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Bank Failure Model for Asian Financial Crisis and Subprime Mortgage Crisis: A Comparison*

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This paper is to examine the determinants of bank failure/merger timing in 10 East Asian countries during 1999-2007, using a multivariate logit model and a split population duration analysis, as well as 6 North American & West European countries during July 2008-September 2009. It shows that capital adequacy, asset quality, earnings, sensitivity to market risk and private sector credit/GDP ratio significantly affected the financial institutions failure probability during both crises. The deposit growth and the liquidity had weekly significant effect on due to the government bailouts and the unconventional Quantity Easing (QE) Monetary Policies during the Global Financial Crisis. However, liquidity and asset scale variables are two important factors to lower the failure probability during the Asian Financial Crisis.

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1. INTRODUCTION

During the past two decades, many countries with developed and emerging market economies have experienced large-scale financial sector crises. Of particular note are the Mexican currency crisis (1994-1995), the Asian financial crisis (1997-1998), the Russian debt crisis (1998), the Brazilian financial crisis (1998-1999), the Turkish financial crisis (2000-2001), Argentina's external debt crisis (2001), and the U.S. subprime mortgage crisis (2007-2009). As a result, both the academic and official sectors have begun to develop early warning system (EWS) models to predict the future risk of financial institution failure.[1) Many EWS studies have been primarily concerned with explaining bank failure and most have tended to focus on either individual country's financial institutions or on financial institutions among a large number of countries with widely differing economic and financial systems. The EWS model in this paper firstly focuses on ten East Asian countries after the Asian financial crisis of 1997-1998, and secondly on six North American and West European countries, that exhibit similarities among their economic and financial systems and are geographically proximate to one another. Our goal is to examine factors influencing bank failure and survival time. Bank-specific factors, macroeconomic factors and financial factors are the major determinants with which we are concerned.

The empirical period that we chose is divided in two periods. One is from 1999-2007, and the other is from July 2008-September 2009. The reasons for such kind of separation has three meanings. Firstly, two different kinds of financial crises with large different degrees of scale and geographical areas of financial contagion. The Asian Financial Turmoil is a regional financial crisis and thus reveals relative small scale and contagion impact on the East Asian Economy and Financial Markets. Moreover, the origin shock of the Asian Financial Crisis was due to the speculative attacks on different currency and equity markets. However, the Subprime

[1)] See Wu *et al*. (2000) and Sahajwala and Bergh (2000).

Mortgage Crisis was due to the government negligence supervision, financial liberalization policies, highly growth of financial innovation, as well as the low interest rate monetary policy in 2003-2005 and lax enforcement of financial regulation as pointed by Taylor (2014, p. 63).[2)]

Secondly, this study focuses on ten East Asian countries after the Asian financial crisis of 1997-1998, and on six North American and West European countries during the Subprime Mortgage Financial Crisis, that exhibit similarities among their economic and financial systems and are geographically proximate to one another. The reason why we had chosen the sample period for different regions is due to the fact that during the GFC period there were 35 large financial institutions with failure and acquisition/bailout were not in East Asia, including HSBC Bank, Citygroup Inc., Wels Fargo & Company, etc. And the government bailouts during GFC are quite huge comparing with those during the Asian Financial Crisis. Furthermore, for the data chosen, in the Asian Financial Crisis case those in the countries experienced financial crisis and not experienced (e.g., Japan and Singapore) are included. However, only those countries had experienced serious financial crisis during the Subprime Mortgage Financial Crisis are explored.

Thirdly, most East Asian governments during the study period started to do financial reforms after the great shock of Asian financial crisis and Russia debt turmoil. For example, the Japanese government had adopted the swift removal of remaining financial regulations to bring Japan up to the international level of deregulation, and to place Japanese financial institutions on an equal footing with world competition. The revision of the Foreign Exchange Law took effect in April 1998. And the Japanese version of the “Big Bang” of the financial deregulation program was implemented between 1997 and 2000. The deregulation to encourage competition among financial market players in the world inevitably resulted in more bankruptcies among financial institutions. Likewise, Taiwan government also reformed the financial industry from 2001 to 2011. These

[2)] See Hsu and Tsai (2017).

actions allowed those banks with serious bad loan problem to exit the market. As for Singapore, despite its highly open economy, Singapore did not bear the full brunt of the crisis. Nevertheless, Singapore was still affected by the crisis, even as its fundamental economic policies remained sound. Specifically, the contagion effects of the Asian Financial Crisis adversely affected Singapore's currency and asset markets, banking and corporate sectors, and overall prospects for economic growth. However, Monetary Authority of Singapore reiterated the government's commitment to currency stability and short-term capital mobility, and Singapore's response to the Asian Crisis relied heavily on fiscal measure. Basically, Singapore's banking and financial system is sound in the East Asia. Moreover, most of the East Asian countries accumulated lots foreign reserves after the Asian financial crisis. These could explain why after the Asian Financial Crisis the financial institutions in Japan, Singapore, Taiwan, etc. came over the strongly impact of the Global Subprime Financial Crises.

2. LITERATURE REVIEW

The empirical literature on the EWS model of banking failure is large and makes use of a wide variety of different techniques. For example, Altman (1968) first used U.S. financial ratio data and applied multiple discriminant analysis (MDA) to predict corporate bankruptcies.[3] MDA is not easy to utilize in practice because it must meet the requirements of normal distribution and an equal covariance assumption. Subsequently, both logit and probit regression techniques have been used to provide a measure of probability for bank failure. Studies that have adopted the latter approach include Cole *et al*. (1995), Demirquc and Detragiache (1998), Poon *et al*. (1999), Hardy and Pazarbasioglu (1999), Bongini *et al*. (2001), Daniel (2004), and Daley *et al*. (2008).

There are also numerous other techniques that have been applied to bank

[3] See Sinkey (1975) and Altman *et al.* (1981).

failure prediction. Lane *et al*. (1986) based a survival analysis on Cox's proportional hazard model, utilizing data from the U.S. bank failures from the period 1979-1984. Later, Whalen (1991) and Wheelock and Wilson (1995, 2000) also used Cox's proportional hazard model to explain failure and survival of the U.S. commercial banks. These studies found that capital adequacy, return on assets, and non-performing loans are useful in explaining the probability of bank failure and survival time. Wheelock and Wilson (2000) further showed that the number of branches and technical efficiency were important factors in determining bank bankruptcies.

Cole and Gunther (1995) applied the split-population survival time model to predict the time of failure for 1043 banks in the United States during the period 1986-1992. Their empirical results show that the factors influencing the probability of bank failure may be different from those that explain survival time. Additionally, Dahl and Spivey (1995), Hunter *et al*. (1996) and De Young (1999, 2003) applied the split-population survival time model to de novo banks, undercapitalized banks and commercial banks. Maggiolini and Mistrulli (2005) also used the model to examine the determinants of survival and survival probability of the Italian Cooperative Credit bank during the period 1990-2000. Their results show that survival is related to both the market share of large banks and local GDP. Evrensel (2008) applied parametric and non-parametric survival analysis to explain the effects of bank concentration, regulations, and macroeconomic policies on bank failures. Her results showed that a lower inflation rate, a lower domestic credit growth, a lower real interest rate, a higher real GDP growth, and a depreciation of home currency result in a low probability of bank failure.

Arena (2008) estimated the logit and survival duration models by using bank-level data from banking crises occurring in the 1990s in East Asia and Latin America to examine the determinants of bank failure; the results showed that bank-level characteristics not only significantly affect the likelihood of bank failure but also explain why banks are likely to fail. He also completed a survival time analysis in the Latin American case and found that bank system liquidity and macroeconomic variables (such as real exchange rate volatility and GDP growth rate) also help explain the likelihood of failure.

A number of papers have studied Taiwan's financial institutions. For example, Lee (1993) applied the accelerated failure time model to Taiwan's credit union data to estimate the hazard function and the determinants of survival time. Chuan and Jang (2002) employed a parametric survival analysis model to examine the determinants of the exit of foreign banks in Taiwan. Hsu *et al*. (2003) used parametric survival analysis to explain the effects of bank failure in six East Asian countries, including Taiwan, Korea, Thailand, Indonesia, the Philippines, and Malaysia, during the period 1997-2000. Their results found that macroeconomic variables, bank scale, operating efficiency and capital adequacy play significant roles in explaining survival times and crisis probabilities of banks in those countries.

