HONG KONG MONETARY AUTHORITY

Working Paper 22/2007

18 December 2007

A LEADING INDICATOR MODEL OF BANKING DISTRESS – DEVELOPING AN EARLY WARNING SYSTEM FOR HONG KONG AND OTHER EMEAP ECONOMIES

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Abstract

This study develops a probit econometric model to identify a set of leading indicators of banking distress and estimate banking distress probability for Hong Kong and other EMEAP economies. Macroeconomic fundamentals, currency crisis vulnerability, credit risk of banks and companies, asset price bubbles, credit growth, and the occurrence of distress of other economies in the region are found to be important leading indicators of banking distress in the home economy. The predictive power of the model is reasonably good. A case study of Hong Kong based on the latest estimate of banking distress probability and stress testing results shows that currently the banking sector in Hong Kong is healthy and should be able to withstand well certain possible adverse shocks. Under some extreme shocks originating from real GDP growth and property prices such as those that occurred during the Asian financial crisis, the model indicates a non-negligible risk of an occurrence of banking distress in Hong Kong. However, the chances of the occurrence of such severe events are extremely low. Simulation results also suggest that compared to the period before the Asian financial crisis, the local banking sector is currently more capable of withstanding shocks similar to those that occurred during that crisis. The study also finds that banking distress is contagious, suggesting that to be effective in monitoring banking distress, close cooperation between central banks should be in place.

JEL Classification Numbers: E44, E47, G21

Keywords: Banking distress, Asia Pacific economies, econometric model

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[1] The authors are grateful to Hans Genberg and Cho-Hoi Hui for their suggestions and comments.

Executive Summary

- *With the aid of a quarterly panel data set of the 11 EMEAP economies in the Asia-Pacific region covering the period from 1990 Q2 to 2007 Q1, this study identifies a set of leading indicators of banking distress and develops an econometric model that is capable of estimating the probability of an occurrence of banking distress.*

- *The model suggests that weakening macroeconomic fundamentals, an increase in money supply relative to foreign reserves, deteriorations in the creditworthiness of banks and companies, and significant asset price misalignments over their fundamental values in property and equity markets, in particular if fuelled by strong credit growth, are useful leading indicators of banking distress for the EMEAP economies.*

- *In addition, the occurrence of distress of other economies in the region and the institutional quality of the home economy also play an important role in determining the likelihood of banking distress. The predictive power of the model as assessed by the in-sample and out-sample performance is reasonably good.*

- *Based on latest available information, the estimated value of banking distress probability in Hong Kong is low, suggesting that currently the risk of an occurrence of banking distress in Hong Kong is small. Stress testing results based on some hypothetical stress scenarios, which represent some possible adverse movements of economic variables, suggest that currently the banking sector in Hong Kong is healthy and should be able to withstand well the assumed shocks, even at the 95% confidence level.*

- *Under some extreme shocks originated from real GDP growth and property prices as those occurred during the Asian financial crisis, the stress testing results suggest that Hong Kong could be subject to an occurrence of banking distress. However, the probabilities of the occurrence of such severe shocks, given current economic environments, are extremely low. The simulation results also suggest that the banking sector is currently more capable of withstanding the assumed shocks than it was before the Asian financial crisis.*

- *Monitoring the banking sector vulnerability and preventing banking distress are principal duties of most central banks. The episode of the Asian financial crisis in 1997 demonstrates that banking distress could spill over across economies, particularly among economies with strong economic and financial linkages. Consistent with the past episode, this study shows that banking distress is contagious, suggesting that to be effective in monitoring banking distress, close cooperation between central banks should be in place.*

I. INTRODUCTION

The economic costs of an occurrence of banking distress to an economy could be severe. According to estimations by the International Monetary Fund (1998) and the World Bank (2000), the fiscal costs of restructuring a banking sector to restore its intermediate functions effectively after a banking crisis or an occurrence of banking distress can be as large as a half of a country's annual GDP.[2,3] The total adverse economic impacts could be substantially higher than this estimate, given that banking distress may cause other crises, such as currency crises, which would further adversely affect the weakening economy.[4] In addition, any credit tightening after an occurrence of banking distress could lead to misallocation and underutilisation of funds, which would hamper the potential growth of the crisis or distress economy. Because of the serious expected economic consequences, the prevention of banking distress is one of the key duties of central banks. The development of leading indicators of banking distress and early-warning systems has therefore long been a core interest of central banks and academics.[5,6]

In the literature, econometric analyses, in particular the application of multivariate logit or probit models, are one main tool to develop and assess such indicators. Another commonly adopted approach is the signal extraction approach.[7] In this paper, the first approach is chosen as it has a number of advantages over the signal extraction approach: First, it facilitates multivariate analyses in which correlations between the indicators are incorporated into the analysis. Second, an estimated probability of occurrence of banking distress can be obtained, which is crucial for policy analyses. Third, the capacity of the

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[2] According to International Monetary Fund (1998), resolution costs for banking crises or distress in Chile and Argentina in early 1980s amounted to over 40% of GDP. World Bank (2000) estimated the recapitalisation costs of banks in four affected countries in the Asian financial crisis, and found that they ranged from 10% (Malaysia) to 58% (Thailand) as a share of GDP.

[3] Note that as pointed out by International Monetary Fund (1998), the fiscal costs associated with restructuring operations of banking sectors after banking crises or distress have likely overstated the true welfare cost, given that resolutions of banking crises or distress generally involve some net resource transfers among different groups in an economy.

[4] In the literature, this phenomenon is generally referred to as the twin crises. During a banking crisis or an occurrence of banking distress, investors may reallocate their portfolios away from domestic assets to foreign assets. A large capital outflow due to reallocation of portfolios can lead to a significant run-out of foreign exchange reserves, and may encourage currency speculations. For empirical studies, see Kaminsky and Reinhart (1999) and Falcetti and Tudela (2006).

[5] See Caprio and Klingebiel (1996), Lindgren, Garcia and Saal (1996), Sachs, Tornell and Velasco (1996), Honohan (1997), Eichengreen and Rose (1998), Demirgüç-Kunt and Detragiache (1998a, 1998b, 2000, 2002, 2005), Hardy and Pazarbasioglu (1998, 1999), Hutchison and McDill (1999), Glick and Hutchison (1999), Goldstein et al. (2000), González-Hermosillo (1996, 1999), Kaminsky and Reinhart (1999), Bell and Pain (2000), Domac and Martinez-Peria (2000), Eichengreen and Arteta (2000), Rojas Suarez (2001), Lestano et al. (2003), and Dabos and Escudero (2004).

[6] A survey by Oosterloo et al. (2007) reveals that the number of central banks that regularly publish a financial stability review to monitor financial stability has increased substantially from 1 in 1996 to 40 in 2005. Assessing the banking sector vulnerability, in general, is a core subject of these financial stability reviews.

[7] Advocated by Kaminsky and Reinhart (1999).

econometric approach is broader – with the empirical contribution by Berg and Pattillo (1999), the signal extraction approach can be incorporated into the econometric approach.

A large number of empirical investigations have been carried out by adopting the econometric approach for developing the indicators. However, these have been subject to a number of restrictions, which have limited the usefulness of their findings for developing early-warning systems. First, most of the past works took the form of international studies which implicitly assume that there are common causes of banking crises or distress for all countries and in all past episodes, irrespective of the differences in economic developments of the crisis or distress countries. This assumption was criticised by Bell and Pain (2000). Second, in most studies, contagion effects across countries have not been incorporated into the analysis. This is contrary to the past episodes which generally suggest that banking crises or distress is contagious, especially among economies with significant economic and financial linkages. The Asian financial crisis is a case in point. From a central bank perspective, this indicates that in the monitoring of banking sector vulnerability, regional surveillance could be more efficient than single country approach. Developing leading indicators of banking distress in Asia may therefore be useful for central banks in the region. Third, the past studies usually use low-frequency data, mainly annual data, which has restricted the timeliness of the use of the indicators. Finally, most past empirical studies predicting banking crises or distress is from a macroeconomic perspective that focuses on the relationship between banking crises and some macroeconomic variables. By comparison, empirical works from a microeconomic perspective that predict banking crises or distress using firm level data are relatively scant. As noted by Demirgüc-Kunt and Detragiache (2005), in order to have richer understanding on banking crises or distress, these two perspectives must be brought together.

Attempting to fill the gaps, this study applies the econometric approach to develop an early warning system of banking distress for the banking sectors of 11 member economies of Executives' Meeting of East Asia-Pacific Central Banks (EMEAP) in the Asia-Pacific region, namely Australia, China, Hong Kong (of China), Indonesia, Japan, Korea, Malaysia, New Zealand, the Philippines, Singapore, and Thailand. By using the panel data of EMEAP member economies in the study, an assessment of the contagion effect within Asia can be made. It also remedies the problem of a lack of distress observations in the quantitative analysis. This approach faces the same drawbacks as most other international studies by implicitly assuming there are common causes of banking distress for the economies in the region and they in general share similar economic characteristics. However, given the geographical proximity of these economies and their significant economic and financial linkages, the extent of the problem may be less severe. In the study, similar to other international studies, institutional factors are introduced to take care of the shortcoming. A quarterly panel data set is used for estimations, so that more timely detection of possible distress can be facilitated. In order to obtain a better understanding of this issue, we analyse banking distress with both macro and micro level information. For the latter, default risk measures for banks and for non-financial companies derived from firm level data are introduced to explain banking distress.

The rest of the paper is organised as follows. A literature review, particularly of the two empirical approaches and highlighting limitations of past studies, is presented in the next section. Sections III and IV describe the empirical specifications, and data and estimation methods respectively. Section V presents the estimation results. Section VI discusses the application of the empirical results as an early warning system and Section VII evaluates the current banking sector risk of Hong Kong and stress tests the sector's vulnerability to extreme shocks. Section VIII concludes.

II. LITERATURE REVIEW

Most past empirical studies have tried to identify the determinants of banking crises or distress based on historical episodes. The potential determinants considered generally follow the theoretical literature in which general macroeconomic environments, the health of the fiscal and the external sectors, as well as the banking sector performance were considered to explain banking crises or distress. A comprehensive review of the empirical literature can be found in Bell and Pain (2000) and Gaytán and Johnson (2002). This section broadly discusses the main empirical approaches used in the past studies and their limitations.

In the empirical literature, there are two main approaches, namely the econometric approach and the signal extraction approach. The multivariate logit or probit models are usually applied for the econometric approach. Demirgüc-Kunt and Detragiache (1998a) adopted this approach to study the determinants of banking crises or distress using annual data of 65 developed and developing economies for the period of 1980-1994. In the study, a binary banking distress variable was defined and served as the dependent variable in regressions.[8] The explanatory variables considered were classified into four groups, namely macroeconomic variables[9], financial variables[10], institutional variables[11], and past distress variable[12]. The empirical results indicated that systemic banking distress was associated with a macroeconomic environment of low economic growth, high inflation, and high real interest rates. In addition, balance of payments crises are found to be associated with systemic banking problems. Studies such as Demirgüc-Kunt and Detragiache (1998b, 2000, 2002, 2005), Hutchison and McDill (1999), Domac and Martinez-Peria (2000), Lestano et al. (2003)

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8 The variable is defined as one if there is an occurrence of distress, and zero otherwise.

9 For example, real GDP growth, real interest rate, and inflation rate.

10 For example, the ratio of money supply to reserves, and lagged real credit growth rate.

11 For example, real GDP per capita, and a dummy variable indicating the presence of a deposit insurance scheme.

12 The duration of the last banking distress.

essentially followed this econometric approach, while Hardy and Pazarbasioglu (1998, 1999) generalised the approach using multinomial logit model.[13]

One example of the signal extraction approach is Kaminsky and Reinhart (1999), in which both banking and currency crises or distress were studied. 26 banking crises or distress and 76 currency crises were first identified from 20 economies for the period 1970-1995. A set of 16 potential indicators were selected, mainly measuring the degree of financial liberalisation (e.g. money multiplier, and the ratio of domestic credit to GDP), balance-of-payment conditions (e.g. terms of trade, real exchange rates, and reserves), and real and fiscal sector developments (e.g. industrial production and public sector deficits as a share of GDP respectively). At any point of time, a signal of a crisis or an occurrence of distress is given if the value of an indicator exceeds a threshold value. If an indicator signals a crisis or an occurrence of distress and a banking crisis or distress actually occurs in the following 12 months, the signal is considered as a good signal, and a false alarm otherwise. The threshold value of an indicator is selected to minimize a noise-to-signal ratio.[14] Judging from the in-sample noise-to-signal ratio, real exchange rates, stock prices, and the ratio of public sector deficits to GDP are found to be the three most useful indicators. Later studies such as Goldstein et al. (2000) and Rojas-Suarez (2001) followed this method. The former extended the analysis of Kaminsky and Reinhart (1999)[15], while the latter focused on the construction of banking crisis or distress leading indicators for emerging markets.

