How good is the market at assessing bank fragility?

A horse race between different indicators[1]

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Abstract: We explore for individual banks, active in the East Asian countries during the years 1996-1998, the performance of three sets of indicators of bank fragility that can be computed from publicly available information: accounting data, stock market prices, and credit ratings. We find significantly different patterns among the three groups of indicators both in their ability of forecasting financial distress at a specific point in time and over time. More specifically, in the South East Asia crisis episode the information based on stock prices or on judgmental assessments of credit rating agencies did not outpace backward looking information contained in balance sheet data. Stock market based information, though, has responded more quickly to changing financial conditions than ratings of credit risk agencies. Overall, the evidence supports the policy conclusion that, where the information processing is quite costly, as in most developing countries, it is important to use simultaneously a plurality of indicators to assess bank fragility.

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1. Introduction.

The large number of banking crises which have hit developed and developing countries in the last decades (Caprio, 1999) and the high cost of their resolution (Honohan and Klingebiel, 2000) have prompted a renewed interest in the features of an effective financial regulatory framework. At the same time the extraordinary development of national and international capital markets in the last decades has induced to consider more seriously the contribution of market discipline to the effectiveness of prudential supervision. As a result, the undergoing revision of financial regulation has been increasingly characterized, both in developed and developing financial systems, by a shift from the traditional set of prescriptions and prohibitions to a new set of rules intended to integrate regulatory and market control and to increasingly rely on incentives. The general perception is that, while the need for regulatory intervention will not disappear in well functioning markets, the efficiency of regulatory activity can be enhanced and its complexity be reduced by a more effective market monitoring.

The policy question that financial regulators then face is: to what extent can market signals of bank fragility be relied upon? And, where should we look for good quality indicators? In fact, although, markets are in principle able to summarize the information dispersed among market participants, quite often the cost of the information extraction may represent an obstacle to the existence of market prices and their informative power may differ considerably across countries. The previous questions become even more relevant for economies where market forces have often been dormant and only recently have shown signs of new vitality. Do markets possess the ability to effectively process the available information and send signals which are informative and have a disciplining effect on market participants? The question cannot be answered at the theoretical level and need to be dealt with empirically. In addition to the evidence available for developed countries, also for some developing countries there seems to be evidence of the positive role plaid by market discipline. Martinez-Peria and Schmukler (2001), for instance, find evidence that deposit interest rates are higher for riskier banks, in Argentina. Such evidence may in turn provide the basis for revising the design of the safety net and of other relevant regulatory frameworks.

This paper intends to contribute to the policy debate by providing some new evidence about the behavior of three different sets of indicators of bank fragility based on publicly observable information. We focus on the experience of banks located in the South East Asian crisis countries and look at indicators based on balance sheet information, on stock prices information, and credit ratings. The choice of a crisis period provides us with an unambiguous distinction between fragile and robust institutions on the basis of ex-post evidence of intervened or not intervened banks.

The different timing and accuracy of different indicators are likely to have important implications on the definition of an effective regulatory framework. For instance bank regulation could put the emphasis on a larger use of the grades assigned by rating agencies (as suggested in the recent Basle consultative document on revision of the Capital Accord) if these indicators appear to provide a sufficiently accurate indicator of financial fragility. On the other hand, if this were not the case or if the scope of coverage of rating agencies could not be extended to mid-size firms worldwide, then alternative forms of indicators should be supported. This could be done, for example, by promoting a larger availability of accurate financial information (by setting credit registers or better loan classification criteria) and/or in general by reforming those institutions which may provide an obstacle to transparency.

This paper provides the first comprehensive comparison of the three classes of indicators for a group of banks located in developing countries, that we are aware of. While it is not possible to generalize our empirical findings to different periods or different countries, four results emerge from the empirical analysis of the East Asian crisis countries:

- There is no apparent evidence in our sample that being listed or being rated has had disciplining effects. This may partly be explained by the large size of listed and rated banks and by the fact that "too big to fail" considerations may have prevented market discipline from being fully effective.
- None of the three indicators considered has strong predictive power in forecasting bank distress, after controlling for the effect of macroeconomic factors and for banks'

size. Credit rating agencies' grades have shown the lowest discriminatory power between sound and insolvent banks among the three classes of indicators considered.

- Implicit deposit insurance risk premiums, built on listed banks stock prices, showed on average a more timely adjustment than credit rating grades, with a lead that, for banks operating in South East Asia, has reached a maximum of three quarters.

The paper is structured as follows. Section 2 reviews the literature on empirical bank fragility studies. Section 3 introduces three indicators of bank fragility. Section 4 illustrates how these indicators behaved around the onset of the financial crisis. Section 5 presents the empirical tests and results. Section 6 concludes and offers some policy implications.

2. Survey of the Literature

Studies attempting to empirically identify the causes and origins of the East Asian banking crisis have mainly focused on the macro-economic factors that can help predict banking and currency crises.[2] So far, few studies have investigated the micro-foundations of the East Asian crisis using data on individual banks. An exception is Bongini, Claessens and Ferri (2001), who build on models that have been developed to predict the failure of individual financial institutions, so called early warning systems[3], and find that traditional, CAMEL-type indicators help to predict subsequent distress and closure of banks and non-bank financial institutions in the East Asian crisis countries. Another paper is Laeven (1999), who uses individual bank data to explain the differences in risk-taking and performance of the East Asian banks, and finds that banks with concentrated ownership are the riskiest, as reflected by excessive credit growth.[4]

In addition to accounting data, some authors have looked at the information content of two other sources of information, namely the stock market and the credit rating agencies.

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[2] See, among others, Demirguc-Kunt and Detragiache (2000), Kaminsky and Reinhart (1999), Radelet and Sachs (1998), and Furman and Stiglitz (1998).
[3] See Altman (1981) for a comprehensive survey of this literature.
[4] The widespread diffusion of concentrated ownership of East Asian corporations in general has been put forward by Claessens, Djankov and Lang (2000).

Since the East Asian stock markets are relatively liquid[5], the markets can be thought of as being relatively efficient and share prices are thought to be indicative for the financial health of firms. Laeven (2001) uses market price data of the banks in East Asia to estimate the costs of insuring bank's deposits and uses this estimate as a measure of bank risk. One of its main findings shows that banks with concentrated ownership suffer more of moral hazard problems.