Chen and Wang (2007) took a sample of merging financial institutions and financial holding companies and applied the parametric survival analysis model to measure the spell lengths of hazard rates. They showed that with fewer branches, lower total asset turnovers and smaller ownership by directors and supervisors, financial institutions might reduce the spell lengths required to merge. Yu *et al*. (2008) chose a mixed distribution function for the split population duration model to investigate bank runs in the credit department of Farmer's Institution. Their results found that higher ratios of insured borrowing to total borrowing or joint deposit insurance were likely to both postpone bank runs and lower the risk of bank runs.

In this paper, firstly we apply the split-population survival model as well as the basic duration model like the logit model and the survival analysis models to investigate the factors determining bank failure in ten East Asian countries during the period 1999-2007. The former methodology is adopted because it assumes that some banks will never experience exits and, therefore, the results are more appropriate than those resulting from standard survival analysis. This is the first study to use the split population survival model to predict bank failure in East Asian countries. For comparison purposes, we also apply both logit and parametric survival analysis models. It should be noted in this study, we had adopted some results from Hsu and Liu (2014).

As pointed out in previous split-population duration studies such as Schmidt and Witte (1989), Cole and Gunther (1995), De Young (2003), the basic duration model's shortcoming lies in its forced assumption that every bank would eventually fail as time at risk becomes sufficiently large. The other shortcoming, as pointed out by Cole and Gunther (1995), is that the likelihood function fails to distinguish between the determinants of failure and the factors influences the timing of failure.

How do we rationalize the assumption that some banks in the population data will never fail? As we will see in the following estimation results of subsection 4.1.2, in East Asian Countries the bank scale in terms of asset is relevant to the bank survival in the long run. And the estimation result also shows that high leverage ratio to raise bank asset is also statistically significant to bank increase survival duration. Large banks are typically better diversified, and ceteris paribus, large size may indicate a better managed or otherwise more successful bank. However, this may also support the "too big to fail doctrine", since in most countries during this financial crisis those endangered or at-risk larger bank received financial and other assistance from regulatory authorities.

Moreover, in this study we did not extend the sample period for East Asian countries to include the effect of 2008 Global Financial Crisis (GFC). The reason is that during the GFC period there were 35 large financial institutions with failure and acquisition/bailout were not in East Asia, including HSBC Bank, Citygroup Inc., Wels Fargo & Company, etc. as we could see from table A2 in the Appendix. And the government bailouts during GFC are quite huge comparing with those during the Asian Financial Crisis.

Secondly, we apply both logit and survival analysis models, including parametric and nonparametric ones to analyze bank failure in North American and West European countries in 2008-2009. It should be noted that the split-population survival model was not utilized to analyze the

Subprime Mortgage Financial Crisis case and only applied to the Asian Financial Crisis case. This is due to the fact that there were bailouts and the too big to fail policy during the study period.

This paper is organized as follows. Section 1 is introduction and section 2 is literature survey. Section 3 discusses our sample data and describes the methodology used. Section 4 summarizes the empirical results. Section 5 discusses the conclusions of the study.

3. DATA AND METHODOLOGY

3.1. Data Description

In this paper, we firstly investigate the failures of commercial banks in ten East Asian countries: Taiwan, Japan, Hong Kong, Korea, Singapore, China, Indonesia, Malaysia, the Philippines, and Thailand. The data cover the period 1999-2007 and the countries were observed annually. The sample contains 349 banks, including 297 normal banks and 52 failed banks, with complete records from 1999 to either the year of exit or to the final sample date, 2007.

Secondly, we go further to analyze the failures of different kinds of banks and financial holding companies in North American and West European countries. The sample contains 696 banks, including 661 normal banks and 35 failed banks during July 2008 and September 2009. These 35 failed banks are in 6 countries: 18 in the US, 10 in the UK, 3 in Iceland, 2 in Belgium, 1 in Germany, 1 in Ireland. Among these 35 failed banks, there are 16 commercial banks, 11 financial holding companies, 1 investment bank, 4 mortgage banks, 3 savings banks.

Macroeconomic and financial data for each country were collected from World Development Indicators (WDI). The bank-level balance sheets and income statement data used are from the BankScope database, published by the Bureau van Dijk (BvD). The sample was split into two groups: failed

Table1 Number of Bank Mergers and Duration by Country and Year

(unit: number, years)

Country	Number of banks			Duration (in years)			
	Exited	Other	Total	Mean	Standard deviation	Min	Max
Taiwan	4	28	32	42.03	31.59	10	108
Japan	19	113	132	75.94	27.15	7	134
Hong Kong	5	20	25	58.76	17.87	25	95
Korea	3	14	17	45.94	21.34	24	110
Singapore	2	5	7	55.00	13.53	39	75
China	1	37	38	20.11	22.13	9	99
Indonesia	6	33	39	30.38	20.10	10	94
Malaysia	8	18	26	48.42	32.34	8	132
Philippines	3	17	20	50.60	32.00	10	156
Thailand	1	12	13	60.92	15.79	38	101
Total	52 (14.90%)	297 (85.10%)	349 (100%)	54.48	32.27	7	156

Notes: Data come from author. The number in parentheses indicates the number of event banks as a fraction of the total number of sample banks.

and non-failed banks. Table 1 provides the frequency distribution of our sample with respect to surviving and distressed banks in the East Asian countries. Total of 349 banks were assessed, 52 of which were classified as failed.[4] The average survival time was 54.48 years. Japan had the most failed banks, followed by Malaysia and Indonesia. Thailand and China had the lowest number of failed institutions. The maximum survival time is 156 years (in the Philippines). The minimum survival time was 7 years (in Japan).

The bank-specific variables studied are mainly based on the CAMELS rating categories (capital adequacy, asset quality, management, earnings, liquidity, sensitivity to market risk), and growth and size, which are taken from banks' financial statements. For macroeconomic and financial

[4] A bank is identified as being in distress when at least one of the following criteria is met, according to the information from the BankScope database: bankruptcy, dissolved merger or in liquidation. Of the 52 distressed banks, 1 was further classified as in bankruptcy, and the remaining 49 were classified as dissolved mergers.

variables, we used six indicative measures, which are commonly adopted in the literature: GDP per capita growth, inflation, real interest rate, M2/foreign exchange reserves, domestic credit growth and the volatility of the exchange rate.[5] Table A1 in the Appendix summarizes bank-specific, macroeconomic and financial variables, along with the expected signs of their impact on the likelihood of a bank's failure and survival time.

3.2. Methodology

Our empirical analysis of banking failure adopted a survival analysis. Most studies of survival analysis are based on the parametric model and Cox's (1972, 1975) proportional hazard rate model; however, these models' assumption that each bank will eventually experience an exit is not appropriate. In fact, it is possible that some banks will never experience exits. The split-population duration model relaxes this assumption by essentially splitting the sample into two groups: one group that will eventually experience an exit and another group that will not. Thus we assume that the probability that δ a bank will eventually exit is less than one. Let F be a binary variable that equals one for banks that eventually exit and zero for those that will never exit. Then, we assume

$$P(F=1)=\delta. \tag{1}$$

$$P(F=0)=(1-\delta). \tag{2}$$

The parameter $\delta<1$ is the "split population parameter" that denotes the probability of eventual exit, and $1-\delta$ is the survival rate.

We define a cumulative distribution function $F(t|F=1)=P(T\le t|F=1)$ for banks that ultimately exit, and let $f(t|F=1)$ be the corresponding probability density function. Let T be the length of time that passes before a bank ultimately exits. Similarly, the survival function conditional on F=1

[5] See Demirgüc-Kunt and Detragiache (1998, 2005), Kaminsky and Reinhart (1999), and Davis and Karim (2008).

can be written as $S(t|F=1)=1-F(t|F=1)$.

The hazard function $h(t)$ can be written as a function of $F(t)$ and $f(t)$ as follows:

$$h(t) = f(t)/[1-F(t)] = f(t)/S(t), \tag{3}$$

where $1-F(t) = S(t)$ is the survival function, the probability that a bank has not failed as of time t. The function $h(T)$ gives the probability that a bank will fail at T conditional on surviving until T. When estimated, the general shape of the hazard function is constrained by the functional form of the probability distribution $F(t)$ imposed on the data. The log-logistic distribution, a relatively flexible form that yields a hazard function that is non-monotonic in t with up to two inflection points, is used here.

