PREDICTING BANK RATING CHANGES IN THE ASIA PACIFIC REGION: THE ACCURACY OF ACCOUNTING AND STOCK MARKET INDICATORS

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Abstract

We aim to assess the accuracy of accounting and stock market indicators to predict rating changes of Asian banks. We specify a multinomial logit model using upgrades and downgrades by rating agencies and conduct a stepwise process to determine the optimal set of early indicators. We also test for the possible influence of bank size and bank characteristics on the effectiveness of early indicators. Our results indicate that accounting and market indicators are useful leading indicators but that they perform better in explaining future upgrades than downgrades. Specifically, both types of indicators are significant in predicting upgrades but not downgrades of large banks. For small banks, only market indicators contribute to the early detection of downgrades. Moreover, early indicators are only significant in predicting rating changes for banks, which are more focused on deposits and loans activities. Eventually, a higher reliance of banks on subordinated debt tends to improve the accuracy of early indicators.

JEL classification: G21, G28

Keywords: Bank, Bank Failure, Bank Risk, Ratings, South East Asia

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1. Introduction

Given the critical role of banks as intermediaries in the financial system, the assessment of a bank's financial health is essential for supervisors. To identify risk in banking institutions, supervisors rely on early-warning systems (EWS) to predict an improvement or a deterioration of their financial condition. Whereas most traditional EWS focus on accounting data, a strand of the literature has recommended the use of market data (Berger, Davies, and Flannery, 2000; Flannery, 1998). Market indicators are expected to improve the assessment of bank financial conditions and provide useful signals for bank supervisors. Thus, market data could be used as a complement to accounting information to evaluate bank financial health (Flannery, 2001).

Studies on US banks generally show that market indicators add to the predictive power of EWS models solely based on accounting data.[1] Various definitions of a change in financial health are used in the literature. Curry, Fissel, and Hanweck [2008], Evanoff and Wall [2001] and Krainer and Lopez [2004] consider supervisory risk ratings as proxies for default risk whereas Curry, Elmer and Fissel [2007] focus on actual bank failures. In all cases, the inclusion of market information in traditional models improves the prediction of bank financial conditions. Similar results are obtained for European banks. Gropp, Vesala, and Vulpes [2006] show that indicators derived from market prices are able to predict downgrades by private rating agencies at relatively long time horizons. The findings of Distinguin, Rous, and Tarazi [2006] also indicate that market-based variables add value to models relying on accounting data. However, in their study, the predictive power of such indicators depends on the extent to which bank liabilities are market traded.

While Asian banks were at the heart of the financial crisis of 1997 and played a major role in its propagation, the literature has mainly focused on contagion effects (Kaminsky and Reinhart, 2000) and on the design of early-warning models of banking crises (Demirgüc-Kunt and Detragiache, 2000). To our knowledge previous work has neglected the issue of the prediction of bank financial health at the individual level, which is crucial for supervisors especially under the new regulatory framework introduced by the Basel Committee on Banking and Supervision (Basel II accord). Under this new framework, which emphasizes on disclosure and market forces, market discipline is expected to play an important role and

[1] Other papers study the accuracy of market indicators to reflect actual bank risk (Flannery and Sorescu, 1996) and the timeliness of market information for supervision under a different framework (Berger and Davies, 1998; Berger, Davies, and Flannery, 2000).

regulators could use market prices as signals to improve their supervisory actions. Assessing the accuracy of market and accounting indicators to predict changes in financial health is therefore an important issue for banking systems in the Asia pacific region.

In this paper, we assess the accuracy of market and accounting indicators by constructing, in the Asian case, a prediction model for changes in banks' financial health. We extend the approaches used in the existing literature in several directions. Most US and European studies look at the prediction of financial deterioration (rating downgrades or bank failures). An exception is the work by Curry, Fissel, and Hanweck [2008], where several outcomes are taken into account (downgrade, upgrade, no rating change). However, their work considers, within an ordered logistic framework, that the generating process is the same for the different outcomes of the BOPEC[2] supervisory ratings that they use. Because theory postulates that banks are opaque institutions (Diamond, 1984), a hypothesis which is generally supported by empirical evidence (Morgan, 2002), we question the accuracy of indicators to significantly contribute to the early detection of negative events as opposed to positive events. Indicators might be more effective to predict upgrades than downgrades because bad news is generally less rapidly and less frequently conveyed to the market than is good news (Berger and Davies, 1998).

We focus on the prediction of both downgrades and upgrades announced by three rating agencies (Moody's, Standard and Poor's, and Fitch). Instead of considering the binary or ordered logit models used in the previous literature, we therefore develop a multinomial model, allowing for possible asymmetric effects. We hence go further by questioning the capability of leading indicators to predict both positive and negative changes in financial health. We show that the use of an ordered logit model can be misleading because in our sample indicators that appear as significant in an ordered framework lose their predictive power in a more general multinomial approach. Besides, indicators significant to predict positive changes are not necessarily significant predictors of negative changes. With a multinomial logit model, asymmetric effects can be captured by differences in the significance and value of coefficients for negative (downgrade) and positive (upgrade) outcomes.

Our aim is also to discriminate the ability of a very large variety of market and accounting indicators by selecting the optimal set of variables through a stepwise process as in

[2] BOPEC (Bank subsidiaries, Other subsidiaries, Parent company, consolidated Earnings and consolidated Capital) is a rating assigned to bank holding companies (BHC) by supervisors. This rating is from 1 to 5, 1 corresponding to a sound BHC, and 5 to a BHC with serious difficulties (near insolvency).

Distinguin, Rous, and Tarazi [2006]. We further investigate the accuracy of different indicators for small and large banks. Because large banking institutions might be perceived as too-big-to-fail, analysts and market participants might react less promptly and less strongly to bad news than to good news. Eventually, as shown by Distinguin, Rous, and Tarazi [2006], the market might be less efficient in predicting the financial deterioration of particularly opaque institutions. We therefore test the ability of early indicators to predict rating changes for specific financial institutions. On the whole, our hypothesis is that the accuracy of early indicators to predict changes in financial health could be different for downgrades and upgrades. Moreover, some indicators might perform better than others depending on various factors such as size and main activity (traditional intermediation, fee income or market activities).

The paper is organized as follows: section 2 presents the method used to estimate our prediction model. Section 3 describes our sample and the different early warning indicators that we construct. Section 4 defines our hypotheses tests. Section 5 presents our results and reports a series of robustness checks. Finally, section 6 concludes.

2. Multinomial logit prediction model

The main purpose of this study is to assess the reliability of leading indicators by constructing a model to predict Asian banks' rating changes using both accounting and market indicators. We need to develop an approach to select the most accurate variables (to predict upgrades and downgrades) among a very large number of potential indicators. Our objective is also to consider a setting that allows for asymmetric effects (downgrades versus upgrades) and in which the stability of the predictive power of indicators can be tested with respect to bank characteristics.

The first step in designing an early-warning model is to define an event that could represent a change in the financial condition of a bank. As mentioned above, to capture financial deteriorations, most US studies either use actual bank failures or downgrades in supervisory ratings as with Curry, Fissel, and Hanweck [2008], Kolari, Glenn, and Caputo [2002], and Gunther, Levonian, and Moore [2001]. Due to insufficient data on explicit failures, studies on European banks use ratings performed by private agencies. Downgrades below a certain level (level C) are considered as proxies for bank failure (Gropp, Vesala, and Vulpes [2006]), or more generally downgrade announcements are simply used to capture a deterioration in financial health (Distinguin, Rous, and Tarazi [2006]). In our approach we consider both financial improvements and financial deteriorations. We therefore use both upgrading and downgrading announcements by private agencies. These rating changes were obtained from the three major rating agencies: Fitch, Moody's and Standard and Poor's. From this perspective our work is linked to the literature that investigates the determinants of the ratings provided by private agencies (Firth, and Poon, 2005) However, in this paper the issue is different in the sense that we consider the changes in the ratings (downgrades or upgrades) as proxies of a deterioration or an improvement of a bank's financial health. Moreover, we focus on early indicators of changes in financial health (downgrades and upgrades) and on their predictive rather than their explanatory power. Our aim is not to explain the process followed by private agencies to assign a given rating but to assess the accuracy of leading indicators of changes in financial health.

