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The Use of Accounting and Stock Market Data to Predict Bank Financial Distress: The Case of East Asian Banks

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This paper investigates whether market information could add to accounting information in the prediction of bank financial distress in Asia. A stepwise logit model is first estimated to isolate the optimal set of accounting indicators and then extended to include market indicators. Dummy variables are also introduced in the model to account for the possible existence of balance sheet structure effects. Our results show that market indicators bring in additional information in the prediction process and this contribution holds whatever the importance of the ratio of market funded liabilities over total assets. We also find that market indicators are significant to predict banks' financial distress whatever assets structure. However, for non traditional banks, that is for banks with a low ratio of net loans to total assets, market information seems difficult to interpret.

Keywords: bank, bank failure, bank risk, East Asia

1 Introduction

Given the major role played by banks as intermediaries in the financial system, it is essential that supervisors assess banks' financial health on a frequent basis. To predict banks' financial situation, early warning systems (EWS) have been designed but most models mainly focus on accounting data which are backward looking. Moreover, the reliability of accounting data has always been questioned given the very persistent issues of information quality and diversity in the application of accounting principles.¹ As a result, users of financial information also look into other available information that could aid them in making more informed decisions. Market data are considered as a viable complement to accounting information in the conduct of assessing bank financial health. Thus, the use of market data is more and more considered to enhance the supervisory process (Berger, Davies, & Flannery, 2000; Flannery, 1998).

Several studies have been conducted to determine if market information can complete accounting information to predict banks' financial health. In the US case, Curry, Elmer, and Fissel (2007) and Evanoff and Wall (2001) show that the use of market indicators improves the assessment of banks financial health. It is also the case in Europe. Indeed, Gropp, Vesala and Vulpes (2006) and Distinguin, Rous and Tarazi (2006) show that market indicators add to the predictive power of accounting indicators and that they can predict deteriorations in banks' financial condition at relatively long horizons.

With the occurrence of the Asian Crisis, there was heightened interest in the role of the banking sector in Asian economies especially since most studies in this area pinpoint particular weaknesses in the sector that aggravated the crisis. However, in the Asian case, little has been written on the prediction of banks' financial degradations since most studies focus on early-warning models of banking crises (Demirgüç-Kunt & Degatriache, 2000).

The objective of this paper is to determine if, in the Asian banking sector, equity market information can complete accounting information to predict banks' financial distress. The paper also looks into the reliability and stability of market indicators given the presence of balance sheet structure effects. Indeed, it may be more difficult for market participants to assess the financial

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¹ Users of financial information are on the alert with respect to the quality of accounting information since management (the company) has the incentive to "select" generally accepted accounting principles that could favorably present financial performance. On the other hand, the development and adoption of International Accounting Standards (IAS) aim to eliminate diversity and country differences in the application of accounting principles.

health of banks heavily involved in loan activities as they are supposed to be more opaque (Diamond, 1984). In contrast, the market may be able to accurately scrutinize banks heavily relying on market funding. Using eight Asian countries as a point of study, this paper also aims to further investigate potential differences between banks from the tiger economies and banks from emerging markets.

The paper is organized as follows: Section two presents the methodology adopted for our study. Section three describes the data and the set of early accounting and market indicators used in our estimations. Section four presents the results and Section five concludes.

2 Methodology

The main purpose of this study is to determine if equity market indicators can bring in information not yet contained in accounting data to predict bank financial distress. In order to do this, a stepwise process is employed that initially solely considers the set of accounting indicators for the prediction model. The process is later on extended to include a large set of market indicators to determine the marginal contribution of these indicators in the prediction process. Then, to test the existence of balance sheet structure effects, dummy variables are introduced. Thus, we determine the effect of balance sheet structure on the effectiveness of the selected market indicators.

To begin with, we need to determine an event that could represent a change in the financial situation of a bank. Studies conducted in the US mainly use explicit bank failures or supervisory ratings downgrades as in Curry, et al. (2007), Kolari, Glennon, Shin and Caputo (2002) and Gunther, Levonian and Moore (2001). In the European case, sharp downgrades (Gropp et al., 2006) are used as proxies for actual bank failure or downgrade announcements by private rating agencies² (Distinguin et al., 2006) as proxies for financial distress. In Asia, there have been only few actual bank failures. Thus, in this paper, following Distinguin et al. (2006), we consider downgrading announcements from the three major rating agencies Fitch, Moody's and Standard and Poor's to represent deteriorations in the bank's financial condition.

Accounting C_{ji} and market M_{li} indicators are computed to estimate the probability of a downgrade. However, accounting and market data are not available at the same frequencies. As such, the starting point for this study is December 31st of each year – when accounting information is available. Events taking place during the following calendar year are then considered, which avoids the interpolation of missing accounting data and ensures that the information content of accounting data is not inappropriately upward biased.

For each bank in the sample, the dependent variable Y is equal to:

- 1, if the bank is downgraded by at least one rating agency with no upgrading taking place during the entire calendar year and no downgrade or upgrade during the last quarter of the preceding year;
- 0, if the rating remains unaltered or if the bank experienced an upgrade during the calendar year; and;
- NA (not available), for all other cases.

Figure 1 illustrates the definition of the dependent variable Y (0, 1, NA).

As in Distinguin, et al. (2006), the following logit model is employed to estimate the probability of a downgrade:

$$\Pr\{Y_i = 1\} = \Phi \left(\alpha + \sum_{j=1}^J \beta_j C_{ji} + \sum_{l=1}^L \gamma_l M_{li} \right)$$

where C_{ji} and M_{li} are the j^{th} accounting indicator and the l^{th} market indicator, respectively, and $\Phi(\cdot)$ denotes the cumulated logistic distribution function. Maximum likelihood estimators of the coefficients $(\alpha, \beta_j, \gamma_l)$ are used and robust Huber-White covariance matrix estimation allows for possible misspecification of the error term distribution.

² Due to confidentiality laws in most countries, it is difficult to gain access to explicit supervisory ratings in Europe.