Next, let Q_i be an indicator variable that equals one for an uncensored observation and equals zero otherwise, i.e., Q_i=1 for a bank that exits, and Q_i=0 for a bank that survived the entire sample period. The number of banks in the sample is denoted as N. For cases that experience exit, Q_i=1, which implies that F=1. For these observations, the appropriate density is as follows:

$$P(F=1)P(t_i \le T|F=1) = \delta f(t|F=1). \tag{4}$$

On the other hand, for sample banks that would never exit, we observe only F=0. The probability of this event is as follows:

$$P(F=0)+P(F=1)P(t_i > T_i|F=1) = (1-\delta)+\delta S(t_i|F=1). \tag{5}$$

Therefore, the likelihood function for the split-population duration model consists of expressions (1) and (2):

$$L = \prod_{i=1}^{N} \delta f(t_i|F=1)^{Q_i}[(1-\delta)+\delta S(t_i|F=1)]^{(1-Q_i)}. \tag{6}$$

Then, a log transformation produces the log-likelihood as follows:

$$\ln L = \sum_{i=1}^{N} Q_i [\ln \delta + \ln f(t_i | F = 1)] + [(1 - Q_i) \ln[(1-\delta) + \delta S(t_i | F = 1)]. \qquad (7)$$

We fit split-population durations to our data using the log-logistic distribution. The log-logistic hazard and survival functions are given by the following:

$$h(t) = \frac{\lambda p(\lambda t)^{p-1}}{1 + (\lambda t)^p}, \qquad (8)$$

$$S(t) = \frac{1}{1 + (\lambda t)^p}, \qquad (9)$$

where λ>0 and p>0 are the definition parameters, respectively. The estimable parameters p and λ give the hazard function its exact shape. The parameter p determines the rate at which hazard rate increases(p>1) or decreases(p<1) across time, while he parameter λ determines the portion of the hazard rate that is time invariant.

The probability of failure δ and the cross-sectional parameter λ can be made bank-specific as follows:

$$\delta = 1 / [1 + \exp(\alpha' x)], \qquad (10)$$

$$\lambda = \exp(-\beta' x), \qquad (11)$$

where x is a vector of bank characteristics and time invariant covariant.

The substitution of equation (8) and equation (9) into equation (6) results in the complete likelihood function. The parameters can be estimated using maximum likelihood estimation procedures. A significantly negative coefficient indicates that an increase in that variable reduces the chances that the bank will exit.[6)]

[6)] For a detailed discussion of split population duration models, see Schmidt and Witte (1989) and Cole and Gunther (1995).

4. EMPIRICAL RESULTS

4.1. The Asian Financial Crisis and Bank Failure/Acquisition of East Asian Countries During 1999-2007

4.1.1. Descriptive statistics and correlations for the East Asian banks

We calculated the differences in the means of the explanatory variables of both groups and tested the statistical significance of those differences. The mean differences of the variables for both non-failed and failed banks are given in table 2. In the first and second columns, the mean values for both failed and non-failed banks are shown. The last column shows the *p*-value of the mean difference test. According to the mean difference test, 11 variables have significant differences in their means. Comparing these differences, we find that failed banks had a lower average equity to asset ratio (5.778%); a higher average ratio of loan loss reserve to the sum of equity and loan loss reserve (96.43%); a higher average ratio of loan loss reserve to total loans (6.833%); a higher average cost-to-income ratio (123.20%); a higher average operating expense ratio (4.176%); a higher average non-interest ratio (3.913%); a lower average return on total assets (−0.871); a lower average liquidity ratio (22.57%); a lower average deposit growth (0.450%); a lower average loan growth (−1.515%); and a lower average total assets growth (−1.501%). These statistics show that the performance of surviving banks was better than that of failed banks. The failed banks presented a lower capital adequacy, less relative managerial efficiency, weaker asset quality, lower profitability, less liquidity and lower growth during the sample period.

Table 3 shows summary statistics for the major macroeconomic variables. Over the sample period, China's average GDP per capita growth rate 10.02% and its domestic private credit growth rate 14.26%, the highest among the studied economies. Japan's GDP per capita growth rate and domestic private credit growth rate were lowest. The ratio of M2 to foreign exchange reserve was largest in Japan (11.90%) and smallest in Singapore (1.23%).

Indonesia had the highest average inflation rate (13.89%). The volatility of the exchange rate was largest in the Philippines, Indonesia, and Thailand (−6.091%, −5.936%, and −5.630%, respectively); Hong Kong and Taiwan had the lowest volatility of the exchange rate (−0.0691% and −0.326%, respectively). The average exchange rate depreciation was positive only in Japan, indicating the yen depreciated over the period, while the other countries' currencies appreciated. Hong Kong, South Korea and Singapore had the highest average real interest rates (8.779%, 6.285% and 5.013, respectively); Thailand, Mainland China and Taiwan had the lowest (2.409%, 2.465% and 2.699%, respectively). It is noteworthy that the volatility of the standard deviation of the overall macroeconomic and financial indicators in Taiwan was smallest; i.e., Taiwan's macroeconomic performance was relatively stable over the studied period.

Table 4 reports the results of the correlation matrix and the variance inflation factor (VIF) of the variables.[7] The variance inflation factor values are less than 10 for all variables, indicating a low degree of multicollinearity. The correlation coefficients are markedly higher in several variables. First, the correlation between the cost-to-income ratio and the return on assets is 0.78. Second, loan growth is positively and highly correlated with deposit growth, with a correlation coefficient of 0.65. Third, the correlation between deposit growth and total assets growth is 0.74. Fourth, loan growth is strongly correlated with total asset growth, with a correlation coefficient of 0.79. It appears that these variables are highly correlated over the sample period. These correlations suggest that, if all of these variables were included in each regression, multicollinearity might be a serious problem. Therefore, only one variable was included in each regression.

[7] As a rule of thumb, a VIF greater than 10 indicates a problem with multicollinearity.

Table 2 Descriptive Statistics

Variable name	Exit Banks	Other Banks	All Banks	t-Statistics (p-value)
Capital adequacy				
Tier 1 capital ratio	7.255	11.76	11.31	0.1896
	(5.295)	(18.01)	(17.23)	
Equity / total assets	5.778	8.253	7.884	0.0287**
	(7.556)	(7.480)	(7.532)	
BIS	12.09	15.15	14.75	0.2777
	(7.483)	(18.00)	(17.03)	
Asset quality				
Loan loss reserve / (equity+	96.43	91.52	92.25	0.0013**
loan loss reserve)	(4.069)	(10.77)	(10.20)	
Loan loss reserve / total	6.833	2.927	3.509	0.0001***
loans	(10.03)	(5.581)	(6.570)	
Management				
Cost-to-income ratio	123.2	74.13	81.44	0.0000***
	(94.04)	(35.68)	(51.82)	
Operating expenses / total	4.176	2.200	2.495	0.0000***
assets	(6.778)	(1.950)	(3.235)	
Non-interest expense /	3.913	2.268	2.513	0.0001***
average assets	(5.734)	(1.678)	(2.749)	
Earnings				
Return on average assets	−0.871	0.660	0.431	0.0000 ***
	(4.791)	(1.278)	(2.247)	
Return on average equity	14.49	2.983	4.697	0.2055
	(94.58)	(52.23)	(60.40)	
Net interest margin	2.488	2.677	2.649	0.3957
	(1.110)	(1.530)	(1.475)	
Net interest Spread	4.348	−2.267	−1.281	0.6626
	(3.791)	(109.1)	(100.6)	
Liquidity				
Liquidity ratio	22.57	28.21	27.37	0.0297**
	(13.75)	(17.69)	(17.26)	
Loans/Deposits	84.42	270.5	242.8	0.6188
	(23.96)	(2,690.9)	(2,482.7)	
Growth				
Deposit Growth	0.450	9.868	8.464	0.0020***
	(14.96)	(20.92)	(20.40)	
Loan Growth	−1.515	12.830	10.692	0.0100***
	(16.60)	(39.27)	(37.13)	
Asset Growth	−1.501	11.295	9.389	0.0000***
	(13.14)	(20.73)	(20.29)	
Scale				
Log (total assets)	8.164	8.534	8.479	0.2892
	(2.165)	(2.345)	(2.320)	

Notes: Numbers in parentheses are standard errors. ***, ** and * indicate significant differences between failed and non-failed banks at the 1%, 5%, and 10% level, respectively. Capital ratio is the book value of shareholder equity divided by total assets.

