Isabelle Distinguin – Iftekhar Hasan – Amine Tarazi

Predicting rating changes for banks: How accurate are accounting and stock market indicators?

SUOMEN PANKKI · FINLANDS BANK
EUROJÄRJESTELMÄ
EUROSYSTEMET

Bank of Finland Research
Discussion Papers
15 • 2012

PREDICTING RATING CHANGES FOR BANKS: HOW ACCURATE ARE ACCOUNTING AND STOCK MARKET INDICATORS?

Isabelle Distinguin[a], Iftekhar Hasan[bc*] and Amine Tarazi[a]

Abstract

We aim to assess how accurately accounting and stock market indicators predict rating changes for Asian banks. We conduct a stepwise process to determine the optimal set of early indicators by tracing upgrades and downgrades from rating agencies, as well as other relevant factors. Our results indicate that both accounting and market indicators are useful leading indicators but are more effective in predicting upgrades than downgrades, especially for large banks. Moreover, early indicators are only significant in predicting rating changes for banks that are more focused on traditional banking activities such as deposit and loan activities. Finally, a higher reliance of banks on subordinated debt is associated with better accuracy of early indicators.

Keywords: Bank Failure, Bank Risk, Ratings, Emerging Market

JEL classification: G21, G28

---

[a] *Université de Limoges, LAPE, 5, rue Félix Eboué, 87031 Limoges, France*

[b] *Fordham University, 1790 Broadway, 11th Floor, New York, NY 10019, USA.*

[c] *Bank of Finland, Helsinki, Finland.*

*Corresponding author: Telephone, 646 312-8278; Fax: 1 646 312 8295; E-mail address: ihasan@fordham.edu

This paper was prepared for the European Commission ASIA-LINK project B7-3010/2005/105-139: Safety and Soundness of the Financial System. The contents of this paper are the sole responsibility of the authors and can under no circumstances be regarded as reflecting the position of the European Commission or the Bank of Finland.

1. Introduction

Given the critical role of banks as intermediaries in the financial system, assessing a bank's financial health is essential for regulators. To identify risk in banking institutions, supervisors rely on early warning systems (EWS) to predict an improvement or deterioration in financial condition. Whereas most traditional EWS focus on accounting data, a strand of the literature recommends 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 complement accounting information when evaluating bank financial health (Flannery 2001).

Studies on banks in developed countries frequently tend to address bank failures or focus on reporting that market indicators add significantly to the predictive power of EWS models based solely on accounting data.[1] Most of these papers consider supervisory risk ratings as proxies for default risk (Curry, Fissel, and Hanweck 2008; Evanoff and Wall 2001; and Krainer and Lopez 2004) and show that including market information in traditional models improves predictions of bank financial conditions. Gropp, Vesala, and Vulpes (2006) report that for European banks, indicators derived from market prices are able to predict downgrades by private rating agencies over relatively long time horizons.

In the emerging markets, most studies on bank failures focus on Asian banks, especially after the financial crisis of 1997. However, these studies primarily focus on contagion effects (Kaminsky and Reinhart 2000) or on the design of early warning models for banking crises (Demirgüc-Kunt and Detragiache 2000). Previous work neglects the issue of predicting bank financial health at the individual level, which is crucial for supervisors and especially so under the new regulatory framework introduced by the Basel Committee on Banking and Supervision (Basel II accord).

Under this new framework, which emphasizes disclosure and market forces, market discipline is expected to play an important role, and regulators can use market prices as signals to improve supervision. Assessing the accuracy of market and accounting indicators to predict changes in financial health is therefore an important issue for banking systems in general. This is even more crucial for developing economies with emerging banking sectors

[1] Other papers study how accurately market indicators 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).

that influence economic growth (Barth, Caprio, and Levine 2005; Khan 2001; Aghion, Howitt, and Mayer-Foulkes 2005).

In this paper we assess the accuracy of market and accounting indicators by constructing a prediction model for changes in ratings assigned by private agencies.[2] We extend the approaches used in the existing literature in several directions. While most studies look at predicting financial deterioration (rating downgrades or bank failures), we focus on predicting both downgrades and upgrades announced by three rating agencies (Moody's, Standard and Poor's, and Fitch) that we use as proxies of a deterioration (bad event) or an improvement (good event) in financial health.[3]

We begin our investigation by considering the standard binary and ordered logit models used in the previous literature, but we also develop a multinomial model, which allows for possible asymmetric effects. We therefore go further by questioning how well leading indicators predict both positive and negative changes. We demonstrate that an ordered logit model can, in some cases, be misleading because, in our sample, indicators that appear significant in an ordered framework lose their predictive power in a more general multinomial approach. Moreover, indicators that are significant predictors of positive changes are not necessarily significant predictors of negative changes. With a multinomial logit model, differences in the significance and value of coefficients for negative (downgrade) and positive (upgrade) outcomes capture asymmetric effects.

Our aim is also to select from among a very large variety of market and accounting indicators the optimal set of variables to predict rating changes. 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, 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 with which early indicators

[2] Other variables reflect banks' financial health, such as supervisory risk ratings (Curry, Fissel, and Hanweck 2008), Z-scores (Demirgüç-Kunt, Detragiache, and Tressel 2008), or actual failures (Kolari, Glennon, Shin, and Caputo 2002).

[3] An exception is the work by Curry, Fissel, and Hanweck (2008), which considers downgrade, upgrade, and no-rating-change outcomes, assuming that the generating process is the same for the different outcomes of the BOPEC (Bank subsidiaries, Other subsidiaries, Parent company, consolidated Earnings, and consolidated Capital is a rating that bank supervisors assign to bank holding companies). This rating is from 1 to 5, 1 corresponding to a sound BHC, and 5 to a BHC with serious difficulties (near insolvency). We argue that indicators might predict upgrades better than downgrades because bad news is generally less rapidly and less frequently conveyed to the market than is good news (Berger and Davies 1998).

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), and the extent to which debt holders can exert market discipline (importance of subordinated debt issues).

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. Logit prediction model

Given that we attempt to assess the reliability of leading indicators by constructing a model to predict 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) from 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 we can test the stability of the predictive power of the indicators with respect to bank characteristics.

The first step in designing an early warning model is to define events that could represent a change in the financial condition of a bank. As mentioned, most U.S. studies either use actual bank failures or downgrades in supervisory ratings to capture financial deteriorations, as in Curry, Fissel, and Hanweck (2008); Kolari, Glennon, Shin, and Caputo (2002); and Gunther, Levonian, and Moore (2001). Due to insufficient data on explicit failures, studies on European banks use ratings from private agencies. Downgrades below a certain level (level C) are considered as proxies for bank failures (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 deterioration. We therefore use both upgrade and downgrade announcements by private agencies. These rating changes are from the three major rating agencies: Fitch, Moody's, and Standard and Poor's. From this perspective, our work links to the literature investigating the determinants of the ratings that private agencies assign to banks (Pasiouras, Gaganis, and Doumpos 2007;

Poon and Firth 2005; Poon, Firth, and Fung 1999). However, we do not consider the levels of the ratings; rather, we use rating changes as proxies of bad events (downgrades) or good events (upgrades).[4]

We then use accounting and market indicators to estimate the probability of a rating change. For most sample banks, accounting data are available on a yearly basis and thus at a much lower frequency than are market data. Accounting and market indicators are computed at the end of each calendar year. Because we aim to predict downgrades and upgrades rather than the ratings themselves, for most indicators we consider the changes in ratings rather than the rating levels. We then consider events (downgrades or upgrades) taking place during the following calendar year. Matching market data and accounting data in this fashion avoids the need to interpolate accounting data and ensures that the information content of accounting data is not inappropriately biased upward. Thus, the model's prediction horizon is at the most one year. However, the rating agencies' lack of timely ratings (Association for Financial Professionals 2002)[5] and conflicts of interest during the rating process (Bolton, Freixas, and Shapiro 2009) are often underlined. This implies that a change in bank financial health may have intervened well before the announcement of the rating change. In that case, our indicators may be the determinants of the rating changes rather than the predictors of changes in bank financial health.