Ferri, Liu and Stiglitz (1999) and IMF (1999) have investigated the informational value embedded in the sovereign rating of credit rating agencies. They find that the East Asian countries had incorrect ratings at the onset of the crisis. In fact, they demonstrate that credit rating agencies failed to predict the emergence of the crisis. Moreover, they aggravated the East Asian crisis by downgrading East Asian crisis countries more than the worsening in these countries' economic fundamentals would have justified. In a companion paper Ferri, Liu and Majnoni (2000) show how, differently from corporate ratings, banks ratings tend to be strictly dependent on sovereign ratings and therefore are bound to share the same problems. No study we know of has, however, looked at the informational content of credit ratings of individual banks comparing them with other indicators of financial fragility. Also, a comparison of the value of the three information providers (accounting firms, stock markets, and credit rating agencies) in timing a crisis has not been carried out yet. This study aims to fill this gap.

3. Data

To compare the value of the information provided by accounting firms, stock markets, and credit rating agencies we use three indicators of financial distress. The first indicator is based on accounting data of banks. The second indicator is the implicit cost of deposit insurance of an individual bank. Laeven (2001) shows that this cost is positively correlated to bank risk and can therefore be used as a measure of the probability of bank distress. The third indicator is derived from the credit rating of the bank. An improvement

[5] The monthly turnover of the stock markets is relatively high. In June 1999, for example, the turnover of shares was 5.3% of the total market capitalization in Indonesia, 13.7% in Korea, 5.2% in Malaysia, 5.45 in the Philippines, and 12.5% in Thailand (monthly averages).

in the credit rating is considered to be an indication of a reduced likelihood of financial distress as measured by the observed historical default frequencies computed over long spans of time.

We have collected data on 246 financial institutions in the four East Asian crisis countries: Indonesia, Korea, Malaysia, and Thailand. Balance sheet and income statement data of individual financial institutions are from Bankscope. Daily market values of the equity of banks are from Datastream or Bloomberg. Credit ratings of financial institutions and their corresponding default frequencies are from Moody's. Data on foreign ownership, connectedness and the type of financial institution are from Bongini et al. (2001).

3.1 Balance sheet indicator

Balance sheet based indicators have long been used to help predict the failure of individual banks[6]. The focus of this strand of literature is on the early identification of institutions that are developing financial difficulties. For this reason, these models are frequently called "early warning systems". These analyses build on the comparison of the specific characteristics of financially troubled banks vis-à-vis sound banks.

Empirical work on bank failure prediction shares the following approach. First, the dependent variable is constructed on the basis of ex-post information on bank distress. Typically, the dependent variable is a dummy variable that distinguishes between failure and no failure. Second, a subset of bank-specific and country-specific variables is chosen on the basis of their predictive power. Most widely used bank-specific indicators are generally referred to the five CAMEL categories: Capital adequacy, Asset quality, Management quality, Earnings and Liquidity.

[6] The literature dates back to the early '70s, with the works of Meyer and Pifer (1970), Sinkey (1975), Altman (1977), Martin (1977), Pettaway and Sinkey (1980). Altman (1981) represents a thorough survey of this early wave of the literature, while Demirguc-Kunt (1989) is a comprehensive survey for models developed in the '80s. More recent studies include Whalen (1991), Thomson (1992), and Gonzales-Hermosillo (1998).

In constructing our balance sheet indicator, we use the CAMEL ratios that Bongini, Claessens and Ferri (2001) have found to be robustly correlated to distress. These variables include the ratio of loan loss reserves to capital, loan growth, net interest income to total income, and return on assets. Our balance sheet indicator aims to condense the information embedded in all the CAMEL variables to one variable, and is constructed as follows. First, we transform each CAMEL indicator in a dummy variable that takes value one if the bank's CAMEL ratio is worse than that of 75% of all the sampled banks, and zero otherwise[7]. Second, we sum the four dummy variables to create a balance sheet indicator that takes values 0, 1, 2, 3, or 4 depending on the number of CAMEL ratios that indicate relatively high risk. The higher the value for the balance sheet indicator, the higher the bank's perceived risk.

3.2. Insurance premiums

The estimation of deposit insurance premiums follows the implementation of Merton's (1977) model suggested by Ronn and Verma (1986). For a more detailed description of this technique, we refer to Laeven (2001). Merton (1977) models deposit insurance as a put option on the value of the bank's assets. The key assumptions of the model are that the bank's asset values follow geometric Brownian motion and that all bank debt is insured. Merton (1977) shows that the annual deposit insurance per dollar of deposits can be modelled as follows:

$$g = \Phi(\sigma - h) - \frac{V}{D}\Phi(-h), \tag{1}$$

where $h = \dfrac{\ln\left(\dfrac{V}{D}\right) + \dfrac{\sigma^2}{2}}{\sigma}$, g is the value of the deposit insurance guarantee per dollar of insured deposits, σ is the instantaneous expected standard deviation of assets returns, Φ is the cumulative normal distribution function, and D is the face value of the bank's debt.

[7] For instance, if a bank's return on assets is lower than the 25th percentile value, then its CAMEL ratio would take the value one.

In order to implement the model, the two unobservable variables, the bank's asset value V and the asset's volatility parameter σ, have to be estimated. Ronn and Verma (1986) suggest using two restrictions for the identification of these two unknowns. The first restriction is obtained by viewing the equity value of the bank, which is directly observable, as a call option on the bank's assets with a strike price equal to the value of the bank's debt

$$E = V\Phi(h) - D\Phi(h-\sigma)\,. \tag{2}$$

The relationship between the equity and asset volatility, which can be obtained by applying Ito's Lemma to equation (2), is used by Ronn and Verma (1986) as the second restriction

$$\sigma = \frac{\sigma_E E}{V\Phi(h)}\,, \tag{3}$$

where σ_E is the standard deviation of equity returns.

Since the market value of equity is observable and the equity volatility can be estimated, two non-linear restrictions are now in place for identifying two unknowns. Using data on total debt (deposits), bank equity, and equity volatility, equations (2) and (3) can be solved simultaneously for V and σ. Given these values, equation (1) is used to solve for the value of deposit insurance per dollar of deposits. Ronn and Verma (1986) use Merton's (1977) assumption that the time until maturity of the debt is equal to the time until the next audit, and interpret the strike price of the put option to be equal to total debt of the bank instead of total deposits only. This assumes that all the debts of the bank are insured and that they are issued at the risk-free interest rate.

