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Are early market indicators of financial deterioration accurate for Too Big To Fail banks? Evidence from East Asia

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Abstract

This paper investigates whether market information is reliable to predict financial deterioration of large Too Big To Fail banks in Asia. A stepwise logit model is first estimated to isolate the optimal set of accounting indicators to predict rating downgrades. The model is then extended to assess the added value of market indicators and to test for the possible presence of a Too Big To Fail effect. While some results show that market indicators bring in additional information in the prediction process, there is consistent evidence of a Too Big To Fail effect.

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1. Introduction

Banks play a major role in the financial system due to their intermediation function. Consequently, supervisors need to frequently assess banks' financial health using early warning systems (EWS). Such models mainly focus on accounting data which are backward looking and the reliability of accounting data is debatable given the very persistent issues of information quality and diversity in the application of accounting principles.[1] Thus, to improve the supervisory process, there has been a growing interest in the use of market data (Berger, Davies, and Flannery 2000, Flannery 1998) which are considered as a viable complement to accounting information in the conduct of assessing bank financial health. However, to be useful, market information must correctly reflect the riskiness of bank activities. Market participants should have incentives to monitor banks; they must credibly perceive that they will not be compensated if the bank defaults. Thus, the use of market information to complement accounting information in the prediction process of banks' financial distress may be questionable for banks that are considered as Too Big To Fail by the market.

Studies in the US conducted in this area show that market variables add to the predictive power of accounting indicators. The findings of Curry, Elmer, and Fissel (2007) and Evanoff and Wall (2001) show that market indicators improve the assessment of bank financial health. The results of Gropp, Vesala and Vulpes (2006) and Distinguin, Rous and Tarazi (2006) on European banks also show that market indicators could predict deteriorations in banks' financial condition at relatively long horizons. They also demonstrate the additional contribution of market indicators to accounting information in the prediction process and that equity market indicators are not affected by a Too Big To Fail effect.

In Asia, little has been written on the prediction of bank failures. Most studies focus on early-warning models of banking crises (Demirgüc-Kunt and Degatriache 2000) and do not consider the prediction of bank's financial deterioration at the individual level There is also a need for considering the possible existence of a Too Big To Fail effect as it may highlight limits in the use of market information to predict financial distress of East Asian banks.[2]

The objective of this paper is to determine if, in the Asian banking sector, market indicators can bring in specific/additional information in the prediction of bank financial distress for both small and large banks. The paper looks into the reliability and stability of market indicators given the presence of a Too Big To Fail effect. Indeed, market participants might react less strongly to financial deteriorations of large banks because of the perception of a bail-out in case of default.

The paper is organized as follows: Section 2 presents the methodology adopted for our study. Section 3 describes the data and the set of early accounting and market indicators used in our estimations. Section 4 presents the results and section 5 concludes.

2. Methodology

The main purpose of this study is to test the possible existence of a Too Big To Fail effect in East Asia. More precisely, we question the ability of market indicators to predict bank financial distress for large institutions. Indeed, if a bank is considered as Too Big To

[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 favourably present financial performance. Also, the development and adoption of International Accounting Standards (IAS) aim to eliminate diversity and country differences in the application of accounting principles.
[2] Distinguin, Tarazi, and Trinidad (2010) consider the contribution of market indicators in the prediction of Asian banks distress but they do not take into account the existence of a Too Big To Fail effect. They focus on the influence of banks' balance sheet structure on the effectiveness of market indicators.

Fail by the market, that is if market participants perceive the existence of an implicit insurance, they have no incentives to monitor banks and market indicators should bring no useful information to predict banks financial distress. Thus, in order to test the existence of a Too Big To Fail effect, we first construct a model including the most accurate accounting and market indicators to predict banks financial distress. We then study the impact of size on the effectiveness of market indicators.