Table 3 Descriptive Statistics for Macro Data

(unit: %)

	Taiwan	Japan	Hong Kong	Korea	Singapore	China	Indonesia	Malaysia	Philippines	Thailand	Total
GDP per capita growth	3.681 (2.71)	2.073 (0.62)	5.816 (1.74)	4.738 (0.86)	3.637 (4.05)	10.020 (0.40)	3.879 (1.31)	3.935 (0.66)	3.203 (0.69)	4.449 (0.57)	4.009 (2.70)
Inflation	−1.079 (0.14)	−0.934 (0.21)	−1.085 (2.00)	−0.061 (0.97)	0.425 (1.64)	3.560 (0.25)	13.890 (1.75)	3.336 (1.65)	5.533 (0.88)	4.728 (1.02)	2.157 (4.83)
Real interest rates	2.699 (0.35)	2.667 (0.33)	8.779 (2.32)	6.285 (0.69)	5.013 (1.62)	2.465 (0.21)	2.703 (2.84)	3.499 (2.50)	4.229 (0.29)	2.409 (0.64)	3.455 (2.20)
M2/ Reserves	3.043 (0.31)	11.900 (5.85)	3.895 (0.20)	2.719 (0.36)	1.233 (0.05)	4.162 (0.90)	3.459 (0.19)	2.662 (0.56)	2.941 (0.10)	3.269 (0.20)	6.543 (5.55)
Credit growth	5.143 (2.41)	−0.651 (0.92)	1.280 (1.81)	13.550 (7.60)	8.326 (2.29)	14.260 (0.47)	8.753 (18.68)	4.118 (2.94)	7.065 (3.18)	6.484 (7.02)	4.628 (8.54)
Exchange rate	−0.326 (1.48)	4.464 (4.22)	−0.0691 (0.16)	−5.651 (5.21)	−2.433 (3.65)	−2.624 (0.44)	−5.936 (5.58)	−2.796 (0.99)	−6.091 (2.35)	−5.630 (0.66)	−0.387 (5.47)

Note: Standards errors are in parentheses.

Table 4 Results of the Test of Multicollinearity Diagnosis

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	VIF value
(1)	1.00															3.29
(2)	−0.54	1.00														2.39
(3)	0.07	0.18	1.00													3.27
(4)	−0.41	0.33	0.38	1.00												3.39
(5)	0.51	−0.28	−0.55	−0.78	1.00											6.72
(6)	0.38	−0.36	0.17	−0.18	0.20	1.00										2.01
(7)	0.29	−0.19	−0.02	−0.23	0.19	0.17	1.00									2.89
(8)	0.05	−0.08	−0.12	−0.14	0.11	0.14	0.65	1.00								3.02
(9)	0.15	−0.17	−0.20	−0.31	0.29	0.28	0.74	0.79	1.00							4.61
(10)	0.18	−0.26	−0.11	−0.34	0.19	0.22	0.35	0.22	0.36	1.00						2.12
(11)	0.26	0.01	0.31	−0.05	0.04	0.52	0.22	0.21	0.22	0.20	1.00					2.73
(12)	0.10	−0.26	0.05	−0.06	0.12	0.07	−0.12	−0.04	−0.03	0.04	−0.23	1.00				1.96
(13)	−0.28	0.19	−0.10	0.23	−0.17	−0.36	−0.20	−0.17	−0.26	−0.43	−0.38	−0.15	1.00			1.78
(14)	0.20	−0.09	−0.10	−0.24	0.13	0.19	0.37	0.28	0.39	0.59	0.31	−0.28	−0.38	1.00		2.14
(15)	−0.27	0.03	−0.23	0.11	−0.19	−0.39	−0.19	−0.13	−0.23	−0.31	−0.52	−0.28	0.33	−0.20	1.00	2.24

Notes: (1) Equity / total assets; (2) Loan loss reserve / (equity + loan loss; (3) Loan loss reserve / total loans; (4) Cost-to-income ratio; (5) Return on average assets; (6) Liquidity ratio; (7) Deposit Growth; (8) Loan Growth; (9) Asset Growth; (10) GDP per capita growth; (11) Inflation; (12) Real interest rates; (13) M2 / Reserves; (14) Credit growth; (15) Exchange rate.

4.1.2. Results

We first use the logit model to estimate the determinants of bank failure/merger. The logit model has a binary outcome. It is used to assess whether bank-specific variables and macroeconomic factors are important in explaining East Asian countries' differences in bank failure rates. The dependent variable takes a value of one if a bank is identified as failed in any of the categories during the sample period. Table 5 reports the results of our estimation. We specified ten different models. Columns (1) to (5) take account of the cost to income ratio variable. Columns (6)-(10) incorporate the return on average assets. Columns (1) and (6) only consider the results of bank-specific variables, while columns (2)-(5) and (7)-(10) include not only the bank-specific variables but also macroeconomic and financial variables. Table 5 also shows the overall model selection criteria, i.e., Akaike's information criteria (AIC), and the pseudo R^2. According to both criteria, the estimates in the full model specification, which uses bank-specific, macroeconomic and financial variables, provide higher pseudo R^2 and lower AIC values than those of the former model, which uses only bank-specific variables. In addition, a high overall classification accuracy suggests that the model is good and fits the data well. The logit model displays good predictive power: between 86% and 94% of financial institutions were correctly classified. From table 5, model (3) and (8) seem to have the highest pseudo R^2 values, the lowest AIC values and the highest predictive powers.

For comparison purposes, we discuss only columns (3) and (8). As shown in columns (3) and (8) of table 5, the ratio of loan loss reserve to the sum of equity and loan loss reserve and the cost-to-income ratio are both positive and statistically significant; the ROA and liquidity ratios are negative and statistically significant, as expected. This means that banks with weaker asset quality, management inefficiency, lower earnings and lower liquidity have a higher risk of failure. With regard to macroeconomic and financial variables, the inflation rate, the real interest rate and the ratio of M2 to foreign exchange reserves have a positive effect on the probability of

Table 5 Results of Logit Estimation

	Including cost-to-income ratio					Including return on average assets				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Constant	−14.500***	−25.990***	−26.400***	−22.880***	−23.980***	−1.223***	−1.659***	−4.835***	−4.026***	−3.656***
	(2.60)	(3.76)	(4.06)	(3.61)	(3.51)	(3.62)	(3.48)	(5.64)	(4.74)	(4.52)
Total equity / total assets	0.059	0.040	0.048	0.024	0.033	0.028	−0.043	−0.0001	0.025	0.015
	(1.61)	(1.00)	(1.16)	(0.54)	(0.70)	(0.94)	(1.01)	(0.00)	(0.66)	(0.40)
Loan loss reserve / (equity + loan loss reserve)	0.130**	0.226***	0.203***	0.178***	0.185***					
	(2.24)	(3.23)	(3.12)	(2.79)	(2.76)					
Loan loss reserve / total loans	0.027	0.006	0.005	0.034	0.035					
	(1.02)	(0.24)	(0.18)	(1.28)	(1.26)					
Cost-to-income ratio	0.008**	0.011**	0.011*	0.010**	0.010**					
	(2.21)	(2.51)	(1.93)	(2.00)	(2.06)					
Return on average assets						−0.319***	−0.426***	−0.458***	−0.346***	−0.297***
						(2.96)	(2.98)	(3.07)	(2.88)	(2.72)
Liquidity ratio	−0.026*	−0.044**	−0.046**	−0.016	−0.016	−0.020	−0.041**	−0.053**	−0.025	−0.018
	(1.83)	(2.32)	(2.16)	(0.84)	(0.83)	(1.50)	(2.25)	(2.55)	(1.46)	(1.10)
Deposit Growth	−0.037**	−0.029*	−0.030	−0.023	−0.026	−0.040***	−0.014	−0.027	−0.022	−0.016
	(2.46)	(1.73)	(1.48)	(1.15)	(1.26)	(2.71)	(0.91)	(1.52)	(1.20)	(0.94)
GDP per capita growth					0.041		−0.469***			−0.224*
					(0.33)		(3.41)			(1.94)
Inflation		0.095*	0.305***				0.198***	0.315***		
		(1.65)	(4.19)				(3.20)	(4.27)		