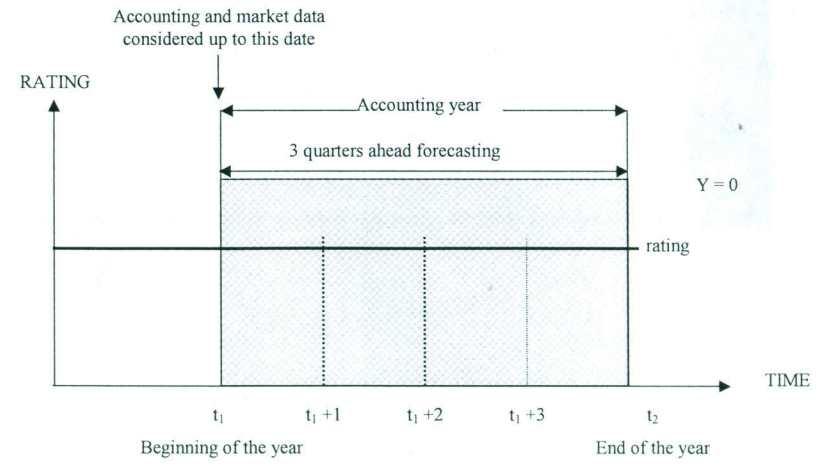
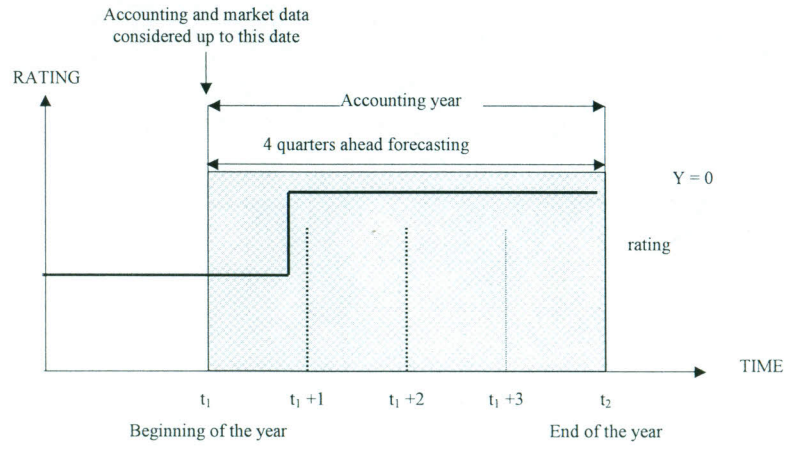
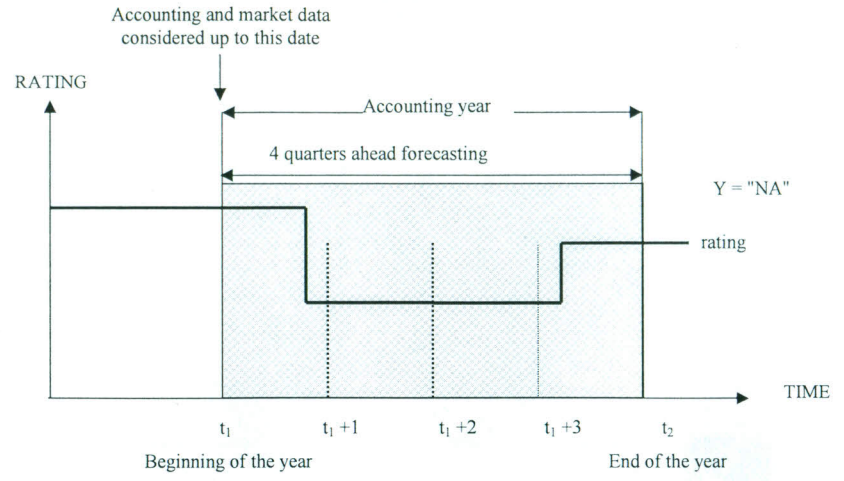
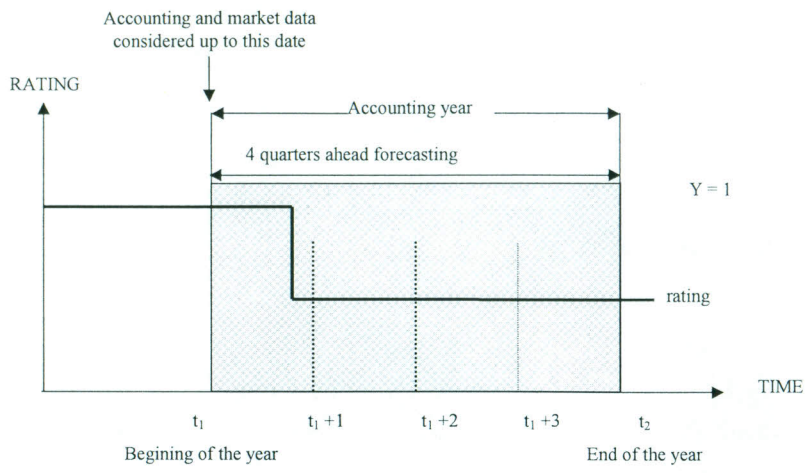


Figure 1. Definition of the Dependent Variable Y

In the selection of the optimal predictors of bank financial distress, only the predictive power of the accounting indicators is considered first. The best indicators are selected through a stepwise process.³ The procedure is then extended to include market indicators in order to determine their marginal contribution to the prediction model. Market indicators are added to the optimal subset of accounting indicators obtained in the first step.

However, due to the possible existence of balance sheet structure effects, there is a need to test for the stability of the contribution of market indicators in the prediction process. This is tested in the model through the inclusion of dummy variables. We also conduct estimations of the different models on restricted samples of banks.

3 Sample and Indicators

3.1 Sample

Our sample consists of 64 banks from Hong Kong, Korea, Taiwan, Singapore, Malaysia, Thailand, Indonesia and the Philippines. These banks are publicly-listed in their home countries and are rated by at least one of the three rating agencies Fitch, Moody's and Standard and Poor's.

The banks are categorized into two groups A and B. The bank is classified as group A, if it is from Hong Kong, Korea, Taiwan or Singapore; then group B, if from Malaysia, Thailand, Indonesia or the Philippines. It is more prudent to group the banks into country categories as the two country groups exhibit different characteristics particularly with respect to the level of development of their financial system.

Table 1 presents the distribution of banks by country and specialization for the combined groups A and B, group A and group B. Information is taken from Bankscope Fitch IBCA.

Table 1. Distribution of Banks by Country and Specialization

Distribution of banks by country:

Country	No. of Banks
Group A:	
Hong Kong	8
Korea	6
Singapore	2
Taiwan	13
Group B:	
Malaysia	3
Indonesia	11
Thailand	12
Philippines	9
Total	64

Distribution of banks by specialization:

Specialization	No. of Banks		
	A and B	A	B
Bank holding and holding company	2	2	
Commercial bank	56	24	32
Cooperative bank	1	1	
Investment bank	5	2	3
Total	64	29	35

Source: Bankscope Fitch IBCA

³ As a rule of thumb, a 10% level for type 1 error is retained and a Max (Min) LR statistic is used as a criterion for adding (ruling out) each potential indicator to (from) the selected set.