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.

Our investigation uses several types of models. First, to estimate the probability of a rating change, we employ the following multinomial logit model[6,7]:

[4] In another strand of the literature, ratings are used as proxy variables for bank financial condition. For instance, Gaganis, Pasiouras, and Zopounidis (2006), in a cross-country analysis, use Fitch ratings to assess the soundness of banks and to classify them into several groups.
[5] Nevertheless, Cheng and Neamtiu (2009) show that rating agencies have improved rating timeliness and accuracy.
[6] See Greene (2003) for more details about multinomial logit models.

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

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. In this general specification, which allows us to capture asymmetric effects, the underlying assumption is that the same factors do not necessarily drive a bad event (downgrade) and a good event (upgrade). Alternatively, in order to check for robustness and consistency with the existing literature, we also estimate ordered logit models and binary logit models that only consider downgrades. To compare the different outcomes, we estimate binary logit models to predict upgrades. To select the set of optimal predictors of bank rating changes, we use a stepwise process. As a rule of thumb, we retain a 5% level for type 1 errors 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 major listed banks in Hong Kong, Korea, Taiwan, Singapore, Malaysia, Thailand, Indonesia, and the Philippines.[8] On average, the sample banks constitute over 65% of the banking assets of listed banks in the respective sample countries. These sample banks are 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.

Our choice to focus on Asian banks is based on a number of considerations. First, as discussed, the relevant literature focuses on U.S. and European data. The increased flow of trade and foreign direct investment in both financial and nonfinancial sectors in the period following the 1997 Asian financial crisis also warrants a better understanding of the relevance

[7] We could also use a panel multinomial logit model. However, this would considerably reduce the number of observations. Indeed, only the observations for individuals who switched from one category to the other can be used to estimate fixed-effects panel logit models (see Baltagi 2005). In our case, this would eliminate almost half of our sample.

[8] The distribution of banks is: Hong Kong (8), Korea (6), Taiwan (13), Singapore (2), Malaysia (3), Thailand (12), Indonesia (11), and the Philippines (9). Of these banks, 58 are commercial banks and six are investment banks and cooperatives.

of accounting and market information, as well as an investigation into the ability and perception of rating agencies, especially in the opaque banking industry. Additionally, in developed countries with advanced reporting and regulatory controls, accounting drives ratings, which reflect well-established ratios or other performance measures. But in countries where transparency is weak, rating analysts might rely on soft data sources and base their opinions on criteria obtained through indirect means (Fons 1999).

Accounting data (annual financial statements) for individual banks are obtained from Bankscope Fitch IBCA; 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 1999–2005.[9] Our econometric specification imposes the use of accounting and market data ranging from 1999 to 2004 to predict rating changes (downgrades and upgrades) that occurred between 2001 and 2005. Table 1 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 1

3.2. Dependent variable

Table 2 provides information on the downgrades and upgrades announced by Fitch, Moody's, and Standard and Poor's[10] from 2001 to 2005, which we use to construct the dependent variable. Because several restrictions are introduced to construct the dependent variable *Y*, this study only considers a limited number of clean downgrades and upgrades. Out of the 45 total combined downgrades from the rating agencies, only 24 are used for the estimations; out of the 284 upgrades, only 75 are retained. More precisely, if several

[9] In their work on the U.S. case, Curry, Fissel, and Hanweck (2008) study the impact of cyclical shifts in economic conditions on the prediction of changes in supervisory ratings. They divide the period under study (1988–2000) into three distinct economic periods (recession, recovery, expansion). In our work, which focuses on a shorter period, we do not explicitly consider such factors. Nevertheless, we attempt to capture such effects by introducing dummy variables in our regressions. These variables are not significant in our framework, which is restricted to a short-term, stable economic period.

[10] The three rating agencies use slightly different criteria. Standard and Poor's ratings seek to capture only the forward-looking probability of the occurrence of default. They provide no assessment of the expected time of default or mode of default resolution and recovery values (S&P 2007). By contrast, Moody's ratings focus on the Expected Loss (*EL*), which is a function of both the Probability of Default (*PD*) and the expected Recovery Rate (*RE*) (Moody's 2009). Fitch's ratings also focus on both *PD* and *RE* (Fitch 2005), and analysts are reminded to be forward-looking and alert to possible discontinuities between past track records and future trends. Rating committees rather than individual analysts assign credit ratings at Moody's and Standard and Poor's. Ratings reflect both quantitative assessments of credit risk and expert judgment of a rating committee. Thus, no particular set of data inputs or formal rules can unequivocally explain a rating.

downgrades (upgrades) occur during the calendar year, we consider them as a single event. Furthermore, for the sake of 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 actually predict a downgrade (upgrade) (i.e., a movement in the opposite direction).

Insert Table 2

3.3. Independent variables

Table 3 presents the set of accounting ratios commonly considered in the assessment of bank financial health. The ratios are grouped into the four categories of the CAEL rating, which stands for capital, asset quality, earnings, and liquidity.

Insert Table 3

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). Because 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 ratios. Indeed, our approach considers banks regardless of their initial financial strength; only the annual change in the ratios captures the downgrade of a sound and safe bank as compared to a modestly performing bank.

Table 4 shows the set of market indicators derived from weekly stock prices. The variables—such as the difference between the natural logarithm of market price and its moving average (*LOGP*), cumulative return *(RCUM),* cumulative market excess return *(EXCRCUM),* or cumulative abnormal returns (*CAR*)—capture the effects of shocks or the presence of abnormal returns. The change in the market model beta (*ΔBETA*) and the change in the distance to default (*ΔDD*) 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 that are consistent with the literature in order to study their actual contribution to predict downgrades and upgrades.

Insert Table 4

4. Hypotheses tests

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

As a preliminary step, we conduct simple regressions to investigate the predictive power of each early indicator taken separately. We estimate a multinomial logit model where the benchmark case is Y=0 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 relative to an unchanged rating. Estimating a model more general 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 uses an ordered logit framework—we check if the findings are significantly different.

Hypothesis 1: The same early indicators might not predict both upgrades and downgrades accurately. Some indicators might perform better than others in predicting upgrades and/or downgrades.

As discussed, the effectiveness of early indicators might also depend on bank characteristics. For example, market participants could behave differently toward large and small banks. We can expect that market participants consider negative information regarding the financial health of banks deemed “too big to fail” less thoroughly than they consider positive information about such institutions, because they are convinced that such institutions cannot fail.

