Ratio 1 & 2 (Off1 & Off2): Off Balance Sheet Items include guarantees, acceptances and documentary credits reported off-balance sheet and Other Contingent Liabilities. These items do not form part of the bank's Balance Sheet, but the database we have used, Bankscope, publishes this additional information in the form of a Memo to the Balance Sheet.

For Off1, we divide the total Off Balance Sheet Items by Total Liabilities and for Off2, we divide the total Off Balance Sheet Items by Total Assets. A bank's performance could be misleading due to its Off Balance Sheet items. Because of this, it is important to track the percentage of these Items against the bank's liabilities and assets to ensure a more accurate representation of the bank's position. The Off Balance sheet ratio figures should be higher for inactive banks compared to active banks.

Derivatives Ratio 1, 2,3 & 4 (Dvt 1,2,3 & 4): Derivative ratios were not a common indicator for banks in Asia but have become more relevant after the global financial crisis in 2008. Dvt 1 is a comparison between Total Notional Derivatives and Total Equity, Dvt 2 is the Derivatives Asset ratio, Dvt 3 is the Derivatives Liabilities ratio and Dvt 4 is Total Notional Derivatives divide by Off Balance Sheet Items.

The Derivatives Liabilities component captures the out-of-money derivatives used for trading and hedging which has been netted off against market value, then divided by Total Notional Derivatives. The Derivatives Assets component captures the at-the-money derivatives used for the same purposes. Total Notional Derivatives represents the combined value of these two components.

Credit Risk Ratio 1, 2, 3 & 4 (CR 1,2,3 & 4): We measure a bank's Credit Risk by calculating different formulas which compare the bank's loans, deposits and loan loss provisions against the bank's total assets and liabilities. Higher levels of these ratios are a warning signal that a bank is facing financial problems and is at risk of becoming insolvent (Rahman et al, 2004). We expect the Credit Risk ratios to be lower in active banks compared to inactive banks.

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