While the methodologies are different fundamentally, the two approaches are not contradictory to each other. As shown by Berg and Pattillo (1999), they can be unified into a probit econometric framework. Using the Berg and Pattillo (1999) method, indicators exhibiting a jump relationship with the probability of banking crisis or distress, as assumed in the signal extraction approach, can be tested and modelled within a probit model. Since the econometric approach is capable of encompassing the signal extraction approach, it is adopted in this study.

The econometric approach and past empirical works are not without drawbacks, however. Major weaknesses include the unduly focus on international studies which tries to identify the common causes of banking crises or distress for countries around the globe and in all past episodes, the negligence of contagion effects across countries,

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13 Specifically, the distress dependent variable is defined as 2 in the period of banking distress, 1 in the preceding period of the occurrence of distress, and 0 otherwise.

14 It is the ratio of false signal rate to the good signal rate. For details, see footnote 16 of Kaminsky and Reinhart (1999).

15 Specifically, Goldstein et al. (2000) enlarged the sample of countries from 20 (used in Kaminsky and Reinhart (1999)) to 25, with nine additional indicators being introduced. The analysis was also extended from univariate analysis of the indicators to a multivariate analysis by constructing a composite index of the indicators, which was introduced in Kaminsky (1998). Crisis or distress contagion across economies was also analysed based on Kaminsky and Reinhart (2000).

and the use of low-frequency data. In addition, the use of micro level data to predict banking distress is not yet developed comprehensively.[16]

Many past studies modelled banking crises or distress with a large panel data set from a large number of economies, covering both developed and emerging economies.[17] The underlying hypothesis of these studies is that there are some common causes of banking crises or distress across the countries. This empirical direction is criticised by Bell and Pain (2000). At the same time, various studies have found that country-specific and regional factors need to be considered when modelling banking crises or distress.[18] In fact, the past episodes of banking crises or distress show that the spillover of banking crises or distress tends to be confined domestically or regionally, and the impact weakens as it extends globally.[19]

Regarding the contagion effect across countries, only few of the past studies based on the econometric approach attempted to incorporate this factor in predicting banking crises or distress. However, as shown in Kaminsky and Reinhart (2000) and Goldstein et al. (2000), which are based on the signal extraction approach, contagion effects need to be incorporated when assessing banking crises or distress.[20] Specifically, they show that incorporating the contagion effects substantially improves the accuracy of crisis or distress predictions for some recent episodes, including the Mexican crisis of 1994, and the Asian crisis of 1997. This indicates that domestic factors of a crisis or distress economy may not fully explain the causes of a banking crisis or an occurrence of banking distress. As stated in Kaminsky and Reinhart (2000), the role of contagion effects from other economies warrants further scrutiny.

The use of low-frequency data, mainly annual data, in most empirical studies using the econometric approach has also limited the usefulness of the indicators.[21] One drawback of using annual data is that the contemporaneous explanatory variables were usually found to be relatively better in explaining banking distress than the lagged terms. However, when using annual data, either using the contemporaneous or lagged terms of the explanatory variables to predict banking distress may be subject to some limitations. For the

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[16] See for exceptions, González-Hermosillo (1999), Rojas-Suarez (2001), and Bongini et al. (2002).

[17] These include Kaminsky and Reinhart (1999), Goldstein et al. (2000), Demirgüc-Kunt and Detragiache (1998a, 2000, 2002, 2005), and Domac and Martinez-Peria (2000).

[18] See for example, Hardy and Pazarbasioglu (1998, 1999), Hutchison and McDill (1999), and Rojas-Suarez (2001). It appears that recent empirical studies have become more focused on studying regional banking crises or distress. See Lestano et al. (2003), and Dabos and Escudero (2004), for example.

[19] Kaminsky and Reinhart (2000) found that the contagion of financial crises or distress is more regional than global empirically.

[20] Goldstein et al. (2000) followed Kaminsky and Reinhart (2000) and considered four fundamental-based channels of transmission of the contagion effects. Specifically, countries with common bank lenders, higher correlations of asset returns in stock markets, higher degree of bilateral trade, or greater similarity in types of exporting goods and services to the same third parties tend to exhibit higher contagion effects when some of the economies are confronted with a systemic banking problem.

[21] These include Demirgüc-Kunt and Detragiache (1998a, 2000, 2002, 2005), Hutchison and McDill (1999), Hardy and Pazarbasioglu (1998, 1999), and Domac and Martinez-Peria (2000).

former case, as shown in Demirgüc-Kunt and Detragiache (2000) and Bell and Pain (2000), the model's accuracy unduly depends on the accuracy of the forecast values of the explanatory variables, which severely restricts the usefulness of indicators practically. For the latter case, while by construction (using the lagged terms) the explanatory variables can serve as leading indicators of banking crises or distress, many potential indicators that are useful to predict banking crises or distress may be found to be not significant and thus are omitted in the analyses. This is because some potential indictors may be capable of signalling banking crises or distress during a sub-period in the preceding year of the crises or distress and the signals may become insignificant when data are complied annually and averaged out. As pointed out by Demirgüc-Kunt and Detragiache (2005), future empirical research on this area should consider using higher frequency data.

Most past studies tried to explore the determinants of banking crises or distress from a macroeconomic perspective which emphasises the use of macro level data. In such framework, banking crises or distress is assumed to stem primarily from macroeconomic problems, such as low output growth or high money supply (relative to foreign reserves). However, Rojas-Suarez (2001) found that bank level data are useful to predict banking crises or distress empirically, in particular the recent banking crises or distress in emerging markets. This indicates that system-wide banking crises or distress could be also revealed from micro surveillance on the banking sector. As noted by Demirgüc-Kunt and Detragiache (2005), exploring more comprehensively on how bank level information can be useful in developing banking crisis or distress leading indicators would be a new direction for future research.

III. THE EMPIRICAL SPECIFICATION

In our application of the econometric approach to study banking distress indicators for the 11 economies in the Asia-Pacific region, the following equation is estimated with a panel dataset.

$$Y^*_{i,t} = \mathbf{X}_{i,t-}b + e_{i,t} \qquad (1)$$

where $Y^*_{i,t}$ is a latent variable to measure the likelihood of an occurrence of banking distress in economy i at time t. $Y^*_{i,t}$ is not observable, but rather $Y_{i,t}$ is observed, which takes on values of 1 if banking distress actually occurs in economy i at time t, and 0 otherwise, using the following rule

$$Y_{i,t} = \begin{cases} 1 & \text{if } Y^*_{i,t} > 0 \\ 0 & \text{otherwise} \end{cases} .$$

$\mathbf{X}_{i,t-}$ is a vector of explanatory variables to explain banking distress and b is a vector of corresponding estimated coefficients. The error terms $e_{i,t}$ is assumed to consist of two components: $e_{i,t} = a_i + n_{i,t}$, where a_i and $n_{i,t}$ are independent identically distributed with $a_i \sim N(0, s_a^2)$ and $n_{i,t} \sim N(0, s_n^2)$. a_i and $n_{i,t}$ are assumed to be independent. This is a random effects model specification in which a_i captures time-invariant country-specific factors that are not being reflected in $\mathbf{X}_{i,t-}$.

With the specification in equation (1), the estimated probability of an occurrence of banking distress taking place in economy *i* at *t* is given by

$$\Pr(Y_{i,t} = 1) = F(Y_{i,t}^*)$$
$$\Pr(Y_{i,t} = 0) = 1 - F(Y_{i,t}^*)$$

where *F*(.) is the cumulative distribution function of the standard normal distribution.

For the dependent variable $Y_{i,t}$, we adopt the same definition used in Demirgüc-Kunt and Detragiache (1998a). An economy *i* at time *t* is classified as a distress economy if any one, or more than one, of the following four conditions are satisfied:

(a) The nonperforming loan ratio[22] in the banking sector is larger than 10%[23],
(b) the rescuing costs of the banking sector is larger than or equal to 2% of GDP,
(c) there is a significant large scale nationalisation of banks in response to banking problems, and
(d) a systemic bank run takes place or emergency measures are enacted for rescuing systemic banking problems.

The choice of the explanatory variables follows both the theoretical and empirical contributions of the literature. The explanatory variables are broadly classified into five categories: (1) macroeconomic environments, (2) the financial health of the banking and non-financial corporate sectors, (3) asset price bubbles, (4) contagion, and (5) institutional variables.

Regarding the macroeconomic variables, the annual growth rate of real GDP (*GROWTH*), the inflation rate (*INF*), the real interest rate (*RIR*), and the real exchange rate index (*RER*) are included as the explanatory variables. As these variables are commonly

[22] It is defined as the ratio of nonperforming loans to total loans in the banking system. For Australia and New Zealand, the ratio of nonperforming assets to total assets is used.

[23] The definition of non-performing loans varies across economies.

considered in the literature, detailed theoretical discussions are skipped.[24] In general, an economy with weak economic fundamentals such as slowing economic growth, high inflation rates and real interest rates, or a deterioration in international trade competitiveness (as indicated by a higher real exchange rate index) would be more likely to amplify an initial adverse shock to become a systemic banking distress. Therefore, the estimated coefficient for *GROWTH* is expected to be negative, while that for *INF, RIR*, and *RER* are expected to be positive.

In addition, the ratio of money supply to foreign reserves (*MR*) in logarithm form is added into estimations. The inclusion of this variable is inspired by past empirical findings that there is a strong linkage between currency crisis and system-wide banking problems. A high value of *MR* indicates that the economy is more vulnerable to currency speculations (particularly for those with an exchange rate peg). An expected currency devaluation resulting from a threat of currency crises would simulate investors' incentive to reallocate their asset portfolios away from local assets (e.g. local currency deposits) to foreign assets which could lead to a systemic bank run. A positive estimated coefficient is implied from such relationship.

The second group of explanatory variables represent the financial health of banks and non-financial companies. The inclusion of this group of variables is consistent with the empirical results by Hardy and Pazarbasioglu (1998, 1999) which found that the stresses in banking and corporate sectors are the best leading indicators for the Asian financial crisis. This is also motivated by the empirical results of Rojas-Suarez (2001) which found that micro level data are useful to predict banking crises or distress. Theoretically, a default of a single bank or a few banks could post a major threat of systemic banking crises or distress through the contagion effect within the banking sector.[25] Similar contagion effect could be transmitted from the non-financial corporate sector to the banking sector, given that the banking sector has substantial exposures to the corporate sector. In this study, we include separately bankruptcy risk indicators for listed commerical banks and listed non-financial companies to explain banking distress. The former is the default probability of listed commercial banks (*PDB*) derived from a structural model proposed by Merton (1974), in which equity prices, equity volatility, and banks' financial liabilities are the determinants of banks' default risk. The latter is the Altman's Z-score (*ZS*) which is based on some selected accounting ratios of non-financial companies.[26] Note that a lower Z-score indicates a higher likelihood of company default. Given that a system-wide banking problem is more likely

[24] See Demirgüc-Kunt and Detragiache (1998a) and Kaminsky and Reinhart (1999) for comprehensive discussions.

[25] See for example, Diamond and Dybvig (1983), Allen and Gale (2000b), and Giesecke and Weber (2006).

[26] See Altman (2000). The accounting ratios used to derive the Z-score are working capital/total assets, retained earnings/total assets, earnings before interest and taxes/total assets, market value of equity/book value of total liabilities, and sales/total assets.

inherent in the low credit quality banks or companies[27], we measure *PDB* and *ZS* using the 90 percentile of the default probabilities of listed banks and the 10 percentile of the Z-score of non-financial companies respectively. The sign of the estimated coefficients for *PDB* and *ZS* are expected to be positive and negative respectively.