We follow Ronn and Verma (1986) in assuming that all deposits are fully insured. Although this was not officially the case in the East Asian countries, their governments were expected to fully guarantee depositor's funds, i.e. implicit deposit insurance was in place. We make the common assumption that banks' next audit will take place in one year time, and that the maturity of the debt equals one year as well. We thus model deposit insurance as a limited term contract. In estimating annual equity volatility we have also excluded outliers associated with large changes in the capital of the banks and have approximated the implied volatility as perceived by the market by the volatility of daily stock market returns over the preceding three months. Our estimates of the annual deposit insurance premium are expressed in basis points per US dollar of deposits.

3.3 Credit ratings

We reconstructed the monthly history of credit ratings of each sampled bank based on Moody's ratings and converted every alphabetic rating into a numerical value in order to make it comparable with the other two indicators described so far. We opt for a non linear conversion criterion in order to properly reflect the fact that rating changes tend to be associated with increasingly larger changes in default frequencies when they take place at the lower end of the rating scale. More specifically, every grade has been transformed into the value of the historical default frequency as observed over the period 1982-1999.[8] We do not consider the credit-watch status as a separate grade, lacking evidence of its numerical equivalent in terms of average cumulative default frequencies. We also limit our analysis to the most commonly available category of ratings, namely those related to long-term foreign currency deposits. Financial strength ratings, which refer to the fragility of a bank independently from the presence of public guarantees, are not considered, due to the evidence that in this episode they have moved very much in line with the ratings of long-term deposits and, also, because we could not rely on the historical evidence of the average cumulative default frequency associated with each rating level.

4. Timing of the crisis

We start our analysis with some descriptive statistics that can provide some intuitive perception of the behavior of these indicators before and after the crisis period. This requires that a crisis periods be defined for each of the countries under study. Timing a crisis is, however, a difficult task. Should one time a crisis when problems become evident, that is using ad hoc assessments, or should one in retrospect date a crisis using the available information, that is an ex post analysis? In this section, we shall rely on an ad hoc assessment by assuming that the ability of these indicators to detect banking problems is associated to large changes of their values. Figures 1 to 4 show the trend of a number of variables that are based on our three sources of information. As an accounting variable we include the inverse of the leverage of the bank, as measured by the ratio of the market value of equity to book value of liabilities. We compute monthly data for deposits by interpolating linearly their end of year values. As a second variable we plot the deposit insurance premium, measured as a percentage of total deposits. The third variable is the historical default rate associated with each credit rating. A positive change in the credit rating indicates a deterioration in the rating (or alternatively, an increased likelihood of default). We also plot the volatility of equity as measured by the annualized monthly standard deviations of daily stock market returns. All variables are averaged across all banks in each of the four countries. In retrospect we know that the East Asian financial crisis started in Thailand where, already in 1996, it became evident that some banks and finance companies had much higher than anticipated volumes of non-performing loans, and some companies had huge foreign borrowing outstanding. As early as May 1996, one of Thailand's major banks, Bangkok Bank of Commerce, experienced bank runs when the fraudulent behavior by its top management became publicly known. The bank was rescued by the Bank of Thailand through an injection of funds. This action was interpreted as an implicit state guarantee by other banks in the system. The crisis in Thailand deteriorated after the resignation in July 1996 of the Central Bank Governor. In March 1997 the government announced that ten finance companies faced serious problems and that it intended to buy US$ 4 billion in bad property debt from financial institutions. On June 27th 1997, the operation of 16 finance companies was suspended. The crisis exploded when on July 2nd, 1997 the Bank of Thailand abandoned the exchange rate peg and Thailand started negotiations with the IMF.

The four graphs provide us with a first assessment of the behavior of our three indicators of bank fragility. For Thailand (Figure 1), we see that the market value of the banks (expressed as a fraction of total liabilities) started to decrease around June 1996,

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[8] For more details, see Moody's (2000).

just after the first signs of bank weaknesses became apparent. An increase in equity volatility followed around November 1996. Deposit insurance premiums did not increase until January 1997, but ahead of the removal of the fixed exchange regime in July 1997. The credit rating agencies were clearly late. Although a minor deterioration in the credit ratings had been carried out in April 1997, a major change did not take place until November 1997, almost one quarter after the explosion of the crisis onset.

We see similar patterns in the other three countries. In Korea, the first signs of a crisis became public in August 1997 when the government announced it would help troubled financial institutions by buying bad assets and providing special loans. The crisis exploded in on November, 21st 1997 when Korea announced it would ask the IMF for assistance. A letter of Intent was reached on December the 5th, 1997. Again we see the same sequence in the timing of the crisis of the three indicators (Figure 2). It is interesting to note, though, that stock market volatility started increasing at the end of 1996 and that market value as a share of total liabilities was decreasing from the beginning of 1995. Credit ratings were adjusted in December 1997, while deposit insurance premiums started to increase in November 1997. Market values already started to deteriorate in September 1997.

In Indonesia, banks' market values started decreasing at a later stage, compared to the two previous countries, but still before any increase in equity volatility and deposit insurance premiums. The changes in credit ratings are always late and take place after major crisis events. Indonesia floated its currency on August 14th, 1997 and presented its Letter of Intent with the IMF on October 31st, 1997. Although major changes in market values, equity volatilities and deposit insurance premiums did take place from September 1997 onwards, credit ratings were not strongly adjusted until November 1997 (Figure 3).

Malaysia came last and did not finalize any IMF program. On December 5th, 1997, the Malaysian Finance Minister announced an economic plan to improve the health of banks. Equity values of the banks became, however, extremely volatile from August 1997 onwards, well ahead of government intervention (Figure 4). Again, credit ratings did not react fast. The first substantial deterioration in the ratings of the banks appeared in April

1998. More detailed information on government intervention in the four East Asian crisis countries and a chronology of events can be found in Klingebiel et al. (2000).

Two additional observations are suggested by the average behavior of our indicators in the four countries. First, it becomes apparent that during periods of extreme volatility, deposit insurance premiums are largely driven by the volatility of the underlying equities. Second, the reaction of the public at large as represented by stock markets prices and by credit rating agencies' grades seems to be very delayed and very extreme. This suggests that both these categories of indicators may have experienced a slow adjustment followed by a subsequent "overshooting". In particular, in the case of Thailand, it seems unlikely that the ratings' dynamics in September 1997 and in November 1997 could have mirrored the underlying risk of Thai banks in those same months, as argued by Ferri, Liu, and Stiglitz (1999).