Accounting data come from Bankscope Fitch IBCA and weekly market data are obtained from Datastream International. In order to avoid noise related to the 1997 financial crisis, we restrict our sample to the post-crisis period 1999-2004. Table 2 shows some descriptive statistics on summary accounting information for combined and separate bank groups.

Table 2. Descriptive Statistics on Summary Accounting Information

Groups A and B	Mean²	Standard Deviation²	Minimum	Maximum
Total Assets (in million USD)	16447.57	23789.04	162.75	176576.30
Net Loans ¹ / Total Assets (%)	52.14	17.87	5.57	94.15
Deposits/ Total Assets (%)	77.37	16.38	0.00	93.51
Subordinated Debt/ Total Assets (%)	1.69	1.66	0.00	6.79
Deposits (in million USD)	13142.94	18174.79	0.00	126694.20
Subordinated Debt (in million USD)	397.86	750.03	0.00	6014.69
Tier 1 Ratio (%)	12.70	13.72	4.60	24.80
ROA	0.78	1.88	-12.13	12.79
Group A				
Total Assets (in million USD)	26462.82	31953.78	271.40	176576.30
Net Loans ¹ / Total Assets (%)	59.35	15.40	5.57	80.42
Deposits/ Total Assets (%)	78.29	18.26	4.52	93.51
Subordinated Debt/ Total Assets (%)	2.10	1.45	0.00	5.63
Deposits (in million USD)	20984.88	24062.07	54.62	126694.20
Subordinated Debt (in million USD)	811.40	1122.54	0.00	6014.69
Tier 1 Ratio (%)	13.72	18.49	4.60	20.30
ROA	0.48	1.13	-5.53	4.24
Group B				
Total Assets (in million USD)	8518.84	8151.21	162.75	36006.70
Net Loans ¹ / Total Assets (%)	46.43	17.66	8.19	94.15
Deposits/ Total Assets (%)	76.64	14.74	0.00	92.59
Subordinated Debt/ Total Assets (%)	1.49	1.73	0.00	6.79
Deposits (in million USD)	6934.73	6928.68	0.00	30802.41
Subordinated Debt (in million USD)	188.26	289.38	0.00	1089.29
Tier 1 Ratio (%)	11.58	4.70	5.20	24.80
ROA	1.02	2.28	-12.13	12.79

¹ Net loans are defined as gross loans less loan loss reserves.

² Each mean is calculated as $\bar{X} = \frac{1}{NT} \sum_{t=1}^T \sum_{j=1}^N X_{jt}$ where N is the number of banks and T is the number of financial reports. Standard deviations were computed on a similar basis.

3.2 Financial deterioration indicator

The downgrades used in this study are announced by the rating agencies Fitch, Moody's and Standard and Poor's. This information is obtained from Bankscope Fitch IBCA and FinInfo. Table 3 gives details on the downgrades considered in this study. Since several restrictions are applied on the construction of the binary dependent variable Y, only a limited number of "clean" downgrades are subsequently considered in this study. For example, if several downgrades occur during the calendar year, we consider them as a single event. Of the total forty-five (45) combined downgrades from the ratings agencies, only twenty (20) "clean" downgrades are used for the estimations.

**Table 3. Downgrades and Upgrades Information
(Number of Clean Downgrades or Upgrades in Parenthesis)**

Groups A and B:		2001	2002	2003	2004	2005
45 (24)	Total downgrades	18 (8)	9 (7)	1 (1)	3 (2)	14 (6)
4 (1)	Downgrades by Standard and Poor's	3 (0)	1 (1)	0 (0)	0 (0)	0 (0)
21 (13)	Downgrades by Fitch	5 (3)	8 (6)	1 (1)	0 (0)	7 (3)
20 (6)	Downgrades by Moody's	10 (3)	0 (0)	0 (0)	3 (1)	7 (2)
Group A						
21 (13)	Total downgrades	9 (4)	9 (7)	1 (1)	0 (0)	2 (1)
1 (1)	Downgrades by Standard and Poor's	0 (0)	1 (1)	0 (0)	0 (0)	0 (0)
14 (11)	Downgrades by Fitch	5 (3)	8 (6)	1 (1)	0 (0)	0 (0)
6 (2)	Downgrades by Moody's	4 (1)	0 (0)	0 (0)	0 (0)	2 (1)
Group B						
24 (7)	Total downgrades	9 (2)	0 (0)	0 (0)	3 (1)	12 (4)
3 (0)	Downgrades by Standard and Poor's	3 (0)	0 (0)	0 (0)	0 (0)	0 (0)
7 (3)	Downgrades by Fitch	0 (0)	0 (0)	0 (0)	0 (0)	7 (3)
14 (4)	Downgrades by Moody's	6 (2)	0 (0)	0 (0)	3 (1)	5 (1)

Source: *Bankscope Fitch IBCA and FinInfo*

3.3 Accounting indicators

We use a set of accounting ratios (see Table 4) commonly used in the assessment of bank financial health. These ratios can be grouped into four categories corresponding to the CAEL rating categories: Capital, Asset quality, Earnings and Liquidity.

Following Distinguin et al. (2006), we consider first order differences of these ratios as explanatory variables which seem preferable to the use of ratios in level as Curry et al. (2007), Gunther et al. (2001). Indeed, we aim to predict changes in the financial condition of the bank not its financial condition. More importantly, our study requires equal consideration of banks regardless of their initial financial strength. More precisely, the downgrade of a sound and safe bank as compared to a modestly performing bank can only be captured by a change in the values of the ratios of this bank. Consequently, C_{ji} is defined as the annual change in the value of the accounting ratio R_{ji} .

Table 4. Accounting Ratios R_{ji}

Category	Name	Definitions
Capital	KP_NL	Equity/ Net Loans
	KP_DEPSTF	Equity/ Customer and ST Fundings
	KP_LIAB	Equity/ Liabilities
	TCR	Total Capital Ratio
	TIER1_RAT	Tier 1/ Risk-weighted Assets and Off-balance Sheet Risks
Asset Quality	LLP_TA	Loan Loss Provision/ Total Assets
	LLP_GL	Loan Loss Provision/ Gross Loans
	RWA_TA ⁴	Risk-weighted Assets and Off-balance Sheet Risks (inferred from the Cooke ratio)/ Total Assets
	LLR_TA	Loan Loss Reserves/ Total Assets
	LLR_GL	Loan Loss Reserves/ Gross Loans
Earnings	LLP_NETIR	Loan Loss Provision/ Net Interest Revenue
	NIR_NINC	Net Interest Revenue/ Net Income
	NIR_EA	Net Interest Revenue/ Total Earning Assets
	ROAA	Return on Assets = Net Income/ Total Assets
Liquidity	ROAE	Return on Equity = Net Income/ Equity
	INTERBK	Interbank Assets/ Interbank Liabilities
	LIQASS_TOTDB	Liquid Assets/ Total Deposits and Borrowings
	NL_DEP	Net Loans/ Customer and ST Fundings
	NL_TEA	Net Loans/ Total Earning Assets
	TRAD_OPINC	(Trading Income-Trading Expense)/ Operating Income

⁴ See Goyeau, Sauviat and Tarazi (1998) for details about RWA_TA.