Accounting and market indicators are then used to estimate the probability of a rating change. For Asian banks, accounting data are available on a yearly basis and thus at a much lower frequency than are market data. To deal with this issue, we follow the method used by Distinguin, Rous, and Tarazi [2006] in their binary logit model and extend it to our multinomial setting. Accounting and market indicators are computed at the end of each calendar year, i.e., when accounting information is available. Events (downgrades or upgrades) taking place during the following calendar year are then taken into account. Matching market data and accounting data in such a way avoids the need to interpolate accounting data and ensures that the information content of accounting data is not inappropriately upward biased. Besides, because we aim to predict downgrades and upgrades rather than the ratings themselves, for most indicators we consider the changes instead of the levels.

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

- 1, if the bank is upgraded by at least one rating agency and never downgraded during the entire calendar year and if no upgrading took place during the last quarter of the preceding year (which could be considered as the same event announced by a different rating agency);
- -1, if the bank is downgraded and never upgraded during the entire calendar year and if no downgrading occurred during the last quarter of the preceding year;

- 0, if the rating remains unaltered during the year; and
- NA (not available), for all other cases.

Insert Figure 1

The following multinomial logit model[3] is employed to estimate the probability of a rating change:

$$\Pr ob(Y_i = m) = \frac{e^{\left(\alpha_m + \sum_{j=1}^{J} \beta_{jm} C_{ji} + \sum_{l=1}^{L} \gamma_{lm} M_{li}\right)}}{1 + \sum_{k \in \{-1,1\}} e^{\left(\alpha_k + \sum_{j=1}^{J} \beta_{jk} C_{ji} + \sum_{l=1}^{L} \gamma_{lk} M_{li}\right)}} \quad \text{for m =-1, 0, 1, } \beta_{j0} = \gamma_{l0} = \alpha_0 = 0 \ \forall j, l$$

where C_{ji} and M_{li} are the j^{th} accounting indicator and the l^{th} market indicator, respectively. Alternatively, to check for robustness and consistency with the existing literature we also estimate ordered logit models (Curry, Fissel, and Hanweck, 2008), and binary logit models in which only downgrades are considered (Distinguin, Rous and Tarazi, 2006). Eventually, binary logit models to predict upgrades are also estimated to compare the different outcomes.

To select the set of optimal predictors of bank rating changes, we use a stepwise process. As a rule of thumb, a 5% level for type 1 error is retained as forward and backward criteria. A Max (Min) LR statistic is used as a criterion for adding (removing) each potential indicator to (from) the selected set.

3. Data and variables

3.1. Sample

Our sample consists of 64 listed Asian banks from Hong Kong, Korea, Taiwan, Singapore, Malaysia, Thailand, Indonesia, and the Philippines. The banks in our sample 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 1 presents the distribution of banks by country and specialization. Information is taken from Bankscope Fitch IBCA.

[3] See Greene (2003) for more details about multinomial logit models.

Insert Table 1

Accounting data (annual financial statements) for individual banks are obtained from Bankscope Fitch IBCA, and weekly market data come from Datastream International. To avoid noise related to the 1997 financial crisis, our sample is restricted to the post-crisis period 1999-2004. Table 2 shows descriptive statistics for our sample of banks. The data exhibit a high level of heterogeneity, enabling us to investigate the accuracy of accounting and market indicators to predict banks' rating changes for different sizes and types of institutions.

Insert Table 2

3.2. Dependent variable

Table 3 provides information on the downgrades and upgrades announced by Fitch, Moody's and Standard and Poor's, which we use to construct the dependent variable. Since several restrictions are introduced to construct the dependent variable Y, only a limited number of clean downgrades and upgrades are subsequently considered in this study. Out of the total of 45 combined downgrades from the rating agencies, only 24 are used for the estimations and out of the 104 upgrades, only 75 are retained. More precisely, if several downgrades (upgrades) occur during the calendar year, we only consider the first one. Besides, for accuracy, we do not take into account downgrades (upgrades) that are preceded or followed by an upgrade (downgrade) during the same calendar year. In such cases indicators expected to predict an upgrade (downgrade) might be actually predicting a downgrade (upgrade), that is a movement in the opposite direction.

Insert Table 3

3.3. Independent variables

Table 4 presents the set of accounting ratios commonly considered in the assessment of bank financial health that are used in this study. The ratios are grouped into the four categories of the CAEL rating which stands for capital, asset quality, earnings, and liquidity.

Insert Table 4

Prediction models for bank failure make use of accounting indicators in level, as with Curry, Elmer, and Fissel [2007] and Gunther, Levonian, and Moore [2001] or in variation (first order difference) as with Distinguin, Rous, and Tarazi [2006]. Since the focus of this study is on the change (improvement or deterioration) in the financial condition of the bank, it is more appropriate to consider the changes in the values of the ratios. Indeed, in our approach banks need to be considered regardless of their initial level of financial strength, and the downgrade of a sound and safe bank as compared to a modestly performing bank can only be captured by the annual change in the values of the ratios.

Table 5 shows the set of market indicators, used in this study, derived from weekly stock prices. The variables *LOGP, RCUM, EXCRCUM, RCUM_NEG, EXCRCUM_NEG,* and *CAR* are used to capture the effects of shocks or the presence of abnormal returns, while *ΔBETA* and *ΔDD* are used to detect risk changes and changes in the probability of failure, respectively.

On the whole, our objective is to consider the largest possible set of indicators similar to the ones used by Distinguin, Rous, and Tarazi [2006] and Curry, Fissel, and Hanweck [2008] to study their actual contribution to predict downgrades and upgrades.

Insert Table 5

4. Hypotheses tests

We aim to assess the accuracy of accounting and market indicators to predict both upgrades and downgrades of Asian banks. As argued above in section 1, the effectiveness of such indicators is likely to vary depending on several factors.

As a preliminary step, simple regressions are conducted to investigate the predictive power of each early indicator taken separately. We estimate a multinomial logit model where the benchmark case is Y=0, that is, when ratings remain unchanged. Thus, we have a different set of coefficients for upgrades and for downgrades, with “no rating change” taken as the benchmark. For instance, a positive and significant coefficient assigned to a variable for upgrades indicates that a higher value of this variable increases the probability of an upgrade relatively to an unchanged rating. Estimating a more general model than an ordered logit prevents the significance of coefficients from being driven by the occurrence (downgrade or upgrade) that might be more easily predicted.

We then consider the predictive power of accounting and market indicators *via* a stepwise process to investigate which indicators are better suited to explain downgrades versus upgrades. For consistency with the existing literature which has used an ordered logit framework we check if the findings are significantly different.

Hypothesis 1: The same early indicators might not be accurate to predict both upgrades and downgrades. Some indicators might perform better than others to predict upgrades and/or downgrades.