Some recent research found that there is a positive relationship between asset price bubbles and occurrences of banking crises or distress.[28] A number of past studies consider asset prices, in particular equity prices, as one of the leading indicators of banking crises or distress.[29] To measure the extent to which asset price bubbles affect the likelihood of banking distress, we introduce two explanatory variables, the property price bubble (*PPB*) and stock price bubble (*SPB*). In this study, asset price bubbles are measured by the gap between prevailing asset prices and their fundamental values, which are derived from the Hodrick-Prescott filter. *PPB* is defined to be the property price gap as a percentage of the fundamental property prices. *SPB* is defined in a similar manner, but using stock price indexes. A positive value for *SPB* or *PPB* indicates that there may be a misalignment in asset prices over their fundamental values. The inflated asset prices could fall drastically when market sentiments change or as a result of economic shocks, and banks are vulnerable to such burst of asset price bubbles. The increase in default and sharp declines in the value of collateral could cause significant damages to banks' balance sheets. According to the theoretical framework by Allen and Gale (2000a), asset price bubbles are usually fuelled by massive credit expansion and the bubbles in turn generate even a higher likelihood of crises or distress. In fact, empirical evidence such as Demirgüc-Kunt and Detragiache (1998a) supports that credit expansion is positively related to the likelihood of banking crises or distress. Based on the theoretical and empirical considerations, we also include the annual growth rate of real domestic credit (*RCG*) as one explanatory variable. A positive sign is expected for the estimated coefficients of all the above variables.[30]

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27 For any given adverse economic shock, the direct impacts on low quality (i.e. high default risk) banks and companies should be more severe and obvious than that of high quality banks and companies, as the latter usually hold larger buffers to withstand shocks. The impacts on the default risk of high quality banks or companies may become evident if substantial contagious effects arising from the default events of low quality banks and companies. Therefore, the impacts of high quality banks or companies tend to lag behind substantially from the initial shock. In view of this, the default risk of low quality banks and companies is chosen to serve as leading indicators of banking distress.

28 For theoretical discussions, see Allen and Gale (2000a), for example; for empirical studies, see Vila (2000).

29 For example, see Kaminsky and Reinhart (1999) for international studies and Lestano et al. (2003) for empirical research of the Asian crisis.

30 Past studies such as Kaminsky and Reinhart (1999) usually use asset price indexes as explanatory variables instead of the asset price bubble variables. The former implies a negative estimated coefficient while the latter implies a positive estimated coefficient. It should be noted that the differences in sign of the estimated coefficients are not contradictory. According to Allen and Gale (2000a), a financial crisis with a bubble usually contains three distinct phases: (1) asset price inflations, followed by (2) a collapse in asset prices, and (3) a widespread of bank defaults. The asset price bubble variables used in this study capture the movement of asset prices in phase (1), while the asset price indexes used in other studies capture the movement of asset prices in phase (2).

For the contagion effect across economies, a variable *CONTAGION* is included to assess how banking distress events in neighbouring economies may spread to the home economy, and whether the same banking distress is looming at home. Various studies support that contagion effects are significant in explaining banking crises or distress (See Kaminsky and Reinhart (2000) and Goldstein et al. (2000)), but they are mainly based on the signal extraction approach. By comparison, empirical analyses of the contagion effect based on the econometric approach are rare.[31] In this study, the computation of *CONTAGION* essentially follows the method proposed by Eichengreen et al. (1996) which explains the contagion effects of currency crises. By construction, for any given point of time, the value of *CONTAGION* of an economy is the weighted sum of the number of neighbouring economies in the region (i.e. the 10 other EMEAP economies in this study) which suffered a banking distress recently, where the weights reflect the similarities in macroeconomic conditions between the home economy and each of the neighbouring economies. Details of the calculation of the weights are shown in Appendix A. By constructing *CONTAGION* on this basis, we hypothesise that the likelihood of an occurrence of banking distress in a given economy increases with the occurrence of distress elsewhere in the region. The contagion effect of banking distress from one economy to another is assumed to be more pronounced if their macroeconomic fundamentals are more similar. These two hypotheses imply a positive estimated coefficient for *CONTAGION*.

As past empirical findings generally suggest that institutional factors are important indicators of banking crises or distress, the domestic credits to private sector as a percentage of GDP (*DC*), real GDP per capita (*GDPC*), and the presence of deposit insurance (*DEPINS*) (defined as one at any given point of time for an economy if there is an explicit deposit insurance scheme in place, and zero otherwise) are introduced as regressors. In this study, *DC* serves as a proxy for the degree of financial liberalisation. According to Demirgüc-Kunt and Detragiache (1998a), a higher degree of financial liberalisation could increase the opportunities for excessive risk taking of banks and therefore may increase the banking sector fragility, implying a positive estimated coefficient for *DC*.

We use *GDPC* as a proxy for the institutional quality. The selection of this proxy follows Demirgüc-Kunt and Detragiache (1998a, 1998b) and is consistent with the empirical results by Rodrik (2002) which found that institutional quality is positively correlated with *GDPC*.[32] Demirgüc-Kunt and Detragiache (1998b) argues that where institutional quality is good, an effective system of banking regulation and supervision is more likely to be in place, leading to a lower probability of banking crises or distress. This implies a negative estimated coefficient of *GDPC*.

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[31] This is contrary to the significant attention of the contagion effect in studies of currency crises (See Gerlach and Smets (1995), and Eichengreen et al. (1996)).

[32] According to Rodrik (2002), institutional quality refers to the quality of formal and informal socio-political arrangements, ranging from the legal system to broader political institutions.

There are controversies on how the presence of deposit insurance may effect banking distress. One view argues that it would weaken the banking sector stability. Demirgüc-Kunt and Detragiache (1998b) listed two reasons to support this argument. First, deposit insurances lead to the problem of moral hazard and encourage banks to take excessive risks. Second, it leads to lower incentive for bank shareholders to monitor bank risks. On the other hand, it is argued that deposit insurance may enhance the banking sector stability, as it reduces the possibility of self-fulfilling deposit runs. Therefore, the sign of the estimated coefficient for *DEPINS* is ambiguous.

IV. DATA AND ESTIMATION METHOD

We employ in the estimation a panel data set that contains 11 economies in the Asia-Pacific region, namely Australia, China, Hong Kong (of China), Indonesia, Japan, Korea, Malaysia, New Zealand, the Philippines, Singapore, and Thailand. The data set contains quarterly data during the period 1990 Q2 to 2007 Q1, with the data availability varying across the economies (i.e. unbalanced panel data set). Detailed definitions and sources of data can be found in Appendix B. It should be noted that while all non-distress observations in the data set are included in estimations, some distress observations are excluded. Specifically, for each occurrence of banking distress, only the first four distress observations from the onset of the banking distress are included. The remaining distress observations (after the fourth quarter of an occurrence of distress) are excluded as the explanatory variables of these distress observations may be directly affected by the distress itself or indirectly affected by some macroeconomic policies relating to the distress. Inclusion of these distress observations in estimations may subject to the problem of endogeneity, and could generate biased estimation results. Similar data treatment is adopted in Demirgüc-Kunt and Detragiache (1998a).

In this study, only the lagged terms of the explanatory variables (i.e. $\mathbf{X}_{i,t-}$) are used in estimations, as their contemporaneous terms may cause the problem of endogeneity. Using the lagged terms can enhance the usefulness of the model as leading indicators of banking distress because the model forecasts only rely on the past values of the explanatory variables which are readily available by the time that the predictions are being produced. Since the literature on banking crises or distress does not provide sufficient guidance about the appropriate time lag for the explanatory variables, we allow the explanatory variables to lag up to one year, with the exception of the credit growth variable, *RCG*, which we allow it to lag up to two years, following the empirical specifications by Demirgüc-Kunt and Detragiache (1998a, 1998b, and 1999).

The random effects probit model specified in equations (1) is estimated by the maximum likelihood method. To avoid the problems associated with non-stationarity, a panel unit root test by Choi (2001) is adopted to test the stationarity of the explanatory variables.[33,34] For any given variable, the first difference form of the variable is used in estimations if the panel unit-root test of the variable does not reject the unit-root null hypothesis at the 10% level.

V. ESTIMATION RESULTS

Estimation results are presented in Table 1. The likelihood ratio index of the model, which measures the goodness of fit, is 0.6232, indicating that the specifications are reasonably adequate.[35] The *chi-squared* statistic for the model rejects the null hypothesis that the set of selected explanatory variables do not give significant explanatory powers on *Y* at the 1% level, suggesting that the explanatory variables selected are generally relevant in predicting banking distress. Key findings are summarised as follows:

1. Regarding the macroeconomic variables, the estimated coefficient for *GROWTH* is negative, while that of *INF* are positive, with both being significant at the 1% level. This indicates that banking distress is typically preceded by weakening macroeconomic fundamentals, such as slowing economic growth and high inflation rates. This is consistent with the empirical findings by Demirgüc-Kunt and Detragiache (1998a, 1998b, and 1999) and Hardy and Pazarbasioglu (1998, 1999). However, *RIR* and *RER* are found to be not statistically significant factors when combining with other explanatory variables, and are therefore dropped from the regression equation.

2. *MR* is found to be positively related to the risk of banking distress and is statistically significant at the 1% level. As *MR* is an indicator of currency crises, this suggests that an economy that is more susceptible to currency crises (as indicated by a high value of *MR*) is also more likely to suffer from banking sector problems. This is consistent with empirical findings by Kaminsky and Reinhart (1999) that after 1980s banking and currency crises or distress generally occurred jointly, and a rising *MR* resulting from rapid increases of money supply and significant declines in foreign currency reserves was generally observed prior to the onset of past distress events.

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33 Using non-stationary data series in estimations may lead to the problem of spurious regressions, and invalidity of traditional statistical tests.

34 Among the alterative panel unit root tests such as Im et al. (2003), Choi's test is found to be more powerful and is therefore chosen. While there are three types of test statistics proposed by Choi (2001), the *Z* test statistic is shown to outperform the other two statistics, all the panel unit root tests conducted in this study are thus based on the *Z* test statistic.

35 The likelihood ratio index is defined as $1-(\ln L/\ln(L_0))$, where $\ln L$ is the log-likelihood statistic of the model, and $\ln L_0$ is the log-likelihood statistic computed with only a constant term. The index ranges from 0 to 1 and increases as the fit of the model improves.

3. The financial health of the banking and corporate sectors, as defined by their asset quality, appears to be useful leading indicators of banking distress. The estimated coefficients for *PDB* and *ZS* are positive and negative respectively and statistically significant at the 1% level.

4. For the asset price bubble variables, the estimation results are largely consistent with the theory by Allen and Gale (2000a), which suggests that inflated asset prices in equity and property markets fuelled by credit expansion could lead to a widespread of defaults and systemic banking problems when they burst. Specifically, *PPB*, *SPB*, and *RCG* are found to be positively related to the likelihood of banking distress, and statistically significant at the 1% level. Strong credit expansion is found generally ahead of banking distress by around 2 years which is consistent with the empirical results by Demirgüc-Kunt and Detragiache (1998a, 1998b, and 1999).

5. Regarding the contagion effects across economies, the estimated coefficient for *CONTAGION* is found to be positive and statistically significant at the 1% level. The result suggests that the chance of a banking distress in the home economy increases with the occurrence of distress in its neighbouring economies. In addition, it appears that macroeconomic similarities play a significant role in explaining the contagion effects of banking distress. This empirical result is consistent with the studies by Kaminsky and Reinhart (2000) and Goldstein et al. (2000).

6. Institutional quality measured by *GDPC* is negatively related to banking distress and is statistically significant at the 1% level. An economy with higher institutional quality is found to be less vulnerable to banking distress, which is consistent with Demirgüc-Kunt and Detragiache (1998b). However, the other two institutional variables *DC* and *DEPINS* are not statistically significant when putting together with other explanatory variables in the estimations, and are therefore dropped from the regression equation.

VI. EARLY WARNING SYSTEMS

As the objective of this study is to develop an early-warning system for banking distress, the predictive power of the leading indicator model is crucial. One conventional method to evaluate a model's predictive power is to construct a two-way contingency table by classifying the number of predictive outcomes into the cells in the following two-by-two matrix (See Kaminsky and Reinhart (1999)) based on the available sample.

Events	No banking distress occurs	Banking distress actually occurs
The model does not issue a distress signal	A	B
The model issues a distress signal	C	D

There are four commonly used measures that can be derived from the contingency table to assess the accuracy of the model prediction: (1) the percentage of correct classification (=*(A+D)/(A+B+C+D)*), (2) the proportion of correct signals conditional on occurrences of distress (= *D/(B+D)*), (3) type I error which is the probability of not issuing a distress signal conditional on an occurrence of distress (= *B/(B+D)*), and (4) type II error which is the probability of producing a distress signal conditional on no distress taking place (= *C/(A+C)*). The higher the values of (1) and (2), and the lower the values of (3) and (4), the higher the predictive power of the model is. However, it should be noted that a lower value of type I error must be at the expense of a higher value of type II error, and *vice versa*.