To start off, we need to consider an event that could represent a change in the financial condition of a bank. Most studies in the US conducted in this area either make use of explicit bank failures or supervisory ratings downgrades as in Curry, Elmer and Fissel (2007), Kolari, *et al.* (2002) and Gunther, Levonian, and Moore (2001). Studies on European banks make use of sharp downgrades (Gropp, Vesala and Vulpes 2006) as proxies for actual bank failure or downgrade announcements by private agencies[3] (Distinguin, Rous and Tarazi 2006) as proxies for financial distress. Since actual bank failure is quite limited in Asia, this paper will follow on Distinguin, Rous and Tarazi (2006) using downgrade announcements to capture deteriorations in a bank's financial condition. These downgrade announcements are obtained from the three major rating agencies Fitch, Moody's and Standard and Poor's.

Accounting C_{ji} and market M_{li} indicators are computed at the end of a given year to estimate the probability of a downgrade occurring in the following year.
For each bank in the sample, the dependent variable Y is equal to:

- 1, if the bank is downgraded in the following year 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 following calendar year; and;
- NA (not available), for all other cases.

As in Distinguin, Rous and Tarazi [2006], the following logit model is employed to estimate the probability of a downgrade:

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

where C_{ji} and M_{li} are the j^{th} accounting indicator and the l^{th} market indicator, respectively, and $\Phi(.)$ 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.

We first select the optimal set of accounting and market indicators[4] and we then test the stability of the contribution of market indicators in the prediction process by introducing a

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

[4] Following Distinguin, Rous, and Tarazi (2006), 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 where, 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. The procedure is then extended to include market indicators in order to determine their marginal contribution to

dummy variable. This dummy variable DBIG takes the value of 1, if the bank is considered as "Too Big to Fail"; 0, otherwise. Two criteria are used to define a bank as "Too Big to Fail":

- If the FitchRatings Support rating is 1 or 2, the bank is considered as Too Big to Fail. This support rating indicates the likelihood of public or private support on a scale from 1 to 4; a grade of 1 (the highest) indicates the presence of an assured legal guarantee. FitchRatings Support Ratings are commonly used in the literature to identify Too Big To Fail banks operating outside the US (see Gropp, Vesala, and Vulpes 2006 and Distinguin, Rous, and Tarazi 2006).
- Banks with asset country ranks 1 or 2 are considered as Too Big To Fail.[5]
- If both the FitchRatings Support rating and asset country ranks are not available, banks with asset size ranks 1 or 2 within the country sample are considered as Too-Big to Fail.[6]

The model specification to capture the effects of size is as follows:

$$\text{Prob } \left(Y_i = 1\right) = \Phi\left(\alpha + \delta GRPB_i + \sum_{j=1}^{J} \beta_j C_{ji} + \sum_{l=1}^{L} \gamma_l M_{li} + \sum_{l=1}^{L} \gamma_l ' DBIG_i M_{li}\right) \tag{2}$$

where $DBIG_i$ is a dummy variable which captures the effect of size. The banks are categorized in 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. The two country groups exhibit different characteristics particularly with respect to the level of development of their financial system. We control for country group differences by introducing a dummy variable GRPB which is equal to one for banks belonging to group B.

A test to assess the hypothesis that size neutralizes the predictive power of each market indicator ($H_0 : \gamma_l + \gamma'_l = 0 \forall 1$) is conducted. Estimations are also conducted on two sub-samples defined on the basis of the value of the dummy variable DBIG.

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 regularly 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.

Table I presents the distribution of banks by country and specialization[7]. Information is taken from Bankscope Fitch IBCA.

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the prediction model. Market indicators are added to the optimal subset of accounting indicators obtained in the first step.

[5] FitchRatings Support ratings and asset country rank information are taken from Bankscope Fitch IBCA.

[6] Out of the 64 banks that are included in our sample the first criterion (FitchRating support rating) can be used for 55 banks for which a Fitch Support rating is available. On the basis of this criterion, 16 banks can be considered as Too Big to Fail. We can use the second criterion for 60 banks and 11 of them can be considered as Too Big To Fail. The third criterion is used for two banks in the sample and only one of them can be considered as Too Big To Fail on this basis (this bank is the fifth largest bank in our whole sample on the basis of total assets).