As discussed above, the effectiveness of early indicators might also depend on banks' characteristics. For example, market participants could behave differently for large and small banks. For banks considered as too-big-to-fail, we can expect that market participants consider negative prospects of their financial health less thoroughly than positive anticipations because they are convinced that such institutions would never fail. We can also assume that bank size affects the reliability of accounting indicators. For smaller banks, market indicators may be more informative than accounting indicators. Market participants might consider accounting information as less reliable for smaller banks because accounting standards are generally less stringent for smaller banks (lower quality and lower disclosure frequency). Therefore, the market might monitor small banks more closely than large banks on the basis of a broader set of information which in turn is conveyed by the bank's stock price[4]. A dummy variable (DBIG) taking into account the size of banks is introduced in the model to test for the stability of the contribution of accounting and market indicators to predict rating changes. This dummy variable is equal to 1, if the bank is considered as "too-big-to-fail"; 0, otherwise. Two criteria are combined to define a bank as too-big-to-fail:

- If the FitchRatings Support rating is 1 or 2, the bank is considered 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

[4] 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.

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]).

- If[5] total bank assets are higher than $ 50 billion (a significant threshold in our sample asset size distribution), the bank is considered too-big-to-fail.

The model specification to capture the effects of size and balance sheet structure is as follows:

$$\Pr ob(Y_i = m) = \frac{e^{\left(\alpha_m + \sum_{j=1}^{J}\beta_{jm}C_{ji} + \sum_{l=1}^{L}\gamma_{lm}M_{li} + \sum_{j=1}^{J}\beta'_{jm}DBIG_iC_{ji} + \sum_{l=1}^{L}\gamma'_{lm}DBIG_iM_{li}\right)}}{1 + \sum_{k\in\{-1,1\}} e^{\left(\alpha_k + \sum_{j=1}^{J}\beta_{jk}C_{ji} + \sum_{l=1}^{L}\gamma_{lk}M_{li} + \sum_{j=1}^{J}\beta'_{jk}DBIG_iC_{ji} + \sum_{l=1}^{L}\gamma'_{lk}DBIG_iM_{li}\right)}} \quad \text{for m=-1, 0, 1,}$$

$$\beta_{j0} = \gamma_{l0} = \alpha_0 = \beta'_{j0} = \gamma'_{l0} = 0 \ \forall j, l$$

where $DBIG_i$ is a dummy variable which captures the effects of size.

To assess the impact of size on the predictive power of indicators we extend the method used by Distinguin, Rous and Tarazi [2006] which consists in testing whether size neutralizes the predictive power of an indicator ($H_0 : \beta_{jm} + \beta'_{jm} = 0 \forall j$ or $H_0 : \gamma_{lm} + \gamma'_{lm} = 0 \forall 1$ for m=-1 or 1). If market indicators are not effective to predict downgrades of too-big-to-fail banks but are good indicators for upgrades, we should not reject $H_0 : \gamma_{l,-1} + \gamma'_{l,-1} = 0\ \forall 1$ but reject $H_0 : \gamma_{l,1} + \gamma'_{l,1} = 0\ \forall 1$. For small banks, if accounting information is not reliable, we would expect that β_{jm} ($\forall j$) are not significantly different from 0 whereas γ_{lm} ($\forall 1$) are significant (for m=-1 or 1).

Hypothesis 2: For large too-big-to-fail banks, accounting and market indicators might not be good predictors of downgrades.

[5] We consider this second criterion because Fitch Support Ratings are not available for all banks. Out of the 64 banks that are included in our sample the first criterion (FitchRating support rating) can be used for 54 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. 8 banks are considered as too-big-to-fail on the basis of the second criteria. We check that all the banks that comply with the second criteria also comply with the first criteria when the information is available. When we combine these two criteria, we find that 17 banks can be considered as too-big-to-fail in our sample. As banks that might be considered as relatively small in our sample might have a major position in their domestic banking system, we check when Fitch Support ratings are not available (i.e. when we can only use the second criterion), that a bank which is the first or the second in its country ranking is actually classified as too-big-to-fail.

Hypothesis 2’: For small banks, market indicators might be more effective than accounting indicators

Banks’ main activities should also impact the effectiveness of early indicators. In the light of modern banking theory, banks are considered as inherently opaque institutions (Diamond, 1984). Such a hypothesis is generally supported by empirical evidence (Morgan, 2002; Crouzille, Lepetit and Tarazi, 2004; Iannotta, 2006). Opacity is likely to be higher for banks that are more heavily involved in traditional intermediation activities (transformation of deposits into loans) than in market or fee activities. However, a higher reliance on market funding and specifically on market debt which is not insured, such as subordinated debt, is expected to encourage market participants to monitor banks more closely and to promote market discipline in the banking industry (Bliss, 2001). In this sense because subordinated debt holders have strong incentives to accurately anticipate any change in a bank’s financial health, market prices should have a strong predictive power. To test for an opacity effect, three dummy variables are considered: a variable based on the ratio of net loans to total assets (DNLTA), a variable based on the ratio of deposits to total assets (DDEPTA), and a variable based on the ratio of subordinated debt to total assets (DSUBDTA). We consider both the structure of assets and the structure of liabilities to distinguish banks that are mainly engaged in traditional intermediation activities (transformation of deposits into loans) and banks which are more involved in market activities or in other non traditional activities such as the provision of services. The dummy variable is equal to 1 for banks which are relatively more involved in traditional intermediation activities (i.e., if the ratio is higher than the median); 0, otherwise. In our sample the median value of the ratio of deposits to total assets is equal to 80.9%, and the median value of the ratio of net loans to total assets is equal to 54.72%. We also consider the importance of the ratio of subordinated debt to total assets because subordinated debt holders are expected to monitor banks more closely than insured depositors. To test such a market discipline effect, we define a dummy variable that is equal to 1 for banks which have relatively less subordinated debt (i.e. if the ratio is lower than the median which is equal to 1.5%); 0, otherwise. The model specification and the tests are similar to those performed to capture the size effect above.

Hypothesis 3: The effectiveness of accounting and market indicators to predict rating changes is affected by the relative weight of traditional intermediation activities (loans and/or deposits) in a bank’s balance sheet.

Hypothesis 3': Higher reliance on subordinated debt and therefore higher exposure to market discipline is expected to improve the accuracy of indicators.

5. Empirical results and robustness checks

5.1. Results

Table 6 shows the results for the simple univariate regressions in which each accounting and market indicator is separately introduced. Results are only reported when the coefficients are significant at least at the 10% significance level for upgrades or downgrades. We report both the results obtained with a multinomial logit setting and those obtained with an ordered logit model. These preliminary results suggest that the prediction of upgrades might be easier to perform than the prediction of downgrades.

Insert Table 6

In the multinomial logit model, five indicators appear as significant predictors of upgrades, whereas only three indicators are significant for downgrades. Besides, the level of significance is higher for upgrade predictors. Changes in capital and liquidity ratios are significant in predicting upgrades; whereas for downgrades, only a change in the ratio of net interest revenue to total earning assets has a significant coefficient. For both upgrades and downgrades, two different market indicators are significant predictors: LOGP which captures changes in stock price trends and RCUM (cumulative return) for upgrades and EXCRCUM (cumulative market excess return) and ΔDD (change in the distance to default) for downgrades. The signs of the coefficients of these indicators are the expected ones except for ΔDD. This surprising result can be explained by the relatively lower increase in liabilities for downgraded banks compared to other banks, suggesting that when they are close to being downgraded banks might experience difficulties in increasing the amount of deposits or in issuing debt on the market. In any case, the distance to default, based on the Merton-Black-Scholes model, which combines both market and accounting data, appears to be a misleading indicator in our setting.[6] Nevertheless, market indicators constructed solely with market prices perform as expected.