We can also assume that bank size affects the reliability of accounting indicators. For smaller banks, for instance, market indicators may be more informative than accounting indicators. Market participants might consider accounting information 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, which the bank's stock price reflects.[11]

We introduce a dummy variable (*DBIG*) that takes bank size into account to test whether the reliability of accounting and market indicators to predict rating changes is affected by bank size. This dummy variable is equal to 1 if the bank is considered "too big to fail" and is 0 otherwise. Two criteria combine to determine whether a bank is too big to fail:

- If the Fitch Ratings Support rating is 1 or 2, the bank is too big to fail. Support ratings indicate 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. The literature commonly uses Fitch Ratings Support Ratings to identify too-big-to-fail banks operating outside the U.S. (see Gropp, Vesala, and Vulpes 2006).

- If 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.[12]

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

$$\Pr ob(Y_i = m) = \frac{e^{\left(\alpha_m + \beta_{0m} DBIG_i + \sum_{j=1}^{J} \beta_{jm} C_{ji} + \sum_{l=1}^{L} \gamma_{lm} M_{li} + \sum_{j=1}^{J} \beta'_{jm} DBIG_i C_{ji} + \sum_{l=1}^{L} \gamma'_{lm} DBIG_i M_{li}\right)}}{1 + \sum_{k \in \{-1,1\}} e^{\left(\alpha_k + \beta_{0k} DBIG_i + \sum_{j=1}^{J} \beta_{jk} C_{ji} + \sum_{l=1}^{L} \gamma_{lk} M_{li} + \sum_{j=1}^{J} \beta'_{jk} DBIG_i C_{ji} + \sum_{l=1}^{L} \gamma'_{lk} DBIG_i M_{li}\right)}} \qquad (2)$$

$$\text{for } m=-1, 0, 1, \ \beta_{j0} = \gamma_{l0} = \alpha_0 = \beta'_{j0} = \gamma'_{l0} = 0 \ \forall j, l$$

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

---

[11] 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 U.S. 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.

[12] We consider this second criterion because Fitch Support Ratings are not available for all banks. Of the 64 banks in our sample, the first criterion (Fitch Rating support rating) applies to 54 banks for which a Fitch Support rating is available. On the basis of this criterion, 16 banks are too big to fail. Eight banks are too big to fail on the basis of the second criterion. We check that all of the banks that comply with the second criterion also comply with the first criterion when the information is available. When we combine these two criteria, we find that 17 banks are too big to fail in our sample. If Fitch Support ratings are not available (i.e., when we can only use the second criterion) for a bank that is ranked first or second in its country, we check that it is too big to fail on the basis of the second criterion, because banks that might be relatively small in our sample might have major positions in their domestic banking systems.

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 of 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 at predicting 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 $\beta_{jm}\ (\forall j)$ are not significantly different from 0, whereas $\gamma_{lm}\ (\forall 1)$ are significant (for *m*=-1 or 1).

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

Hypothesis 2': For small banks, market indicators are more effective than accounting indicators at predicting ratings.

Banks' main activities should also affect the accuracy of early indicators. In terms of modern banking theory, banks are considered inherently opaque institutions (Diamond 1984). Empirical evidence generally supports such a hypothesis (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, we expect that a higher reliance on market funding and specifically a higher reliance on market debt that is not insured (such as subordinated debt) encourages market participants to monitor banks more closely, which promotes market discipline in the banking industry (Bliss 2001). In this sense, because subordinated debt holders have strong incentives to anticipate accurately any change to a bank's financial health, market prices should have a strong predictive power.

To test for an opacity effect, we consider three dummy variables: 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) from banks that are more involved in market activities or in other nontraditional activities, such as providing services.

The dummy variable is equal to 1 for banks that are relatively more involved in traditional intermediation activities (i.e., if the ratio is higher than the median); it equals 0 otherwise. In our sample, the median value of the ratio of deposits to total assets is 80.9%, and the median value of the ratio of net loans to total assets is 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 do. To test such a market-discipline effect, we define a dummy variable that is equal to 1 for banks that have relatively less subordinated debt (i.e., if the ratio is lower than the median, which is 1.5%); it equals 0 otherwise. The model specification and the tests are similar to those performed to capture the size effect.

Hypothesis 3: The relative weight of traditional intermediation activities (loans and/or deposits) on a bank's balance sheet affects the accuracy of accounting and market indicators in predicting rating changes.

Hypothesis 3': Higher reliance on subordinated debt and therefore higher exposure to market discipline improves the accuracy of accounting and market indicators in predicting rating changes.

5. Empirical results and robustness checks

5.1. Results

Table 5 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 predicting upgrades is easier than predicting downgrades.

Insert Table 5

In the multinomial logit model, five indicators appear as significant predictors of upgrades, whereas only three indicators are significant for downgrades. Moreover, the level of significance is higher for upgrade predictors. We find that changes in capital ratios and liquidity ratios are significant in predicting upgrades; for downgrades, only the 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. The difference between the natural logarithm of the stock price and its moving average (*LOGP*) and the cumulative return (*RCUM*) are significant to predict upgrades. The cumulative market excess return (*EXCRCUM*) and the change in the distance to default (*ΔDD*) are significant for downgrades. The signs of the coefficients are the expected ones, except for the change in the distance to default.

This surprising result can be explained by the relatively lower increase in liabilities for downgraded banks as 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.[13] In any case, the change in the distance to default, as based on the Merton-Black-Scholes model, which combines both market and accounting data, appears to be a misleading indicator in our setting.[14] Nevertheless, market indicators constructed solely with market prices perform as expected.

Several indicators are significant in the ordered logit model but not in the multinomial estimation: the changes in the ratios loan loss reserves to gross loans (*ΔLLR_GL*) and loan loss provision to net interest revenue (*ΔLLP_NETIR*) and the existence of persistent, negative cumulative returns (*RCUMNEG*). Moreover, when both models yield the same significant indicators, these are only significant in predicting upgrades in the multinomial framework. Therefore, the multinomial approach appears better suited to capture different effects for downgrades and for upgrades that the ordered logit framework cannot distinguish in a straightforward manner.

Insert Table 6

[13] 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.

[14] Other studies find that the distance to default is a significant indicator (Gropp et al. 2002, 2006). However, they do not consider the annual change in the distance to default. Thus, it does not directly compare to our results. Besides, Gropp et al. (2002) find that the distance to default is not a significant variable three months before a downgrade. They suggest that "many eventually downgraded banks exhibit a lowering in the equity volatility just before the downgrading, which causes the derived asset volatility measure to decrease as well, reducing the (-DD) value." This may also explain our result, as it implies a positive change in the distance to default for downgraded banks.

Table 6 reports the multinomial logit estimation results with a set of independent variables[15] selected by our stepwise process[16] defined earlier.[17] For the sake of accuracy, Table 6 also shows the results from the ordered logit model. Our findings confirm the conjecture that upgrades are easier to predict than downgrades, as shown by the tests at the bottom of Table 6. All the indicators selected by the stepwise process in the multinomial model are significant predictors of upgrades. In contrast only one market indicator, the cumulative market excess return (*EXCRCUM*), has a significant coefficient for downgrades.

Consistent with the simple regressions, the accounting indicators that most help 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 no accounting indicator can 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 significant market indicator, cumulative market excess return (*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 are significant: the change in the ratio net loans to total earning assets (*ΔNL_TEA*) and the difference between the natural logarithm of market price and its moving average (*LOGP*). However, these two variables do not significantly predict upgrades or downgrades in the multinomial logit model. Therefore, in the rest of our study we focus on the multinomial model and consider the ordered logit model for robustness considerations only.