[7] Commercial banks represent 87.5 percent of the sample banks considered in our study. We have checked that performing our estimations on a sample restricted only to those commercial banks does not alter our main conclusions.

Table I: 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**

Source: Bankscope Fitch IBCA

Distribution of banks by specialization:

Specialization	No. of banks
Bank holding and holding company	2
Commercial bank	56
Cooperative bank	1
Investment bank	5
Total	64

Source: Bankscope Fitch IBCA

Accounting data (annual financial statements) for the banks in our sample are obtained from Bankscope Fitch IBCA and weekly market data come from Datastream International. Our sample is restricted to the post-crisis period 1999-2004 in order to avoid noise related to the 1997 financial crisis. Table II shows some descriptive statistics on summary accounting information.

Table II: Descriptive Statistics on Summary Accounting Information

	Mean[2]	Standard Deviation[2]	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

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

[2] Each mean is calculated as $\overline{X} = \frac{1}{NT}\sum_{t=1}^{T}\sum_{j=1}^{N} X_{jt}$ 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

Table III provides information on the downgrades used in this study. These downgrades are announced by the rating agencies Fitch, Moody's and Standard and Poor's. Ratings information is obtained from Bankscope Fitch IBCA and FinInfo. 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 only consider the first one. Of the total forty-five (45) combined downgrades from the ratings agencies, only twenty (20) "clean" downgrades are used for the estimations.

Table III: Downgrades Information
(Number of clean downgrades in parenthesis)

		2001	**2002**	**2003**	**2004**	**2005**
45 (20)	Total downgrades	18 (6)	9 (7)	1 (1)	3 (1)	14 (5)
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)

3.3. Accounting Indicators

In this study, we consider a set of accounting ratios (see Table IV) commonly used in the assessment of bank financial health. We group these ratios into the four categories of the CAEL (Capital, Asset quality, Earnings and Liquidity) rating.

Previous studies in this area either consider accounting ratios in level (Curry, Elmer and Fissel 2007, Gunther, Levonian, and Moore 2001) or in variation (first order difference) (Distinguin, Rous and Tarazi 2006). In this study, as we aim to predict changes in the financial condition of the bank, it seems more appropriate to consider the changes in the values of the ratios. 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 IV: Accounting Ratios R_j

Category	Name	Definitions
Capital	KP_NL	Equity/ Net Loans
	KP_DEPSTF	Equity/ Customer and ST Fundings
	KP_LIAB	Equity/ Liabilities
	TCR	Total Capital Ratio
Asset Quality	LLP_TA	Loan Loss Provision/ Total Assets
	LLP_GL	Loan Loss Provision/ Gross Loans
	RWA_TA[8]	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
	ROAE	Return on Equity = Net Income/ Equity
Liquidity	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

3.4. Market Indicators

The set of market indicators used in this study and their expected relationship with the probability of bank failure are presented in Table V. They are derived from weekly equity prices.

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 *ΔBETA* to detect risk changes.

[8] This ratio is obtained by dividing the denominator of the Cooke ratio by total assets. Note that if we were to omit off-balance sheet risks the value of this ratio would range from 0 (lowest possible level of asset risk) to 1 (highest possible level of asset risk). Because the Cooke ratio also accounts for off-balance sheet risks, the value of this indicator can be larger than 1, indicating an even higher exposure to risk.