In the ordered logit model, we find several significant indicators which are not significant when we consider the multinomial setting (ΔRWA_TA, ΔLLP_NETIR, ΔLLR_GL, RCUMNEG). Besides, when both models yield the same indicators, the results show that the indicators which are significant in the ordered logit framework are only significant in predicting upgrades in the multinomial framework. Therefore the multinomial approach appears to be better suited to capture different effects for downgrades and for upgrades which cannot be straightforwardly distinguished within the ordered logit framework.

Insert Table 7

Table 7 reports the multinomial logit estimation results with a set of independent variables selected by our stepwise process defined above. For accuracy considerations, this table also shows the results obtained with the ordered logit model. Our findings confirm the conjecture that upgrades can be predicted more easily than can downgrades as shown by the tests at the bottom of table 7. All the indicators selected by the stepwise process in the multinomial model are significant predictors of upgrades. In contrast, for downgrades, only one market indicator, the cumulative market excess return (EXCRCUM), has a significant coefficient but with a significance level which is lower than one of the variables that accurately predict upgrades (ΔEQU_LIAB). Consistent with the simple regressions, the accounting indicators that better contribute to explain future upgrades are the changes in liquidity and capital ratios.

The stepwise process selects no accounting indicator to predict downgrades. However, our results do not imply that not any accounting indicator can be used to explain future downgrades. Because our multinomial approach accounts for upgrades and downgrades simultaneously, our findings merely suggest that accounting indicators seem better suited to explain future upgrades in line with the results obtained in the simple regressions. In contrast, the coefficient of the market indicator EXCRCUM exhibits a higher significance level for downgrades than for upgrades. Market information seems useful to predict both downgrades and upgrades. In the ordered logit model only two variables (ΔNL_TEA and LOGP) are

[6] The amount of liabilities (the value of debt) is the strike price of the Call option used to calculate the distance to default. A lower strike price implies a lower default probability. In our sample, the median of the annual change in total liabilities is $ 98.47 million for downgraded banks and $ 261.39 million for banks with a stable rating. Therefore a possible explanation is that, although the market value of bank equity starts decreasing before the actual downgrade, 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.

significant. However, these two variables are not significant predictors of upgrades or of downgrades in the multinomial logit model. Therefore, in the rest of our study we focus our investigation using the multinomial model by considering the ordered logit model for robustness considerations only.

As previously mentioned, the possible existence of size and balance sheet structure effects might limit the accuracy of early indicators in the prediction process. Because of the existence of public safety nets for too-big-to-fail banks, the market might be less concerned about anticipated downgrades than about anticipated upgrades for such banks. In contrast, it can also be argued that the market might look more closely into the financials of these large banks whom they believe present more reliable accounting information compared to the smaller banks. Hence, for smaller banks, market indicators could be more effective than would accounting indicators. Also, the effectiveness of early indicators might be different for banks engaged in different lines of businesses. A way to capture such differences and their implications for early warning models is to investigate banks' balance sheet structures to trace their main activities (traditional intermediation activity or market-oriented activities).

Insert Table 8

The results presented in Table 8 indicate that bank size affects the effectiveness of early indicators differently for downgrades and for upgrades. For upgrades of small banks the indicators previously selected by the stepwise process lose their predictive power: only the change in the capital ratio is still significant but only at the 10% level. In contrast, for large banks, all the indicators remain highly significant as shown by the results of the tests at the bottom of the table 8. Thus, accounting and market indicators are better predictors of upgrades for large banks, suggesting that accounting information is more reliable for these banks.

We obtain the opposite results for downgrades. EXCRCUM, which is the market indicator previously selected by the stepwise process, is significant for small banks but no longer significant for large banks. Such a result is consistent with the "Too-big-to-fail" hypothesis: market participants might not value bad news affecting large banks because of the existence of public safety nets for such banks.

Tables 9 and 10 present the results obtained to capture the effectiveness of early indicators for different balance sheet profiles. The structure of bank assets significantly affects the predictive power of early indicators.

Insert Table 9

For either upgrades or downgrades, no indicator is able to predict changes for banks with a relatively low ratio of net loans to total assets. In contrast, for banks with a high proportion of loans in the balance sheet, the indicators previously selected through the stepwise process, except ΔNL_DEP, recover their significance (see tests at the bottom of the table). Therefore, both accounting and market indicators appear useful to predict rating changes only for banks heavily involved in traditional lending activities.

Insert Table 10

The results obtained using the ratio of deposits to total assets to construct the dummy variable (see table 10) indicate that future rating changes are more difficult to predict for banks with a low ratio of deposits to total assets : only one indicator, ΔNL_DEP, is significant for upgrades. Moreover, the tests at the bottom of table 10 show that, for banks heavily reliant on deposits (that is banks with DDEPTA equal to one) the market indicator EXCRCUM is highly significant to predict both upgrades and downgrades. Therefore, the prediction of rating changes appears to be more accurate for banks turned towards deposit taking. As a whole, early indicators seem better suited to explain future financial changes of banks involved in traditional deposit taking and loan activities to a larger extent.

These results are opposite to those obtained by Distinguin, Rous, and Tarazi [2006] for European banks in their setting where only downgrades are used to define the dependent variable. Our findings therefore suggest that Asian banks that are more involved in traditional intermediation products, which are not market traded, might not be more opaque than other banking institutions as indicated in their study. A possible explanation could be the lack of sufficiently deep financial markets and efficient secondary markets in South East Asia. The market might therefore not convey sufficient information even for institutions that issue a larger amount of market debt and invest in marketable assets. Nevertheless, market participants might engage more efforts to monitor traditional banking institutions than other institutions because of their higher vulnerability to changes in macroeconomic conditions.

Table 11 presents the results obtained for the market discipline effect that might be exerted by subordinated debt holders.

Insert Table 11

For banks with a high ratio of subordinated debt to total assets, only one accounting indicator appears to be significant to predict upgrades and, for banks with a low ratio of subordinated debt to total assets, only one market indicator is significant to predict downgrades but only at a 10% level of significance. To go further, we run the estimations on two different sub-samples of banks depending on the relative weight of subordinated debt in total liabilities and we also run the stepwise process on these two different sub-samples. We first consider the set of significant variables initially obtained for the whole sample of banks in table 7 (see table 12). We find that no indicator is significant to predict rating changes of banks with a low ratio of subordinated debt to total assets (below the median) whereas one accounting indicator is significant to predict upgrades of banks with a high ratio (above the median). We then rerun the stepwise process on the two sub-samples (see table 13). Our results clearly indicate that no indicator is useful to predict rating changes of banks with a low ratio of subordinated debt to total assets whereas two market indicators and one accounting indicator are significant predictors of rating changes for banks with a high ratio. These results show that the relative weight of subordinated debt in total liabilities affects the effectiveness of market indicators. Predicting rating changes appears to be easier for banks issuing a relatively high proportion of subordinated debt which is consistent with the presence of a market discipline effect.

Insert Table 12 and Table 13

5.2. Robustness checks

Several robustness checks are performed. We estimate logit models separately for upgrades and downgrades. The results also indicate that a number of accounting and market indicators are significant to explain future changes in financial health. In the estimations presented in table 8 we have found that no indicator was significant to predict downgrades of large banks. However, this result could be due to the fact that the indicators selected by the stepwise process that applied to the whole sample of banks are not the best indicators for the sub-sample of large banks. Therefore, we run the stepwise process on the sub-sample of large banks separately. The results confirm the absence of significant indicators to predict downgrades for these banks. Besides, simple logit estimations also show that no indicator is individually significant to predict these events. For upgrades, when the stepwise process is performed separately on the sub-sample of small banks, one market indicator appears as significant.