Real interest rates		0.661^{***}	0.966^{***}	0.696^{***}	0.710^{***}		0.686^{***}	0.731^{***}	0.451^{***}	0.501^{***}
		(5.96)	(6.31)	(5.42)	(5.44)		(6.03)	(6.33)	(4.87)	(5.48)
M2/ Reserves			0.189^{***}	0.132^{***}	0.146^{***}			0.195^{***}	0.160^{***}	0.152^{***}
			(3.19)	(2.92)	(3.32)			(3.69)	(3.01)	(3.04)
Credit growth			-0.066^{*}	−0.015				−0.055	−0.032	
			(1.70)	(0.40)				(1.40)	(0.78)	
Exchange rate				−0.007	0.007				-0.085^{*}	-0.090^{*}
				(0.16)	(0.14)				(1.73)	(2.01)
Log likelihood	−121.869	−94.766	−77.449	−85.966	−85.996	−131.346	−101.344	−90.449	−97.620	−95.742
χ^2	50.10^{***}	104.30^{***}	138.94^{***}	121.90^{***}	121.84^{***}	31.14^{***}	91.15^{***}	112.94^{***}	98.59^{***}	102.35^{***}
Pseudo R^2	0.1705	0.3550	0.4728	0.4149	0.4147	0.1060	0.3102	0.3844	0.3355	0.3483
AIC	257.738	207.532	176.898	193.933	193.992	272.691	218.687	198.897	213.241	209.484
Overall predicted power	86.82%	88.83%	94.56%	93.12%	93.41%	86.25%	91.40%	93.12%	91.69%	92.84%

Notes: A *t*-statistic is reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively. The estimation software package used is STATA 10.0.

failure. The results reveal that a high ratio of M2 to foreign exchange reserves, high inflation and a high real interest rate are the main macroeconomic and financial factors that explain banking failure in these ten East Asian countries. These findings are consistent with those of Demirgüc-Kunt and Detragiache (1998, 2005) who suggested that high inflation, the real interest rate and the ratio of M2 to foreign exchange reserves are associated with banking distress and increase the likelihood of bank failure. Hardy and Pazarbasioglu (1999) also reported similar findings.[8)] Finally, except for that reported in column (3) of table 5, none of the coefficients on the domestic private credit growth rate are statistically significant. The results suggest that the probability of bank failure and merger is not related to credit growth.

To highlight the characteristics of this behavior and facilitate comparison, the next table of the survival model is based on both models (3) and (8). Table 6 reports the results of the re-estimation of two specifications of both models (3) and (8) using a standard parametric survival model. We applied the maximum likelihood method to estimate four different distribution types: Weibull, Exponential, Log-logistic and Log-normal distributions. The four distributions of the model may be compared using the AIC and log-likelihood value. On the basis of both criteria, the Weibull regression model is preferred: it has the smallest AIC value and the largest log-likelihood. To conserve space, we only report the results of the estimation of the Weibull regression model, as shown in table 6. The estimated values of the scale parameter (σ) are significantly less than 1 (i.e., $p = 1/\sigma > 1$), indicating that the hazard function is monotonically decreasing in duration. This means that the probability of bank failure increases over time. Among the bank-specific variables, only the coefficients of ratio of loan loss reserve to the sum of equity and loan loss reserve, the return on average assets and the liquidity ratio have the expected signs and are statistically significant. This suggests that a weaker assets quality, a lower return on assets, and a lower

8) Their results also show that high inflation and real interest rate cause a higher risk of bank failure.

Table 6 Results of Estimations of Parametric Survival Model

Explanatory variables	Weibull		Exponential		Log-logistic		Log-normal	
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
Constant	11.127^{***} (4.95)	6.006^{***} (20.33)	17.999^{***} (4.17)	7.593^{***} (15.47)	11.009^{***} (5.08)	5.791^{***} (19.14)	11.992^{***} (5.02)	6.063^{***} (16.77)
Total equity / total assets	−0.004 (0.21)	0.002 (0.11)	−0.008 (0.26)	0.003 (0.09)	−0.018 (1.14)	−0.011 (0.62)	−0.025 (1.43)	−0.017 (0.85)
Loan loss reserve / (equity + loan loss reserve)	-0.053^{**} (2.35)		-0.106^{**} (2.40)		-0.053^{**} (2.42)		-0.059^{**} (2.44)	
Loan loss reserve / total loans	−0.011 (1.03)		−0.015 (0.76)		−0.007 (0.69)		−0.004 (0.29)	
Cost-to-income ratio	−0.001 (0.49)		−0.002 (0.78)		−0.002 (1.34)		-0.003^{*} (1.77)	
Return on average assets		0.054^{*} (1.92)		0.091^{*} (1.65)		0.063^{**} (2.12)		0.078^{**} (2.09)
Liquidity ratio	0.016^{**} (2.43)	0.016^{**} (2.29)	0.025^{*} (1.90)	0.026^{**} (1.98)	0.024^{***} (3.00)	0.023^{***} (2.84)	0.026^{***} (2.98)	0.028^{***} (3.10)
Deposit Growth	0.007 (1.31)	0.007 (1.30)	0.012 (1.10)	0.014 (1.23)	0.007 (1.32)	0.007 (1.25)	0.008 (1.15)	0.008 (1.18)
Inflation	-0.085^{***} (4.34)	-0.097^{***} (4.84)	-0.111^{***} (2.77)	-0.132^{***} (3.29)	-0.104^{***} (4.70)	-0.112^{***} (5.12)	-0.113^{***} (4.55)	-0.127^{***} (5.24)
Real interest rates	-0.222^{***} (7.18)	-0.210^{***} (6.62)	-0.376^{***} (6.99)	-0.355^{***} (6.32)	-0.222^{***} (6.56)	-0.212^{***} (6.18)	-0.238^{***} (5.62)	-0.228^{***} (5.44)
M2 / Reserves	-0.037^{***} (4.14)	-0.043^{***} (4.63)	-0.069^{***} (4.04)	-0.082^{***} (4.88)	-0.030^{***} (2.72)	-0.041^{***} (3.62)	-0.042^{***} (3.02)	-0.053^{***} (3.75)
Credit growth	-0.017^{***} (2.62)	−0.01 (1.53)	-0.028^{**} (2.16)	−0.015 (1.10)	−0.008 (1.07)	−0.003 (0.42)	−0.011 (1.16)	−0.004 (0.38)
Scale parameter (σ)	0.482^{***} (8.46)	0.485^{***} (8.49)			0.425^{***} (8.63)	0.435^{***} (8.39)	0.922^{***} (9.16)	0.948^{***} (8.94)
Log likelihood	−111.995	−117.975	−126.319	−132.168	−114.457	−121.423	−119.054	−125.865
χ^2	99.06^{***}	87.10^{***}	83.00^{***}	71.30^{***}	93.61^{***}	79.68^{***}	85.55^{***}	71.93^{***}
AIC	247.990	255.950	274.638	282.337	252.913	262.845	262.108	271.730

Notes: A *t*-statistic is reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level respectively. The estimation software package used is STATA 10.0.

liquidity ratio yield a higher risk of failure and a shorter survival time. This is consistent with the result of Wheelock and Wilson (2000). With respect to the role of macroeconomic and financial variables, the inflation rate, the real interest rate, the ratio of M2 to foreign exchange reserves, and the domestic private credit growth rate have a negative influence and are significant, as expected. The results reveal that asset quality, profitability, liquidity, and macroeconomic and financial factors explain the survival time of banks in the ten Asian countries studied.