Table 5. Market Indicators

Indicators	Definition	Expected sign of the coefficient
LOGP	Difference between the natural logarithm of weekly market price and its moving average calculated on one year.	Negative
RCUM	Cumulative return: $RCUM_{bt} = [\prod_{k=1}^{13}(1 + r_{b,t-k+1}) - 1]$ with $r_{b,t+1} = (P_{b,t+1} - P_{b,t})/P_{b,t}$ where r_{bt} is the weekly return of the stock b ; we calculate this cumulative return on the fourth quarter of the accounting period (financial year) preceding the event, P_{bt} is the weekly stock price of bank b .	Negative
RCUMNEG	Dummy variable equal to one if the cumulative return is negative in the two last quarters of the accounting period (financial year) preceding the event, and zero otherwise.	Positive
EXCRCUM	Cumulative market excess return: $EXCRCUM_{bt} = \{[\prod_{k=1}^{13}(1 + r_{b,t-k+1}) - 1] - [\prod_{k=1}^{13}(1 + r_{m,t-k+1}) - 1]\}$ We obtain $r_{m,t}$, the weekly market return, which we calculate from the country-specific market index, from Datastream International for the fourth quarter of the financial exercise preceding the event.	Negative
EXCRCUMNEG	Dummy variable equal to one if the cumulative market excess return is negative in the two last quarters of the accounting period (financial year) preceding the event, and zero otherwise.	Positive
CAR	Cumulative abnormal returns on the fourth quarter of the accounting period (financial year) preceding the event: $RAC_{bt} = \sum_{k=1}^{13} RA_{b,t-k+1}$ with $RA_{bt} = R_{bt} - \hat{\alpha} + \hat{\beta}R_{mt}$. We estimate the market model on the third quarter of the accounting period (financial year) preceding the event	Negative
Δ RISK_TOT	Change in the standard deviation of weekly returns between the third and fourth quarter of the accounting period (financial year) preceding the event.	Positive
Δ BETA	Change in the market model beta ($\hat{R}_{bt} = \hat{\alpha} + \hat{\beta}R_{mt}$) between the third and fourth quarter of the accounting period (financial year) preceding the event.	Positive
Δ RISK_SPEC	Change in specific risk: standard deviation of the market model residual between the third and fourth quarter of the accounting period (financial year) preceding the event.	Positive
Δ Z	Change in the Z-score between the third and fourth quarter of the accounting period (financial year) preceding the event with: $Z = (1 + \bar{r}_b)/\sigma_r$, where \bar{r}_b is the mean return of stock b on the preceding quarter and σ_r the standard deviation of the return.	Negative
Δ DD	Annual change in the distance to default: estimated at the end of the accounting period (financial year) preceding the event. We infer the distance to default from the market value of a risky debt (Merton, 1977) based on the Black and Scholes (1973) option pricing formula (see Appendix).	Negative

3.4 Market Indicators

We use weekly equity prices to compute the set of market indicators used in this study. These indicators and their expected relationship with the probability of bank failure are presented in Table 5.

The effects of shocks or the presence of abnormal returns can be captured by the variables *LOGP*, *RCUM*, *EXCRCUM*, *RCUM_NEG*, *EXCRCUM_NEG* and *CAR*, while we use $\Delta BETA$ and ΔDD to detect risk changes and changes in the probability of failure, respectively.

4 Empirical Results

First, we consider the predictive power of the sole accounting indicators *via* a stepwise process. Then, the process is extended to include market indicators. This enables assessment of their marginal contribution to the prediction process. Dummy variables, to capture possible balance sheet structure effects, are also introduced in the model in order to test for the stability of the contribution of market indicators.

As a preliminary step, univariate regressions are conducted. Regional results pertain to combined groups A and B; while group A pertains to banks from Hong Kong, Singapore, Korea and Taiwan; and group B to banks from Malaysia, Indonesia, Thailand and the Philippines. For regional estimations, we take into account country group differences by introducing a dummy variable *GRPB* that is equal to one for banks belonging to group B.

4.1 Univariate regression results

Table 6 shows the results for the univariate regressions on the accounting and market indicators for Asian banks. Results are only reported when the coefficients are at least significant at the 10% level.

Regional results show that changes in the profitability/earnings ratios *NIR_EA* and *ROAA* are significant at the 5% level. The negative sign of the coefficients is consistent with the expected negative relationship between profitability and bank financial distress. The changes in the liquidity ratios *NL_DEP* and *NL_TEA* are also significant at 1% and 5%, respectively. But, the negative sign of the coefficients is not consistent with the expected negative relationship between liquidity and bank financial distress. For market indicators, *EXCRCUM* and ΔDD are significant at the 5% level. The sign of the coefficient of *EXCRCUM* is the expected one but the sign of the coefficient associated to the change in the distance to default ΔDD is opposite to the presumed one.⁵

For group A, three liquidity indicators, $\Delta LIQASS_TOTDB$, ΔNL_TEA , and ΔNL_DEP , are significant at the 5%, 10% and 1% levels respectively but with the wrong signs. Significant market indicators are *CAR*, *EXCRCUM*, *LOGP*, *RCUM*, *RCUMNEG* and $\Delta BETA$. The signs of the coefficients of these indicators all conform to the expected relationship with bank financial distress, except for $\Delta BETA$.

Group B results also prove to be interesting showing that the accounting indicators ΔKP_DEPSTF , ΔKP_LIAB , ΔNL_DEP and $\Delta ROAA$ appear as significant. For these banks, capital ratios are also meaningful in the prediction process. The sign of the coefficients all conform to the expected relationship with bank financial distress except for ΔNL_DEP . *LOGP*, ΔDD and $\Delta RISK_TOT$ are the significant market indicators for group B. However, only the sign of the coefficient of the variable $\Delta RISK_TOT$ is consistent with the expected relationship with bank financial distress.