Table V: 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: $RCUM_{bt} = \left(\left(\prod_{k=1}^{13}\left(1+r_{b,t-k+1}\right)\right)-1\right)$ 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: $EXCRCUM_{b,t} = \left(\left(\prod_{k=1}^{13}\left(1+r_{b,t-k+1}\right)\right)-1\right) - \left(\left(\prod_{k=1}^{13}\left(1+r_{m,t-k+1}\right)\right)-1\right)$ We obtain $r_{m,}$ 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
ΔRISK_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
ΔBETA	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
ΔRISK_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
ΔZ	Change in the Z-score between the third and fourth quarter of the accounting period (financial year) preceding the event with: $Z=\left(1+\overline{r}_b\right)/\sigma_r$ where $\overline{r}_b$ is the mean return of stock b on the preceding quarter and σ_r the standard deviation of the return.	Negative

4. Empirical Results

We first consider the predictive power of accounting indicators *via* a stepwise process. The process is then extended to include market indicators in order to assess their marginal contribution to the prediction process. Finally, to capture a possible Too Big To Fail effect, dummy variables are introduced in the model and estimations are run on restricted samples of banks.

4.1. Predictive added value of Market Indicators

Table VI: Financial Deterioration and Early Indicators: Stepwise Results

Model Specification:

Stepwise 1: Prob $\{Y_i = 1\} = \Phi\left(\alpha + \delta GRPB_i + \sum_{j=1}^{J} \beta_j C_{ji}\right)$ (3)

Stepwise 2: Prob $\{Y_i = 1\} = \Phi\left(\alpha + \delta GRPB_i + \sum_{j=1}^{J} \beta_j C_{ji} + \sum_{l=1}^{L} \gamma_l M_{li}\right)$ (4)

		Stepwise 1	Stepwise 2
Constant		-1.8368*** *-6.2013*	-1.8782 *** *-6.2811*
GRPB		-0.9708** *-1.928*	-0.9662 * *-1.8453*
Earnings	ΔNIR_EA	-0.6261** *-2.1678*	-0.6242 * *-1.9548*
Earnings	ΔROAE	-0.0092* *-1.7313*	-0.0125 *-1.5527*
Market Indicators	EXCRCUM		-31.9800 ** *-2.0277*
Risk level to reject $\gamma_l = 0\ \forall l$			4.39%**
McFadden R^2 Total Observations Nb of observations with Y=1		0.079 231 20	0.110 213 20

This table shows logit estimation results where the dependent variable is regressed, for the column stepwise 1, on a constant and the accounting indicators selected by a stepwise process and, for the column stepwise 2, on a constant, the accounting indicators previously selected and the market indicators selected by a second stepwise process. A dummy variable (GRPB), which is equal to 1, if the bank belongs to group B (ie banks from Malaysia, Thailand, Indonesia, and the Philippines); and 0, otherwise (ie banks from Hong Kong, Korea, Taiwan, and Singapore) 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-Stats are in italics.

Variables definition: ΔNIR_EA = annual change of (Net Interest Revenue/ Total Earning Assets), ΔROAE = annual change of (Net Income/ Equity), EXCRCUM = cumulative market excess return on the fourth quarter of the accounting period (financial year) preceding the event.

The results of the first stepwise process considering only accounting indicators (table VI, column stepwise 1) show that earnings ratios are the optimal accounting predictors of bank financial distress. ΔNIR_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. The results of the second stepwise procedure (table VI, column stepwise 2) indicate that the market indicator that significantly adds to the predictive power of the accounting indicators is EXCRCUM that is cumulative market excess return. This indicator is significant at the 5% level of significance. The sign of the coefficient conforms to the expected negative relationship with bank financial distress.

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 and we can test the stability of the contribution of market indicators depending on the size of the bank.

4.2. Too Big To Fail effect

As previously mentioned, the possible existence of a size effect might play a crucial role in the prediction process. As Distinguin, Rous and Tarazi (2006) point out, the presence of this effect might imply that market information is less powerful for the prediction of financial distress for specific institutions. For instance, the existence of public safety nets for Too Big To Fail banks may bring the market to react less to significant changes in the financial condition of these banks[9]. On the other hand, as the market may believe that large banks provide more reliable accounting information than smaller banks, it can look more closely into the financials of these large banks.

The results obtained for the Too Big To Fail tests are presented in Table VII[10]. The results obtained when we introduce the dummy variable DBIG (Table VII, column Whole sample) show that the market indicator EXCRCUM is significant at the 5% significance level to predict downgrades of small banks. The test at the bottom of the table shows that this indicator is not significant for large banks. Therefore, the conjecture of a Too Big To Fail effect cannot be rejected.