In-sample classifications are reported at the bottom of Table 6. The percentage of overall correct classification is above 50% for both estimation methods and higher with the

[15] We consider this set of independent variables rather than construct an index on the basis of these indicators. Indeed, constructing an index with these variables would be restrictive, as we suspect that variables relevant to predict upgrades are not the same as those that are relevant to predict downgrades. Even if we construct two different indexes, it would not be possible to determine whether market or accounting indicators behave differently. Moreover, we also consider different subsamples for which the optimal index may be different.

[16] Alternatively, to select the set of optimal predictors, we consider a general-to-specific criterion. We do not include all the potential indicators simultaneously because of the high correlation between several indicators. We consider a subset of indicators that corresponds to the indicators significant in the univariate regressions, except *ΔNL_TEA*, which is highly correlated with *ΔNL_DEP*. We then run a backward stepwise process. We obtain an optimal set of indicators very close to the one in this study. The only difference is the absence of *ΔEQU_LIAB*, which is not in the initial subset.

[17] To account for possible differences among banks from the tiger economies and banks from emerging markets, we introduce a dummy variable equal to 1 for banks from the Philippines, Indonesia, Malaysia, and Thailand; it equals 0 otherwise. This variable does not appear as significant and therefore we do not retain it in the rest of our study.

multinomial logit model. The percentage of correct predictions of downgrades is 0% in both specifications. By contrast, the percentage of correct predictions of upgrades is 36.06% in the multinomial logit model and only 16.92% in the ordered logit. To assess the predictive power of our model, we also run out-of-sample tests on the 2005–2008 period.[18]

Out-of-sample classifications are at the bottom of Table 6. We find similar results. The overall percentage of correct predictions is equal to 59.63% for the multinomial logit model and 65.17% for the ordered logit model. For downgrades we still find 0% in both specifications, and for upgrades the percentage of correct predictions is higher with the multinomial logit model (21.21%) than with the ordered logit model (6.06%). These results confirm that upgrades are easier to predict than downgrades and that the multinomial logit model predicts rating changes more accurately than the ordered logit model.

As 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 expectations of downgrades than about expectations of upgrades for such banks. In contrast, the market might look more closely at the financials of these large banks, which presumably issue more reliable accounting information as compared to the smaller banks. Hence, for smaller banks, market indicators could be more accurate than 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 7

The results presented in Table 7 indicate that bank size affects the accuracy 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. In contrast, for large banks, only the market indicator remains significant, as shown by the results of the tests at the bottom of Table 7. Thus, market indicators are better predictors of upgrades for large banks.

We obtain the opposite results for downgrades. The cumulative market excess return (*EXCRCUM*), which is the market indicator previously selected by the stepwise process, is

[18] Thus, we aim to predict rating changes occurring in the period 2006–2009.

significant for small banks but not 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 public safety nets for such banks. However, another possible explanation is that the market might be less efficient at processing information for large and complex institutions than for small institutions that are more focused on traditional intermediation activities. Furthermore, because of a potential systemic risk, rating agencies might be more reluctant to downgrade large banks than small banks. Thus, the lack of timeliness of downgrades might be higher for large banks. This might explain why market indicators are significant predictors of downgrades for small banks but not for large banks. Rating agencies also might be more conservative toward small banks than large banks regarding good news; that is, agencies might adjust the ratings of small banks more slowly following good news. This might explain why market indicators are not significant predictors of upgrades for small banks.

Table 7 reports in-sample classifications[19] for large and small banks. Predictions are better for large banks than small banks. Indeed, the overall correct classification is 75.55% for large banks and 63.02% for small banks. Interestingly, none of the downgrade predictions are correct for small banks, but 50% of the downgrade predictions for large banks are correct. The difference is even larger for upgrades, as only 9.37% of upgrade predictions are correct for small banks and 93.10% of upgrade predictions are correct for large banks.

The fourth and fifth columns of Table 7 show that the structure of bank assets significantly affects the predictive power of early indicators. No indicator is able to predict changes for banks with a relatively low ratio of net loans to total assets. In contrast, the indicators selected through the stepwise process (except for the change in the ratio of net loans to total deposits, *ΔNL_DEP*) recover their significance for banks with a high proportion of loans on their balance sheets (see tests at the bottom of the table). Indeed, the change in the ratio equity to total liabilities (*ΔEQU_LIAB*) is significant at the 1% level to predict upgrades, but the market indicator reflecting cumulative market excess returns (*EXCRCUM*) is significant in predicting downgrades.

Therefore, accounting and market indicators are only useful in predicting rating changes of banks heavily involved in traditional lending activities. In-sample classifications confirm that predictions are easier for banks heavily involved in lending activities, as the overall correct classification is 65.85% for these banks and only 60.97% for banks less

[19] We do not perform out-of-sample classifications on the different subsamples because of an insufficient number of rating changes in each separate group.

involved in lending activities. More important, none of the downgrade predictions are correct for banks with a low ratio of net loans/total assets, whereas 50% of the downgrade predictions for banks with a high ratio are correct. The correct predictions of upgrades are also much more important for these banks (67.65% versus 29.63%).

The results obtained by using the ratio of deposits to total assets to construct the dummy variable (see the fifth column of Table 7) indicate that future rating changes are more difficult to predict for banks with a low ratio of deposits to total assets. Only one indicator, the change in the ratio of net loans to total deposits (*ΔNL_DEP*), is significant for upgrades. Moreover, the tests at the bottom of Table 7 show that for banks that are heavily reliant on deposits, the market indicator is significant in predicting both upgrades and downgrades. Therefore, predicting rating changes appears to be more accurate for banks turned toward taking deposits. The in-sample classifications at the bottom of Table 7 confirm this. Only 33.33% of the upgrade predictions and none of the downgrade predictions are correct for banks less turned toward deposits, but 74.19% of the upgrade predictions and 42.86% of the downgrade predictions are correct for banks heavily relying on deposits.

As a whole, early indicators seem better suited to explain future financial changes for banks involved in traditional deposit-taking and loan activities. These results are the opposite of those obtained by Distinguin, Rous, and Tarazi (2006), who use only downgrades to define the dependent variable in a European context. Our findings therefore suggest that Asian banks that are more involved in traditional intermediation products and are not market traded might not be more opaque than other banking institutions, as indicated by Distinguin, Rous, and Tarazi (2006). A possible explanation could be the lack of sufficiently deep financial markets and efficient secondary markets in Southeast Asia. The market might accordingly not convey sufficient information, even for institutions that issue a larger amount of market debt and invest in marketable assets. Nevertheless, market participants might make more effort to monitor traditional banking institutions because of their higher vulnerability to changes in macroeconomic conditions.

We also consider the role played by subordinated debt holders (Table 8).

Insert Table 8

No indicator is significant in predicting rating changes for banks that have a low ratio of subordinated debt to total assets, and only one accounting indicator is significant in predicting upgrades for banks that have a high subordinated debt ratio.

For further insight, we run the estimations on two different subsamples of banks depending on the relative weight of subordinated debt to total assets; we also run the stepwise process on these two subsamples. We first consider the initial set of significant variables for the whole sample of banks in Table 6 (see Table 9). No indicator is significant in predicting rating changes for banks with a low ratio of subordinated debt to total assets (below the median), but one accounting indicator is significant in predicting upgrades for banks with a high ratio (above the median).