For further checks we also run the stepwise process on different sub-samples of banks depending on the structure of their balance sheet, and we also run simple logit estimations for each indicator individually for different sub-samples. On the whole, our findings are not affected. Indicators are better suited to explain future financial changes for banks more involved in loan and deposit activities. Similarly, performing our estimations on a sample restricted to commercial banks which represent 56 banks out of the 64 considered in our study does not alter our main conclusions.

6. Conclusion

The main objective of this study is to assess the accuracy of accounting and market indicators to predict changes in financial health for a sample of 64 banks from South East Asia for the period 1999-2004. Our results show that accounting and market indicators can be useful in predicting future changes in financial conditions but that their performance is better for upgrades than for downgrades.

Accounting and market indicators are significant in predicting upgrades of large banks but not downgrades. For small banks, accounting information is generally less reliable and market indicators perform relatively better than do accounting indicators for the early detection of downgrades. Moreover, early indicators only appear to be significant in predicting the rating changes of banks that are mainly engaged in traditional intermediation activities (loans and deposits). Such a result is surprising because studies dedicated to US and European banks consider such banks as being more opaque than are institutions that are involved, to a larger extent, in market-traded assets and more reliant on market debt. Nevertheless, our findings show that the presence of larger amounts of subordinated debt issued by banks tends to improve the effectiveness of early indicators which is consistent with the reform proposals aiming to impose a minimum ratio of subordinated debt in the banking industry (mandatory subordinated debt policy).

On the whole, our findings raise the issue of how regulators could rely on early warning models to improve their supervisory actions. Specifically, if the market is unable to assess a deterioration in the financial health of some banking institutions, market discipline might not be reliable for the design of the new supervisory framework (Basel II) which is expected to articulate supervisory efforts and market forces.

Figure 1: Definition of the dependent variable

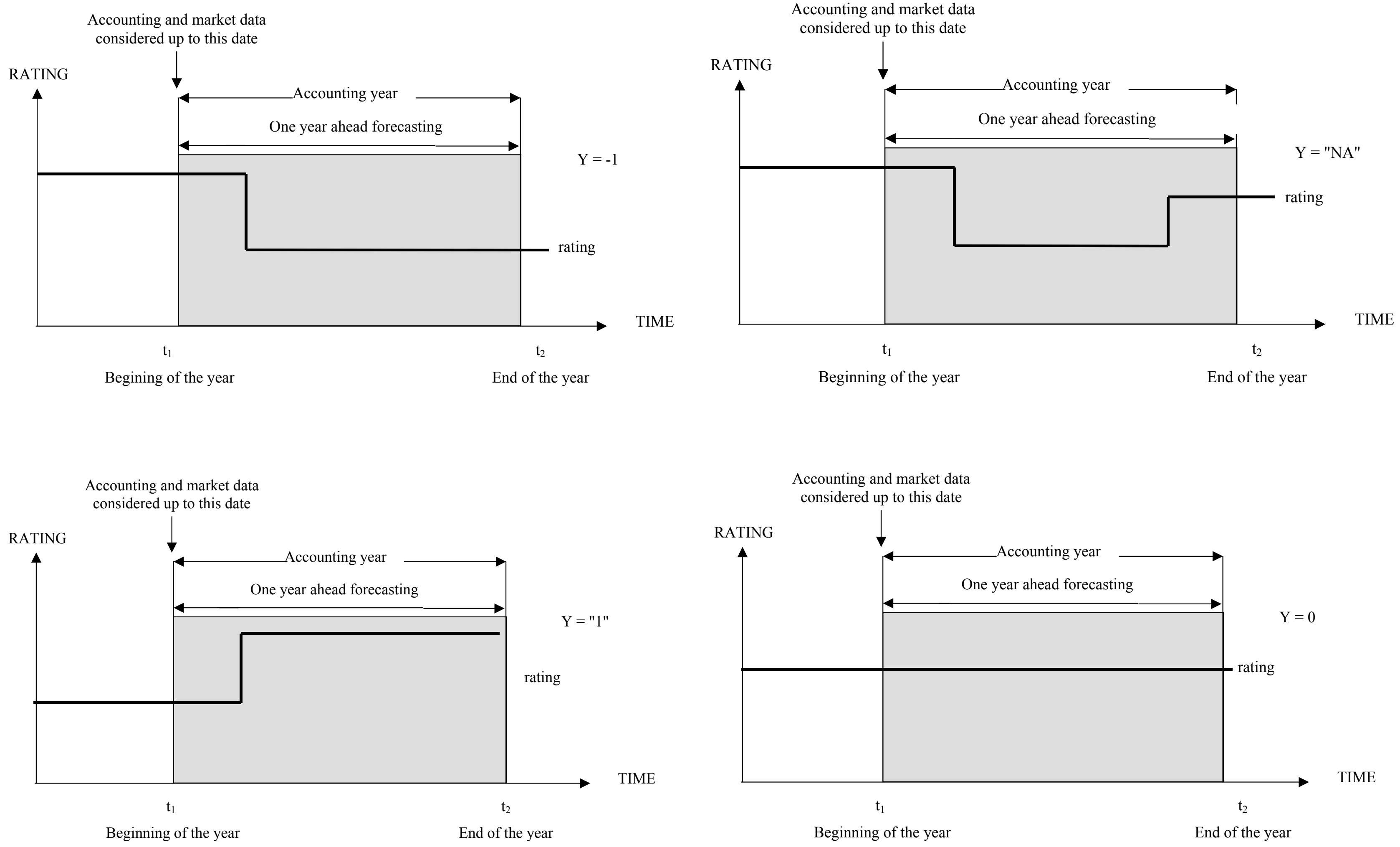

Table 1. Distribution of Banks by Country and Specialization

Distribution of banks by country:

Country	Number of banks
Hong Kong	8
Korea	6
Singapore	2
Taiwan	13
Malaysia	3
Indonesia	11
Thailand	12
Philippines	9
Total	64

Source: Bankscope Fitch IBCA

Distribution of banks by specialization:

Specialization	Number of banks
Bank holding and holding company	2
Commercial bank	56
Cooperative bank	1
Investment bank	5
Total	64

Source: Bankscope Fitch IBCA

Table 2. Descriptive Statistics on Summary Accounting Information

	Mean[2]	Standard Deviation[2]	Minimum	Maximum
Total Assets ($ million)	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 ($ million)	13142.94	18174.79	0.00	126694.20
Subordinated Debt (($ million)	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.

Table 3. Downgrades and upgrades information

(Number of clean downgrades or upgrades in parentheses)

		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 (10)	Downgrades by Moody’s	10 (5)	0 (0)	0 (0)	3 (2)	7 (3)
284 (75)	Total upgrades	25 (4)	59 (17)	58 (18)	45 (11)	97 (25)
104 (23)	Upgrades by Standard and Poor’s	7 (1)	18 (4)	20 (6)	19 (5)	40 (7)
86 (34)	Upgrades by Fitch	1 (0)	16 (8)	12 (5)	14 (5)	43 (16)
94 (18)	Upgrades by Moody’s	17 (3)	25 (5)	26 (7)	12 (1)	14 (2)