Interestingly, ΔDD , which is the annual change of the distance to default, is a significant indicator for the regional and group B results but its coefficient has the wrong sign. ΔDD_TRIM ⁶ (the quarterly

⁵ An explanation for this result may be that, in our sample of banks, the median of the annual change in total liabilities is \$ 179.84 million for downgraded banks and \$ 354.06 for banks with a stable rating or an upgrade. Thus, even if the market value of bank equity starts decreasing before the actual downgrade, it is possible that the relatively lower increase in the value of debt for downgraded banks is driving the distance to default in the opposite direction for these banks. Indeed, the strike price of the Call option used to calculate the distance to default is the value of debt. And, a lower strike price implies a lower default probability.

⁶ ΔDD_TRIM is not retained in the study because interpolated accounting data is needed for the computation of this indicator which may create bias in the results.

change of the distance to default) was also calculated, eventually emerging significant at 10% for group B with a coefficient that has the expected sign. In this case, the same variable computed on a different basis behaves inconsistently. The sign of the coefficient associated with ΔBETA also exhibits the wrong relationship with bank financial distress. The behaviour of these two market indicators is noteworthy at this point. The variables seem to show a certain level of sensitivity with respect to the assumptions used in the computation particularly with the case of ΔDD . ΔBETA is also a variable that can be computed on the basis of several measures.

Table 6. Financial Deterioration and Early Indicators: Univariate Regressions

Model					
Specification:		$\Pr\{Y_i = 1\} = \Phi(\alpha + \beta X_i)$ for groups A and B			
		$\Pr\{Y_i = 1\} = \Phi(\alpha + \delta\text{GRP}_i + \beta X_i)$ for Regional			
		Regional	Grp A	Grp B	
Accounting Indicators	Earnings	$\Delta\text{NIR_EA}$	-0.5783 ** <i>2.1516</i>	-1.1414 * <i>-1.8172</i>	
	Earnings	ΔROAA	-0.1183 ** <i>-2.0399</i>		-0.0889 ** <i>-2.1900</i>
	Liquidity	$\Delta\text{NL_DEP}$	-0.0686 *** <i>-3.0984</i>	-0.1105 *** <i>-2.5313</i>	-0.0512 ** <i>-2.4117</i>
	Liquidity	$\Delta\text{NL_TEA}$	-0.0293 ** <i>-1.9355</i>	-0.0794 * <i>-1.6703</i>	
	Liquidity	$\Delta\text{LIQASS_TOTDB}$		0.0466 ** <i>2.0615</i>	
	Capital	$\Delta\text{KP_DEPSTF}$			-0.0628 * <i>-1.8405</i>
	Capital	$\Delta\text{KP_LIAB}$			-0.0902 ** <i>-2.0113</i>
	Market Indicators		EXCRCUM	-37.1165 ** <i>2.3148</i>	-75.4909 *** <i>-2.6605</i>
		ΔDD	0.5853 ** <i>1.9898</i>		0.7156 * <i>1.8449</i>
		CAR		-2.2359 ** <i>-2.0397</i>	
		LOGP		-4.5224 *** <i>-2.6669</i>	1.8601 ** <i>2.3191</i>
		RCUM		-43.6537 * <i>-1.7512</i>	
		RCUMNEG		1.3218 ** <i>2.1266</i>	
		ΔBETA		-2.9976 * <i>-1.7018</i>	
		$\Delta\text{RISK_TOT}$			64.0651 * <i>1.8185</i>

*This table shows simple logit estimation results where the dependent variable is separately regressed on each explanatory variable and a constant. For regional estimations, a dummy variable (GRP_B), which is equal to 1, if the bank belongs to group B; and 0, otherwise, is added. This model explains downgrades (whatever their extent) that occur in the next calendar year. Standard errors are adjusted using the Huber-White method. ***, ** and * pertain to 1, 5 and 10% level of significance, respectively. Z-Statistics are in italics.*

4.2 Contribution of accounting indicators

After conducting the univariate regressions and initially determining the set of indicators that are significant, stepwise procedures are considered. Table 7 is a presentation of the results for the stepwise procedure based on the full set of accounting indicators.

For the combined groups A and B, the stepwise results show that earnings ratios are the optimal predictors of bank financial distress. $\Delta\text{NIR_EA}$ and ΔROAE are significant at the 5% and 10% levels, respectively. The sign of the coefficients also conform to the expected inverse relationship of profitability with bank financial distress. These results are consistent with the results of the univariate regressions conducted on the regional set of banks where earnings ratios emerge as significant. Also, the dummy variable GRPB, that takes the value of one for group B banks, is significant at 5% showing that Group A and Group B banks behave differently.

For group A banks, the stepwise procedure yields earnings ($\Delta\text{NIR_EA}$) and asset quality ($\Delta\text{LLR_TA}$) indicators as the best predictors of bank financial distress, while it was mostly liquidity ratios that emerged as significant in the initial regressions. The signs of the coefficients conform to the expected relationship with bank distress. Only one accounting indicator emerges after the stepwise procedure for group B banks: $\Delta\text{NL_DEP}$ at the 5% significance level but with the wrong sign.

Table 7. Financial Deterioration and Early Indicators: Stepwise Results – Accounting Indicators

Model Specification:		$\Pr\{Y_i = 1\} = \Phi(\alpha + \sum_{j=1}^J \beta_j C_{ji})$ for groups A and B		
		$\Pr\{Y_i = 1\} = \Phi(\alpha + \delta \text{GRPB}_i + \sum_{j=1}^J \beta_j C_{ji})$ for Regional		
		Regional	Grp A	Grp B
Constant		-1.8368 ***	-1.7837 ***	-3.1393 ***
		<i>-6.2013</i>	<i>-5.4857</i>	<i>-6.8583</i>
GRPB		<i>-0.9708 **</i>		
		<i>-1.928</i>		
Earnings	$\Delta\text{NIR_EA}$	<i>-0.6261 **</i>	<i>-1.5751 **</i>	
		<i>-2.1678</i>	<i>-2.0533</i>	
Earnings	ΔROAE	<i>-0.0092 *</i>		
		<i>-1.7313</i>		
Asset Quality	$\Delta\text{LLR_TA}$		1.2584 **	
			2.058	
Liquidity	$\Delta\text{NL_DEP}$			<i>-0.0512 **</i>
				<i>-2.4116</i>
McFadden R ²		0.079	0.075	0.030
Total Observations		231	88	120
# of observations with Y=1		20	13	5

*This table shows logit estimation results where the dependent variable is regressed on a constant and the accounting indicators selected by a stepwise process. For regional estimations, a dummy variable (GRPB), which is equal to 1, if the bank belongs to group B; and 0, otherwise, is added. This model explains downgrades (whatever their extent) that occur in the next calendar year. Standard errors are adjusted using the Huber-White method. ***, ** and * pertain to 1, 5 and 10% level of significance, respectively. Z-statistics are in italics. The number of observations in the regional model is not equal to the sum of the number of observations of Group A and Group B models because all data are not available for each bank, each year and each indicator.*

4.3 Additional contribution of market indicators

To determine the set of market indicators that contribute further to the prediction of bank distress, the accounting information based model is extended to include market indicators. Table 8 shows the results of the stepwise procedure.