We then rerun the stepwise process on the two subsamples (see Table 10). Our results clearly indicate that no indicator is useful in predicting rating changes for banks with a low subordinated debt ratio, but one market indicator and one accounting indicator are significant predictors of rating changes for banks with a high ratio. These results show that the proportion of subordinated debt in total liabilities affects the potency of market indicators.[20] Moreover, in-sample classifications at the bottom of Table 8 and Table 9 indicate that the overall correct classification is higher for banks with a high subordinated debt ratio (68.11% versus 62.06%). Predicting rating changes appears to be easier for banks with relatively high proportions of subordinated debt, which is consistent with the presence of a market-discipline effect.

Insert Table 9 and Table 10

5.2. Robustness checks

We perform several robustness checks. 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 in Table 7, we find that no indicator is significant in predicting downgrades for large banks. However, this result could be due to the fact that the indicators selected by the stepwise process for the whole sample are not the best indicators for the subsample of large banks. Therefore, we run the stepwise process on the subsample of large banks separately. The results confirm the absence of significant indicators to predict downgrades for these banks. Furthermore, univariate logit estimations show that no indicator is individually significant in

[20] Because the median value of the ratio of subordinated debt to total assets (1.5%) is relatively low in our sample, we consider 2% as a cut-off to construct the dummy variable *DSUBDTA*. A value of 2% is consistent with many mandatory subordinated debt proposals documented in the literature (see BGFRS 2000). Considering this value instead of the median does not alter our conclusions.

predicting these events. For upgrades, when we perform the stepwise process separately on the subsample of small banks, one market indicator appears significant.

Additionally, we estimate the stepwise process on different subsamples of banks depending on the structure of their balance sheet, and we run univariate logit estimations for each indicator individually for different subsamples. On the whole, this does not affect our findings. Indicators are better suited to explain future financial changes for banks that are more involved in loan and deposit activities. Similarly, performing our estimations on a sample of commercial banks—which represent 88% of the banks in our study—does not alter our main conclusions.

6. Conclusion

The main objective of this study is to assess how accurately accounting and market indicators predict changes in the financial health of a sample of leading banks from East Asia for the 1999–2005 period. 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.

Market indicators are significant in predicting upgrades for large banks but not downgrades. For small banks, market indicators perform relatively better than accounting indicators when it comes to predicting downgrades. Moreover, early indicators are only significant in predicting rating changes for banks that are mainly engaged in traditional intermediation activities (loans and deposits). Such a result is surprising because studies on U.S. and European banks consider such banks more opaque than institutions that are more involved in market-traded assets and that are more reliant on market debt.

Our findings suggest that Asian banks that are mainly engaged in traditional intermediation activities are easier to monitor than other types of banks. Nevertheless, our findings also show that the early indicators tend to be more effective for banks with more subordinated debt, 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 address the issue of how regulators might rely on early warning models to improve their supervisory actions. Specifically, if the market is unable to predict or simply reflect a decline in the financial health of some banking institutions, such models might not be reliable.

Table 1. Descriptive Statistics on Summary Accounting Information

	Mean[2]	**Standard Deviation**[2]	**Minimum**	**Maximum**
Total Assets ($ millions)	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 ($ millions)	13142.94	18174.79	0.00	126694.20
Subordinated Debt ($ millions)	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 (1999–2004). Standard deviations were computed on a similar basis.

Table 2. Downgrades and Upgrades Information

(Number of clean downgrades or upgrades in parentheses)

		2001	2002	2003	2004	2005
45 (24)[21]	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)[22]	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)

[21] These 24 downgrades correspond to nine banks downgraded one time, six banks downgraded two times, and one bank downgraded three times.
[22] These 75 upgrades correspond to 15 banks upgraded one time, 19 banks upgraded two times, six banks upgraded three times, and one bank upgraded four times.

Table 3. 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 Short-Term 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
	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 Short-Term 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

Table 4. 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 for 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 for 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 1 if the cumulative return is negative in the two quarters of the accounting period (financial year) preceding the event; it equals 0 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 1 if the cumulative market excess return is negative in the two last quarters of the accounting period (financial year) preceding the event; it equals 0 otherwise.	0.23	0.42	Positive
CAR	Cumulative abnormal returns on the fourth quarter of the accounting period (financial year) preceding the event: $CAR_{bt} = \sum_{k=1}^{13} RA_{b,t-k+1}$ 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: $Z = (1+\overline{r}_b) / \sigma_r$ 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[23]	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

[23] Weekly market values of the bank's equity are from Datastream. The volatility of the bank's equity for the quarter preceding the end of the calendar year (i.e., 65 trading days) is 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 1 (i.e., one year). Interbank rates from Datastream are used to compute risk-free rates. Data on debt liabilities are from Bankscope. The total amount of liabilities is calculated as the total amount of deposits, money-market funding, bonds, subordinated debt, and hybrid capital.

Table 5. Early Indicators: Univariate Regressions
Multinomial logit model specification:

$$\Pr ob(Y_i = m) = \frac{e^{(\alpha_m + \beta_m X_i)}}{1 + \sum_{k \in \{-1,1\}} e^{(\alpha_k + \beta_k X_i)}} \qquad \text{for m =-1, 0, 1, } \alpha_0 = \beta_0 = 0$$

Ordered logit model specification:

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

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

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.[24]

		Variables	**Downgrades**	**Upgrades**	**Ordered Logit**
Accounting indicators	CAPITAL	ΔTIER1_RAT	0.092 (0.240)	0.200* (1.801)	0.123*** (2.625)
	ASSET QUALITY	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)
		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 downgrades and upgrades (whatever their extent) to occur in the calendar year. The ***, **, and *symbols indicate the 1%, 5%, and 10% level of significance, respectively. Z-statistics are in parentheses. Variables definition: ΔTIER1_RAT = annual change of (Tier 1/Risk-Weighted Assets and Off-Balance Sheet Risks); ΔLLR_GL = annual change of (Loan Loss Reserves/Gross Loans); ΔLLP_NETIR = annual change of (Loan Loss Provision/Net Interest Revenue); ΔNL_DEP = annual change of (Net Loans/Customer and Short-Term Fundings); ΔNL_TEA = annual change of (Net Loans/Total Earning Assets); ΔNIR_EA = annual change of (Net Interest Revenue/Total Earning Assets); RCUMNEG = Dummy variable equal to 1 if the cumulative return is negative in the two last quarters of the accounting period (financial year) preceding the event, and 0 otherwise; LOGP = Difference between the natural logarithm of market price and its moving average calculated for one year; RCUM = cumulative return on the fourth quarter of the accounting period (financial year) preceding the event; EXCRCUM = cumulative market excess return on the fourth quarter of the accounting period (financial year) preceding the event; and ΔDD = annual change of the "distance to default."*

[24] See Greene (2003) for more details.