Table 4. Annual changes in accounting ratios

Category	Name	Definitions of the ratios	Mean of the indicator	Std. Dev.
Capital	ΔEQU_NL	Equity/ Net Loans	1.31	31.4
	ΔEQU_DEPSTF	Equity/ Customer and ST Fundings	0.18	12.67
	ΔEQU_LIAB	Equity/ Liabilities	0.15	5.79
	ΔTCR	Total Capital Ratio	0.44	13.4
	ΔTIER1_RAT	Tier 1/ Risk-weighted Assets and Off-balance Sheet Risks	-0.61	2.62
Asset Quality	ΔLLP_TA	Loan Loss Provision/ Total Assets	-0.37	4.90
	ΔLLP_GL	Loan Loss Provision/ Gross Loans	-0.49	7.47
	ΔRWA_TA[7]	Risk-weighted Assets and Off-balance Sheet Risks (inferred from the Cooke ratio)/ Total Assets	0.58	4.47
	ΔLLR_TA	Loan Loss Reserves/ Total Assets	-0.33	2.81
	ΔLLR_GL	Loan Loss Reserves/ Gross Loans	-0.52	5.04
	ΔLLP_NETIR	Loan Loss Provision/ Net Interest Revenue	1.83	731.34
Earnings	ΔNIR_NINC	Net Interest Revenue/ Net Income	-61.67	3806.79
	ΔNIR_EA	Net Interest Revenue/ Total Earning Assets	0.43	4.73
	ΔROAA	Return on Assets = Net Income/ Total Assets	0.52	4.73
	ΔROAE	Return on Equity = Net Income/ Equity	2.58	32.38
Liquidity	ΔLIQASS_TOTDB	Liquid Assets/ Total Deposits and Borrowings	-0.66	9.47
	ΔNL_DEP	Net Loans/ Customer and ST Fundings	0.37	7.38
	ΔNL_TEA	Net Loans/ Total Earning Assets	-0.25	7.14
	ΔTRAD_OPINC	(Trading Income-Trading Expense)/ Operating Income	17.47	212.87

[7] See Goyeau, Sauviat, and Tarazi [1998] for details about RWA_TA.

Table 5. Market Indicators

Indicators	Definition	Mean	Std. Dev.	Expected sign of the coefficient for downgrades
LOGP	Difference between the natural logarithm of market price and its moving average calculated on one year.	0	0.24	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.	0	0.01	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.	0.26	0.44	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.	0	0.01	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.	0.23	0.42	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	-0.02	0.24	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.	0	0.01	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	0.02	0.17	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.	0	0.01	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.	0.41	4.33	Negative

ΔDD[8]	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 Crosbie and Bohn, 2003).	0.30	0.85	Negative

[8] Weekly market values of the bank's equity were obtained from Datastream. The volatility of the bank's equity on the quarter preceding the end of the calendar year (i.e., 65 trading days) 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.

Table 6. Early Indicators: Simple Regressions

Multinomial logit model Specification:

$$\Pr ob(Y_i = m) = \frac{e^{(\alpha_m + \beta_m X_i)}}{1 + \sum_{k \in \{-1,1\}} e^{(\alpha_k + \beta_k X_i)}} \qquad \text{for m =-1, 0, 1, } \beta_0 = 0$$

Ordered logit model specification:

Prob(Y_i=-1)= $\Phi\left(\lambda_L - \beta X_i\right)$

Prob(Y_i=0)= $\Phi\left(\lambda_U - \beta X_i\right) - \Phi\left(\lambda_L - \beta X_i\right)$ for m=-1,0,1

Prob(Y_i=1)=1-Prob(Y_i=-1)- Prob(Y_i=0)

With Φ(.) the cumulated logistic distribution function and λ_L and λ_U the cutpoints.[9]

		Variables	Downgrades	Upgrades	Ordered Logit
ACCOUNTING INDICATORS	CAPITAL	ΔTIER1RAT	0.092 (0.240)	0.200* (1.801)	0.123*** (2.625)
	ASSET QUALITY	ΔRWA_TA			0.103** (2.137)
		ΔLLR_GL			-0.031* (-1.844)
		ΔLLP_NETIR			-0.0002** (-1.966)
	LIQUIDITY	ΔNL_DEP	-0.036 (-0.713)	0.073*** (2.793)	0.064*** (3.662)
		ΔNL_TEA	-0.001 (-0.024)	0.071*** (2.739)	0.045*** (3.310)
	EARNINGS	ΔNIR_EA	-0.672* (-1.807)	-0.048 (-0.423)	
MARKET INDICATORS		RCUMNEG			-0.591* (-1.876)
		LOGP	-0.431 (-0.454)	1.634** (2.539)	1.521** (2.456)

[9] See Greene [2003] for more details.

		RCUM	-6.704 (-0.427)	18.784* (1.793)	9.095* (1.956)
		EXCRCUM	-26.359* (-1.906)	12.680 (1.096)	
		ΔDD	0.408* (1.699)	-0.005 (-0.028)	

*This table reports multinomial logit estimation results and ordered logit estimation results where the dependent variable is separately regressed on each explanatory variable and a constant. This model explains downgradings and upgradings (whatever their extent) to occur in the calendar year. ***, ** and * pertain to 1, 5 and 10% level of significance, respectively. Z-Stats are in parentheses.*

Table 7. Early indicators: Multiple Regression

Multinomial logit model Specification:

$$\Pr ob(Y_i = m) = \frac{e^{\left(\alpha_m + \sum_{j=1}^{J}\beta_{jm}C_{ji} + \sum_{l=1}^{L}\gamma_{lm}M_{li}\right)}}{1 + \sum_{k\in\{-1,1\}} e^{\left(\alpha_k + \sum_{j=1}^{J}\beta_{jk}C_{ji} + \sum_{l=1}^{L}\gamma_{lk}M_{li}\right)}} \quad \text{for m =-1, 0, 1, } \beta_0 = 0$$

Ordered logit model specification:

$$\text{Prob}(Y_i=-1)=\Phi\left(\lambda_L - \left(\sum_{j=1}^{J}\beta_{jk}C_{ji} + \sum_{l=1}^{L}\gamma_{lk}M_{li}\right)\right)$$

$$\text{Prob}(Y_i=0)=\Phi\left(\lambda_U - \left(\sum_{j=1}^{J}\beta_{jk}C_{ji} + \sum_{l=1}^{L}\gamma_{lk}M_{li}\right)\right) - \Phi\left(\lambda_L - \left(\sum_{j=1}^{J}\beta_{jk}C_{ji} + \sum_{l=1}^{L}\gamma_{lk}M_{li}\right)\right) \text{ for m=-1,0,1}$$

Prob(Y_i=1)=1-Prob(Y_i=-1)- Prob(Y_i=0)

With $\Phi(.)$ the cumulated logistic distribution function and λ_L and λ_U the cutpoints.[10]

	Variables	Downgrades	Upgrades	Ordered logit
	Constant	**-1.937*** (-5.416)**	**-0.399** (-2.175)**	
	λ_L			**-2.025*** (-8.736)**
	λ_U			**0.669*** (4.307)**
Accounting indicators	ΔNL_DEP	-0.047 (-0.719)	**0.055* (1.952)**	
	ΔEQU_LIAB	0.088 (0.474)	**0.114*** (2.732)**	
	ΔNL_TEA			**0.044*** (2.936)**
Market indicator	EXCRCUM	**-36.920** (-2.100)**	**25.790* (1.682)**	
	LOGP			**1.536** (2.503)**
	Risk level to reject $\beta_1 = \beta_2 = \gamma_1 = 0$	16.57%	0.8%	
	Risk level to reject $\beta_1 = \gamma_1 = 0$			0.04%
	Mc Fadden R^2 (%)		7.381	3.445
	Total number of observations		164	188
	Number of observations of type Y=-1		16	
	Number of observations of type Y=1		61	

[10] See Greene [2003] for more details.