These results are confirmed by running the regressions on two sub-samples of banks (large and small). When only large banks are included in the regression (sub-sample 1), the market indicator is not significant. When only small banks (sub-sample 2) are considered in the estimation, EXCRCUM emerges as significant at the 5% significance level.

[9] A formal insurance deposit system was implemented in 1963 in Philippines, in 1985 in Taiwan, in 1996 in Korea, in 1997 in Thailand, in 1998 in Malaysia and Indonesia, and in 2006 in Hong Kong and Singapore. Coverage limits are often relatively low compared with US or European standards but banks, specifically large institutions, have also benefited from an implicit insurance system before and after the introduction of explicit systems for systemic risk and safety net considerations. In this study, we are more concerned about the existence of implicit insurance for large banks which may deter market discipline for such institutions than by the introduction of explicit insurance systems for depositors. Implicit insurance for large banks such as bailouts is expected to be effective in both explicit (formal) and implicit deposit insurance systems.

[10] On the basis of the criteria defined in 2., 22 banks are considered as Too Big To Fail in our sample: ten in group A and twelve in group B.

Table VII: Market Indicators and Bank Size

Model Specification:

$$\text{Prob}\{Y_i = 1\} = \Phi\left(\alpha + \delta GRPB_i + \sum_{j=1}^{J}\beta_j C_{ji} + \sum_{l=1}^{L}\gamma_l M_{li} + \sum_{l=1}^{L}\gamma'_l\left(DBIG_i \times M_{li}\right)\right) \quad (5)$$

, for the whole sample

$$\text{Prob}\ \{Y_i = 1\} = \Phi\left(\alpha + \delta GRPB_i + \sum_{j=1}^{J}\beta_j C_{ji} + \sum_{l=1}^{L}\gamma_l M_{li}\right) \quad (6)$$

, for sub-samples

	Whole sample	Sub-sample 1	Sub-sample 2
Constant	**-1.900** ***	**-2.101** ***	**-1.805** ***
	-6393	*-4.031*	*-4.858*
GRPB	**-0.967** *	-0.212	**-1.389** **
	-1.828	*-0.270*	*-1.977*
ΔNIR_EA	**-0.631** **	-0.607	**-0.686** *
	-1.973	*-0.982*	*-1.656*
ΔROAE	-0.010	-0.006	-0.019
	-1.348	*-1.252*	*-0.896*
EXCRCUM	**-37.640** **	-2.111	**-37.197** **
	-2.291	*-0.046*	*-1.973*
EXCRCUM*DBIG	32.872		
	0.659		
McFadden R^2	0.114	0.025	0.180
Total Observations	213	75	138
Nb. of observations with Y=1	20	7	13
Risk level to reject $\gamma_1 + \gamma'_1 = 0$	91.45%		

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), which is equal to 1, if the bank belongs to group B (ie banks from Malaysia, Thailand, Indonesia, and the Philippines); and 0, otherwise (ie banks from Hong Kong, Korea, Taiwan, and Singapore). This model explains downgrades (whatever their extent) that occur in the next calendar year. Size effect is taken into account in the first column with the dummy variable DBIG associated with market indicators. DBIG is equal to 1, if: the Fitch Support rating is 1 or 2; a bank's asset country rank is 1 or 2; or a bank's asset size rank is 1 or 2 within the country sample if both FitchSupport rating and asset country ranks are not available. Standard errors are adjusted using the Huber-White method. ***, ** and * pertain to 1, 5 and 10% level of significance, respectively. Z-Stats are in italics. Sub-sample 1 includes Too Big To Fail banks that is banks for which DBIG=1, while sub-sample 2 includes relatively smaller banks (i.e., banks for which DBIG=0).

