

Can macroeconomic indicators predict a currency crisis? Evidence from selected Southeast Asian countries

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Abstract: This paper examines the probability of currency crises using a signal approach and a multivariate probit model. The results indicate that the signal approach can provide an effective warning system despite its nonparametric nature. The top three indicators that are useful in anticipating crises include international reserves, stock market indices, and GDP, respectively. Excess money balances and the ratio of domestic credit to GDP are significant and have positive correlation with the probability of a crisis. The growth rate of exports and stock indices are significant and have a negative relationship with a crisis probability. Overall, the results indicate that government policies, the macroeconomic environment, and investor panic/self-fulfilling expectations all play a role in the making of a crisis.

Key words: Currency crises; forecasting; signaling model; probit model

JEL classifications: F33; F32; C32; G15

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1. Introduction

Perhaps the most dramatic exchange rate crisis in recent memory is the Asian crisis of 1997. Before the crisis, Southeastern Asian economies recorded impressive GDP growth rates, attracted significant short-term capital inflows, and offered sizable asset returns. Then suddenly, the economies that were the envy of many developing countries became vulnerable to panic, experiencing capital flight and a sharp downturn in asset prices. What started as a currency crisis in Thailand engulfed the entire region, sending these economies into a deep recession. For example, the Indonesian GDP contracted by more than 15 percent in 1998 and the Korean and Thai economies contracted by approximately 7 and 10 percent, respectively. As the crisis attracted considerable attention in the literature, two main views regarding the crisis have emerged. One view held by Radelet and Sachs (1998), Marshall (1998), and Chang and Velasco (1999), among others, attributes the crisis to shifts in market expectations, herd behavior, investor panic, and regional contagion more than the worsening of the underlying macroeconomic fundamentals.

Another view held by Davidson (2005), Dooley (1999), Corsetti, Pesenti, and Roubini (1998), among others, contends that the Asian crisis was the result of weak macroeconomic fundamentals and a poor institutional environment. According to this view, investor sentiment, herd behavior, and panic made a bad situation only worse. As the Asian crisis threatened growth of other emerging and transition economies, it is important to understand whether such crises emerge as a result of investor panic/ self-fulfilling prophecies or whether the underlying macroeconomic policies/environment is to blame.

Many authors stress the role of deteriorating economic fundamentals prior to currency crises. Kamin and Rogers (1996) point out that exchange rate based stabilization policies are useful in accelerating a disinflation process, but they typically lead to overvalued exchange rates and large current account deficits. These factors, in turn, make it difficult to sustain exchange rate pegs. The longer a disinflation program lasts, the dimmer will be memories of the cost of high inflation. Such developments make the stabilization programs increasingly reliant on a tight monetary policy. Under these circumstances, a tight monetary policy to protect the exchange rate requires a shift in the monetary reaction function, which makes the economy more vulnerable to adverse shocks. Frenkel (1997) further emphasizes that in the world in which capital markets are large, there are not enough official reserves to enable pegging at the wrong rate, and there is no exchange rate policy that can protect the economy from mistakes in economic fundamentals. Shimpalee and Breuer (2006) argue that institutional as well as economic factors affect the probability of currency crises. They find that worse institutions are associated with bigger contractions in output and corruption, a de facto fixed exchange rate regime, weak government stability, and weak law and order increase the probability of a currency crisis.

Indeed, the experiences of many developing countries indicate that fixed exchange rate regimes are vulnerable to crises, causing either sharp devaluations or regime shifts. The question is whether the potential causes and symptoms can be detected in advance allowing governments to adopt preemptive measures.

The primary objective of this paper is to empirically assess whether the Asian crisis was caused by a deterioration of identifiable economic fundamentals or by speculative pressures unrelated to the macroeconomic environment. To that end, we focus on assessing various indicators that can serve as an early warning system (EWS) for alternative explanations of the

Asian crisis. In examining the probability of a currency crisis, we use two alternative approaches, the signal approach and a multivariate probit model. We use quarterly data from five countries, namely Thailand, Malaysia, Indonesia, Philippines, and the Republic of Korea from 1975:1 to 1997:4 to assess whether there were warning signals prior to the Asian crisis. These countries are among the most adversely affected by the Asian crisis and the results should shed light on whether some observable macroeconomic indicators are useful in predicting a financial crisis. Section 2 of the paper details the data set and the sources while Section 3 outlines the methodology. Section 4 presents the empirical results, and the conclusions are presented in Section 5.