In order to construct the contingency table, a threshold level, a , for the estimated probability of banking distress must be identified such that an occurrence of distress is signaled if the estimated probability from the model is above a . While a natural choice of a is 0.5, it may not be optimal if the sample is unbalanced between the occurrence of distress and non-distress observations. In our case, since the non-distress observations dominate the distress observations in the panel data set, setting a = 0.5 may fail to predict most of the banking distress.[36]

Demirgüc-Kunt and Detragiache (2000) proposed a practical way to select a suitable a . In essence, Demirgüc-Kunt and Detragiache (2000) suggested selecting an a by minimizing a loss function which involves three factors: (1) type I error and type II error, (2) the unconditional probability of distress (i.e. the average probability of banking distress in the sample), and (3) the cost of taking preventive measures relative to the cost of failing to predict an occurrence of distress.

In practice, however, there may not exist a general formula for choosing the best value of a that can be applied equally well for all economies, as the tolerance levels of type I and type II errors of each economy are different. As pointed out by Demirgüc-Kunt and Detragiache (2000), a risk-averse central bank would prefer placing greater weights on

[36] In our panel data set, there are 366 observations in which 36 are classified as distress observations. This implies the average probability of distress in the sample is about 10%. Due to this data property (i.e. rare events of banking distress), to produce an estimated probability of distress over 0.5, very extreme values of explanatory variables are required. For detailed technical discussions on the problem of choosing the threshold value, see Chapter 19, Greene (1997).

minimizing type I error which should imply a lower a value at the expense of having a higher false alarm rate. In addition, setting an optimal a for an economy requires rigorous assessments on the preventive costs and the costs of failing to anticipate an occurrence of banking distress. Such assessments require much more information of an economy, which may not be readily available.

In this study, we only consider a simple way to select a for illustrative purposes. We assume a central bank places equal weights on the type I and type II errors, and therefore a is being selected by minimizing the sum of in-sample type I and type II errors.[37] The value of a is found to be 0.0259.

Table 2 shows the in-sample performance of the estimated model for the aggregate sample and for individual economies. The model correctly predicts 34 out of the 36 distress events and 270 out of 330 non-distress events in the aggregate sample. Specifically, the proportion of correct classification is 83%, the share of correct signals conditional on occurrences of distress is 94%, type I error is 6%, and type II error is 18%. Overall, the in-sample accuracy of the model to predict an occurrence of distress is reasonably good.

The predictive power of the model is also examined by studying the out-sample performance. The out-sample forecasts are generated by the following method: we first split the full sample into two blocks, Block A and Block B, with Block A containing the data of the "Home" economy and Block B containing the data of the remaining 10 economies. Using the same set of explanatory variables reported in Table 1, a new set of estimated coefficients are estimated and a a (which minimizes the in-sample sum of type I and type II errors) is selected using the data of Block B (i.e. the block with 10 economies). Based on the new set of estimated coefficients and a , we generate the out-sample forecasts for the sample of Block A, the "Home" economy. We repeat the above process by eleven times and each of the 11 economies will be held out one time to obtain its out-sample forecasts. The signs of the estimated coefficients in the 11 estimated models are found to be consistent with the model reported in Table 1, indicating that the specification of the model is reasonably robust.

The out-sample accuracy of distress prediction of the model is also reasonably good, although it is not as good as the in-sample performance. As shown in Table 3, the model correctly predicts 29 out of the 36 distress events and 266 out of 330 non-distress events in the aggregate sample. The share of correct classification and that of correct signals conditional on occurrences of distress are same at 81%. Type I and type II errors are same at 19%.

[37] Alternatively, Demirgüc-Kunt and Detragiache (1998a) selects a by focusing on the in-sample distress frequency (i.e. a is selected based on factor (2) only), which implies an a of 0.05, which is substantially lower than the natural choice of 0.5.

As for the out-sample predictive power for individual economies, we further evaluate the performance by studying whether the model could produce signals ahead of the taking place of banking distress. Since all the explanatory variables in the model are lagged at least by three quarters, the model, in practice, could produce three-quarter-ahead forecasts of the likelihood of banking distress based on currently available information of the explanatory variables. Evaluating on this basis, the model's predictive power for individual economies is summarised below:

The model's predictive power for Hong Kong:

The model's predictive power for Hong Kong is reasonably good, with the estimated probability producing distress signals three quarters ahead of the onset of distress on 1999 Q1 (See Table 4). An examination of the evolution of the estimated probability of banking distress over time (Panel A, Chart 1) shows that the first distress signal was produced for 1998 Q1, which was issued based on mainly data of 1997 Q2. It is worth noting by the time when the model produced the distress signal, the problem loan ratio of retail banks in Hong Kong remained at a very low level (at 2.12% as of end-June 1997) and there was no obvious upward trend of the ratio to indicate rising potential risks. It was not until the second half of 1998 that the problem loan ratio began to increase.[38] In addition, for the six-quarter period after the issuing of the first distress signal until the onset of distress on 1999 Q1, the model produced another 5 distress signals out of the 6 quarters. Overall, the proportion of correct classification is 83%. The model combined with the estimated threshold of issuing distress signals has thus performed well as an early warning system for banking distress in Hong Kong.

The model's predictive power for other EMEAP economies:

The model's predictive power for China[39], Japan, Malaysia, the Philippines, and Singapore is high, as shown by the estimated probability which is able to produce distress signals three quarters ahead of the onset of distress (see Table 4). The model produces distress signals two quarters ahead of the occurrence of distress in Indonesia and Korea and one quarter ahead of Thailand's. The evolution of the estimated probability of banking distress for these economies also suggests that the model performs reasonably well for predicting banking distress. (Panels B to I, Chart 1)

[38] The quarterly average of the ratio between March 1997 to March 1998 was 2.3%.The ratio was 4.1% as of June 1998 and it increased and reached the peak at 10.6% on September 1999.

[39] Since some explanatory variables for China are not available before 1994 Q2, data for China in the estimations only cover the period of 1994 Q2 to 2007 Q1. In estimations, the distress period for China is defined as the first year observations that the China data is available, i.e., the period of 1994 Q2 to 1995 Q1, as the observations in this period meet the distress definition stated in section III. It should be noted that the distress may have started before the occurrence of distress period assumed in the study. Because of this, the predictive power of the model for China should be interpreted with caution.

VII. AN EVALUATION OF CURRENT BANKING SECTOR RISK IN HONG KONG

This section applies the model developed in section V to evaluate current banking sector risk in Hong Kong. The evaluation consists of two parts. The first part is an estimation of probability of banking distress in Hong Kong based on current economic situations.[40] The second part adopts a stress testing framework to assess the likelihood of occurrence of banking distress under some "exceptional but plausible" shocks. While this section evaluates only the banking sector in Hong Kong, the approach could be applied to other EMEAP economies in a similar fashion.

The probability estimate of banking distress:

Based on latest available information as of 2007 Q3, the current value of banking distress probability in Hong Kong is estimated to be 0.0000003, which is far below the threshold of 0.0259 to issue a distress signal.[41] This indicates that currently the risk of an occurrence of banking distress in Hong Kong is low.[42] Compared with the estimate of 0.0000000005 a year ago, the current level of banking distress probability registered a slight increase, as some explanatory variables deteriorate somewhat over the period. In particular, the "stock price bubble" variable has deteriorated due to an increasingly overheated stock market (see Table 5).

Stress testing:

In essence, the stress testing framework consists of two parts: (1) a system of empirical models of banking distress probability and dynamics of economic variables, and (2) a Monte Carlo simulation for generating distributions of banking distress probability. Different shocks are individually introduced into the framework for the stress tests. The magnitudes of the shocks are specified hypothetically to represent some possible adverse movements of economic variables, conditional on current economic environments.

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[40] By the time of writing this paper.

[41] We estimate the probability based on the values of the explanatory variables as of 2007 Q3. However, for those variables that the values for 2007 Q3 are not yet released by the time of writing, we use their values as of 2007 Q2 or 2007 Q1. The estimated probability is therefore a preliminary figure and is subjected to revision. The use of the estimate should be with caution.

[42] We also estimate the probability of banking distress for other EMEAP economies using latest information. The estimated probabilities are found to range from a virtually zero value to 0.0028, all below the model's estimated threshold of issuing a distress signal. This indicates that currently the risk of banking distress in EMEAP economies is low. We further examine the relative risk level of EMEAP economies using the four-level risk rating system proposed by Demirgüc-Kunt and Detragiache (2000). We follow Demirgüc-Kunt and Detragiache (2000) to choose the upper bounds of each of the four fragility classes so that type I error associated with the bounds are 10, 30, 50, and 100 percent, respectively. Based on our data, the implied range of the probability for the lowest fragility class is from 0.000 to 0.039; probabilities between 0.039 to 0.105 are in the second lowest fragility class, up to 0.274 are in the third class, and above 0.274 are in the highest fragility class. It is found that currently all EMEAP economies belong to the lowest fragility class.

The economic situations as of 2007 Q1 are taken as the current states and shocks are introduced from 2007 Q2 to 2008 Q1. We simulate 10,000 future paths of the probability of banking distress for the eight quarter points covering a two-year period from 2007 Q2 to 2009 Q1. In addition to the stress scenarios, a baseline scenario which assumes normal economic situations is also simulated for comparisons. Details of the stress testing methodology are shown in Appendix C.

The banking sector's resilience is stress tested under the following four scenarios, with different economic variables as the shock origin:[43]

(a) Reductions in real GDP growth in each of the four consecutive quarters staring from 2007 Q2 to 2008 Q1, from a year-on-year growth rate of 5.7% in the current quarter of 2007 Q1, to 3.7%, 1.7%, 0.7%, and -0.3% respectively,
(b) Continued rises of default probability of listed banks by 50% in each of the four consecutive quarters,
(c) Continued rises in stock prices by 12.5% in each of the four consecutive quarters, resulting in a significant deterioration in the stock price bubble indicator, and
(d) Continued rises in property prices by 4.7% in each of the four quarters, resulting in a significant deterioration in the property price bubble indicator.

The stress testing results presenting the distribution of banking distress probability for the baseline scenario and for the four stressed scenarios are given in Table 6.

We first assess the expected risk of occurrence of banking distress under the baseline case and each of the stressed scenarios. The average probabilities of banking distress are presented correspondingly at the first row of the table. In the baseline scenario which assumes normal economic situations, the probability of banking distress is estimated to be 0.0024 on average in 2009 Q1, which is far smaller than the threshold of 0.0259 determined by the model, suggesting that given current economic environments, the likelihood of an occurrence of banking distress is low.

Under the assumed shocks, the risk increases in all stressed scenarios, with the average probability of banking distress ranging from 0.0043 (with a shock originating from the banking sector) to 0.0047 (with a shock originating from the property market or GDP

[43] While each explanatory variable in the model could be taken as a stress origin in a scenario, for the sake of brevity, we only focus on four scenarios that are highly relevant to the prevailing economic situations. The first scenario hypothesises an economic slowdown in the Hong Kong economy which could be as a result of a US-led global economic slowdown due to the subprime mortgage problems, while the second scenario hypothesises an increase in the default risk of some banks which may be due to a deterioration of asset quality of banks' subprime mortgage related securities. The third and fourth scenarios are about asset price bubbles in the Hong Kong economy, given the increasingly overheated stock market activities recently and possible falls in local interest rates.

shocks). Nevertheless, even under these stressed cases, no banking distress is expected to occur, with the estimated probabilities remaining well below the threshold.

We then evaluate how the risk under a situation where a shock originating from one source is accompanied with by also more-than-average or extreme adverse responses of other economic variables. Assessments based on such scenarios could help identify structural vulnerability of the banking sector that could lead to systemic problems. Conventionally, the extent of such joint adverse events that may affect the risk of banking distress is revealed from the tail of the distributions of banking distress probability of the shock (e.g. the value at the 95% confidence level). As shown in row 3 of Table 6, the estimated tail values of the various scenarios jumped significantly from the baseline and average scenarios, with the estimated banking distress probability ranging from 0.0058 (with a shock originating from the stock market), to 0.0193 (with a shock originating from real GDP growth). However, the tail values of banking distress probability of all stressed scenarios are still lower than the threshold value of issuing a distress signal.