Table 6. Early Indicators: Multiple Regression
Multinomial logit model specification:

$$\Pr ob(Y_i = m) = \frac{e^{\left(\alpha_m + \sum_{j=1}^{J}\beta_{jm}C_{ji} + \sum_{l=1}^{L}\gamma_{lm}M_{li}\right)}}{1 + \sum_{k\in\{-1,1\}} e^{\left(\alpha_k + \sum_{j=1}^{J}\beta_{jk}C_{ji} + \sum_{l=1}^{L}\gamma_{lk}M_{li}\right)}} \quad \text{for m =-1, 0, 1, } \alpha_0 = \beta_0 = 0$$

Ordered logit model specification:

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

$$\text{Prob}(Y_i\text{=0})=\Phi\left(\lambda_U - \left(\sum_{j=1}^{J}\beta_j C_{ji} + \sum_{l=1}^{L}\gamma_l M_{li}\right)\right) - \Phi\left(\lambda_L - \left(\sum_{j=1}^{J}\beta_j C_{ji} + \sum_{l=1}^{L}\gamma_l M_{li}\right)\right)$$

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.[25]

	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 indicators	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%
	McFadden R^2 (%)		7.381	3.445
	Akaike information criterion		1.822	1.911
	Total number of observations		164	188
	Number of observations of type Y=-1		16	
	Number of observations of type Y=1		61	
In-sample classification	Overall correct classification		56.70%	54.25%
	Y = -1 correct		0%	0%
	Y = 0 correct		81.61%	91.92%
	Y = 1 correct		36.06%	16.92%
Out-of-sample classification: 2000–2004 model applied to 2005–2008	Overall correct classification		59.63%	65.17%
	Y = -1 correct		0%	0%
	Y = 0 correct		79.45%	93.42%
	Y = 1 correct		21.21%	6.06%

[25] 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. The *, **, and ***symbols indicate significance respectively at 10%, 5%, and 1% levels. Z-statistics are shown in parentheses. Variables definition: ΔNL_DEP = annual change of (Net Loans/Customer and Short-Term Fundings); ΔEQU_LIAB = annual change of (Equity/Liabilities); ΔNL_TEA = annual change of (Net Loans/Total Earning Assets); EXCRCUM = cumulative market excess return for the fourth quarter of the accounting period (financial year) preceding the event; LOGP = Difference between the natural logarithm of market price and its moving average calculated for one year.*

Table 7. Bank Size, Structure of Bank Assets, Structure of Bank Liabilities, and Effectiveness of Early Indicators

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

m=-1, 0, 1, $\beta_{j0} = \gamma_{l0} = \alpha_0 = \beta'_{j0} = \gamma'_{l0} = 0 \ \forall j,l$

		Bank Size and Effectiveness of Early Indicators		**Structure of Bank Assets and Effectiveness of Early Indicators**		**Structure of Bank Liabilities and Effectiveness of Early Indicators**	
	Variables	Downgrades	Upgrades	Downgrades	Upgrades	Downgrades	Upgrades
Accounting indicators	Constant	**-1.853*** (-4.991)**	**-0.856*** (-3.752)**	**-1.817*** (-3.664)**	**-0.557** (-2.121)**	**-1.855*** (-3.822)**	**-0.657*** (-2.676)**
	DUM	-2.280 (-0.322)	**1.403*** (2.913)**	-0.979 (-1.060)	25.350 (0.696)	-0.856 (-0.786)	0.429 (0.929)
	ΔNL_DEP	-0.031 (-0.463)	0.045 (1.281)	-0.022 (-0.189)	0.061 (1.532)	-0.039 (-0.322)	**0.104** (2.376)**
	ΔEQU_LIAB	0.059 (0.329)	**0.091* (1.936)**	0.021 (0.074)	0.053 (1.013)	0.018 (0.066)	0.024 (0.283)
	DUM* ΔNL_DEP	-0.190 (-0.248)	0.045 (0.639)	-0.104 (-0.562)	-0.001 (-0.021)	-0.054 (-0.309)	**-0.161** (-2.294)**
	DUM* ΔEQU_LIAB	-0.332 (-0.071)	0.377 (1.276)	0.230 (0.363)	**0.550*** (2.817)**	0.503 (0.982)	**0.786*** (2.896)**
Market indicators	EXCRCUM	**-30.981* (-1.709)**	11.893 (0.679)	35.860 (0.834)	20.273 (1.017)	28.519 (0.664)	11.804 (0.523)
	DUM* EXCRCUM	-193.296 (-0.446)	82.744 (1.414)	**-141.364** (-2.352)**	0.232 (0.591)	**-123.456** (-2.065)**	51.453 (1.293)
	Risk level to reject $\beta_1 + \beta_1' = 0$	77.08%	14.51%	37.29%	18.40%	45.79%	30.06%
	Risk level to reject $\beta_2 + \beta_2' = 0$	95.32%	10.84%	65.36%	**0.13%**	22.31%	**0.16%**
	Risk level to reject $\gamma_1 + \gamma_1' = 0$	60.41%	**9.01%**	**1.20%**	13.39%	**2.25%**	**5.36%**
	McFadden R^2 (%)		16.19		14.35		16.97
	Akaike Information Criterion		1.755		1.790		1.741
	Total number of observations		164		164		164
	Number of observations of type Y=-1		16		16		16
	Number of observations of type Y=1		61		61		61

		Large Banks	Small Banks	Banks with a High Ratio of Net Loans/ Total Assets	Banks with a Low Ratio of Net Loans/ Total Assets	Banks with a High Ratio of Deposits/ Total Assets	Banks with a Low Ratio of Deposits/ Total Assets
In-sample classification	Overall correct classification	75.55%	63.02%	65.85%	60.97%	63.88%	60.87%
	Y = -1 correct	50%	0%	50%	0%	42.86%	0%
	Y = 0 correct	42.86%	98.63%	67.50%	89.36%	58.82%	86.79%
	Y = 1 correct	93.10%	9.37%	67.65%	29.63%	74.19%	33.33%

*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 stepwise process. We take, alternatively, size, structure of assets, and structure of liabilities effects into account with a dummy variable (DUM) associated with the accounting and market indicators. For the size effect, DUM corresponds to DBIG and is equal to 1 if the Fitch Support rating of the bank is 1 or 2 or if total bank assets are higher than $50 billion (a significant threshold in our sample asset-size distribution). For the structure of asset, DUM corresponds to DNLTA and is equal to 1 if the value of the ratio net loans/total assets is higher than its median (54.72%); it equals 0 otherwise. For the structure of liabilities, DUM corresponds to DDEPTA and is equal to 1 if the value of the ratio deposits/total assets is higher than its median (80.9%); it equals 0 otherwise. The *, **, and *** symbols indicate significance respectively at 10%, 5%, and 1% levels. Z-statistics are shown in parentheses. Variables definition: ΔNL_DEP = annual change of (Net Loans/Customer and Short-Term Fundings); ΔEQU_LIAB = annual change of (Equity/Liabilities); EXCRCUM = cumulative market excess return for the fourth quarter of the accounting period (financial year) preceding the event.*

Table 8: Subordinated Debt and Effectiveness of Early Indicators
Model Specification:

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

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

	Variables	**Downgrades**	**Upgrades**
Accounting indicators	Constant	**-2.128*** (-2.984)**	-0.030 (-0.093)
	DSUBDTA	-1.323 5-0.703)	-0.480 (-1.084)
	ΔNL_DEP	-0.154 (-0.819)	-0.010 (-0.181)
	ΔEQU_LIAB	0.184 (0.325)	**0.965*** (3.105)**
	DSUBDTA* ΔNL_DEP	-0 .009 (-0.028)	0.056 (0.771)
	DSUBDTA* ΔEQU_LIAB	-0.109 (-0.156)	**-0.922*** (-2.900)**
Market indicators	EXCRCUM	-70.193 (-1.044)	-2.464 (-0.075)
	DSUBDTA* EXCRCUM	**216.94* (1.929)**	56.130 (1.114)
	Risk level to reject $\beta_1 + \beta_1' = 0$	55.62%	31.81%
	Risk level to reject $\beta_2 + \beta_2' = 0$	85.50%	51.41%
	Risk level to reject $\gamma_1 + \gamma_1' = 0$	10.35%	16.01%
	Mc Fadden R^2 (%)		17.69
	Akaike Information Criterion		1.698
	Total number of observations		127
	Number of observations of type Y=-1		8
	Number of observations of type Y=1		53
		Banks with a High Ratio of Subordinated Debt/Total Assets	Banks with a Low Ratio of Subordinated Debt/Total Assets
In-sample classification	Overall correct classification	68.11%	62.06%
	Y = -1 correct	20%	33.33%
	Y = 0 correct	65.62%	79.41%