While any timing of the crisis is clearly arbitrary, it is widely recognized that the height of the onset of the crisis in all of the four East Asian countries can be posited in the second half of 1997, and that extreme turbulence continued throughout 1998 in all of the four countries. For the purpose of our analysis we have therefore defined as the crisis period the interval between mid-1997 and mid-1998. This is also the period in which our three indicators show their most dramatic changes.

5. Empirical results

We explore the relationship among the three different indicators by mean of three different tests. First, we investigate whether being rated or listed provides additional information, beyond that embedded in CAMEL-type indicators, for forecasting banks' failure. The purpose of this analysis is to investigate the degree of market discipline imposed on financial institutions by credit rating agencies and by capital markets before and during the onset of the financial crisis. To test for the presence of market discipline we extend the distress forecasting model developed by Bongini, Claessens and Ferri (2001) to include two dummy variables that indicate respectively whether the financial institution is rated or whether the financial institution is listed on the local stock exchange. In addition to the balance sheet indicator described in section 3.1, we follow the model in Bongini et al. (2001) by including the following variables: a foreign ownership dummy variable that takes value one if the financial institution is majority foreign owned, and zero otherwise; a connected dummy variable that takes value one if the bank has extensive relationships with corporations or influential families, and zero otherwise; a proxy for bank size, equal to the logarithm of total bank assets; and a dummy variable that takes value one if the financial institution is a non-bank financial institutions, and value zero if the financial institution is a bank.

The results of the market discipline test are presented in Table 1. We run logit regressions that include country dummies (to proxy for differences in macro-economic environment) with and without control variables. Columns 1 in Table I present the results without controlling for being rated or listed; column 2 in Table I shows the results when including the rating and listing dummy variables. We expect a negative sign for the rating and listing dummies as an indication for market pressure on rated and/or listed banks. However, the results indicate that neither rated nor listed banks were subject to a significant degree of market discipline. In particular, the first specification shows that balance sheet information has some power in discriminating strong and weak banks, while the second specification shows that the rating or listing variables do not provide additional predictive power. In fact, although not statistically different from zero, the rating variable has the wrong sign and both specifications of the distress prediction model share the same level of predictive power.

The second exercise investigates which indicator of bank fragility – balance sheet indicators, credit ratings, or deposit insurance premiums – has more power in predicting actual bank distress. We refer to this test as the horse race. We are forced to conduct the horse race on the subset of banks for which we have information on all three measures of bank fragility. We miss deposit insurance premiums for a large part of the full sample of 246 financial institutions, because some financial institutions do not take deposits and some financial institutions are not listed. Furthermore, some of the listed banks were not rated. The subset of banks for which we have data on all three measures is reduced to 43 institutions. We conduct the horse on this set of banks.

The variables considered for the horse race are the balance sheet indicator introduced in section 3.1, the deposit insurance premiums estimated according to the methodology presented in section 3.2, and the cumulative historical default rate associated with the bank's Moody credit rating described in section 3.3. All three indicators are increasing in the probability of predicted default. Our goal is to use data on these three indicators prior to the onset of the crises in the four East Asian countries and to assess which of the three indicators has more predictive power in forecasting bank distress ex post. As follows from the figures presented and described in section 4, it seems valid to consider mid-1997 as the period preceding the onset of the crisis. However, while credit ratings and premiums are, in principle, available on a continuous basis, this is not so for balance sheet information which is typically available only on an annual basis. Given that end-year balance sheet information tends to be publicly available with a lag of several months, it seems valid to use end-1996 balance sheet data, and mid-1997 premiums and credit ratings as the relevant information set available to a market operator in mid-1997. For robustness purposes, however, we have also carried out the same horse race exercise with end-1996 data for all three set of indicators.

Given the limited number of observations, we choose to use macro-economic variables, namely GDP per capita (in thousands of US dollar) and private credit to GDP (in %), rather than country dummies to control for differences across countries. Consistent with the specification in Table I, we also control for connections and bank size[9]. The results of the horse race are presented in Table II.

The results in Table II suggest that, after controlling for country-specific and size factors, none of the three indicators provides a significant amount of information with regard to distinguishing among distressed and non-distressed banks. However, if one were to rank the predictive power of the three indicators based on the statistical significance of the regression coefficient of the indicator, the sign of the regression coefficient of the indicator, and the overall predictive power of the model, the ranking of the indicators would show that premiums rank first, followed by balance sheet indicator,

[9] The smaller sample does not include foreign banks or non-bank financial institutions, as they do not collect deposits; therefore the related dummies are dropped.

and credit rating, in decreasing order of predictive power. In fact, both premiums and balance sheet indicators enter the equation with the expected sign but premiums show a higher level of significance displaying some predictive power at the 15% significance level. Credit ratings, instead, show the incorrect sign and appear to be strongly correlated with country specific control variables. This suggests that credit ratings, though they may distinguish good from bad countries, have limited power in distinguishing good from bad banks. For robustness, we have replicated the exercise using end-1996 data for all three indicators. The results are qualitatively identical to the results presented in Table II and are therefore not reported.

As a further step of the analysis, we investigate the time pattern of changes in the horse race indicators. We limit our exercise to the ratings and the premiums since these are the only two horse race variables that can be observed over time at high frequency. Our aim is to detect whether there exists a significant link, either lagging or leading, between rating agencies' decisions to revise a given rating - e.g., downgrading or upgrading a bank - and the market assessment of the bank's risk as embedded in insurance premiums.

For such a test, we focus on the smaller sample of banks for which we jointly have the relevant indicators under study during the period January 1996-December 1998. This sample includes a total of 29 banks, of which 4 from Indonesia, 12 from Korea, 3 from Malaysia and 10 from Thailand.

For each bank in the sample we calculate downgrades (upgrades) as the positive (negative) difference between the cumulative default rate corresponding to the revised rating assessment and the previous one. We use monthly data and consider the specific month when the rating's change takes place, as the reference period of our analysis. We end up with a sample of 85 rating changes, “delta rating”, which represent our dependent variable. Our explanatory variables comprise the contemporaneous, lagged and leading differences of the contingent claim indicator, "delta premium" on a quarterly basis (i.e. one, two or three quarters before or after the reference month).