Finally, we further examine how the banking sector may fare under similar shocks as occurred in the Asian financial crisis. The estimated expected probabilities of banking distress under the various shock origins and the tail values of risk are given in Table 7. The results indicated that under two specific scenarios, the estimated probability would exceed the threshold, suggesting that Hong Kong could become subject to an occurrence of banking distress. However, the chances of occurrence of such scenarios are extremely low.[44] Compared with the simulation results under the scenarios that same shocks are assumed, but taking the economic situation before the outbreak of Asian financial crisis (as of 1997 Q1) as the initial state (Table 8), the distress probabilities in terms of both the expected and tail values of the banking sector under the current state are significantly smaller, suggesting that currently the banking sector is more resilience to the assumed shocks than before the Asian financial crisis.

VIII. CONCLUSION

With the aid of a quarterly panel data set of the 11 EMEAP economies in the Asia-Pacific region covering the period from 1990 Q2 to 2007 Q1, the study identifies a set of leading indicators of banking distress and develops an econometric model that is capable of estimating the probability of an occurrence of banking distress.

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[44] The estimated probability of banking distress under the GDP growth shock (at the expected risk level, 0.0616) and that of property price shock (at the 95% confidence level, 0.0322) exceed the estimated threshold.

The model suggests that weakening macroeconomic fundamentals (including slowing GDP growth and rising inflation rates), an increase in money supply relative to foreign reserves, deteriorations in the creditworthiness of banks and companies, and significant asset price misalignments over their fundamental values in property and equity markets, in particular if fuelled by strong credit growth, are useful leading indicators of banking distress. In addition, the occurrence of distress of other economies in the region and the institutional quality of the home economy also play an important role in determining the likelihood of banking distress. The predictive power of the model as assessed by the in-sample and out-sample performance is reasonably good.

Based on latest available information (as of 2007 Q3), the estimated value of banking distress probability in Hong Kong is far below the threshold to issue a distress signal (0.0259), indicating that currently the risk of an occurrence of banking distress in Hong Kong is low. Stress testing results based on some hypothetical stress scenarios, which represent some possible adverse movements of economic variables, suggest that currently the banking sector in Hong Kong is healthy and should be able to withstand well the assumed shocks, even at the 95% confidence level. Under some extreme shocks originated from real GDP growth and property markets (as those occurred during the Asian financial crisis), the stress testing results suggest that Hong Kong could be subject to an occurrence of banking distress. However, the probabilities of the occurrence of such severe shocks, given current economic environments, are extremely low. The simulation results also suggest that currently the banking sector is more capable of withstanding the assumed shocks than it was before the Asian financial crisis.

Monitoring and preventing banking distress are principal duties of most central banks. The episode of the Asian financial crisis in 1997 demonstrates that banking distress could spill over across economies, particularly among economies with strong economic and financial linkages. Consistent with the past episode, this study shows that banking distress is contagious, suggesting that to be effective in monitoring banking distress, close cooperation between central banks should be in place.

Table 1: Estimation results of the econometric model

Explanatory variables	Estimated coefficients	Standard errors
$GROWTH_{t-4}$	-0.4299	0.0921
INF_{t-4}	0.2496	0.0743
$D\ ln(MR)_{t-4}$	0.0623	0.0129
$D\ ln(PDB)_{t-4}$	0.6560	0.2390
ZS_{t-4}	-1.5765	0.5300
PPB_{t-4}	0.0704	0.0225
SPB_{t-4}	0.0353	0.0131
RCG_{t-8}	0.0976	0.0196
$D\ (CONTAGION)_{t-3}$	0.7154	0.2525
$D\ ln(GDPC)_{t-4}$	-12.6519	3.7085
Constant	-1.6730	0.6294
Number of observations	366	
Log-likelihood statistic (with a constant term only) $ln\ L_0$	-131.9591	
Log-likelihood statistic *(the model)* $ln\ L$	-49.7277	
Likelihood ratio index $(= 1-(ln\ L/ln\ L_0))$	0.6232	
Wald Chi-squared statistic (degree of freedom = 10)	44.00	

Notes:

(1) $\Delta(x)$ refers to the first difference form of variable x; $ln(x)$ refers to the logarithm of variable x; and $(x)_{t-i}$ refers to the i^{th} quarter lag of variable x.

(2) All explanatory variables are statistically significant at the 1% level.

Table 2: In-sample performance of the model

Full sample:

Events	No banking distress occurs	Banking distress actually occurs
The model does not issue a distress signal	270	2
The model issues a distress signal	60	34
(1) The proportion of correct classification	83%	
(2) The proportion of signals conditional on occurrences of distress	94%	
(3) Type I error	6%	
(4) Type II error	18%	

Australia

Events	No banking distress occurs	Banking distress actually occurs
The model does not issue a distress signal	38	0
The model issues a distress signal	17	0
(1) The proportion of correct classification	69%	
(2) The proportion of signals conditional on occurrences of distress	NA	
(3) Type I error	NA	
(4) Type II error	31%	

China

Events	No banking distress occurs	Banking distress actually occurs
The model does not issue a distress signal	8	0
The model issues a distress signal	0	4
(1) The proportion of correct classification	100%	
(2) The proportion of signals conditional on occurrences of distress	100%	
(3) Type I error	0%	
(4) Type II error	0%	

Hong Kong

Events	No banking distress occurs	Banking distress actually occurs
The model does not issue a distress signal	31	0
The model issues a distress signal	7	4
(1) The proportion of correct classification	83%	
(2) The proportion of signals conditional on occurrences of distress	100%	
(3) Type I error	0%	
(4) Type II error	18%	

Indonesia

Events	No banking distress occurs	Banking distress actually occurs
The model does not issue a distress signal	6	0
The model issues a distress signal	1	4
(1) The proportion of correct classification	91%	
(2) The proportion of signals conditional on occurrences of distress	100%	
(3) Type I error	0%	
(4) Type II error	14%	

Japan

Events	No banking distress occurs	Banking distress actually occurs
The model does not issue a distress signal	10	1
The model issues a distress signal	0	3
(1) The proportion of correct classification	93%	
(2) The proportion of signals conditional on occurrences of distress	75%	
(3) Type I error	25%	
(4) Type II error	0%	

Table 2: In-sample performance of the model (continuous)

Korea

Events	No banking distress occurs	Banking distress actually occurs
The model does not issue a distress signal	33	1
The model issues a distress signal	1	3

(1) The proportion of correct classification	95%
(2) The proportion of signals conditional on occurrences of distress	75%
(3) Type I error	25%
(4) Type II error	3%

Malaysia

Events	No banking distress occurs	Banking distress actually occurs
The model does not issue a distress signal	29	0
The model issues a distress signal	2	4

(1) The proportion of correct classification	94%
(2) The proportion of signals conditional on occurrences of distress	100%
(3) Type I error	0%
(4) Type II error	6%

New Zealand

Events	No banking distress occurs	Banking distress actually occurs
The model does not issue a distress signal	48	0
The model issues a distress signal	9	0

(1) The proportion of correct classification	84%
(2) The proportion of signals conditional on occurrences of distress	NA
(3) Type I error	NA
(4) Type II error	16%

The Philippines

Events	No banking distress occurs	Banking distress actually occurs
The model does not issue a distress signal	10	0
The model issues a distress signal	16	4

(1) The proportion of correct classification	47%
(2) The proportion of signals conditional on occurrences of distress	100%
(3) Type I error	0%
(4) Type II error	62%

Singapore

Events	No banking distress occurs	Banking distress actually occurs
The model does not issue a distress signal	48	0
The model issues a distress signal	5	4

(1) The proportion of correct classification	91%
(2) The proportion of signals conditional on occurrences of distress	100%
(3) Type I error	0%
(4) Type II error	9%

Thailand

Events	No banking distress occurs	Banking distress actually occurs
The model does not issue a distress signal	9	0
The model issues a distress signal	2	4

(1) The proportion of correct classification	87%
(2) The proportion of signals conditional on occurrences of distress	100%
(3) Type I error	0%
(4) Type II error	18%

Table 3: Out-sample performance of the model

Full sample:

Events	No banking distress occurs	Banking distress actually occurs
The model does not issue a distress signal	266	7
The model issues a distress signal	64	29

(1) The proportion of correct classification	81%
(2) The proportion of signals conditional on occurrences of distress	81%
(3) Type I error	19%
(4) Type II error	19%

Australia

Events	No banking distress occurs	Banking distress actually occurs
The model does not issue a distress signal	38	0
The model issues a distress signal	17	0

(1) The proportion of correct classification	69%
(2) The proportion of signals conditional on occurrences of distress	NA
(3) Type I error	NA
(4) Type II error	31%

China

Events	No banking distress occurs	Banking distress actually occurs
The model does not issue a distress signal	8	1
The model issues a distress signal	0	3

(1) The proportion of correct classification	92%
(2) The proportion of signals conditional on occurrences of distress	75%
(3) Type I error	25%
(4) Type II error	0%

Hong Kong

Events	No banking distress occurs	Banking distress actually occurs
The model does not issue a distress signal	32	0
The model issues a distress signal	6	4

(1) The proportion of correct classification	86%
(2) The proportion of signals conditional on occurrences of distress	100%
(3) Type I error	0%
(4) Type II error	16%

Indonesia

Events	No banking distress occurs	Banking distress actually occurs
The model does not issue a distress signal	5	1
The model issues a distress signal	2	3

(1) The proportion of correct classification	73%
(2) The proportion of signals conditional on occurrences of distress	75%
(3) Type I error	25%
(4) Type II error	29%

Japan

Events	No banking distress occurs	Banking distress actually occurs
The model does not issue a distress signal	10	1
The model issues a distress signal	0	3

(1) The proportion of correct classification	93%
(2) The proportion of signals conditional on occurrences of distress	75%
(3) Type I error	25%
(4) Type II error	0%

Table 3: Out-sample performance of the model (continuous)

Korea

Events	No banking distress occurs	Banking distress actually occurs
The model does not issue a distress signal	33	1
The model issues a distress signal	1	3

(1) The proportion of correct classification	95%
(2) The proportion of signals conditional on occurrences of distress	75%
(3) Type I error	25%
(4) Type II error	3%

Malaysia

Events	No banking distress occurs	Banking distress actually occurs
The model does not issue a distress signal	25	0
The model issues a distress signal	6	4

(1) The proportion of correct classification	83%
(2) The proportion of signals conditional on occurrences of distress	100%
(3) Type I error	0%
(4) Type II error	19%

New Zealand

Events	No banking distress occurs	Banking distress actually occurs
The model does not issue a distress signal	46	0
The model issues a distress signal	11	0

(1) The proportion of correct classification	81%
(2) The proportion of signals conditional on occurrences of distress	NA
(3) Type I error	NA
(4) Type II error	19%

The Philippines

Events	No banking distress occurs	Banking distress actually occurs
The model does not issue a distress signal	10	0
The model issues a distress signal	16	4

(1) The proportion of correct classification	47%
(2) The proportion of signals conditional on occurrences of distress	100%
(3) Type I error	0%
(4) Type II error	62%

Singapore

Events	No banking distress occurs	Banking distress actually occurs
The model does not issue a distress signal	49	1
The model issues a distress signal	4	3

(1) The proportion of correct classification	91%
(2) The proportion of signals conditional on occurrences of distress	75%
(3) Type I error	25%
(4) Type II error	8%

Thailand

Events	No banking distress occurs	Banking distress actually occurs
The model does not issue a distress signal	10	2
The model issues a distress signal	1	2

(1) The proportion of correct classification	80%
(2) The proportion of signals conditional on occurrences of distress	50%
(3) Type I error	50%
(4) Type II error	9%

Table 4: Out-sample predictive power for individual economies of banking distress

Economy	Distress signal issued				
	preceding the occurrence of distress by#	for the 1st quarter of an occurrence of distress	for the 2nd quarter of an occurrence of distress	for the 3rd quarter of an occurrence of distress	for the 4th quarter of an occurrence of distress
China	3 quarters	Y		Y	Y
Hong Kong	3 quarters	Y	Y	Y	Y
Indonesia	2 quarters		Y	Y	Y
Japan	3 quarters	Y	Y	Y	
Korea	2 quarters		Y	Y	Y
Malaysia	3 quarters	Y	Y	Y	Y
Philippines	3 quarters	Y	Y	Y	Y
Singapore	3 quarters	Y	Y	Y	
Thailand	1 quarter			Y	Y

Note:

#: The figures are calculated based on the specification of the model reported in Table 1 which could produce three-quarter ahead forecasts based on the data currently available. If the model issues a distress signal for the first, second and, third quarter(s) of the occurrence of distress, the signal, in practice, is issued preceding the onset of the distress by 3, 2, and 1 quarter(s) respectively.