This table reports multinomial logit estimation results and ordered logit estimation results obtained with the dependent variable regressed on a constant and the accounting and market indicators selected by a stepwise process. For m=-1 and 1, we test the hypothesis $\beta_{1,m} = \beta_{2,m} = \gamma_{1,m} = 0$ *that is the significance of early indicators as a whole to predict downgrades or upgrades. We report the risk levels to reject these hypotheses. We also report the risk level to reject* $\beta_1 = \gamma_1 = 0$ *in the ordered logit model. *, ** and *** indicate significance respectively at 10%, 5% and 1% levels. Z-statistics are shown in parentheses.*

Table 8. Bank size and effectiveness of early indicators

Model Specification:

$$\Pr ob(Y_i = m) = \frac{e^{\left(\alpha_m + \sum_{j=1}^{J}\beta_{jm}C_{ji} + \sum_{l=1}^{L}\gamma_{lm}M_{li} + \sum_{j=1}^{J}\beta'_{jm}DBIG_iC_{ji} + \sum_{l=1}^{L}\gamma'_{lm}DBIG_iM_{li}\right)}}{1+\sum_{k\in\{-1,1\}} e^{\left(\alpha_k + \sum_{j=1}^{J}\beta_{jk}C_{ji} + \sum_{l=1}^{L}\gamma_{lk}M_{li} + \sum_{j=1}^{J}\beta'_{jk}DBIG_iC_{ji} + \sum_{l=1}^{L}\gamma'_{lk}DBIG_iM_{li}\right)}} \text{ for m=-1, 0, 1,}$$

$$\beta_{j0} = \gamma_{l0} = \alpha_0 = \beta'_{j0} = \gamma'_{l0} = 0 \ \forall j,l$$

	Variables	Downgrades	Upgrades
Accounting indicators	Constant	**-1.998*** (-5.411)**	**-0.524*** (-2.730)**
	ΔNL_DEP	-0.037 (-0.532)	0.038 (1.124)
	ΔEQU_LIAB	0.069 (0.358)	**0.087* (1.877)**
	DBIG* ΔNL_DEP	-0.077 (-0.261)	**0.111* (1.763)**
	DBIG* ΔEQU_LIAB	-0.020 (-0.019)	**0.455* (1.765)**
Market indicator	EXCRCUM	**-36.079** (-1.968)**	13.061 (0.756)
	DBIG* EXCRCUM	-62.166 (-0.501)	**119.522** (2.372)**
	Risk level to reject $\beta_1 + \beta'_1 = 0$	69.28%	**0.54%**
	Risk level to reject $\beta_2 + \beta'_2 = 0$	96.14%	**3.27%**
	Risk level to reject $\gamma_1 + \gamma'_1 = 0$	42.62%	**0.51%**
	Mc Fadden R^2 (%)		11.47%
	Total number of observations		164
	Number of observations of type Y=-1		16
	Number of observations of type Y=1		61

*This table reports multinomial logit estimation results when we regress the dependent variable on a constant and the accounting and market indicators selected by a stepwise process. We take size effect into account with a dummy variable (DBIG) associated with the accounting and market indicators. DBIG is equal to one if the Fitch Support rating of the bank is 1 or 2, or, if no FitchSupport rating is available, if the bank is ranked first or second in its country. If this information is not available, it takes the value of one if the bank is ranked first or second within the country sample. *, ** and *** indicate significance respectively at 10%, 5% and 1% levels. Z-statistics are shown in parentheses.*

Table 9. Structure of bank assets and effectiveness of early indicators

Model Specification:

$$\Pr ob(Y_i = m) = \frac{e^{\left(\alpha_m + \sum_{j=1}^{J}\beta_{jm}C_{ji} + \sum_{l=1}^{L}\gamma_{lm}M_{li} + \sum_{j=1}^{J}\beta'_{jm}DNLTA_iC_{ji} + \sum_{l=1}^{L}\gamma'_{lm}DNLTA_iM_{li}\right)}}{1 + \sum_{k\in\{-1,1\}} e^{\left(\alpha_k + \sum_{j=1}^{J}\beta_{jk}C_{ji} + \sum_{l=1}^{L}\gamma_{lk}M_{li} + \sum_{j=1}^{J}\beta'_{jk}DNLTA_iC_{ji} + \sum_{l=1}^{L}\gamma'_{lk}DNLTA_iM_{li}\right)}} \text{ for m=-1, 0, 1,}$$

$$\beta_{j0} = \gamma_{l0} = \alpha_0 = \beta'_{j0} = \gamma'_{l0} = 0 \ \forall j,l$$

	Variables	Downgrades	Upgrades
Accounting indicators	Constant	**-2.142***** **(-5.072)**	**-0.453**** **(-2.316)**
	ΔNL_DEP	-0.038 (-0.297)	0.059 (1.499)
	ΔEQU_LIAB	0.024 (0.070)	0.051 (1.012)
	DNLTA* ΔNL_DEP	-0.062 (-0.350)	0.008 (0.144)
	DNLTA* ΔEQU_LIAB	0.188 (0.310)	**0.592***** **(3.125)**
Market indicator	EXCRCUM	43.645 (0.949)	20.067 (0.999)
	DNLTA* EXCRCUM	**-125.609**** **(-2.176)**	28.489 (0.794)
	Risk level to reject $\beta_1 + \beta'_1 = 0$	43.94%	11.31%
	Risk level to reject $\beta_2 + \beta'_2 = 0$	66.59%	**0.05%**
	Risk level to reject $\gamma_1 + \gamma'_1 = 0$	**1.85%**	**9.97%**
	Mc Fadden R^2 (%)		13.61
	Total number of observations		164
	Number of observations of type Y=-1		16
	Number of observations of type Y=1		61

*This table reports multinomial logit estimation results when we regress the dependent variable on a constant and the accounting and market indicators selected by a stepwise process. We take the structure of assets into account with a dummy variable (DNLTA) associated with the accounting and market indicators. DNLTA is equal to one if the value of the ratio net loans / total assets is higher than its median (54.72%) and 0 otherwise. *, ** and *** indicate significance respectively at 10%, 5% and 1% levels. Z-statistics are shown in parentheses.*

Table 10. Structure of bank liabilities and effectiveness of early indicators
Model Specification:

$$\Pr ob(Y_i = m) = \frac{e^{\left(\alpha_m + \sum_{j=1}^{J}\beta_{jm}C_{ji} + \sum_{l=1}^{L}\gamma_{lm}M_{li} + \sum_{j=1}^{J}\beta'_{jm}DDEPTA_i C_{ji} + \sum_{l=1}^{L}\gamma'_{lm}DDEPTA_i M_{li}\right)}}{1 + \sum_{k\in\{-1,1\}} e^{\left(\alpha_k + \sum_{j=1}^{J}\beta_{jk}C_{ji} + \sum_{l=1}^{L}\gamma_{lk}M_{li} + \sum_{j=1}^{J}\beta'_{jk}DDEPTA_i C_{ji} + \sum_{l=1}^{L}\gamma'_{lk}DDEPTA_i M_{li}\right)}} \text{ for m=-1, 0, 1,}$$

$$\beta_{j0} = \gamma_{l0} = \alpha_0 = \beta'_{j0} = \gamma'_{l0} = 0 \ \forall j,l$$

	Variables	Downgrades	Upgrades
Accounting indicators	Constant	**-2.069*** (-4.725)**	**-0.501** (-2.399)**
	ΔNL_DEP	-0.053 (-0.434)	**0.098** (2.241)**
	ΔEQU_LIAB	0.021 (0.072)	0.024 (0.318)
	DDEPTA* ΔNL_DEP	-0.019 (-0.112)	**-0.151** (-2.197)**
	DDEPTA* ΔEQU_LIAB	0.411 (0.827)	**0.868*** (3.471)**
Market indicator	EXCRCUM	31.579 (0.722)	13.068 (0.577)
	DDEPTA* EXCRCUM	**-104.671** (-2.048)**	60.135 (1.630)
	Risk level to reject $\beta_1 + \beta_1' = 0$	55.62%	32.29%
	Risk level to reject $\beta_2 + \beta_2' = 0$	27.43%	22.09%
	Risk level to reject $\gamma_1 + \gamma_1' = 0$	**1.18%**	**0.95%**
	Mc Fadden R^2 (%)		16.11
	Total number of observations		164
	Number of observations of type Y=-1		16
	Number of observations of type Y=1		61