	Y = 1 correct	78.12%	38.10%

*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 1 if the value of the ratio subordinated debt/total assets is lower than its median (1.5%); it equals 0 otherwise. The *, **, and *** symbols indicate significance respectively at 10%, 5%, and 1% levels. Z-statistics are shown in parentheses. Variables definition: ΔNL_DEP = annual change of (Net Loans/Customer and Short-Term Fundings), ΔEQU_LIAB = annual change of (Equity/Liabilities), EXCRCUM = cumulative market excess return for the fourth quarter of the accounting period (financial year) preceding the event.*

Table 9: Subordinated debt and effectiveness of early indicators: estimations on subsamples
Multinomial Logit Model Specification:

$$\Pr ob(Y_i = m) = \frac{e^{\left(\alpha_m + \sum_{j=1}^{J}\beta_{jm}C_{ji} + \sum_{l=1}^{L}\gamma_{lm}M_{li}\right)}}{1 + \sum_{k\in\{-1,1\}} e^{\left(\alpha_k + \sum_{j=1}^{J}\beta_{jk}C_{ji} + \sum_{l=1}^{L}\gamma_{lk}M_{li}\right)}} \quad \text{for m =-1, 0, 1, } \alpha_0 = \beta_0 = \gamma_0 = 0$$

		Subsample of Banks with a Low Ratio of Subordinated Debt/Total Assets		**Subsample 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)
	ΔEQU_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)
	McFadden R^2 (%)		20.13		12.94
	Akaike Information Criterion		1.674		1.728
	Total number of observations		69		58
	Number of observations of type Y=-1		5		3
	Number of observations of type Y=1		32		21
In-sample classification	Overall correct classification		62.06%		68.11%
	Y = -1 correct		33.33%		20%
	Y = 0 correct		79.41%		65.62%
	Y = 1 correct		38.09%		78.12%

*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 subsamples 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%). The *, **, and *** symbols indicate significance respectively at 10%, 5%, and 1% levels. Z-statistics are shown in parentheses. Variables definition: ΔNL_DEP = annual change of (Net Loans/Customer and Short-Term Fundings), ΔEQU_LIAB = annual change of (Equity/Liabilities), EXCRCUM = cumulative market excess return on the fourth quarter of the accounting period (financial year) preceding the event.*

Table 10: Subordinated Debt and Effectiveness of Early Indicators: Estimations on Subsamples Running New Stepwise Processes

Multinomial Logit Model Specification:

$$\Pr ob(Y_i = m) = \frac{e^{\left(\alpha_m + \sum_{j=1}^{J} \beta_{jm} C_{ji} + \sum_{l=1}^{L} \gamma_{lm} M_{li}\right)}}{1 + \sum_{k \in \{-1,1\}} e^{\left(\alpha_k + \sum_{j=1}^{J} \beta_{jk} C_{ji} + \sum_{l=1}^{L} \gamma_{lk} M_{li}\right)}} \text{ for m =-1, 0, 1, } \alpha_0 = \beta_0 = \gamma_0 = 0$$

		Subsample of Banks with a Low Ratio of Subordinated Debt/Total Assets		**Subsample of Banks with a High Ratio of Subordinated Debt/Total Assets**	
	Variables	Downgrades	Upgrades	Downgrades	Upgrades
Accounting indicators	Constant			**-3.326*** (-3.268)**	-0.045 (-0.164)
	ΔNIR_NINC			0.00002 (0.028)	**0.0005** (2.203)**
Market indicator	EXCRCUMNEG			**2.414** (2.013)**	-0.669 (-0.998)
	McFadden R^2 (%)				9.725
	Akaike Information Criterion				1.760
	Total number of observations				76
	Number of observations of type Y=-1				5
	Number of observations of type Y=1				33
In-sample classification	Overall correct classification				57.89%
	Y = -1 correct				0%
	Y = 0 correct				84.21%
	Y = 1 correct				36.36%

*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 process. We take two subsamples 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%). The *, **, and *** symbols indicate significance respectively at 10%, 5%, and 1% levels. Z-statistics are shown in parentheses. Variables definition: ΔNIR_NINC = annual change of (Net Interest Revenue/Net Income), EXCRCUMNEG = Dummy variable equal to 1 if the cumulative market excess return is negative in the two last quarters of the accounting period (financial year) preceding the event; it equals 0 otherwise.*

References

Aghion, P., Howitt, P., Mayer-Foulkes, D.: The Effect of Financial Development on Convergence: Theory and Evidence. The Quarterly Journal of Economics 120 n°1, 173–222 (2005)

Association For Financial Professionals: Ratings Agencies Survey: Accuracy, Timeliness, and Regulation. http://www.afponline.org (2002)

Baltagi, B.H.: Econometric Analysis of Panel Data. Third Edition, John Wiley & Sons Ltd (2005)

Barth, J.R., Caprio, G., Levine, R.: Rethinking Bank Regulation: Till Angels Govern. Cambridge University Press (2005)

Berger, A.N., Davies, S. M.: The Information Content of Bank Examinations. Journal of Financial Services Research 14, 117–145 (1998)

Berger, A.N., Davies, S.M., Flannery, M.J.: Comparing Market and Supervisory Assessments of Bank Performance: Who Knows What When? Journal of Money, Credit and Banking 32, 641–667 (2000)

Black, F., Scholes, M.: The Pricing of Options and Corporate Liabilities. Journal of Political Economy. 81, 637–654 (1973)

Bliss, R.R.: Market Discipline and Subordinated Debt: A Review of Some Salient Issues. Federal Reserve Bank of Chicago Economic Perspectives, 24–45 (2001)

Board Of Governors Of The Federal Reserve System (BGFRS): The Feasibility and Desirability of Mandatory Subordinated Debt, Report submitted to the Congress pursuant to the section 108 of the Gramm-Leach-Bliley Act of 1999 (2000)

Bolton, P., Freixas, X., Shapiro, J.: The Credit Ratings Game. NBER Working Paper 14712, (2009)

Cheng, M., Neamtiu, M.: An Empirical Analysis of Changes in Credit Rating Properties: Timeliness, Accuracy and Volatility. Journal of Accounting and Economics 47 (1-2), 108–130 (2009)

Crosbie, P. J., Bohn, P. R.: Modeling Default Risk. San Francisco: KMV Corporation, (2003)

Crouzille, C., Lepetit, L., Tarazi, A.: Bank stock volatility, news and asymmetric information in banking: an empirical investigation. Journal of Multinational Financial Management 14, 443–461 (2004)

Curry, T.J., Elmer, P.J., Fissel, G.S.: Equity market data, bank failures and market efficiency. Journal of Economics and Business 59, 536–559 (2007)

Curry, T.J., Fissel, G.S., Hanweck, G.A.: Equity market information, bank holding company risk, and market discipline. Journal of Banking and Finance 32, 807–819 (2008)

Demirgüc-Kunt, A., Detragiache, E.: Monitoring Banking Sector Fragility: A Multivariate Logit Approach. The World Bank Economic Review 14 n°2, 287–307 (2000)