The market indicators that significantly add to the predictive power of the accounting indicators for the regional set are EXCRCUM and ΔDD which is consistent with the initial univariate regression results. These indicators are significant at the 5% and 1% level of significance, respectively. The sign of the coefficient of the indicator EXCRCUM conforms to the expected relationship with bank financial distress while ΔDD does not.

Table 8. Financial Deterioration and Early Indicators: Stepwise Results – With Market Indicators

Model Specification: $\Pr\{Y_i = 1\} = \Phi(\alpha + \sum_{j=1}^J \beta_j C_{ji} + \sum_{l=1}^L \gamma_l M_{li})$ for groups A and B				
$\Pr\{Y_i = 1\} = \Phi(\alpha + \delta GRPB_i + \sum_{j=1}^J \beta_j C_{ji} + \sum_{l=1}^L \gamma_l M_{li})$ for Regional				
		Regional	Grp A	Grp B
Constant		-2.0372 *** -5.3066	1.7677 *** -4.8999	-4.4172 *** -4.1608
GRPB		-1.1066 ** -2.1054		
Earnings	ΔNIR_EA	-0.6024 ** -1.9934	-2.8627 -1.4758	
Earnings	$\Delta ROAE$	-0.0215 ** -2.1702		
Asset Quality	ΔLLR_TA		1.8636 * 1.7217	
Liquidity	ΔNL_DEP			-0.1062 *** -2.8877
	EXCRCUM	-37.1166 ** -2.1353		
	ΔDD	0.7621 *** 2.5579		
Market Indicators	LOGP		-4.6914 ** -2.3038	
	$\Delta BETA$		-7.9047 ** -1.9322	
	CAR			7.3578 *** 2.9005
	EXCRCUMNEG			2.0263 * 1.6743
Risk level to reject $\gamma_1 = 0 \forall l$		1.27% **	1.95% **	1.21% **
McFadden R ²		0.163	0.28	0.185
Total Observations		187	85	107
# of observations with Y=1		20	13	5

*This table shows logit estimation results where the dependent variable is regressed on a constant, the accounting indicators previously selected and the market indicators selected by the stepwise process. For regional estimations, a dummy variable (GRPB), which is equal to 1, if the bank belongs to group B; and 0, otherwise, is added. This model explains downgrades (whatever their extent) that occur in the next calendar year. Standard errors are adjusted using the Huber-White method. ***, ** and * pertain to 1, 5 and 10% level of significance, respectively. Z-statistics are in italics. The number of observations in the regional model is not equal to the sum of the number of observations of Group A and Group B models because all data are not available for each bank, each year and each indicator.*

For group A banks, the market indicators LOGP and $\Delta BETA$ increase the predictive power of a model based solely on accounting indicators. These indicators are both significant at the 10% level.

The sign of the coefficient of ΔBETA , however, does not conform to the expected positive relationship with bank financial distress as can be seen in the univariate regression result.

Two market indicators appear to increase the predictive power of the model based only on $\Delta\text{NL_DEP}$ for group B banks: CAR and EXCRCUMNEG . However, only the sign of EXCRCUMNEG conforms to the expected relationship with bank financial distress.

The tests at the bottom of the table indicate that, whatever the group of countries, market information contributes to the model's overall fit as we can reject the null hypothesis that market indicators are not significant at the 5 % significance level.

Therefore our results support the conjecture that the introduction of market indicators in the prediction model can add information not yet contained in accounting data. The signs of the coefficients associated with these indicators, though, are not always the expected ones.

4.4 Balance sheet structure effects

We study the accuracy of market indicators for different balance sheet profiles. First, we consider the structure of assets *via* the importance of the ratio of net loans to total assets. Then, we study the impact of the structure of liabilities on the effectiveness of market indicators by considering the importance of the ratio of market-funded liabilities to total assets. In each case, we consider the impact of the balance sheet structure (assets or liabilities) by introducing a dummy variable that takes the value of one for banks with a value of the considered ratio higher than the median value of the ratio and zero otherwise. We also run the regressions on two sub-samples constructed on the basis of the value of the dummy variable.

The model specification to capture the effects is as follows:

$$\Pr(Y_i = 1) = \Phi \left(\alpha + \delta \text{GRPB}_i \sum_{j=1}^J \beta_j C_{ji} + \sum_{l=1}^L \gamma_l M_{li} + \sum_{l=1}^L \gamma'_l \text{DUM}_i M_{li} \right)$$

where DUM_i is a dummy variable which captures the considered effect.

A test to assess the hypothesis that the considered effect neutralizes the predictive power of each market indicator ($H_0: \gamma_l + \gamma'_l = 0 \forall l$) is conducted.

Estimations are also conducted on two sub-samples defined on the basis of the value of the dummy variable. Due to data limitations, estimations are only run on the regional sample of banks (full sample).

Besides, because the change in the distance to default ΔDD has the wrong sign in our estimations we omit this variable in our further investigations⁷.

4.4.1 Structure of bank assets

We study the effectiveness of market indicators depending on the importance of loan activities. Indeed, banks focused on loans can be considered as more opaque and the effectiveness of market indicators may be weaker for such banks.

When we introduce the dummy variable DNLTA , we notice that the market indicator EXCRCUM is significant only for banks with a high ratio of net loans to total assets, as shown by the result of the test at the bottom of Table 9. This finding is confirmed when we run the regressions on the two sub-samples.

⁷ We also ran the estimation with ΔDD and we found the same results. Besides, running the second stepwise procedure without ΔDD does not lead to the selection of another significant market indicator.