Table 5: Estimated banking distress probability of Hong Kong (as of 2007 Q3)

Explanatory variables	Value		Improved (+)/ deteriorated (-)
	2007 Q3 or latest	2006 Q3	
GROWTH	6.9%*	6.8%	+
INF	0.7%*	-0.4%	-
D ln(MR)	8.2%***	8.8%	+
D ln(PDB)	-17.4%**	-77.7%	-
ZS	1.7#	1.1#	+
PPB	1.5%*	1.3%	-
SPB	27.2%	-3.1%	-
RCG	9.0%***	6.0%^	-
D ln(GDPC)	2.2%*	2.1%	+
Probability of banking distress	0.0000003	0.00000000046	-
Threshold of issuing banking distress signal	0.0259	0.0259	

Notes:
* Values as of 2007 Q2
** Values as of 5th October 2007
*** Value as of 2007 Q1
^ Value as of 2005 Q3
# Figures are estimated from extrapolations

Table 6: Distributions of simulated banking distress probabilities under some adverse shocks (with current economic environments as the initial state)

Simulated probability of banking distress[1]	Baseline Scenario[2]	Stressed scenarios[3]			
		Real GDP shock (*Growth*)[4]	Banking sector shock (*PDB*)[5]	Property market shock (*PPB*)[6]	Stock market shock (*SPB*)[7]
Mean	0.0024	0.0047	0.0043	0.0047	0.0044
90 confidence level	0.0002	0.0055	0.0010	0.0010	0.0007
95 confidence level	0.0017	0.0193	0.0067	0.0079	0.0058

Notes:

(1) All figures are based on simulated probabilities of banking distress for 2009 Q1.

(2) The baseline scenario assumes normal economic situations.

(3) The shocks are introduced in each of the four consecutive quarters staring from 2007 Q2, taking the economic conditions in 2007 Q1 as the current environments. 10,000 future paths of the probability of banking distress are simulated for the eight quarter points covering a two-year period from 2007 Q2 to 2009 Q1.

(4) Reductions in real GDP growth in each of the four consecutive quarters staring from 2007 Q2 to 2008 Q1, from the year-on-year growth rate of 5.7% in the current quarter of 2007 Q1, to 3.7%, 1.7%, 0.7%, and -0.3% respectively.

(5) Continued rises of *PDB* by 50% in each of the four consecutive quarters.

(6) Continued rises in property prices by 4.7% in each of the four quarters, resulting in a significant deterioration in the property price bubble indicator.

(7) Continued rises in stock prices by 12.5% in each of the four consecutive quarters, resulting in a significant deterioration in the stock price bubble indicator.

Table 7: Distributions of simulated banking distress probabilities under similar shocks as the Asian financial crisis (with current economic environments as the initial state)[1]

Simulated probability of banking distress[2]	Baseline Scenario[3]	Stressed scenarios[4]			
		Real GDP shock (*Growth*)[5]	Banking sector shock (*PDB*)[6]	Property market shock (*PPB*)[7]	Stock market shock (*SPB*)[8]
Mean	0.0024	0.0616	0.0059	0.0099	0.0032
90 confidence level	0.0002	0.1949	0.0020	0.0057	0.0003
95 confidence level	0.0017	0.3503	0.0121	0.0322	0.0028

Notes:

(1) The constructions of the scenarios are based on actual changes of the shock variables during the Asian financial crisis.

(2) All figures are based on simulated probabilities of banking distress for 2009 Q1.

(3) The baseline scenario assumes normal economic situations.

(4) The shocks are introduced in each of the four consecutive quarters staring from 2007 Q2, taking the economic conditions in 2007 Q1 as the current environments. 10,000 future paths of the probability of banking distress are simulated for the eight quarter points covering a two-year period from 2007 Q2 to 2009 Q1.

(5) The year-on-year growth rate of quarterly real GDP (*GROWTH*) is assumed to -2.97%, -5.67%, -7.28%, and -5.69% in the first, second, third, and fourth quarters respectively.

(6) Continued rise of *PDB* by 90%, 143%, 3%, and 53% in each of the four consecutive quarters.

(7) The value of *PPB* is assumed to be 0%, 23%, 29%, and 32% in the first, second, third and fourth quarters respectively.

(8) The value of *SPB* is assumed to be 14%, 7%, 23%, and 21% in the first, second, third, and fourth quarters respectively.

Table 8: Distributions of simulated banking distress probabilities under similar shocks as the Asian financial crisis (with economic environments prior to the occurrence of distress as the initial state) [1]

Simulated probability of banking distress[2]	Baseline Scenario[3]	Stressed scenarios[4]			
		Real GDP shock (*Growth*)[5]	Banking sector shock (*PDB*)[6]	Property market shock (*PPB*)[7]	Stock market shock (*SPB*)[8]
Mean	0.1353	0.9383	0.2277	0.3054	0.1515
90 confidence level	0.5442	1.0000	0.7920	0.9092	0.5908
95 confidence level	0.7804	1.0000	0.9256	0.9782	0.8172

Notes:

(1) The constructions of the scenarios are based on actual changes of the shock variables during the Asian financial crisis.

(2) All figures are based on simulated probabilities of banking distress for 1999 Q1.

(3) The baseline scenario assumes normal economic situations.

(4) The shocks are introduced in each of the four consecutive quarters staring from 1997 Q2, taking the economic conditions in 1997 Q1 as the current environments. 10,000 future paths of the probability of banking distress are simulated for the eight quarter points covering a two-year period from 1997 Q2 to 1999 Q1.

(5) The year-on-year growth rate of quarterly real GDP (*GROWTH*) is assumed to -2.97%, -5.67%, -7.28%, and -5.69% in the first, second, third, and fourth quarters respectively.

(6) Continued rise of *PDB* by 90%, 143%, 3%, and 53% in each of the four consecutive quarters.

(7) The value of *PPB* is assumed to be 0%, 23%, 29%, and 32% in the first, second, third and fourth quarters respectively.

(8) The value of *SPB* is assumed to be 14%, 7%, 23%, and 21% in the first, second, third, and fourth quarters respectively.

Table 9: Autoregressive models of risk factors affecting banking distress probability in Hong Kong (sample period: 1980Q1 – 2007Q1)

Variable	Dependent Variables (X_t)								
	$GROWTH_t$	INF_t	$\triangle ln(GDPC)_t$	$\triangle ln(PDB)_t$	ZS_t	RCG_t	$\triangle ln(MR)_t$	PPB_t	SPB_t
Intercept	2.2752***	0.1204	0.0065***	-0.0275	0.0078	0.9255	-0.3739	-0.1916	-0.5378
	(0.4477)	(0.1721)	(0.0022)	(0.0907)	(0.0056)	(0.6546)	(1.2110)	(0.5234)	(1.4829)
X_{t-1}	0.8786***	1.2093***	0.2113*		2.9443***	0.8882***	0.9921***	1.2995***	0.6091***
	(0.0907)	(0.0931)	(0.1206)		(0.0987)	(0.1597)	(0.1437)	(0.0958)	(0.1179)
X_{t-2}	-0.1390	-0.2593***			-3.6099***	0.2350	-0.2367	-0.5446***	0.1391
	(0.1229)	(0.0906)			(0.2529)	(0.2218)	(0.1746)	(0.0949)	(0.1403)
X_{t-3}	0.2532**				2.2713***	-0.2598	0.2417		0.1313
	(0.1222)				(0.2557)	(0.2421)	(0.1739)		(0.1401)
X_{t-4}	-0.4045***				-0.6165***	-0.4097	-0.7602***		-0.3509***
	(0.0889)				(0.1013)	(0.2565)	(0.1737)		(0.1172)
X_{t-5}						0.3322*	0.4487***		
						(0.1709)	(0.1447)		
Adj. R^2	0.6926	0.9398	0.0304	0.0000	0.9967	0.6923	0.6831	0.7916	0.4851
Q(4)	1.3253	7.3868	1.7739	1.9468	5.0769	0.9094	4.0616	2.7559	0.1989
Prob>Q(4)	(0.8571)	(0.1168)	(0.7773)	(0.7455)	(0.2795)	(0.9232)	(0.3977)	(0.5995)	(0.9954)
Q(8)	5.5369	10.6630	6.6201	5.9603	10.6860	4.5467	7.2515	10.8670	0.6815
Prob>Q(8)	(0.6989)	(0.2216)	(0.5781)	(0.6517)	(0.2201)	(0.8047)	(0.5098)	(0.2094)	(0.9996)
No. of obs.	105	107	67	61	74	45	45	79	68

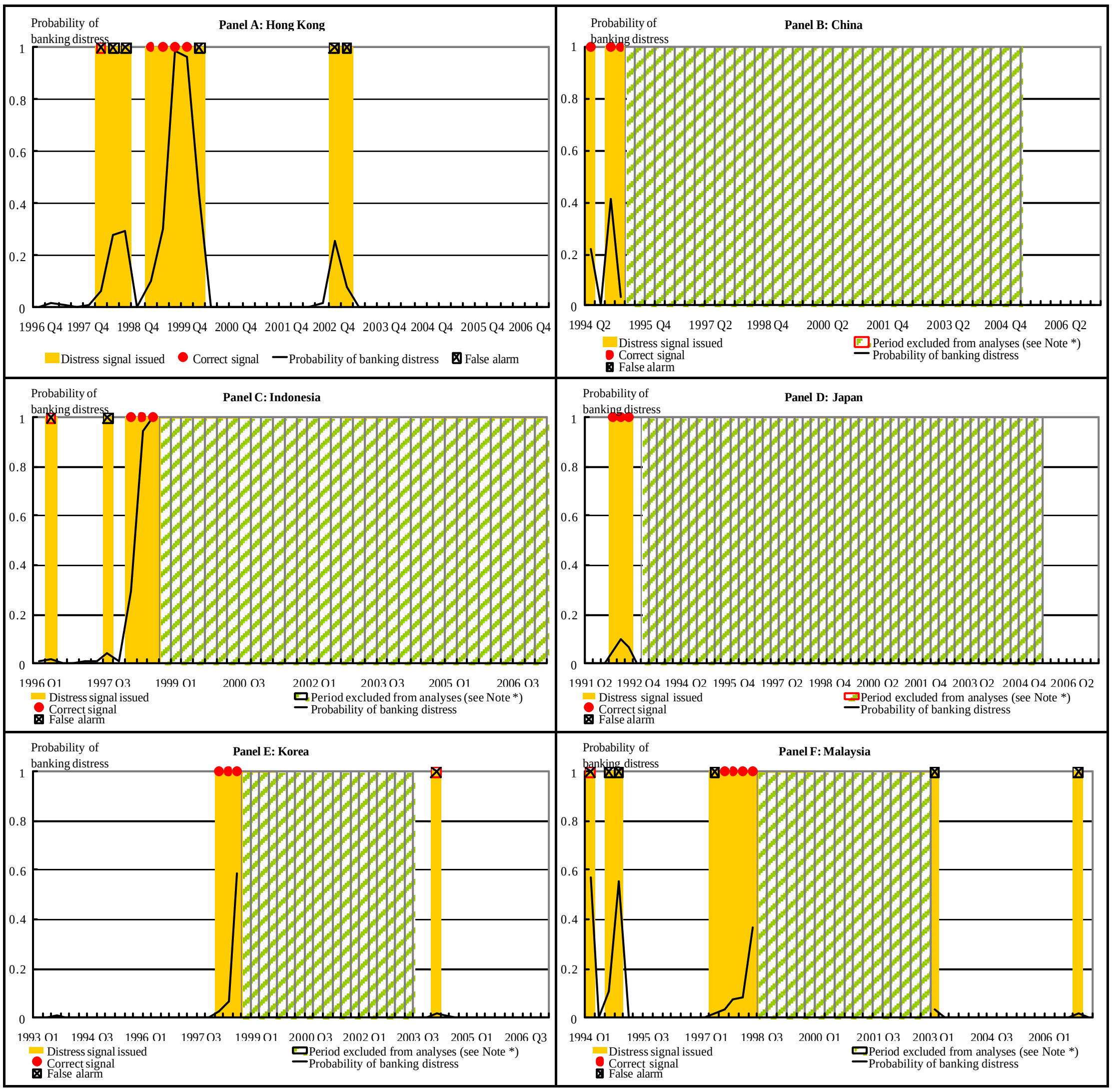
Notes:

(1) Standard errors in parentheses.