Variables definition: ΔNIR_EA = annual change of (Net Interest Revenue/ Total Earning Assets), ΔROAE = annual change of (Net Income/ Equity), EXCRCUM = cumulative market excess return on the fourth quarter of the accounting period (financial year) preceding the event.

In order to check the robustness of these results, we also run the stepwise processes separately on the two sub-samples. Indeed, the fact that the market indicator (EXCRCUM) is not significant for large banks does not imply that no other market indicator is accurate for such banks. In other words, even if EXCRCUM is the best market indicator for the whole sample of bank, it might not be the best one for the sub-sample of large banks. Results are shown in Table VIII.

Table VIII: Market Indicators and Bank Size: new stepwise[11]

Model Specification:

$$\text{Prob } \{Y_i = 1\} = \Phi\left(\alpha + \delta GRPB_i + \sum_{j=1}^{J} \beta_j C_{ji} + \sum_{l=1}^{L} \gamma_l M_{li}\right) \quad (7)$$

	Sub-sample 1[12]	**Sub-sample 2**
Constant	**-3.019** *** *-4.423*	**-1.781** *** *-4.874*
GRPB	0.561 *0.562*	**-1.515** ** *-2.152*
ΔNIR_EA		-0.559 *-1.468*
ΔNL_DEP	**-0.158** *** *-2.694*	
EXCRCUM		**-41.295** ** *-2.315*
McFadden R^2	0.114	0.164
Total Observations	77	140
Nb of observations with Y=1	5	13
χ^2 stats for $\gamma_l = 0 \ \forall l$		**5.36****

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), which is equal to 1, if the bank belongs to group B (ie banks from Malaysia, Thailand, Indonesia, and the Philippines); and 0, otherwise (ie banks from Hong Kong, Korea, Taiwan, and Singapore). 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-Stats are in italics. Sub-sample 1 includes Too Big To Fail banks that is banks for which DBIG=1, while sub-sample 2 includes relatively smaller banks (i.e., banks for which DBIG=0). DBIG is equal to 1, if: the Fitch Support rating is 1 or 2; a bank's asset country rank is 1 or 2; or a bank's asset size rank is 1 or 2 within the country sample if both FitchSupport rating and asset country ranks are not available.
Variables definition: ΔNIR_EA = annual change of (Net Interest Revenue/ Total Earning Assets), ΔNL_DEP = annual change of (Net Loans/ Customer and Short Term Fundings), EXCRCUM = cumulative market excess return on the fourth quarter of the accounting period (financial year) preceding the event.

The results in table VIII show that one market indicator is significant to predict downgrades of small banks: EXCRCUM. Thus, for small banks, market information brings additional information, not already contained in accounting information. For large banks, no market indicator adds to the predictive power of the accounting indicator ΔNL_DEP. Thus, the results are still consistent with a Too Big To Fail effect. By contrast, accounting information is accurate for both small and large banks.

5. Conclusion

The aim of this study is to determine whether equity market information can bring additional information, not already contained in accounting information, to predict Asian banks' financial distress considering the possible existence of a Too Big To Fail effect. We

[11] We run two stepwise procedures: one with the accounting indicators and the other one adding market indicators. Here, we only report the results obtained at the end of the second procedure.

[12] Due to missing data for the accounting variable selected, only 5 observations with Y=1 are included in the estimation on sub-sample 1.

show that equity market indicators significantly contribute to the prediction model's overall fit. These results are consistent with the findings of Krainer and Lopez (2004) and Curry, Elmer, and Fissel (2007) in the US case, and with those of Distinguin, Rous, and Tarazi (2006) in the European case. However, our results also indicate that the conjecture of a Too Big To Fail effect cannot be rejected as market indicators are not significant to predict financial deteriorations of banks that can be perceived as Too Big To Fail. This result is opposite to those obtained in the European case by Gropp, Vesala, and Vulpes (2006) and Distinguin, Rous, and Tarazi (2006) who find that market indicators are significant to predict the financial distress of large banks. Thus, in the Asian case, market information is only useful for banks that are less likely to be bailed out in the event of default.

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