The regression results, reported in Table III, show the presence of a systematic lead of market indicators which is on average equal to two quarters and reaches a maximum of three quarters. There is, instead no systematic lead of rating changes with respect to market values. We have performed the same test using a monthly specification of "delta premiums" and we have found results coherent with the quarterly ones, although the significance of monthly lags are unevenly distributed among the corresponding significant quarterly lags. We therefore report only the results based on quarterly data where variability caused by monthly effects has been averaged out.

6. Conclusions

Overall the available evidence seems to point out that indicators of bank fragility based on publicly available information did not show a common behavior during the onset of the East Asian crisis and did not, ex-post, provide substantial predictive power in forecasting bank distress.

When looked from a cross section perspective, it appears that an ex-post determined set of balance sheet indicators, integrated with information about the size of the bank and country-specific variables has some power in discriminating strong and weak banks. It also appears that neither listed nor rated banks were on average safer than non rated or non listed ones. This evidence is consistent with the notion that in our sample market discipline did not prove to be effective. The coincidence of rated and listed banks with the group of larger banks makes it possible that market discipline had been counteracted by forbearance practices related to the "too big to fail" problem.

Differently from the ex-post indicator, however, an ex-ante defined balance sheet indicator, based on traditional CAMEL like variables, did not prove to have specific predictive power. When comparing the forecasting ability of balance sheet indicators, credit ratings and premiums, none showed substantial power in forecasting bank distress after controlling for size and macroeconomic factors. Among these three indicators, implicit deposit insurance premiums (a market based indicator) showed a relatively higher power, followed by the balance sheet indicator. The rating indicator, instead, proved to be collinear with macroeconomic country specific factors and entered the equation with the wrong, although not significant, sign. Some caution may be needed, when interpreting these results, due the small size of our sample.

When looked from a dynamic perspective, aimed at detecting which indicator is quicker in incorporating new sources of information, stock market based indicators proved to react faster than the others two. In fact, balance sheet based indicators cannot change more frequently than information releases, which is usually annual, while implicit deposit insurance premiums seemed to precede credit ratings with an average semester lag.

Overall, the evidence examined showed that indicators, based on publicly available information, follow different patterns, both across institutions and through time, lending support to the existence of different processing costs. The cause may be found in the noisy measurement of equity returns volatility in less liquid stock markets or during periods of extreme turbulence. In addition, our data support previous findings that credit rating agencies have been slow in adjusting their ratings for the East Asian banks during the onset of the East Asian crisis. Delays could have been generated by the inevitable political component of the rating revision process but they may have also been the consequence of the relatively brief experience of rating agencies in assessing the risk of economic entities in less developed economies.

From the policy point of view these results provide support to the notion that in less developed financial systems it is important to rely on a multiplicity of indicators in order to gather an accurate assessment of individual institutions financial fragility. The availability of a plurality of indicators appears to be particularly important whenever market prices may already discount the presence of a public implicit guarantee of the banking system or when information processing costs are high.

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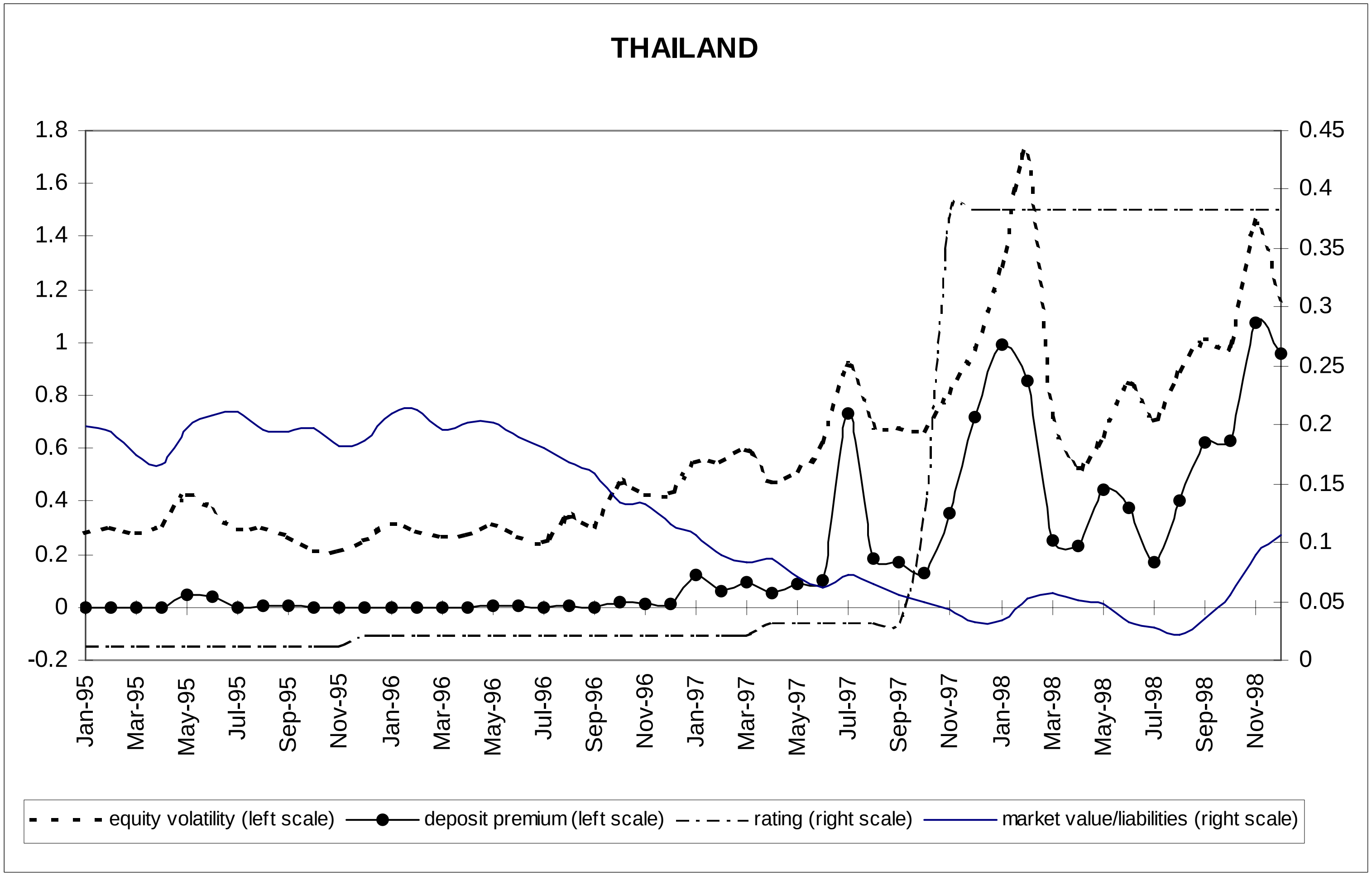
Figure 1