(2) *, **, and *** denote statistical significance at the 10%, 5% and 1% levels respectively.

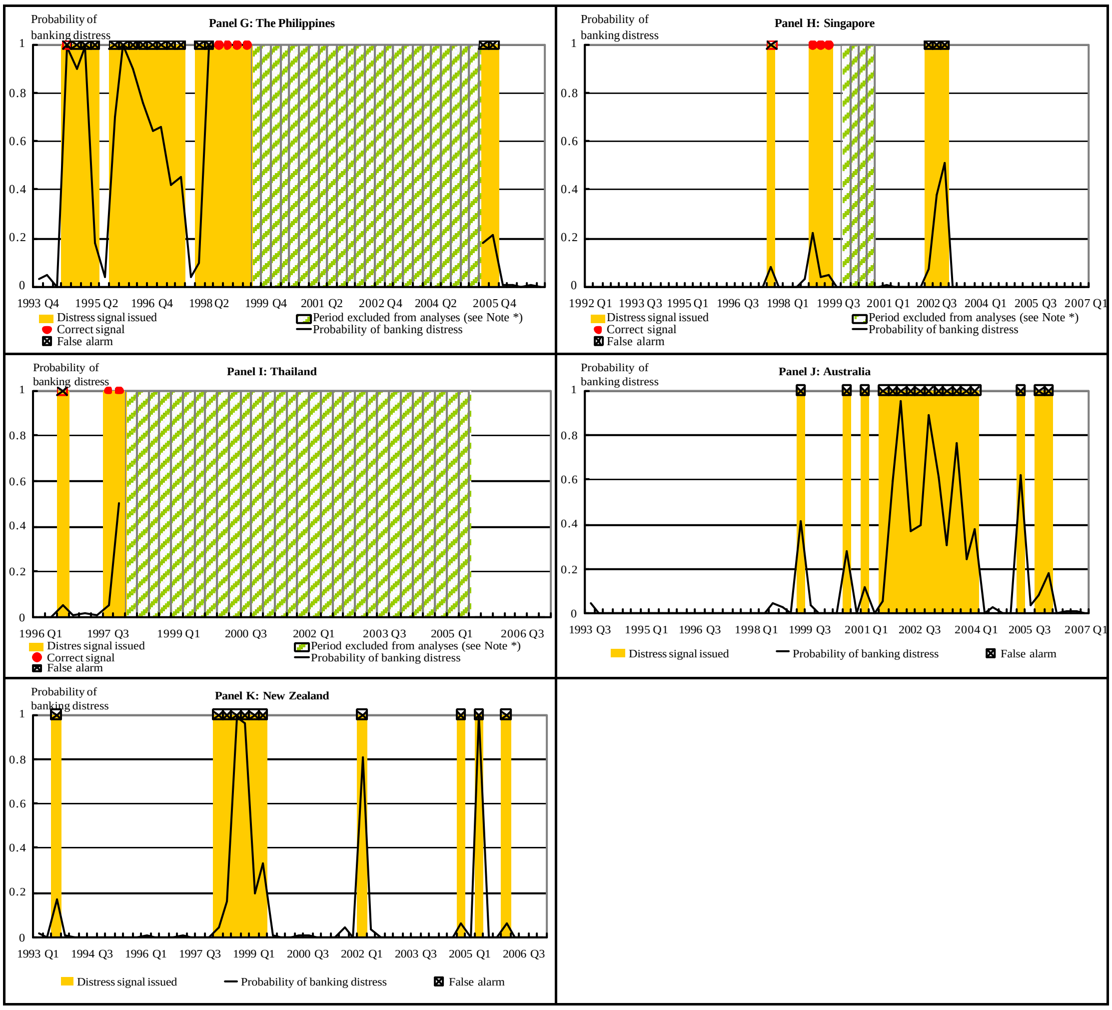
(3) Q(n) reports the Ljung-Box Q-statistic for testing of no autocorrelations of the first *n* residual terms of the estimated models. Significance levels are in parentheses.

Chart 1: Evolution of the estimated probability of banking distress



Note: * The period after the fourth quarter of the onset of distress up to the first tranquil quarter (i.e. the green-colour area) is excluded from the analysis as the explanatory variables may be directly affected by the occurrence of distress or indirectly affected by some macroeconomic policies relating to the occurrence of distress. The banking distress probabilities thus estimated may not accurately reflect the likelihood of occurrences of banking distress.

Chart 1: Evolution of the estimated probability of banking distress (continuous)



Note: * The period after the fourth quarter of the onset of distress up to the first tranquil quarter (i.e. the green-colour area) is excluded from the analysis as the explanatory variables may be directly affected by the occurrence of distress or indirectly affected by some macroeconomic policies relating to the occurrence of distress. The banking distress probabilities thus estimated may not accurately reflect the likelihood of occurrences of banking distress.

Appendix A: The derivation of the contagion variable, *CONTAGION*

The construction of the explanatory variable *CONTAGION* to take care of the contagion effects among the economies mainly follows Eichengreen et al. (1998). In essence, for an economy i at time t, $CONTAGION_{i,t}$ is a weighted sum of a variable $Distress_{j,t}$ of the neighbouring economies, where the weight of each neighbouring economy is given by $W_{ij,t}$. Specifically,

$$CONTAGION_{i,t} = \sum_{j \neq i} Distress_{j,t} W_{ij,t} \ ,$$

$$Distress_{j,t} = \begin{cases} 1, \text{ if economy } j \text{ has an occurrence of distress at time } t \\ 0, \text{ otherwise} \end{cases} \text{, and}$$

$$W_{ij,t} = (1 - \{f[(X_{j,t} - m_j)/s_j] - f[(X_{i,t} - m_i)/s_i]\} \text{ for any } i \neq j \ .$$

$f(.)$ is the cumulative distribution function of the standardised normal function. $X_{j,t}$ is a macroeconomic variable or an macroeconomic index for economy j at time t. m_j and s_j are the sample mean and standard deviation of $X_{j,t}$ respectively.

The weight $W_{ij,t}$ is intended to reflect macroeconomic similarities between economies i and j. In this study, we measure macroeconomic conditions of the economies by their annual growth rates of real GDP. When calculating $W_{ij,t}$, the annual growth rates of real GDP is multiplied by minus one, so that a higher value of $X_{j,t}$ indicates for high risk. $X_{j,t}$ and $X_{i,t}$ are standardised by their own means and standard deviations.

Appendix B: Description and sources of data

Variable	Data definition	Main Sources
Y	A binary variable which is defined as one if banking distress occur, and zero otherwise. The chronology of banking distress for individual economies are shown as follows: Economy — Banking distress China — 1994Q2[45] – 2005Q1 Hong Kong — 1999Q1 – 1999Q4 Indonesia — 1992Q4 – 1995Q4 1997Q4 – 2007Q1[46] Japan — 1992Q1[47] – 2005Q2 Korea — 1997Q4 – 2003Q2 Malaysia — 1997Q3 – 2002Q4 Philippines — 1998Q3 – 2005Q2 Singapore — 1998Q4 – 2000Q3 Thailand — 1997Q1 – 2005Q2	The chronology of banking distress is extracted and updated from various sources: Lindgren et al. (1996), Kaminsky and Reinhart (1999), Caprio and Klingebiel (2003), Lestano et al. (2003), Demirgüc-Kunt and Detragiache (2005), various publications of IMF, and staff estimates.
GROWTH	The annual percentage change of real GDP	CEIC, Datastream and national sources.
INF	Inflation rates measured by the annual percentage change of the GDP deflator	CEIC, Datastream, International Financial Statistics (IFS) and national sources.
RIR	Real interest rates measured by $[(1+r_t)/(1+p_{t+1})]-1$, where r_t and p_{t+1} are the 3-month nominal interest rates at time *t* and the inflation rates at time *t+1* respectively.	Bloomberg, CEIC, IFS (line 60c/ 60/ 60l) and national sources.
RER	Rate of change of real effective exchange rate index. An increase of the index indicates an appreciation of home currency.	The BIS real effective exchange rate indices.

45 It should be noted that official non-performing loan statistics of China's banking sector are only regularly released since 2004 Q1. However, past studies generally suggested that the non-performing loan ratio of China's banking sector in 1990s was substantially higher than 10% (See He (2002) for a summary of past studies). Due to data unavailability, the exact onset date of the distress is not certain. In this study, we have taken 1994 Q2, which is the first available observation for China that all the explanatory variables are available for estimations, as the beginning of the distress. Note that it is possible that the actual onset date is before that used in this study.

46 Indonesia has implemented a gradual removal of blanket guarantee for deposits during 22 September 2005 – 21 March 2007.

47 The exact onset date of the distress is not certain, 1992Q1 is assumed.

Appendix B: Description and sources of data (continuous)

Variable	Data definition	Main Sources
MR	Ratio of money supply (i.e. M2) to foreign exchange reserves of the central bank	IFS. M2 is defined as the sum of money and quasi money (i.e. IFS, lines 34 + 35) divided by total foreign exchange reserves (line 1dd). All values are converted to US dollar)
PDB	The 90th percentile of the default probability of listed commercial banks[48]	Bloomberg and staff estimates.
ZS	The 10th percentile of the Altman's Z-scores of listed non-financial companies [49]	Thomson Financial and staff estimates.
PPB	Real property price gap (the gap between prevailing property prices and their fundamental values[50]) as a percentage of fundamental property prices.	CEIC, Debenham Tie Leung property advisors, national sources and staff estimates.
SPB	Real equity price gap (the gap between prevailing equity price index and their fundamental values[50]) as a percentage of fundamental equity prices.	Bloomberg and staff estimates.
RCG	Annual percentage change of real domestic credit	IFS, line 32d.

48 Details of the methodology can be found in Merton (1974), and J. P. Morgan and Co. (1995).

49 Non-financial companies refer to listed companies, excluding investment companies and those engaged in banking, insurances and finances. The 2006 figures are preliminary and cover only a limited number of companies that had reported their 2006 results by the time of writing. They are subject to revisions and should be used with caution. As audited balance sheet data are available on an annual basis only, quarterly figures are estimated by using a cubic interpolation routine.

50 The fundamental values are derived from the Hodrick-Prescott filter.

Appendix B: Data Description of the variables and sources (continuous)

Variable	Data definition	Main Sources
CONTAGION	A variable that measures the contagion effects of banking distress across economies, taking the similarities in macroeconomic circumstances into considerations.[51]	Staff estimates.
DC	Ratio of domestic credit to the private sector to GDP	IFS, line 32d divided by GDP.
GDPC	Real GDP per capita	CEIC, Datastream and national sources.
DEPINS	Defined as one if the economy has explicit deposit insurance (including blanket guarantees), and zero otherwise	Garcia (2000) and Hoelscher et al. (2006).

[51] For details, please refer to Appendix A.

Appendix C: The stress testing methodology of banking sector vulnerability

This appendix illustrates the methodology for stress testing banking sector vulnerability based on the econometric model developed in section V. The stress testing approach is a simplified version of the works by Boss (2002), Virolainen (2004), and Wong et al. (2006), which are simulation analyses based on econometric models characterizing the relationship between banking sector vulnerability and macroeconomic economic variables. In our case, we select nine explanatory variables that are found useful to predict banking distress to stress test the banking sector.[52] In this framework, each of the selected explanatory variables (henceforth referred to as "the risk factors" of banking distress) is assumed to follow an univariate autoregressive (AR) process of order *n(i)*

$$X_{i,\,t} = m_i + g_{i,1}\,X_{t-1} + \ldots + g_{i,\,n(i)}\,X_{t-n(i)} + h_{i,t}\text{, and}$$

$$h_{\,t} \sim N(\mathbf{0},\ å_h)$$

where $X_{i,t}$ denotes the risk factors $i = 1,\ldots, 9$. m_i is an intercept; $g_{i,1},\ldots, g_{i,n(i)}$ are coefficient estimates, and $h_{i,t}$ is the error term at time t of the AR model for the risk factor *i*. The maximum value of *n(i)* is set to eight (i.e. AR(8) process). $h_{\,\boldsymbol{t}}$ denotes a vector of the error terms of the nine AR models (i.e., $h_{i,t}$) where shocks are introduced in simulations. $å_h$ is the variance-covariance matrix of the error terms in which the interdependences of shocks in the risk factors are taken into account.