Finally, we consider that some banks will never experience exits. We apply the split-population survival time model to our data and compare the

Table 7 Results of Estimations of Split Population Survival Models

	(1)	(2)
Constant	14.751 (0.79)	6.013*** (2.06)
Total equity / total assets	−0.552** (2.40)	−0.827** (2.20)
Loan loss reserve / (equity + loan loss reserve)	−0.041 (0.21)	
Loan loss reserve / total loans	−0.019 (0.08)	
Cost-to-income ratio	−0.054** (2.25)	
Return on average assets		4.180* (1.73)
Liquidity ratio	0.102** (2.04)	0.155* (1.71)
Deposit Growth	0.023 (0.49)	−0.001 (0.02)
Inflation	−0.503* (1.75)	−0.920** (2.14)
Real interest rates	−0.766** (2.53)	−1.039** (2.19)
M2 / Reserves	−0.187 (1.27)	−0.197 (1.60)
Credit growth	0.040 (0.44)	0.066 (0.55)
Scale parameter (σ)	0.425*** (7.38)	0.467*** (8.22)
Log likelihood	−98.459	−105.877
Average predict failure probability	36.68%	43.98%

Notes: A *t*-statistic is reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level, respectively. The estimation software package used is Limdep.

results with those of the parametric survival model and the logit model. The results are shown in table 7.

For the East Asian banks, 7 of the 12 “probability of survival” coefficients are statistically significant with expected signs. High levels of total equity/total assets, cost-to-income ratio, high inflation, and real interest rates at the banks of the ten East Asian countries significantly reduced the long-run probability of survival, while high levels of liquidity ratio, ROA and bank scale (bank total assets) at these banks significantly increased the long-run probability of survival. These imply that bank scale in terms of total assets, earnings and liquidity are crucial to bank survival in the long run.

It is noted that there is weak evidence that banks with low asset quality, low deposit growth, low credit growth and high M2/foreign exchange reserve are less likely to survive in the long run. The high capital/asset ratio or low leverage ratio negatively affect bank duration. These results are different from those in traditional survival duration models tables 5 and 6.

Moreover, comparing the estimated values of the reciprocal of the scale parameter (bank assets) of model (1) and (2) in tables 6 and 7, which is p and greater than 1. That is, in table 6 model 1: (1/0.482= 2.075); model 2: (1/0.485 = 2.062) and in table 7 model 1: (1/0.425 = 2.353); model 2: (1/0.467 = 2.141). This indicates that the hazard function is monotonically decreasing in duration. This means that the probability of bank failure increases over time and when estimated with the split-population duration model the failure probability increases much faster. This implies that if we do not consider that some banks will never experience exits, we may underestimate the probability of failure/exit.

In short, from table 7, we find that the coefficients for the ratio of equity to assets, the cost to income ratio, the return on average assets, inflation, the real interest rate and bank asset scale have the expected signs and are statistically significant. In the split-population survival time model estimation some results are different from those of the standard logit and parametric survival models. However, these three econometric methodologies have consistently demonstrated that bank asset scale, the return on average assets, the liquidity ratio, inflation and the real interest rate are important determinants of bank failure. The scale variable shows that the probability of bank failure is increasing over time. And this scale parameter result also suggests that larger banks are more likely to survive during the period of Asian Financial Crisis. Large banks are typically better diversified, and ceteris paribus, large size may indicate a better managed or otherwise more successful bank. However, this may also support the “too big to fail doctrine”, since in most countries during this financial crisis those endangered or at-risk larger bank received financial and other assistance from regulatory authorities. And this result was correspondent to the significant coefficient of the high leverage ratio or low equity/asset ratio that raised the survival probability over time.

However, most countries during the study period started to do financial reforms after the great shock of Asian financial crisis and Russia debt turmoil. For example, the Japanese government had adopted the swift removal of remaining financial regulations to bring Japan up to the international level of deregulation, and to place Japanese financial institutions on an equal footing with world competition. The revision of the Foreign Exchange Law took effect in April 1998. And the Japanese version of the "Big Bang" of the financial deregulation program was implemented between 1997 and 2000. The deregulation to encourage competition among financial market players in the world inevitably resulted in more bankruptcies among financial institutions. Likewise, Taiwan government also reformed the financial industry from 2001 to 2011. These actions allowed those banks with serious bad loan problem to exit the market.

In the following section we will pay attention the logit and parametric survival models and will not use the split-population survival time model to analyze the financial institution failure problem during the Subprime Mortgage Financial Crisis in the North American and West European Countries. This is due to the fact that there were bailouts and the too big to fail policy during the study period.

4.2. The Subprime Mortgage Financial Crisis and Bank Failure/Acquisition of North American and West European Countries in July 2008-September 2009

In this subsection we go further to study the impact of the US Subprime Mortgage Financial Crisis on the world's financial system, in particular the results of the failure, acquisition, or bailout of some of the largest financial institutions(FIs) in the US and some west European Countries, such as UK, Iceland, Belgium, Germany, Ireland during July 2008 to September 2009.

Table A2 in the Appendix shows those 35 FIs with failure or acquisition or bailout during this financial crisis period. There are 661 normal financial institutions in BankScope Database.

The financial institution specific finance variables used in our empirical statistical analysis in this subsection are reported in table 8. There are 39 variables, which are classified into 8 categories. These variables basically to the extent are which regulators' evaluation of the overall safety and soundness of a bank (or their assignment of a so-called CAMELS rating) depends on financial statement data. The acronym CAMELS stands for capital adequacy, asset quality, management, earnings, liquidity, and sensitivity to market risk. We add two more variable indices, i.e., growth and subprime. Growth index is basically related with management performance index. That is the reason in table 10 only 7 indices of financial institution specific finance variables (instead of 8 indices) were used to do principal component analysis. The macroeconomic variables are expressed in table 9. There are 11 variables and are classified into 6 categories. Theses variables are related the country size measured by GDP per capita, financial competition and regulation policies, financial market development and stability conditions, international balance of payment and foreign reserve conditions, and the government budget condition and foreign debt conditions.

The statistical and econometric models utilized here include Logit and Probit Discrete Models, Survival Analysis Model, and Dynamic Survival Model (see tables A3 and A4). The Survival Analysis Model could be composed of parametric, semiparametric, nonparametric models. The parametric and semiparametric models are classified into log survival model and Cox (1972, 1975) proportional hazard rate model (see tables A3 and A4). Nelson (1972) and Aalen (1978) proposed nonparametric models. Scheike and Zhang (2002) extended Cox proportional parametric models and Aalen nonparametric model by considering time-varying effects on hazard function to present a dynamic survival model.

Table 8 Financial Institution Specific Finance Variables (CAMELS)

Factors	Symbol	Variables
Capital Adequacy Index	C_1	BIS Capital Adequacy Tier 1 Ratio
	C_2	Equity / total assets
	C_3	Equity / total assets
	C_4	Equity / deposits & short-term funding
	C_5	Capital Funds / total asset
	C_6	Equity / total assets & off balance sheet items
Asset Quality Index	A_1	Total problem loan / total Loan
	A_2	Loan loss reserve / impaired loans
	A_3	Total loans / total assets
	A_4	Loan loss provision / net interest revenue
	A_5	Impaired loans / equity
	A_6	Unreserved impaired loans / equity
	A_7	Net loans / Deposits and borrowing
Management Performance Index	M_1	Interest expense / deposits
	M_2	Operating expense /operating revenue
	M_3	Total non-interest expenses / total operating income
Earnings Index	E_1	Operating income / total revenue
	E_2	Return on average assets
	E_3	Net interest margin
	E_4	Net interest revenue / average assets
	E_5	Non operating items / net income
	E_6	Deposits / total non-interest expenses
	E_7	Interest income / pre-tax profit
	E_8	Total operating income / total assets
	E_9	Rate of average equity (ROAE)
	E_{10}	Income net of distribution / average equity
Liquidity Index	L_1	Liquidity ratio
	L_2	Acid ratio
	L_3	Interbank ratio
Sensitivity Index	S_1	Interest sensitivity gap
Growth Index	G_1	Growth rate of loans
Subprime Index	R_1	Net gains (losses) on trading and derivatives
	R_2	Net charge-offs
	R_3	Off balance sheet items
	R_4	Risk assets
	R_5	Trading securities
	R_6	Total securities
	R_7	Interest-bearing liability
	R_8	Unreserved impaired loans / equity

Table 9 Macroeconomic Variables

Factors	Symbol	Variables
Country Size	X_1	Log (Per capita GDP)
Financial Policies	X_2	Foreign Bank Competition
	X_3	Capital Regulatory Index
	X_4	Official Supervisory Power
	X_5	Declaring Insolvency Power
Financial Conditions	X_6	Private sector credit/GDP
Financial Conditions	X_7	the value of Stocks Traded relative to GDP
	X_8	Stock Market Growth
International Imbalances	X_9	Current account/GDP
	X_{10}	Foreign reserve/average monthly import
Macroeconomic Policy	X_{11}	Government budget surplus (deficit)/GDP

The logit model has a binary outcome. The dependent variable takes a value of one if a bank is identified as failed in any of the categories during the sample period. The survival analysis models include parametric, semiparametric, and nonparametric models.