2. Data

There have been two popular methods of assessing the utility of early warning variables in predicting a currency crisis. A signaling method like that used by Kaminsky, Lizondo, and Reinhart (1998) focuses on a set of leading indicators that behave differently before a crisis and examines whether these variables reach a “threshold” value that historically can be associated with the beginning of a financial crisis. Another method due to Berg and Pattillo (1999) uses probit/logit models to test the statistical significance of some variables that can explain a financial crisis.

In this paper we use both the signaling and the probit/logit methodologies to assess whether some variables have explanatory power regarding the Asian crisis. Our choice of the 16 indicators is based on the prior literature and on the availability of quarterly data. The first fourteen of these indicators are suggested by Kaminsky-Lizondo-Reinhart (1998) and the other two indicators are by Berg and Pattillo (1999). Indicators are: 1) international reserves (in US dollars); (2) imports (in US dollars); (3) exports (in US dollars); (4) terms of trade; (5) deviations

of the real exchange rate from a deterministic time trend (in percentage terms); (6) real interest rate differential on domestic and foreign deposits; (7) excess real M1 balances; (8) the money multiplier of M2; (9) the ratio of domestic credit to GDP; (10) the real interest rate on deposits; (11) the ratio of nominal lending to deposit rates; (12) the ratio of broad money to gross international reserves; (13) an index of output (14) index of equity prices (measured in US dollars); (15) the level of M2 to reserves and (16) the ratio of current account to GDP. All indicators except (5), (7), and (10) are defined as the percentage change in the variables. The excess real M1 balances are defined as the residuals from a regression of real M1 balances on real GDP, inflation, and a deterministic time trend. The money multiplier of M2 is obtained from the ratio of M2 and monetary base. The monetary base is equal to the currency in circulation plus total reserve money, and total reserves are the sum of required reserves and excess reserves. The international reserves are the sum of gold, foreign exchange reserves, the reserve position at the IMF, and SDRs. The foreign country here is the United States.

As in Berg and Pattillo (1999), the current account is measured as a moving average of the previous four quarters. The percentage change of the consumer price index (CPI) is the index for inflation. The nominal exchange rate is the period average of the market exchange rate defined as home currency price of the U.S. dollar. The terms of trade is defined as the unit value of imports divided by the unit value of exports. The real exchange rate is defined on a bilateral basis with respect to the US dollar and the increase in the real exchange rate indicates real depreciation.

Most of the macroeconomic data have been taken from IMF data sources such as the International Financial Statistics CD-ROM. The quarterly data are obtained for five countries, Thailand, Malaysia, Indonesia, Philippines, and the Republic of Korea from 1975:1 to 1997:4.

The base year for all indices is 1995=100. Due to the limitation of the availability of the quarterly data, some data have been converted into quarterly data using the quadratic spline method. The monthly stock indices such as the stock exchange of Thailand (SET), the Korea composite stock price index (KOSPI), the Kuala Lumpur stock exchange composite index (KLSE) for Malaysia, the Jakarta composite stock price index (JCSPI) for Indonesia, and the Philippines stock exchange composite index (PSE) for Philippines are obtained from the World Stock Exchange Fact Book 1998. Due to the unavailability of data, the stock market data for Thailand and Malaysia start from 1975; Indonesia from 1977, Korea from 1976, and the Philippines from 1980. Since the unit value of imports and exports for Malaysia, Indonesia, and Philippines have not been reported in the International Financial Statistics, the terms of trade data for Malaysia, Indonesia, and Philippines are obtained from the World Tables 1994 published by the World Bank and the Key Indicators of the Developing Asian and Pacific Countries 1999-2003, published by the Asian Development Bank.¹

3. The Empirical Model

We first use the Kaminsky-Lizondo-Reinhart (KLR) signal approach to monitor several economic indicators that tend to exhibit unusual behavior prior to a crisis. The KLR signal approach is a nonparametric approach evaluating the usefulness of several variables in signaling a crisis. It is used to compare systematic behavior of variables in the period preceding a crisis with that in a control group. An indicator issues a signal whenever it moves beyond a given threshold level. Deviations of these variables from their normal levels beyond a certain threshold value are taken as warning signals of a currency crisis within a specified period of time. The indicators are used to capture the effect in seven categories: (1) the external sector; (2) the

¹ Since the data on unit value of imports for Indonesia are not available, the terms of trade series for Indonesia is calculated by normalizing import prices to one.

financial sector; (3) the real sector; (4) the public finances; (5) institutional and structural variables; and (6) contagion effect. Within this approach, it is possible to estimate the probability of a crisis conditional on the signal issued by the various indicators.