In essence, the framework incorporates two important characteristics of risk factors into the analysis, which is aimed at giving more accurate assessments. First, evolution of each of the risk factors of banking distress, which could be separately considered as a shock origin in this stress testing framework, is modelled to depend on its past values using autoregressive models. It means that an economic shock affects current values, as well as future paths of the risk factor. This specification allows the impacts of a shock on the banking sector to be prolonged, which is consistent with historical experience.[53]

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52 We include all the explanatory variables shown in Table 1, with the exception of *CONTAGION*.

53 See Sorge (2004).

Secondly, dependencies between individual risk factors are taken care of in the framework through the term $\sum_h$. Therefore, the extent to which a shock on a particular risk factor affects banking sector vulnerability not only depends on the direct effect from the shocked risk factor, but also the indirect effect from other risk factors due to their responses to the shock. Conceptually, incorporating these two characteristics into the analysis should improve the quality of assessments, as they embody a closer description of the real world.

The estimation results of the AR models are presented in Table 9. The models are estimated by the ordinary least squares method. The specifications of variables used in the AR models follow the result of stationarity tests discussed in section IV. The estimated AR models are stationary and stable, as all characteristic roots based on the estimated coefficients lie inside the unit circle. For diagnostic checking of the models, the hypothesises of no serial correlation of the residual terms for the first four quarters and for the first eight quarters are not rejected at the 5% level based on the Ljung-Box Q-statistics, indicating that the variables are well approximated by the estimated AR processes.

The AR models of the risk factors of banking distress (i.e. $X_{i,\,t}$) and the resulting å$_h$, together with the econometric model (shown in Table 1) facilitate simulation analyses of probability of banking distress due to a given shock. Since technical details of the simulation analysis can be found from various sources, such as Boss (2002) and Wong et al. (2006), for brevity, we only give a brief discussion on the procedure as follow: For any given magnitude of a shock on $X_{i,t}$, it implies a shock value of $h_{i,t}$ based on the estimated AR model of $X_{i,t}$. The shocked values of $h_{i,t}$ will consequently induce a change for the error terms of other risk factors, which is represented by a vector $\mathrm{h}_{\mathbf{-i,t}}$. The values of $\mathrm{h}_{\mathbf{-i,t}}$ are obtained from simulations in which the relationships between the risk factors are taken into account by å$_h$. For each simulation trail, except for the value of $X_{i,t}$ which is predetermined by the assumed shock, the values of other risk factors which is denoted by a vector $\mathbf{X_{-i,t}}$ can be calculated from the simulated values of $\mathrm{h}_{\mathbf{-i,t}}$. Based on the vector $\{X_{i,t}, \mathbf{X_{-i,t}}\}$, the banking distress probability at time t, $\Pr(Y_{i,t} = 1)$, due to the shock can be calculated.

Repeating the simulations by a large number of trials (e.g. 10,000 trails), a distribution of $\Pr(Y_{i,t}=1)$ can be generated for further analyses, such as examinations of tails of the distribution. It should be noted that since both $X_{i,t}$, and $\mathbf{X_{-i,t}}$ are assumed to follow AR processes, the shock will also affect future values of all the risk factors, and thus the probability of banking distress in future periods (e.g. $\Pr(Y_{i,t+1}=1)$,…, $\Pr(Y_{i,t+8}=1)$). Distribution of banking distress probability in future periods could be obtained as well using the same simulation method. Multi-period shocks on $X_{i,t}$ can be analysed in a similar fashion.

References

Allen, F., and Gale, D. (2000a), "Bubbles and Crises", *The Economic Journal*, 110 (460), pp.236-55.

Allen, F., and Gale, D. (2000b) "Financial Contagion", *Journal of Political Economy*, 108(1), pp.1-33.

Altman, E. (2000), "Predicting Financial Distress of Companies: Revisiting the Z-scores and ZETA Models", Working Paper 7/2000, New York University.

Bell, J., and Pain, D. (2000), "Leading Indicator Models of Banking Crises—a Critical Review", *Financial Stability Review*, Bank of England.

Berg, A., and Pattillo, C. (1999), "Predicting Currency Crises: the Indicators Approach and an Alternative", *Journal of International Money and Finance*, 18(4), pp.561-86.

Bongini, P., Laeven, L., and Majnoni, G. (2002), "How Good is the Market at Assessing Bank Fragility? A Horse Race between Different Indicators", *Journal of Banking and Finance*, 26(5), pp.1011-28.

Boss, M. (2002), "A Macroeconomic Credit Risk Model for Stress Testing the Austrian Credit Portfolio", *Financial Stability Report*, 4, Oesterreichische Nationalbank.

Caprio, G., Jr. and Klingebiel, D. (1996), "Bank Insolvency: Bad luck, Bad Policy or Bad Banking?", Paper presented at the 1996 Annual Bank Conference on Development Economics, *World Bank Economic Review*, January 1997.

Caprio, G., Jr. and Klingebiel, D. (2003), "Episodes of Systemic and Borderline Financial Crises", World Bank.

Choi, I. (2001), "Unit Root Tests for Panel Data", *Journal of International Money and Finance*, 20(2), pp.249-72.

Dabos, M., and Escudero, W. S. (2004), "Explaining and Predicting Bank Failure using Duration Models: the Case of Argentina after the Mexican Crisis", *Revista de Análisis Económico*, 19(1), pp.31-49.

Demirgüc-Kunt, A., and Detragiache, E. (1998a), "The Determinants of Banking Crises in Developing and Developed Countries", *International Monetary Fund Staff Paper*, 45(1), pp.81-109.

Demirgüc-Kunt, A., and Detragiache, E. (1998b), "Financial Liberalization and Financial Fragility", Paper prepared for the Annual World Bank Conference on Development Economics.

Demirgüc-Kunt, A., and Detragiache, E. (2000), "Monitoring Banking Sector Fragility: a Multivariate Logit Approach", *World Bank Economic Review*, 14(2), pp. 287-307.

Demirgüc-Kunt, A., and Detragiache, E. (2002), "Does Deposit Insurance Increase Banking System Stability? An Empirical Investigation", *Journal of Monetary Economics*, 49, pp.1373-406.

Demirgüc-Kunt, A., and Detragiache, E. (2005), "Cross-country Empirical Studies of Systemic Bank Distress: a Survey", Working Paper 05/96, International Monetary Fund.

Diamond, D., and Dybvig, P. (1983), "Bank Runs, Deposit Insurance and Liquidity", *Journal of Political Economy*, 91(3), pp.401-19.

Domac, I., and Martinez-Peria, M. S. (2000), "Banking Crises and Exchange Rate Regimes - Is There a Link?", *World Bank Policy Research Working Paper*, 2489.

Eichengreen, B., and Arteta, C. (2000), "Banking Crises in Emerging Markets: Presumptions and Evidence", Working Papers C00-115, University of California at Berkeley.

Eichengreen, B., and Rose, A. (1998), "Staying Afloat when the Wind Shifts: External Factors and Emerging-market Banking Crises", Working Paper 6370, National Bureau of Economic Research.

Eichengreen, B., Rose, A., and Wyplosz, C. (1996), "Contagious Currency Crises", Working Paper 5681, National Bureau of Economic Research.

Falcetti, E., and Tudela, M. (2006), "Modelling Currency Crises in Emerging Markets: a Dynamic Probit Model with Unobserved Heterogeneity and Autocorrelated Errors", *Oxford Bulletin of Economics and Statistics*, 68(4), pp.445-71.

Gaytán, A., and Johnson, C. A. (2002), "A Review of the Literature on Early Warning Systems for Banking Crises", Working Paper 183, Central Bank of Chile.

Gerlach, S., and Smets, F. (1995), "Contagious Speculative Attacks", *European Journal of Political Economy*, 11(1), pp.45-63.

Giesecke, K., and Weber, S. (2006), "Credit Contagion and Aggregate Losses", *Journal of Economic Dynamics and Control*, 30(5), pp.741-67.

Glick, R., and Hutchison, M. (1999), "Banking and Currency Crises: How Common are Twins?", Working Paper PB99-07, Centre for Pacific Basin Monetary and Economic Studies, Federal Reserve Bank of San Francisco.

Goldstein, M., Kaminsky, G., and Reinhart, C. (2000), "Assessing Financial Vulnerability: An Early Warning System for Emerging Markets", Institute for International Economics, Washington DC.

González-Hermosillo, B. (1996), "Banking Sector Fragility and Systemic Sources of Fragility", Working Paper 96/12, International Monetary Fund.

González-Hermosillo, B. (1999), "Determinants of Ex-ante Banking System Distress: a Macro-Micro Empirical Exploration of Some Recent Episodes", International Monetary Fund Working Paper 99/33.

Greene, W. H., 1997. *Econometric Analysis*, 4th edition, NJ: Prentice Hall.

Hardy, D., and Pazarbasioglu, C. (1998), "Leading Indicators of Banking Crises: Was Asia Different?", Working Paper 98/91, International Monetary Fund.

Hardy, D., and Pazarbasioglu, C. (1999), "Determinants and Leading Indicators of Banking Crises: Further Evidence", *International Monetary Fund Staff Paper*, 46(3), pp.247-58.

He, F. (2002), "How Far is China Away from a Financial Crisis", Paper presented in Thailand Development Research Institute.

Honohan, P. (1997), "Banking System Failures in Developing and Transition Countries: Diagnosis and Predictions", Working Paper 39, Bank for International Settlements.

Hutchison, M., and McDill, K. (1999), "Are All Banking Crises Alike? The Japanese Experience in International Experience", Working Paper PB99-02, Centre for Pacific.
Basin Monetary and Economic Studies, Federal Reserve Bank of San Francisco.

Im, K. S., Pesaran, H. H., and Shin, Y. (2003), "Testing for Unit Roots in Heterogeneous Panels", *Journal of Econometrics*, 115(1), pp.53-74.

International Monetary Fund, (1998). *World Economic Outlook Financial Crises: Causes and Indicators*.

J. P. Morgan & Co. (1995), *RiskMetrics - Technical Document*, 3rd edition, May 26.

Kaminsky, G. (1998). "Currency and Banking Crises: the Early Warnings of Distress", *International Finance Discussion Papers*, 629, Board of Governors of the Federal Reserve System.

Kaminsky, G., and Reinhart, C. M. (1999), "The Twin Crises: the Causes of Banking and Balance-of-payments Problems", *American Economic Review*, 89(3), pp.473-500.

Kaminsky, G., and Reinhart C. M. (2000), "On Crises, Contagion, and Confusion", *Journal of International Economics*, 51(1), pp.145-68.

Lestano, L., Jan, J., and Gerard H. K. (2003), "Indicators of Financial Crises Do Work! An Early-warning System for Six Asian Countries", Working Papers 200313, University of Groningen.

Lindgren, C. J., Garcia, C., and Saal, M. (1996), *Bank Soundness and Macroeconomic Policy*, International Monetary Fund, Washington DC.

Merton, R. C. (1974), "On the Pricing of Corporate Debt: the Risk Structure of Interest Rates", *Journal of Finance*, 29(2), pp.449-70.

Oosterloo, S., de Haan, J., and Jong-A-Pin, R. (2007), "Financial Stability Reviews: a First Empirical Analysis", *Journal of Financial Stability*, 2(4), pp.337-55.

Rodrik, D. (2002), "Institutions, Integration, and Geography: in Search of the Deep Determinants of Economic Growth", Working Paper, Harvard University.

Rojas-Suarez, L. (2001), "Rating Banks in Emerging Markets: What Credit Rating Agencies Should Learn from Financial Indicators", Working Paper, Peterson Institute for International Economics.

Sachs, J. D., Tornell, A., and Velasco, A. (1996), "Financial Crises in Emerging Markets: the Lessons from 1995", Working Paper 5576, National Bureau of Economic Research.

Sorge, M. (2004), "Stress-testing Financial Systems: an Overview of Current Methodologies", Working Paper 165, Bank for International Settlements.

Vila, A. (2000), "Asset Price Crises and Banking Crises: Some Empirical Evidence", Conference Paper, Bank for International Settlements.

Virolainen, K. (2004) "Macro Stress-testing with a Macroeconomic Credit Risk Model for Finland", Discussion Paper 18/2004, Bank of Finland.

Wong, J., Choi, K. F., and Fong, T. (2006), "A Framework for Stress Testing Bank's Credit Risk", Research Memorandum 15/2006, Hong Kong Monetary Authority.

World Bank, 2000. *Global Economic Prospects and the Developing Countries*.