Table 9. Market Indicators and the Structure of Assets

Model Specification: $\Pr\{Y_i = 1\} = \Phi[\alpha + \delta GRPB_i + \sum_{j=1}^J \beta_j C_{ji} + \sum_{l=1}^L \gamma_l M_{li} + \sum_{l=1}^L \gamma'_l (DNLTA_i * M_{li})]$
for the whole sample; $\Pr\{Y_i = 1\} = \Phi(\alpha + \delta GRPB_i + \sum_{j=1}^J \beta_j C_{ji} + \sum_{l=1}^L \gamma_l M_{li})$ for sub-samples

	Whole sample	Sub-sample 1	Sub-sample 2
Constant	-2.038 *** <i>-6.465</i>	-1.815 *** <i>-4.289</i>	-2.752 *** <i>-3.953</i>
GRPB	<i>-0.725</i> <i>-1.449</i>	-2.176 ** <i>-1.975</i>	<i>0.542</i> <i>0.661</i>
Δ NIR_EA	<i>-0.579</i> <i>-1.610</i>	<i>-1.576</i> <i>-1.312</i>	<i>-0.337</i> <i>-1.426</i>
Δ ROAE	<i>-0.012</i> <i>-1.532</i>	<i>-0.018</i> <i>-0.951</i>	<i>-0.003</i> <i>-0.446</i>
EXCRCUM	<i>17.268</i> <i>0.590</i>	-51.915 ** <i>-1.984</i>	<i>22.734</i> <i>0.873</i>
EXCRCUM*DNLTA	-75.609 ** <i>-2.127</i>		
McFadden R ²	<i>0.143</i>	<i>0.311</i>	<i>0.038</i>
Total Observations	<i>213</i>	<i>111</i>	<i>102</i>
# of observations with Y=1	<i>20</i>	<i>12</i>	<i>8</i>
Risk level to reject $\gamma_1 + \gamma'_1 = 0$	<i>0.36%</i>		

*This table shows logit estimation results where the dependent variable is regressed on a constant, the accounting indicators and the market indicators selected by the stepwise processes and a dummy variable (GRPB) equal to 1, if the bank belongs to group B; 0, otherwise. This model explains downgrades (whatever their extent) that occur in the next calendar year. Assets structure effect is taken into account in the first column with the dummy variable DNLTA associated with market indicators. DNLTA is equal to 1, if the ratio net loans/ total assets is higher than its median value (54.72%). Standard errors are adjusted using the Huber-White method. ***, ** and * pertain to 1, 5 and 10% level of significance, respectively. Z-statistics are in italics. Sub-sample 1 includes banks for which DNLTA=1, while sub-sample 2 includes banks for which DNLTA=0.*

Thus, market information seems useful only for traditional banks (i.e., banks highly involved in loan activities). However, to check the robustness of this result, we also run the stepwise processes separately on the two sub-samples. Results are presented in Table 10.

Two market indicators are significant to explain downgrades of banks largely involved in loan activities: cumulative market excess returns (EXCRCUM) and the change in specific risk (Δ RISK_SPEC). These indicators perform as expected. By running the stepwise process on the sub-sample of banks with a low ratio of net loans to total assets, two other market indicators are selected. Thus, market information seems also useful for such banks. However the signs of the coefficient associated with these market indicators are not the expected ones. Thus, it seems difficult to interpret market information for such banks.

Table 10. Market Indicators and the Structure of Assets: New Stepwise⁸

Model Specification: $\Pr\{Y_i = 1\} = \Phi(\alpha + \delta GRPB_i + \sum_{j=1}^J \beta_j C_{ji} + \sum_{l=1}^L \gamma_l M_{li})$ for sub-samples		
	Sub-sample 1	Sub-sample 2
Constant	-1.691 *** <i>-3.471</i>	-2.758 *** <i>-3.722</i>
GRPB	-5.210 *** <i>-3.113</i>	0.596 <i>0.663</i>
Δ NIR_EA	-1.904 <i>-1.622</i>	
Δ KP_DEPSTF	-0.343 * <i>-1.792</i>	
Δ LLR_GL	0.245 <i>1.040</i>	
Δ KP_LIAB		-0.032 <i>-1.135</i>
EXCRCUM	-97.392 *** <i>-2.597</i>	
Δ RISKSPEC	172.47 * <i>1.838</i>	
RCUMNEG		-1.810 ** <i>-2.519</i>
Δ Z		0.136 * <i>1.785</i>
McFadden R ²	0.468	0.112
Total Observations	110	103
# of observations with Y=1	12	8
χ^2 stats for $\gamma_l = 0 \forall l$	6.91 **	10.73 ***

*This table shows logit estimation results where the dependent variable is regressed on a constant, the accounting indicators selected by a first stepwise process and the market indicators selected by a second stepwise process and a dummy variable (GRPB) equal to 1, if the bank belongs to group B; 0, otherwise. This model explains downgrades (whatever their extent) that occur in the next calendar year. Standard errors are adjusted using the Huber-White method. ***, ** and * pertain to 1, 5 and 10% level of significance, respectively. Z-statistics are in italics. Sub-sample 1 includes banks for which DNLTA=1, while sub-sample 2 includes banks for which DNLTA=0*

4.4.2 Structure of bank liabilities

The extent to which banks rely on market funding may affect the ability of market agents to assess the riskiness of banks. Thus, we study the effectiveness of market indicators depending on the importance of the ratio of market funded liabilities to total assets.

We can see in Table 11, considering both the results obtained with the dummy variable DMARKTA or the sub-samples, that the market indicator EXCRCUM is significant only for banks with a low ratio of market funded liabilities to total assets. This result is quite surprising. Thus, to check for robustness, we run stepwise processes on the two sub-samples defined on the basis of the value of the dummy variable DMARKTA.

⁸ We run two stepwise procedures: one with the accounting indicators and the other one adding market indicators. In these stepwise procedures, we make sure that at least 75% of the observations with Y=1 are considered in the regressions. Here, we only report the results obtained at the end of the second procedure.

Table 11 Market Indicators and the Structure of Liabilities

Model Specification: $\Pr\{Y_i = 1\} = \Phi[\alpha + \delta GRPB_i + \sum_{j=1}^J \beta_j C_{ji} + \sum_{l=1}^L \gamma_l M_{li} + \sum_{l=1}^L \gamma'_l (DMARKTA_i M_{li})]$
 for the whole sample; $\Pr\{Y_i = 1\} = \Phi(\alpha + \delta GRPB_i + \sum_{j=1}^J \beta_j C_{ji} + \sum_{l=1}^L \gamma_l M_{li})$ for sub-samples

	Whole sample	Sub-sample 1	Sub-sample 2
Constant	-1.891 ***	-3.247 ***	-1.388 ***
	-6.219	-4.122	-3.672
GRPB	-0.938 *	1.066	-2.759 **
	-1.757	1.092	-2.291
Δ NIR_EA	-0.587 *	-0.562	-0.546
	-1.753	-1.465	-0.996
Δ ROAE	-0.012	-0.045 **	-0.009
	-1.547	-2.028	-0.502
EXCRCUM	-37.005 *	-7.830	-39.211 *
	-1.869	-0.278	-1.695
EXCRCUM*DMARKTA	14.961		
	0.478		
McFadden R ²	0.111	0.083	0.257
Total Observations	213	109	104
# of observations with Y=1	20	8	12
Risk level to reject $\gamma_1 + \gamma'_1 = 0$	37.44%		

This table shows logit estimation results where the dependent variable is regressed on a constant, the accounting indicators and the market indicators selected by the stepwise processes and a dummy variable (GRPB) equal to 1, if the bank belongs to group B; 0, otherwise. This model explains downgrades (whatever their extent) that occur in the next calendar year. Assets structure effect is taken into account in the first column with the dummy variable DNLTA associated with market indicators. DMARKTA is equal to 1, if the ratio market fundings/ total assets is higher than its median value (9.88%). Standard errors are adjusted using the Huber-White method. ***, ** and * pertain to 1, 5 and 10% level of significance, respectively. Z-statistics are in italics. Sub-sample 1 includes banks for which DMARKTA=1, while sub-sample 2 includes banks for which DMARKTA=0.