THAILAND
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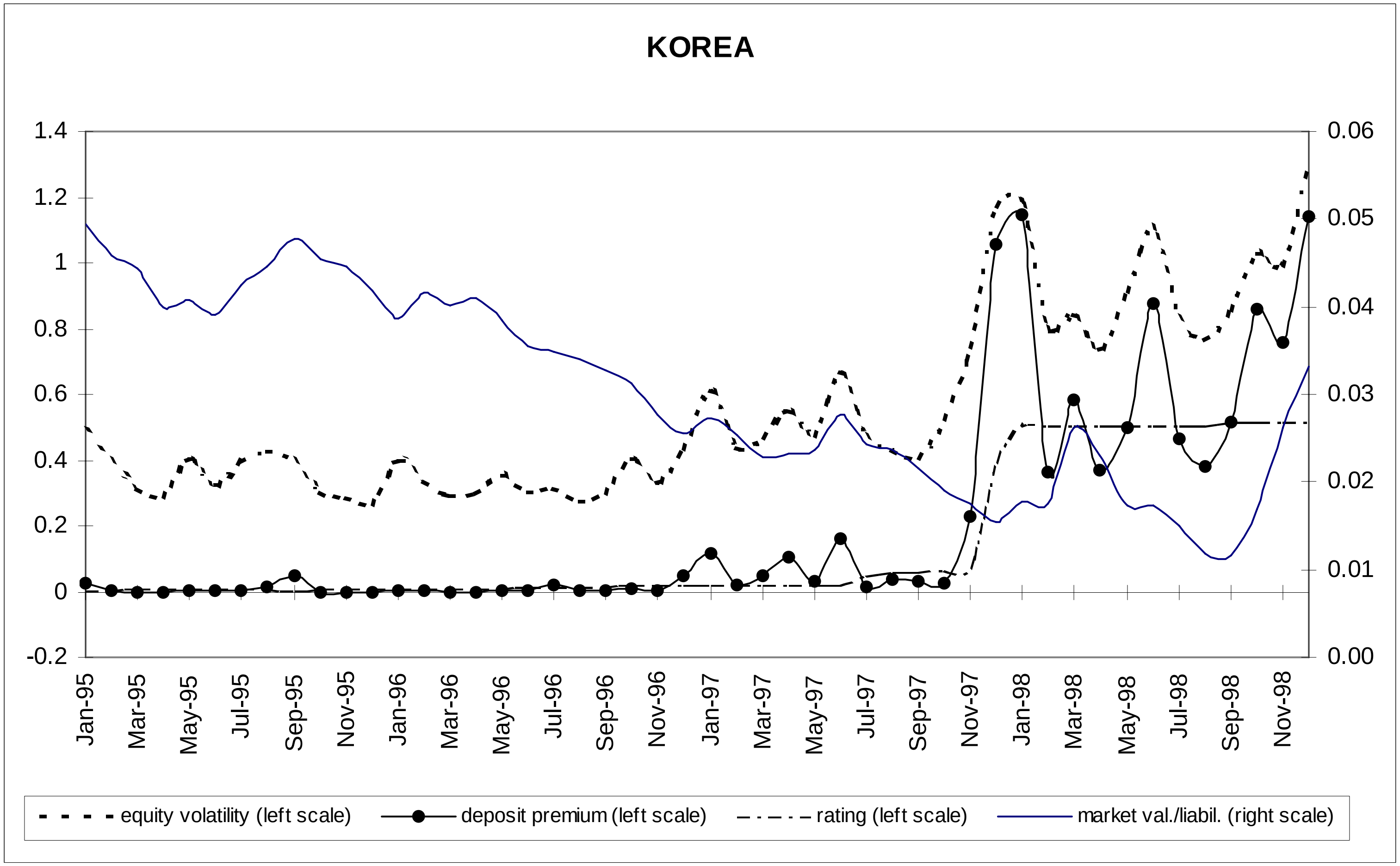
1.6
1.4
1.2
1
0.8
0.6
0.4
0.2
0
-0.2
0.45
0.4
0.35
0.3
0.25
0.2
0.15
0.1
0.05
0
Jan-95
Mar-95
May-95
Jul-95
Sep-95
Nov-95
Jan-96
Mar-96
May-96
Jul-96
Sep-96
Nov-96
Jan-97
Mar-97
May-97
Jul-97
Sep-97
Nov-97
Jan-98
Mar-98
May-98
Jul-98
Sep-98
Nov-98
equity volatility (left scale)
deposit premium (left scale)
rating (right scale)
market value/liabilities (right scale)

Figure 2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1.4
1.2
1
0.8
0.6
0.4
0.2
0
-0.2
0.06
0.05
0.04
0.03
0.02
0.01
0.00
Jan-95
Mar-95
May-95
Jul-95
Sep-95
Nov-95
Jan-96
Mar-96
May-96
Jul-96
Sep-96
Nov-96
Jan-97
Mar-97
May-97
Jul-97
Sep-97
Nov-97
Jan-98
Mar-98
May-98
Jul-98
Sep-98
Nov-98
equity volatility (left scale)
deposit premium (left scale)
rating (left scale)
market val./liabil. (right scale)