For each country, crises are identified (ex post) by the behavior of an index called the foreign exchange market pressure. This index is a weighted average of quarterly percentage changes in exchange rate and percentage changes in gross international reserves. The weights are chosen so that the two components of the index have the same conditional variance. Furthermore, a currency crisis is defined to occur when the index of exchange market pressure exceeds its mean by more than two standard deviations.² Each indicator can be assessed in terms of a matrix given in Table 1.

Table 1: The Signal Approach to Predicting a Currency Crisis

	Crisis within 24 months	No crisis within 24 months
Signal	<i>A</i>	<i>B</i>
No Signal	<i>C</i>	<i>D</i>

The cell in *A* represents the number of quarters in which the indicator issues good signals; cell *B* is the number of quarters in which the indicator issues bad signals or noises; cell *C* is the number of quarters in which the indicator fails to issue a signal but a crisis occurs, and cell *D* is the number of quarters in which the indicator fails to issue a signal and no crisis occurs. For each indicator, the KLR approach finds the optimal threshold, defined as that which minimizes the

² Unlike Berg and Pattillo (1999), we use quarterly data and two standard deviations to identify the currency crises because a measure of three standard deviations is too extreme in capturing signals in our sample. For countries in the sample that experienced very high inflation, the criterion for identifying the crises was modified. If a single level of the index had been used to identify these crises, sizable devaluations and reserve losses in the moderate inflation periods would not be identified as crises because the historic mean and variance would be distorted by the high inflation episodes. To avoid this problem, the sample was divided according to whether inflation in the previous six months was higher than 150 percent, and a different level of the index (based on different mean and variance) was used to identify crises in each sub-sample.

adjusted signal-to-noise ratio, $\left[\frac{B/(B+D)}{A/(A+C)} \right]$. However, according to Berg and Pattillo (1999)

since $(A+C)/(B+D)$ is a function of the frequency of currency crises and does not depend on the threshold, this amounts to minimizing the noise-to-signal ratio B/A . These criteria are used to rank the indicators according to their ability to predict crises while producing few false alarms. The persistence of each signal can be measured by the average number of signals per period. This is a method of evaluating the noisiness of indicators. Following Kaminsky (1998), the weighted sum based probabilities of the crisis is computed while each indicator is weighted by the inverse of its noise-to-signal ratio. Berg and Pattillo (1999) consider only good indicators with noise to signal ratio less than one. It can be interpreted as the predicted probability of crisis within the subsequent 24 months.³

When the dependent variables take values of zero and one, it is natural to ask what fractions of the observations are correctly called. A cut-off level is defined such that a crisis is predicted if the estimated probability is above this threshold. The threshold values are calculated so as to strike a balance between the risk of having many false signals and the risk of missing the crisis altogether. The optimal threshold is constrained to be the same across countries, and it minimizes the noise-to-signal ratio, which is calculated in terms of percentiles.⁴ Minimizing the noise-to-signal ratio for the sample of countries yields an optimal threshold percentile for each

³ Two issues regarding the treatment of missing data in the KLR framework need to be addressed. A key variable is crisis 24, which is defined to equal one if there is a crisis in the following 24 months or 8 quarters. This variable is defined as long as one observation is available in the relevant period. Secondly, the weighted sum based probabilities and the weighted sum of indicator signaling are calculated such that there is data at least in one of the indicators.

⁴ Thresholds are defined in relation to percentile of distribution of the indicators. For example, a possible set of country-specific threshold of the rate of growth exports would be calculated using grid reference percentiles between 10 percent and 20 percent. The optimum threshold is set to minimize the adjusted noise to signal ratio. For variables such as international reserves, exports, the terms of trade, the deviation of real exchange rate from trend, deposit rate, output, and the stock market index, for which a decline in variable increases the probability of the crises, the threshold is set below the mean of the indicator. For other variables, the threshold is above the mean of the indicator.