*This table reports multinomial logit estimation results when we regress the dependent variable on a constant and the accounting and market indicators selected by a stepwise process. We take the structure of liabilities into account with a dummy variable (DDEPTA) associated with the accounting and market indicators. DDEPTA is equal to one if the value of the ratio deposits/ total assets is higher than its median (80.9%) and 0 otherwise. *, ** and *** indicate significance respectively at 10%, 5% and 1% levels. Z-statistics are shown in parentheses.*

Table 11: Subordinated debt and effectiveness of early indicators

Model Specification:

$$\Pr ob(Y_i = m) = \frac{e^{\left(\alpha_m + \sum_{j=1}^{J} \beta_{jm} C_{ji} + \sum_{l=1}^{L} \gamma_{lm} M_{li} + \sum_{j=1}^{J} \beta^{'}_{jm} DSUBDTA_i C_{ji} + \sum_{l=1}^{L} \gamma^{'}_{lm} DSUBDTA_i M_{li}\right)}}{1 + \sum_{k \in \{-1,1\}} e^{\left(\alpha_k + \sum_{j=1}^{J} \beta_{jk} C_{ji} + \sum_{l=1}^{L} \gamma_{lk} M_{li} + \sum_{j=1}^{J} \beta^{'}_{jk} DSUBDTA_i C_{ji} + \sum_{l=1}^{L} \gamma^{'}_{lk} DSUBDTA_i M_{li}\right)}} \text{ for m=-1, 0, 1,}$$

$$\beta_{j0} = \gamma_{l0} = \alpha_0 = \beta'_{j0} = \gamma'_{l0} = 0 \; \forall j,l$$

	Variables	Downgrades	Upgrades
Accounting indicators	Constant	**-2.633*** (-4.057)**	-0.278 (-1.264)
	ΔNL_DEP	-0.177 (-0.926)	0.001 (0.015)
	ΔEQU_LIAB	0.108 (0.187)	**0.983*** (3.205)**
	DSUBDTA* ΔNL_DEP	0.065 (0.284)	0.041 (0.593)
	DSUBDTA* ΔEQU_LIAB	-0.054 (-0.078)	**-0.941*** (-3.016)**
Market indicator	EXCRCUM	-79.275 (-1.137)	1.829 (0.059)
	DSUBDTA* EXCRCUM	**201.941* (1.907)**	52.551 (1.072)
	Risk level to reject $\beta_1 + \beta_1^{'} = 0$	52.23%	35.29%
	Risk level to reject $\beta_2 + \beta_2^{'} = 0$	88.61%	50.91%
	Risk level to reject $\gamma_1 + \gamma_1^{'} = 0$	**9.14%**	15.14%
	Mc Fadden R^2 (%)		16.75
	Total number of observations		127
	Number of observations of type Y=-1		8
	Number of observations of type Y=1		53

*This table reports multinomial logit estimation results when we regress the dependent variable on a constant and the accounting and market indicators selected by a stepwise process. We take subordinated debt into account with a dummy variable (DSUBDTA) associated with the accounting and market indicators. DSUBDTA is equal to one if the value of the ratio subordinated debt/ total assets is lower than its median (1.5%) and 0 otherwise. *, ** and *** indicate significance respectively at 10%, 5% and 1% levels. Z-statistics are shown in parentheses.*

Table 12: Subordinated debt and effectiveness of early indicators: estimations on sub-samples

Multinomial logit model Specification:

$$\Pr ob(Y_i = m) = \frac{e^{\left(\alpha_m + \sum_{j=1}^{J} \beta_{jm} C_{ji} + \sum_{l=1}^{L} \gamma_{lm} M_{li}\right)}}{1 + \sum_{k \in \{-1,1\}} e^{\left(\alpha_k + \sum_{j=1}^{J} \beta_{jk} C_{ji} + \sum_{l=1}^{L} \gamma_{lk} M_{li}\right)}} \quad \text{for m =-1, 0, 1, } \beta_0 = 0$$

		Sub-sample of banks with a low ratio of subordinated debt/total assets		Sub sample of banks with a high ratio of subordinated debt/total assets	
	Variables	Downgrades	Upgrades	Downgrades	Upgrades
Accounting indicators	Constant	**-3.451**** **(-1.985)**	**-0.510*** **(-1.676)**	**-2.128***** **(-2.984)**	-0.030 (-0.093)
	ΔNL_DEP	-0.164 (-0.588)	0.045 (0.998)	-0.154 (-0.818)	-0.010 (-0.181)
	ΔKP_LIAB	0.075 (0.182)	0.043 (0.653)	0.184 (0.324)	**0.965***** **(3.104)**
Market indicator	EXCRCUM	146.749 (1.628)	53.668 (1.404)	-70.159 (-1.044)	-2.461 (-0.075)
	Mc Fadden R^2 (%)		12.94		20.13
	Total number of observations		58		69
	Number of observations of type Y=-1		3		5
	Number of observations of type Y=1		21		32

*This table reports multinomial logit estimation results when we regress the dependent variable on a constant and the accounting and market indicators selected by a stepwise process on the whole sample of banks. We take two sub-samples into account on the basis of the ratio of subordinated debt to total assets. We consider this ratio high if its value is higher than the median value (1.5%). *, ** and *** indicate significance respectively at 10%, 5% and 1% levels. Z-statistics are shown in parentheses.*

Table 13: Subordinated debt and effectiveness of early indicators: estimations on sub-samples running new stepwises

Multinomial logit model Specification:

$$\Pr ob(Y_i = m) = \frac{e^{\left(\alpha_m + \sum_{j=1}^{J} \beta_{jm} C_{ji} + \sum_{l=1}^{L} \gamma_{lm} M_{li}\right)}}{1 + \sum_{k \in \{-1,1\}} e^{\left(\alpha_k + \sum_{j=1}^{J} \beta_{jk} C_{ji} + \sum_{l=1}^{L} \gamma_{lk} M_{li}\right)}} \quad \text{for m =-1, 0, 1, } \beta_0 = 0$$

		Sub-sample of banks with a low ratio of subordinated debt/total assets		Sub sample of banks with a high ratio of subordinated debt/total assets	
	Variables	Downgrades	Upgrades	Downgrades	Upgrades
Accounting indicators	Constant	**-3.411*** (-3.237)**	-0.261 (-0.851)		
	ΔNIR_NINC	-7.76E-06 (-0.010)	**0.285** (2.306)**		
Market indicator	ΔZ	0.185 (0.627)	**-0.744* (1.952)**		
	EXCRCUMNEG	**2.345* (1.947)**	0.0006 (-1.127)		
	Mc Fadden R^2 (%)		14.11		
	Total number of observations		76		
	Number of observations of type Y=-1		5		
	Number of observations of type Y=1		33		

*This table reports multinomial logit estimation results when we regress the dependent variable on a constant and the accounting and market indicators selected by a new stepwise processs We take two sub-samples into account on the basis of the ratio of subordinated debt to total assets. We consider this ratio high if its value is higher than the median value (1.5%). *, ** and *** indicate significance respectively at 10%, 5% and 1% levels. Z-statistics are shown in parentheses.*

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