Figure 3

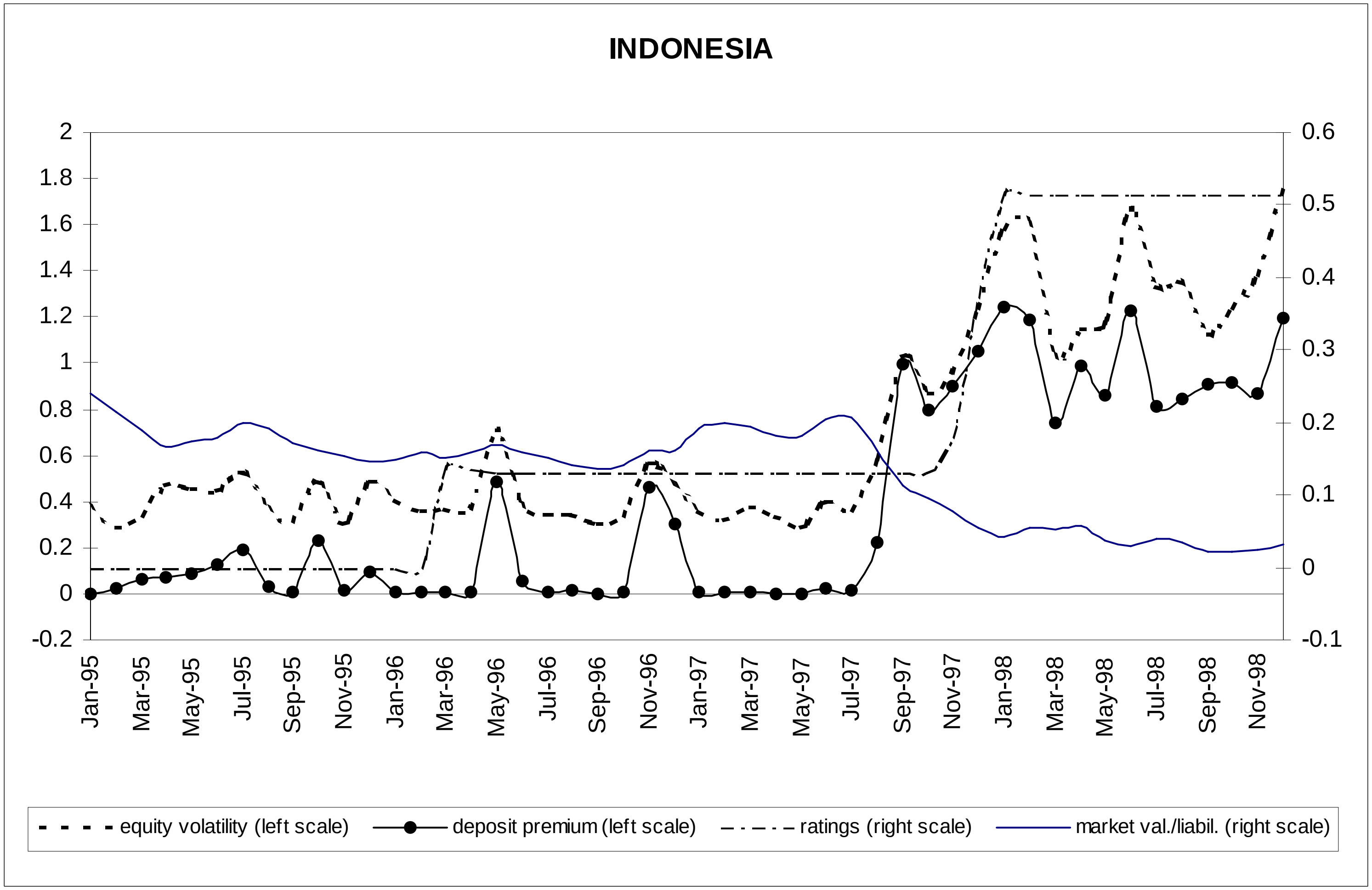
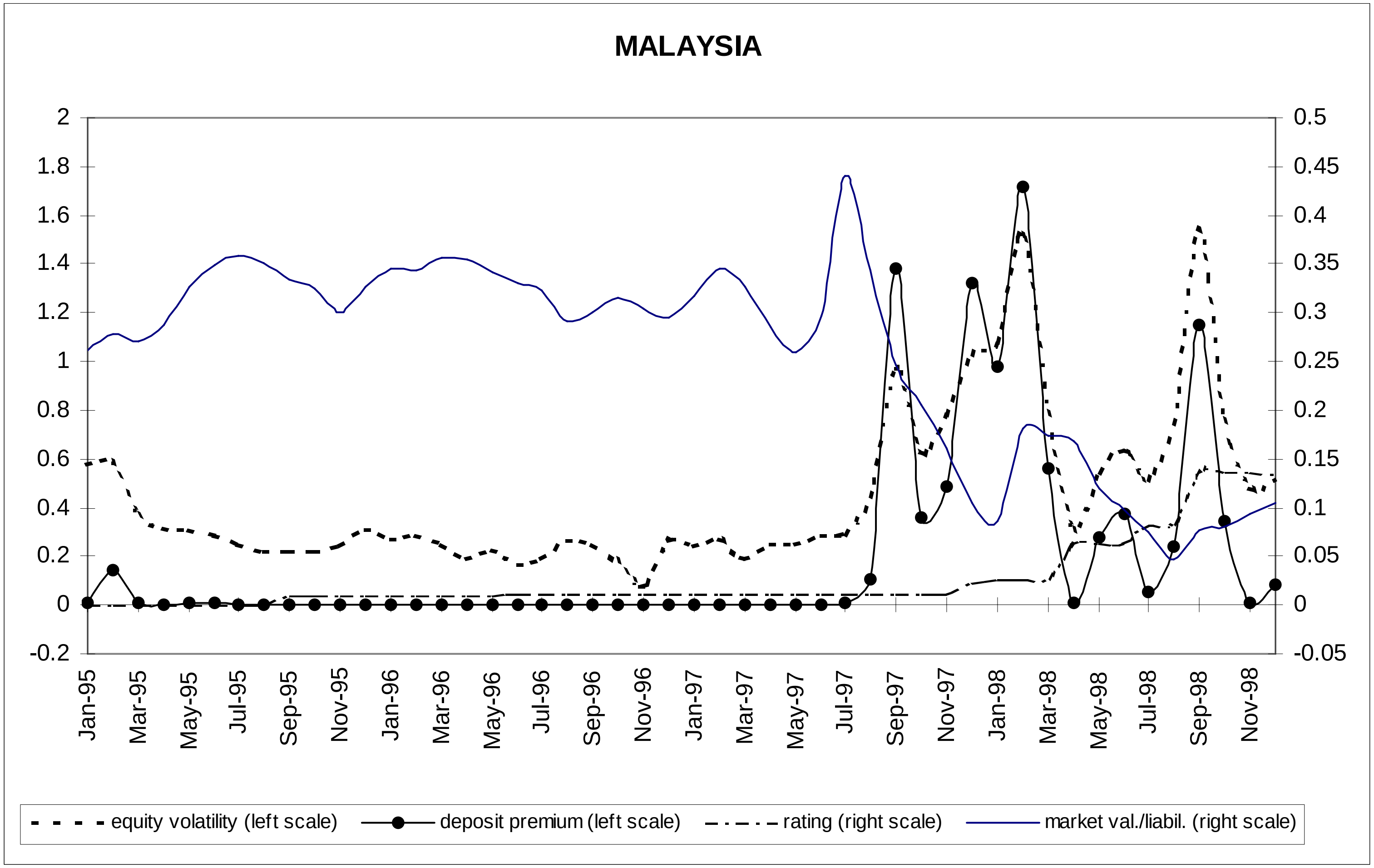