The results presented in Table 12 show that market information is useful for both types of banks but that the effective indicators are not the same. For banks heavily relying on market funding, the change in the standard deviation of weekly returns (Δ RISK_TOT), as well as the dummy variable that takes into account the existence of negative cumulative market excess returns (EXCRCUMNEG), are significant. For banks with a low ratio of market funded liabilities, the significant market variables are the change in the beta (Δ BETA) and the difference between the natural logarithm of weekly market price and its moving average (LOGP). Thus, the structure of liabilities does not seem to affect the effectiveness of market information; the accurate market indicators are simply different in both cases.

Table 12 Market Indicators and the Structure of Liabilities: New Stepwise⁹

Model Specification: $\Pr\{Y_i = 1\} = \Phi(\alpha + \delta GRPB_i + \sum_{j=1}^J \beta_j C_{ji} + \sum_{l=1}^L \gamma_l M_{li})$ for sub-samples		
	Sub-sample 1	Sub-sample 2
Constant	-3.966 *** <i>-5.650</i>	-1.324 *** <i>-3.726</i>
GRPB	1.007 <i>1.153</i>	-3.025 ** <i>-2.296</i>
Δ NIR_EA		-1.371 * <i>-1.877</i>
Δ KP_LIAB	-0.093 ** <i>-2.317</i>	
Δ ROAE	-0.024 <i>-1.371</i>	
Δ BETA		-5.774 ** <i>-2.226</i>
LOGP		-3.080 * <i>-1.701</i>
Δ RISKTOT	97.804 *** <i>2.653</i>	
EXCRCUMNEG	1.648 * <i>1.911</i>	
McFadden R ²	0.175	0.314
Total Observations	110	102
# of observations with Y=1	8	12
χ^2 stats for $\gamma_l = 0 \forall l$	7.80 **	9.64 **

*This table shows logit estimation results where the dependent variable is regressed on a constant, the accounting indicators selected by a first stepwise process and the market indicators selected by a second stepwise process and a dummy variable (GRPB) equal to 1, if the bank belongs to group B; 0, otherwise. This model explains downgrades (whatever their extent) that occur in the next calendar year. Standard errors are adjusted using the Huber-White method. ***, ** and * pertain to 1, 5 and 10% level of significance, respectively. Z-statistics are in italics. Sub-sample 1 includes banks for which DMARKTA=1, while sub-sample 2 includes banks for which DMARKTA=0.*

5 Conclusion

The aim of this study is to determine whether equity market information can complete accounting information to predict Asian banks' financial distress. We show that the use of equity market indicators can improve the prediction model as they bring additional information not already contained in accounting indicators. These results are in line with those of Krainer and Lopez (2004) and Curry et al. (2007) in the US case, and those of Distinguin et al. (2006) in the European case.

By dividing our sample of Asian banks into two sub-groups (i.e., banks from the tiger economies and banks from emerging markets) we show that the contribution of market information to predict banks' financial distress is significant for both groups.

The results concerning balance sheet structure effects are less clear-cut. Market information appears effective to predict downgrades of banks whatever their structure of liabilities even if the accurate indicators are not the same depending on the relative importance of market funded

⁹ We run two stepwise procedures: one with the accounting indicators and the other one adding market indicators. In these stepwise procedures, we make sure that at least 75% of the observations with Y=1 are considered in the regressions. Here, we only report the results obtained at the end of the second procedure.

liabilities in balance sheets. Concerning assets structure, we find that market indicators are significant to predict downgrades for banks that are either weakly or highly focused on loans. However, for banks with a lower extent of loans in their balance sheet, market information seems difficult to interpret.

As a whole, in the case of East Asia, bank stock prices seem to be useful to predict bank financial distress but compared to western economies (U.S. and Western Europe) their information content appears to be less clear.

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Appendix

Distance to Default

The distance to default indicator DD - the number of standard deviations away from the default point (i.e., when the value of assets equals the value of liabilities) - is:

$$DD_t = \frac{\log\left(\frac{V_t}{D_t}\right) + \left(r_f - \frac{\sigma_t^2}{2}\right)T}{\sigma_t\sqrt{T}}$$

where:

V_t = bank's asset value at time t

D_t = book value at time t of the bank's debt of maturity T

T = debt maturity

r_f = risk-free interest rate

σ_t = bank's asset value volatility

To estimate V_t and σ_t , the value of equity as a call option on the underlying assets with a strike price equal to the book value of the bank's debt was considered. Hence, the market value and volatility of the bank's underlying assets can be derived from the equity's market value (VE) and volatility (σ_E) by solving:

$$\begin{cases} V_t = \frac{VE_t + D_t e^{-r_f T} N(d_2)}{N(d_1)} \\ \sigma_t = \frac{\frac{VE_t}{V_t} \sigma_{E,t}}{N(d_1)} \end{cases}$$

where:

$$d_1 = \frac{\log\left(\frac{V_t}{D_t}\right) + \left(r_f + \frac{\sigma_t^2}{2}\right)T}{\sigma_t\sqrt{T}}$$

$$d_2 = d_1 - \sigma_t\sqrt{T}$$

Weekly market values of the bank's equity (VE) were obtained from Datastream. The volatility of the bank's equity (σ_E) on the quarter preceding the end of the calendar year was calculated as the standard deviation of weekly equity returns multiplied by $\sqrt{365}$.

Here, the expiry date of the option (T) is equal to the maturity of the debt. A common assumption is to set it to one, i.e., one year. Interbank rates from Datastream were used to compute risk-free rates. Data on debt liabilities were obtained from Bankscope. The total amount of liabilities was calculated as the total amount of deposits, money-market funding, bonds, subordinated debt and hybrid capital.