Demirgüç-Kunt, A., Detragiache, E., Tressel T.: Banking on the Principles: Compliance with Basel Core Principles and Bank Soundness. Journal of Financial Intermediation 17, 511–542 (2008)

Diamond, D.W.: Financial Intermediation and Delegated Monitoring. Review of Economic Studies 51 n°3, 393–414 (1984)

Distinguin, I., Rous, P., Tarazi, A.: Market Discipline and the Use of Stock Market Data to Predict Bank Financial Distress. Journal of Financial Services Research 30, 151–176 (2006)

Evanoff, D.D., Wall, L.D.: Sub-debt Yield Spreads as Bank Risk Measures. Journal of Financial Services Research 20 (2/3), 121–145 (2001)

Fitch: The Role of Recovery Analysis in Ratings: Enhancing Informational Content and Transparency, www.fitchratings.com February (2005)

Flannery, M.J.: Using Market Information in Prudential Bank Supervision: A Review of the U.S. Empirical Evidence. Journal of Money Credit and Banking 30 n°3, 273–305 (1998)

Flannery, M.J.: The Faces of Market Discipline. Journal of Financial Services Research 20 (2-3), 107-119 (2001)

Flannery, M.J., Sorescu S.M.: Evidence of Bank Market Discipline in Subordinated Debenture Yields: 1983-1991. Journal of Finance 4, 1347–1377 (1996)

Fons, J.S.: Improving Transparency in Asian Banking Systems, in The Asian Financial Crisis: Origins, Implications, and Solutions. Hunter W. C., Kaufman G. G., Krueger T. H. Editors (1999)

Gaganis, Ch., Pasiouras, F., Zopounidis, C.: A Multicriteria Decision Framework for Measuring Banks' Soundness Around the World. Journal of Multi-Criteria Decision Analysis 14 n°.1-3, 103–111 (2006)

Greene, W.H.: Econometrics Analysis. Fifth Edition, Prentice Hall, New Jersey (2003)

Gropp, R., Vesala, J., Vulpes, G.: Equity and Bond Market Signals as Leading Indicators of Bank Fragility. European Central Bank Working Paper, (2002)

Gropp, R., Vesala, J., Vulpes, G.: Equity and Bond Market Signals as Leading Indicators of Bank Fragility. Journal of Money, Credit and Banking, 399–428 (2006)

Gunther, J.W., Levonian, M.E., Moore, R.R.: Can the Stock Market tell Bank Supervisors Anything They Don't Already Know? Economic and Financial Review, Federal Reserve Bank of Dallas (2001)

Iannotta, G.: Testing for Opaqueness in the European Banking Industry: Evidence from Bond Credit Ratings. Journal of Financial Services Research 30, 287–309 (2006)

Kaminsky, J., Reinhart, C.: On Crisis, Contagion and Confusion. Journal of International Economics 51, 145–168 (2000)

Khan, A.: Financial Development and Economic Growth. Macroeconomic Dynamics (2001)

Kolari, J., Glennon, D., Shin, H., Caputo, M.: Predicting large US Commercial bank failures. Journal of Economics and Business 54, 361–387 (2002)

Krainer, J., Lopez, J.A.: Incorporating Equity Market Information into Supervisory Monitoring Models. Journal of Money, Credit and Banking 36, 1043–1067 (2004)

Merton, R.C.: On the Pricing of Contingent Claims and the Modigliani-Miller Theorem. Journal of Financial Economics 5, 241–249 (1977)

Moody's Investors Service: Moody's ratings: symbols & definitions, www.moodys.com June (2009)

Morgan, D.P.: Rating Banks: Risk and Uncertainty in an Opaque Industry. American Economic Review 92 n°4, 874–888 (2002)

Pasourias, F., Gaganis, C., Doumpos, M.: A multicriteria discrimination approach for the credit rating of Asian banks. Annals of Finance 3, 351–367 (2007)

Poon, W.P.H., Firth, M.: Are Unsolicited Credit Ratings Lower? International Evidence From Bank Ratings. Journal of Business Finance and Accounting 32 (9&10), 1741–1771 (2005)

Poon, W.P.H., Firth, M., Fung, H-G.: A multivariate analysis of the determinants of Moody's bank financial strength ratings. Journal of International Financial Markets, Institutions and Money 9 (3), 267–283 (1999)

Standard & Poor's (S&P): Standard & Poor's ratings definitions, www.standardandpoors.com July (2007)

BANK OF FINLAND RESEARCH
DISCUSSION PAPERS

ISSN 1456-6184, online

1/2012 Maria Teresa Punzi **Housing Market and Current Account Imbalances in the International Economy.** 2012. 27 p. ISBN 978-952-462-784-9, online.

2/2012 Luisa Lambertini – Caterina Mendicino – Maria Teresa Punzi **Expectations-Driven Cycles in the Housing Market.** 2012. 61 p. ISBN 978-952-462-785-6, online.

3/2012 George A. Waters **Quantity Rationing of Credit.** 2012. 26 p. ISBN 978-952-462-786-3, online.

4/2012 Karlo Kauko **Why is equity capital expensive for opaque banks?** 2012. 26 p. ISBN 978-952-462-787-0, online.

5/2012 Kaushik Mitra – George W. Evans – Seppo Honkapohja **Fiscal Policy and Learning.** 2012. 32 p. ISBN 978-952-462-788-7, online.

6/2012 Ian W. Marsh – Wolf Wagner **Why is Price Discovery in Credit Default Swap Markets News-Specific?** 2012. 41 p. ISBN 978-952-462-789-4, online.

7/2012 Katja Taipalus **Signaling Asset Price Bubbles with Time-Series Methods.** 2012. 47 p. ISBN 978-952-462-790-0, online.

8/2012 Paavo Miettinen **Information acquisition during a Dutch auction.** 2012. 22 p. ISBN 978-952-462-791-7, online.

9/2012 Diego Moreno – Tuomas Takalo **Optimal Bank Transparency.** 2012. 33 p. ISBN 978-952-462-792-4, online.

10/2012 Alina Barnett – Martin Ellison **Learning by disinflating.** 2012. 20 p. ISBN 978-952-462-795-5, online.

11/2012 Bill Francis – Iftekhar Hasan – Qiang Wu **Do corporate boards affect firm performance? New evidence from the financial crisis?** 2012. 55 p. ISBN 978-952-462-796-2, online.

12/2012 Bill Francis – Iftekhar Hasan – Liang Song **Are firm- and country-specific governance substitutes? Evidence from financial contracts in emerging markets.** 2012. 55 p. ISBN 978-952-462-797-9, online.

13/2012 Chung-Hua Shen – Yu-Li Huang – Iftekhar Hasan **Asymmetric benchmarking in bank credit rating.** 2012. 40 p. ISBN 978-952-462-798-6, online.

14/2012 Bill Francis – Iftekhar Hasan – Qiang Wu **Corporate governance and cost of bank loan.** 2012. 49 p. ISBN 978-952-462-799-3, online.

15/2012 Isabelle Distinguin – Iftekhar Hasan – Amine Tarazi **Predicting rating changes for banks: How accurate are accounting and stock market indicators?** 2012. 34 p. ISBN 978-952-462-800-6, online.

http://www.suomenpankki.fi/en • email: Research@bof.fi
ISBN 978-952-462-800-6, ISSN 1456-6184, online