Tables 10, 11 and 12 give the estimation results of probability of failure coefficients with expected signs as shown in table A1 of Appendix. It shows that low capital adequacy or (high leverage ratio), low asset quality, low earnings, sensitivity to market risk, more subprime activity, high regulators' declaring insolvency power, and high private sector credit/GDP ratio significantly to raise the probability of the financial institutions failure during the global financial crisis period of July 2008 to September 2009. It should be noted that the too big to fail and bailout policies were implemented during this period. This caused the liquidity coefficient is not too significant.

Comparing the estimation of the logit model in table 5 and that in table 11, as well as those in tables 6 and 12 for survival analysis models, we found that low asset quality, low earnings, sensitivity to market risk and high private sector credit/GDP ratio had significantly raised the probability of the financial institutions failure during the Asian Financial Crisis and the Global

Table 10 Principal Component Analysis and CAMELS Factors

I 1 Capital Adequacy Index	0.5934*C2+0.6064*C3+0.5292*C6
I 2 Liquidity Index	0.7195*L1+0.4409*L2+0.1118*L3
I 3 Subprime Index	0.5712*R2+0.5732*R6+0.5875*R7
I 4 Earnings Index	0.3830*E2+0.6585*E9+0.6478*E10
I 5 Asset Quality Index	0.5168*A1+0.6098*A5+0.6009*A6
I 6 Growth Index	Loan growth rate
I 7 Sensitivity Index	Interest rate sensitivity index

Table 11 Results of CA(M)ELS+G+R Logit Estimation

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
Capital Adequacy Index	−5.4085*** (1.3320)							−2.2557*** (0.8695)
Liquidity Index		0.1661 (0.1547)						0.0795 (0.3032)
Subprime Index			0.4223*** (0.0773)					0.2878*** (0.0711)
Earnings Index				−0.3916*** (0.1019)				−0.1599 (0.1021)
Asset Quality Index					0.5062*** (0.0947)			0.4131*** (0.0899)
Growth Index						−0.3693 (0.6226)		0.0016 (0.4826)
Sensitivity Index							−59.0009*** (14.5570)	−55.6114*** (20.2261)
Declaring Insolvency Power	0.1375** (0.053)	0.1522*** (0.051)	0.1280** (0.053)	0.1624*** (0.051)	0.1582 *** (0.053)	0.1502*** (0.051)	0.1595*** (0.0519)	0.1541** (0.0638)
Private sector credit/GDP	0.0256*** (0.009)	0.0271*** (0.009)	0.0293*** (0.009)	0.031671*** (0.009271)	0.0307*** (0.009)	0.0276*** (0.009)	0.0272*** (0.0092)	0.0339*** (0.0094)
Log(Per capita GDP)	−2.4868 (1.635)	−3.1367* (1.633)	−2.7197 (1.667)	−4.097*** (1.531)	−5.3165*** (1.617)	−3.9123*** (1.490)	−0.3687 (1.7321)	−0.9545 (2.3281)
Pseudo-R^2	17.63%	6.42%	21.16%	13.73%	21.96%	6.23%	11.61%	42.99%

Note: ( ) standard error, *,**, ***: 10%, 5%, 1% are significance levels.

Table 12 Results of Survival Analysis Model Estimation

Variable		Weibull	Exponential	Cox	Aalen	Cox-Aalen[9)]
I1	Capital Adequacy Index	−2.0440*** (0.511)	−2.6233*** (0.737)	−3.006*** (0.049)	3.31***	−2.54*** (0.905)
I2	Liquidity Index	0.2760* (0.164)	0.3187 (0.250)	0.4256 (1.531)	2.62	0.0566
I3	Subprime Index	0.0343 (0.025)	0.0788** (0.0354)	0.05543 (1.057)	1.79	0.054
I4	Earnings Index	−0.0636* (0.035)	−0.0845 (0.0532)	−0.1024* (0.9026)	4.54*	−0.0945** (0.0415)
I5	Asset Quality Index	0.1305*** (0.028)	0.185*** (0.0373)	0.1875*** (1.206)	2.52***	0.203*** (0.039)
I6	Growth Index	−0.0019 (0.376)	−0.134 (0.5579)	−0.003 (0.996)	1.72	0.0575
I7	Sensitivity Index	−22.7548* (12.469)	−39.9311** (18.181)	−33.42* (0.000)	1.75*	−23.6 (19.8)
X5	Declaring Insolvency Power	0.1207*** (0.023)	0.1479*** (0.034)	0.1863*** (1.205)		
X6	Private Sector Credit /GDP	0.0145*** (0.004)	0.0214*** (0.005)	0.02307*** (1.023)		
X1	Log(Per capita GDP)	1.4033 (1.096)	0.903 (1.718)	2.329 (10.27)	1.81***	0.623 (1.85)
AIC		497.4894	504.4892	295.2476	−	−

Note: *, **, ***: 10%, 5%, 1% are significance levels.

Subprime Mortgage Financial Crisis.

However, the liquidity variable is weekly significant due to the government bailouts and the unusual easing monetary policies, such as unconventional Quantity Easing (QE) Policies, from the Central Banks during the Global Financial Crisis.

5. CONCLUSIONS

In this paper, we examine various determinants of bank failure timing and merger using data from ten East Asian countries in 1999-2007, as well as using data from North American and West European countries in July 2008-September 2009. The major findings are as follows. Firstly, for the East Asian countries after the Asian Financial Crisis, the logit model and the

[9)] Cox-Aalen puts those insignificant parameters in Cox model into Aalen nonparametric model.

parametric survival time regressions (Weibull) show that individual bank factors, such as asset quality, liquidity, and earnings, bank scale, as well as macroeconomic and financial characteristics, such as real interest rates, inflation and the ratio of M2 to foreign exchange reserves, are important in explaining the likelihood of bank failure.

Secondly, for the Asian Financial Crisis case, using a split-population duration model, the evidence further demonstrates that relative timing had a significantly positive influence on the probability of bank failure during the 1999-2007 period. There is weak evidence that banks with low asset quality, low deposit growth, low credit growth and high M2/foreign exchange reserve are less likely to survive in the long run. The high capital/asset ratio or low leverage ratio negatively affect bank duration. These results are different from those in traditional survival duration models.

Moreover, comparing the estimated values of the reciprocal of the scale parameter (bank assets) of model, which is greater than 1. This indicates that the hazard function is monotonically decreasing in duration. This means that the probability of bank failure increases over time and when estimated with the split-population duration model the failure probability increases much faster. This implies that if we do not consider that some banks will never experience exits, we may underestimate the probability of failure/exit.

Thirdly, for the Asian Financial Crisis case, these three econometric methodologies have consistently demonstrated that bank asset scale, the return on average assets, the liquidity ratio, inflation and the real interest rate are important determinants of bank failure. The scale variable shows that the probability of bank failure is increasing over time. And this scale parameter result also suggests that larger banks are more likely to survive during the period of Asian Financial Crisis. This seems to support the “too big to fail doctrine”, since in most countries during this financial crisis those endangered or at-risk larger bank received financial and other assistance from regulatory authorities. And this result is also correspondent to the significant coefficient estimation of high leverage ratio that raised the survival probability over time.

Finally, for the North American and West European countries, using Logit and Survival Analysis model estimation, we found that capital adequacy, subprime, earnings, asset quality, sensitivity, declaring insolvency power, and private sector credit/GDP ratio could statistically significantly explain the probability of the financial institutions failure during the Global Financial Crisis period of July 2008 to September 2009.