INDONESIA
2
1.8
1.6
1.4
1.2
1
0.8
0.6
0.4
0.2
0
-0.2
0.6
0.5
0.4
0.3
0.2
0.1
0
-0.1
Jan-95
Mar-95
May-95
Jul-95
Sep-95
Nov-95
Jan-96
Mar-96
May-96
Jul-96
Sep-96
Nov-96
Jan-97
Mar-97
May-97
Jul-97
Sep-97
Nov-97
Jan-98
Mar-98
May-98
Jul-98
Sep-98
Nov-98
equity volatility (left scale)
deposit premium (left scale)
ratings (right scale)
market val./liabil. (right scale)

Figure 4



MALAYSIA
2
1.8
1.6
1.4
1.2
1
0.8
0.6
0.4
0.2
0
-0.2
0.5
0.45
0.4
0.35
0.3
0.25
0.2
0.15
0.1
0.05
0
-0.05
Jan-95
Mar-95
May-95
Jul-95
Sep-95
Nov-95
Jan-96
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Jul-96
Sep-96
Nov-96
Jan-97
Mar-97
May-97
Jul-97
Sep-97
Nov-97
Jan-98
Mar-98
May-98
Jul-98
Sep-98
Nov-98
equity volatility (left scale)
deposit premium (left scale)
rating (right scale)
market val./liabil. (right scale)

Table I: Banks fragility: the monitoring effect of external ratings and market participants.

Robust logit estimate of the probability of distress for a sample of East Asian financial institutions. The dependent variable takes the value 1 if the financial institution is experiencing distress (closed, recapitalized suspended or merged), and 0 otherwise. Independent variables comprise a CAMEL indicator (following Bongini, Claessens and Ferri, 2001), and the dummy variables "rated" and "listed" which take the value 1 if the FIs is respectively rated or listed on the local Stock Exchange and zero otherwise. Control variables and country dummies are also included. Type I error refers to the error of considering distressed a sound institution. Numbers in parenthesis are t-statistics.

	Camel	*Camel and market indicators*
Camel rating indicator	0.42	0.42
	(2.08)	(2.06)
Rated		0.14
		(0.02)
Listed		-0.05
		(-0.12)
Size (log TA)	0.42	0.42
	(2.85)	(2.09)
connected	0.76	0.77
	(1.79)	(1.76)
Foreign	-2.01	-2.02
	(-2.74)	(-2.72)
Non-banks	-1.2	-1.16
	(-2.02)	(-1.91)
Connected non-banks	1.09	1.09
	(1.40)	(1.33)
Korea	-0.94	-0.92
	(-1.59)	(-1.39)
Malaysia	-1.77	-1.76
	(-3.35)	(-3. 01)
Thailand	1.73	1.76
	(2.69)	(2.05)
constant (Indonesia)	-5.92	-5..92
	(-2.93)	(-2.26)
Number of Observations	*246*	*246*
Pseudo R-squared	26.59%	26.59%
Overall predictive power	76.83%	76.83%
Type I error	18.80%	19.66%
Type II error	27.13%	26.36%

Table II: Horse race

Logit estimate of the probability of distress for a sample of East Asian banks. The dependent variable takes the value 1 if the bank is experiencing distress (closed, recapitalized suspended or merged), and 0 otherwise. Independent variables comprise a balance sheet indicator (based on end-1996 data), credit ratings assessment as of mid-1997 (transformed in numerical values by using the corresponding historical cumulative default rates) and the deposit insurance premium as of mid-1997. Control variables include a dummy variable indicating whether the bank is connected to another company or a powerful family, the size of the bank (log of total assets in US dollars), GDP per capita (in thousands of US$) and private credit to GDP (%).Type I error refers to the error of considering distressed a sound institution. Numbers in parenthesis are t-statistics.

	Camel rating indicator	*Credit rating*	*Premium*
Camel rating indicator	.58		
	(1.01)		
Credit rating		-.56	
		(-1.19)	
Premium			.01
			(1.45)
Connections	-1.95	-1.94	-1.66
	(-2.10)	(-1.58)	(-1.78)
Size	2.41	2.66	2.60
	(4.33)	(3.99)	(.3.95
GDP per capita	-.64	-1.15	-.59
	(-3.39)	(-2.44)	(-2.52)
Credit-to-GDP	-.07	-.13	-.08
	(-1.90)	(-1.96)	(-1.88)
Number of Observations	43	43	43
Pseudo R-squared	52.37%	53.65%	54.54%
Overall predictive power	83.72%	81.40%	86.05%
Type I error	11.53%	11.54%	7.69%
Type II error	22.53%	29.41%	23.53%

Table IV. Leads and lags of stock market and rating agencies indicators

The dependant variable is given by the difference between the cumulative default rate corresponding to the revised rating assessment and the previous one. The sample is reduced to 72, from the initial 85 observations, due to missing values in some lagged variables. Numbers in parenthesis are t-statistics.

	Lag of delta rating
Delta premium	0.22
	(5.01)
Delta premium (-1 quarter)	0.32
	(2.13)
Delta premium (-2 quarter)	0.60
	(3.79)
Delta premium (-3 quarter)	0.34
	(1.76)
Delta premium (+1 quarter)	0.02
	(0.23)
Delta premium (+2 quarter)	0.08
	(1.00)
Korea	0.02
	(0.49)
Malaysia	-0.20
	(-2.99)
Thailand	0.04
	(0.86)
Constant	0.04
	(0.65)
Number of observations	72
R-squared	53%