indicator that is the same for all countries. A pre-crisis period is correctly called when the estimated probability of crisis is above the cut-off probability and a crisis occurs within 24 months. A tranquil period is correctly called when the estimated probability of crisis is below the cut-off probability and no crisis occurs within 24 months. A false alarm occurs when an estimated probability of crisis is above the cut-off probability, but no crisis occurs within 24 months.⁵

To examine the predictability of crises, a standard multivariate panel probit model in which the dependent variable represents the choice between maintenance of the current exchange rate or a change to floating is used. The advantage of this approach is that it summarizes information about the likelihood of a crisis in a useful number, the probability of devaluation. It considers all of the variables simultaneously, and disregards those variables that do not contribute sufficient information. However, this method does not provide a ranking of indicators according to their ability to accurately predict crises and avoid false signals, since a variable either enters the regression significantly or it does not. The nonlinear nature of probit models makes it difficult to assess the marginal contribution of an indicator at a point in time to a probability of a crisis. Thus, it does not provide a transparent reading of where and how widespread the macroeconomic problems are. Nevertheless, using panel data has several advantages. First, the panel nature of the data permits the evaluation of the correlation of one time period to the next. Second, panel data usually provides an increased number of data points generating additional degrees of freedom, which presumably lead to more efficient estimation. Last, incorporating information relating to both cross-section and time series variables can substantially diminish the problems that arise when there is an omitted variable problem. The

⁵ The cut-off probabilities used by Berg and Pattillo (1999) are 25 percent and 50 percent, respectively.

multivariate panel probit model is a nonlinear model, precisely non-linear in parameters, which takes the form:

$$(1) \quad y_{it} = \beta' X_{it} + v_{it}, \text{ where}$$

$$y_{it} = \begin{cases} 1 & \text{if crisis within 24 months} \\ 0 & \text{otherwise} \end{cases}$$

and $\Pr(y_t = 1 | \mathbf{X}_t, \boldsymbol{\beta}_t) = F(\mathbf{X}_t, \boldsymbol{\beta}_t)$, where \mathbf{X}_t is a set of explanatory variables belonging to the information set of agents at time t , $\boldsymbol{\beta}_t$ is a vector of free parameters to be estimated, F is the cumulative normal distribution function, and y_t is a dummy of crisis series.

The binary dependent variable captures the change in policy. It is set to one in the case of devaluation and zero otherwise. As the actual number of devaluations for each country is relatively small, data are pooled across countries and over time. The analysis proceeds in three steps. First, fundamental macroeconomic factors, which have played a crucial role in triggering exchange rate crises, are identified. Second, the weighted average of the significant fundamentals is calculated. This measure is viewed as an index of macroeconomic performance from which the probabilities of devaluation can be derived. Assuming uncovered interest parity, the probabilities of devaluation are used to calculate the predicted size of devaluation, which will be used to compare with actual devaluations. Given the discrete binary dummy as an endogenous or dependent variable, the estimation of the ordinary least square (OLS) and the two-stage least square (2SLS) are not appropriate. Since the probit model is a nonlinear model, precisely non-linear in parameters, the model faces misspecification and heteroscedasticity problems. The consequences of misspecification in models estimated by maximum likelihood appear to be straightforward. If we maximize the correct likelihood function, we get consistent estimates. If

we maximize the wrong function, we get biased estimates. Estimates for β_t are found by recursively maximizing the log likelihood function given by

$$(2) \ln(L_t) = \sum_{\{y_j=1, j \leq t\}} F(X_j, \beta_j) + \sum_{\{y_j=1, j \leq t\}} [1 - F(X_j, \beta_j)]$$

The joint density of y_{it} is given by⁶: $\prod_{i=1}^N \prod_{t=1}^t \left[1 - F\left(\frac{-\beta' x_{it}}{\sigma_v}\right) \right]^{y_{it}} \left[F\left(\frac{-\beta' x_{it}}{\sigma_v}\right) \right]^{1-y_{it}}$

An estimate obtained from maximizing an incorrect likelihood function is often referred to as a quasi-maximum likelihood (QML) estimate. According to Johnston and Dinardo (1997), the MLE is consistent even in the face of heteroscedasticity, non-normal errors, and serial correlation as long as $\text{plim} (1/N)X'\varepsilon = 0$. Heteroscedasticity does not generate an inconsistent $\hat{\beta}$, but the standard errors will have to be modified to account for the misspecification. However, in a probit or logit model, any misspecification of the likelihood function will result in inconsistency. White (1982) showed that even when the model is misspecified, under suitable conditions, the estimator $\hat{\beta}$ that is the solution to the maximization of the likelihood converges to some parameter β^* . In particular, $\hat{\beta}$ is distributed asymptotically normally with a covariance matrix Ω .