Comparing the estimation results of the models, we found that low capital adequacy or (high leverage ratio), low asset quality, low earnings, sensitivity to market risk and high private sector credit/GDP ratio had significantly raised the probability of the financial institutions failure during the Asian Financial Crisis and the Global Subprime Mortgage Financial Crisis. And there were significantly impacts on the financial institution failure probability from the subprime business activities and regulators' declaring insolvency power during the Subprime Financial Crisis. However, the deposit growth and the liquidity variable had weekly significant effects on the failure probability of financial institutions due to the government bailouts and the unusual easing monetary policies, like unconventional Quantity Easing (QE) Policies, from the Central Banks during the Global Financial Crisis. While liquidity and asset scale variables are two important factors to lower the failure probability during the Asian Financial Crisis.

APPENDIX

Table A1 Description of the Variables

Item	Variables name	Definition	Source	Expected Sign on Survival Time/ Failure Rate
Capital adequacy	Tier 1 capital ratio	The ratio of a bank's core equity capital to total risk-weighted assets.	BankScope	+/−
	Total equity / total assets	The ratio of total equity to total assets.	BankScope	+/−
	BIS ratio (bank of international settlement ratio)	The rate of equity capital to risk-weighted assets.	BankScope	+/−
Asset quality	(loan loss reserve / (equity + loan loss reserve)	The rate of loan loss reserve to the sum of equity and loan loss reserve.	BankScope	−/+
	loan loss reserve / total loans	The rate of loan loss reserve to total loans.	BankScope	−/+
Management	Cost-to-income ratio	Overheads to net interest income plus other operating income.	BankScope	−/+
	Operating expenses / total assets	The rate of operating expenses to total assets.	BankScope	−/+
	Non-interest expense / average assets	Non-Interest Expense as a percent of Average Assets.	BankScope	−/+
Earnings	Return on average assets (ROAA)	The ratio of net income to Average assets.	BankScope	+/−
	Return on average equity (ROAE)	The ratio of net income to shareholder equity.	BankScope	+/−
	Net interest margin	Total interest income less total interest expense (annualized) as a percent of average earning assets.	BankScope	+/−
	Net interest spread	Interest yield on earning assets minus interest rates paid on borrowed funds.	BankScope	+/−
Liquidity	Liquidity ratio	The liquid asset as a percentage of total assets.	BankScope	+/−
	Loans / Deposits	Total loans as a percentage of total deposit.	BankScope	−/+
Growth	Deposit Growth	The growth rate of total deposit.	BankScope	+/−
	Loan Growth	The growth rate of total loans.	BankScope	?/?
	Asset Growth	The growth rate of total assets.	BankScope	+/−
Scale	Log (total assets)	The logarithm of total assets.	BankScope	?/?
Macroeconomic Variables	GDP per capita growth	The growth rate of real per cap GDP.	WDI	+/−
	Inflation	Rate of change of the GDP deflator.	WDI	−/+
	Real interest rate	Nominal interest rate minus the contemporaneous rate of inflation.	WDI	−/+
Financial Variables	M2 / foreign reserves	The ratio of M2 to foreign exchange reserves.	WDI	−/+
	Domestic credit growth	Rate of growth of real domestic credit to private sector.	WDI	−/+
	The volatility of exchange rate	Change in the exchange rate.	WDI	−/+

Note: Data come from author.

Table A2 The Financial Institutions with Failure/ Acquisition/Bailout

No.	Financial Institution (FI)	Nation	FI type	Establish-ment date	Failure / Acquisition / Bailout date	Asset Scale (Million US dollars)
1	Dexia	BELGIUM	Bank Holding & Holding Companies	1996	2008/9	905,999
2	Fortis	BELGIUM	Bank Holding & Holding Companies	1990	2008/9	129,246
3	Hypo Real Estate Holding AG	GERMANY	Bank Holding & Holding Companies	2003	2008/9	584,028
4	Glitnir Bank	ICELAND	Commercial Banks	1990	2008/9	48,852
5	Kaupthing Bank hf	ICELAND	Commercial Banks	1982	2008/9	83,517
6	National Bank of Iceland Ltd-Landsbanki Islands	ICELAND	Commercial Banks	1886	2008/9	50,213
7	Anglo Irish Bank Corporation Limited	IRELAND	Commercial Banks	1964	2008/12	144,920
8	Abbey National Plc	UK	Real Estate / Mortgage Bank	1944	2008/9	337,831
9	Bank of Scotland Plc	UK	Commercial Banks	1695	2008/10	938,784
10	Barclays Bank Plc	UK	Commercial Banks	1896	2008/10	2,992,884
11	Bradford & Bingley Plc	UK	Commercial Banks	1964	2008/9	81,523
12	HBOS Plc	UK	Bank Holding & Holding Companies	2001	2008/10	1,005,753
13	HSBC Bank plc	UK	Commercial Banks	1836	2008/10	1,347,334
14	Lloyds TSB Bank Plc	UK	Commercial Banks	1765	2008/10	635,874
15	Nationwide Building Society	UK	Real Estate / Mortgage Bank	1848	2008/10	355,988
16	Northern Rock Plc	UK	Commercial Banks	1965	2008/2	152,114
17	Standard Chartered Bank	UK	Commercial Banks	1863	2008/10	434,989
18	Bank of New York Mellon Corporation	USA	Bank Holding & Holding Companies	2007	2008/10	237,512
19	BankUnited, FSB	USA	Savings Bank	NA	2009/5	13,951
20	Citigroup Inc	USA	Bank Holding & Holding Companies	1998	2008/10	1,938,470
21	Colonial Bank	USA	Commercial Banks	1974	2009/8	25,858
22	Corus Bank N.A.	USA	Commercial Banks	1913	2009/9	8,387

No.	Financial Institution (FI)	Nation	FI type	Establish-ment date	Failure / Acquisition / Bailout date	Asset Scale (Million US dollars)
23	Fannie Mae-Federal National Mortgage Association	USA	Real Estate / Mortgage Bank	1968	2008/9	912,404
24	Freddie Mac	USA	Real Estate / Mortgage Bank	1970	2008/9	850,963
25	Goldman Sachs Group, Inc	USA	Bank Holding & Holding Companies	1869	2008/10	884,547
26	Guaranty Bank	USA	Savings Bank	1988	2009/8	15,058
27	JP Morgan Chase & Co.	USA	Bank Holding & Holding Companies	NA	2008/10	2,175,052
28	Meridian Bank, National Association	USA	Commercial Banks	1978	2008/10	2,090
29	Merrill Lynch & Co., Inc.	USA	Investment Banks	1914	2008/10	246,024
30	Morgan Stanley	USA	Bank Holding & Holding Companies	1935	2008/10	658,812
31	Silverton Bank NA	USA	Commercial Banks	NA	2009/5	3,155
32	State Street Corporation	USA	Bank Holding & Holding Companies	1792	2008/10	173,631
33	TeamBank, National Association	USA	Commercial Banks	NA	2009/3	669
34	Vantus Bank	USA	Savings Bank	1923	2009/9	523
35	Wells Fargo & Company	USA	Bank Holding & Holding Companies	1852	2008/10	1,309,639

Table A3 Parameter Models

	Survival	Log survival	Parametric proportional hazard
Pattern	Linear regression	Exponential Weibull Log-normal Log-logistic Gamma	Exponential Weibull Gompertz

Table A4 Proportional Hazard Rate Model

Distributions	Hazard function	Characteristics
Exponential	$h(t \mid x_j) = \exp(\beta_0 + x_j \beta_x)$	Hazard function and survival time(t) are independent
Weibull	$h(t \mid x_j) = pt^{p-1} \exp(\beta_0 + x_j \beta_x)$	If size parameter $\gamma \le 1$ or scale parameter $p \ge 1$, $\frac{dh(t)}{dt} \ge 0$. If $\gamma > 1$ or $p < 1$, $\frac{dh(t)}{dt} < 0$.
Gompertz	$h(t \mid x_j) = \exp(\gamma t) \exp(\beta_0 + x_j \beta_x)$	If $\gamma > 0$, $\frac{dh(t)}{dt} > 0$. If $\gamma < 0$, $\frac{dh(t)}{dt} < 0$. If $\gamma = 0$, $h(t) = \exp(\beta_0)$ and t are independent.

Sources：Lin (1993), Lee (1993), Hsu-Liu-Hsieh (2003), where $h = \exp(-\beta_0 - x_j \beta_x)$.

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