It is known in forecasting that a leading indicator is only as good as the rule used to interpret its movements. The rules that yield early warning would minimize false alarms. This is analogous to the construction of statistical tests that measures type I and type II errors. The leading indicators can be evaluated based on a number of attributes, including accuracy, calibration, and resolution. Accuracy refers to the closeness, on average, of predicted

⁶ See Pindyck and Rubinfeld (1998) for details.

probabilities and observed realizations. Berg and Pattillo (1999) use three methods to evaluate the accuracy of probability forecasts, which are the mean squared error (MSE), the quadratic probability score (QPS), and log probability score (LPS). Let $P_t = Prob(C_{t,t+8})$ be the probability of a crisis within 8 quarters (24months) and $R_t = 1$ if a crisis occurs within 24 months and equal to zero otherwise. Then

$$(3) \quad QPS = \frac{1}{T} \sum_{t=1}^T 2(P_t - R_t)^2$$

$$(4) \quad LPS = \frac{1}{T} \sum_{t=1}^T [(1 - R_t) \ln(1 - P_t) + R_t \ln(P_t)]$$

The QPS ranges from 0 to 2, with a score of 0 corresponding to perfect accuracy. The LPS is another accuracy-scoring rule while it ranges from 0 to ∞ , with a score of 0 corresponding to perfect accuracy. The LPS depends exclusively on the probability forecast of the event that actually occurred, and it is a fully general scoring rule as large mistakes are heavily penalized compared to QPS . The calibration of probability forecasts refers to closeness of forecast probabilities and observed relative frequencies. Overall, forecast calibration is measured by the global squared bias, GSB :

$$(5) \quad GSB = 2(\bar{P} - \bar{R})^2$$

where $\bar{P} = \frac{1}{T} \sum_{t=1}^T P_t$ and $\bar{R} = \frac{1}{T} \sum_{t=1}^T R_t$. The GSB ranges from 0 to 2, with $GSB = 0$ corresponding to

perfect global calibration, which occurs when the average probability forecast equals the average realization. Resolution (RES) measures the extent to which different forecasts are followed by different realizations. The RES is a weighted average of squared deviations of mean cell realization from the grand mean, where the weights are given by the number of probability forecasts falling within each cell:

$$(6) \quad RES = \frac{1}{T} \sum_{j=1}^J 2T^j (\bar{R}^j - \bar{R})^2$$

where $j=1,2,3,\dots,J$ cells with T^j forecasts in each cell ($\sum T^j = T$) and \bar{R}^j is the average realization of turning points associated with these forecasts. High *RES* implies that on average different forecasts tend to be followed by different realizations. That is, there is discriminating predictive information.⁷ Canova (1994) introduces another statistic, the number of incorrect cases (*INCORRECT*). The number of incorrect cases shows how many times the model fails to predict with at least 50 percent probability the events that actually occur. It roughly measures the performance of the models when a 50 percent cut-off probability rule is used. A concentration of incorrect cases at the crisis dates indicates a failure of the model.

4. Empirical Results

The effectiveness of the signal approach can be examined at the level of individual indicators and at the level of a set of indicators. At the level of individual indicators, each indicator provides some useful information in anticipating crises, and when all indicators are grouped together in the prediction, the results tend to indicate the average probability of the crises. In the process of examining the effectiveness of individual indicators, an ideal indicator would only issue the signal when there is the crisis in its time span, so that $A > 0$ and $C = 0$, and it would refrain from issuing a signal in the quarter that is not followed by crisis, so that $B = 0$ and $D > 0$. In an ideal world, the indicators fit the data perfectly; however, this is not the case and we can only try to assess how close these indicators can predict the outcomes; see Kaminsky, Lizondo and Reinhart (1998), p.19.

⁷ See Diebold and Rudebusch (1989) for details.

Information regarding the success of each indicator is presented in Table 2. The column labeled “Index” shows the variables used, and the star indicates an inverse relationship between the indicator and the probability of the crisis.⁸ The ranking of these indicators is presented in the next column. Unsurprisingly, the percentage change of international reserves is the best indicator followed by the movement in stock indices and the percentage change in GDP. The ranking in Table 2 is based on the adjusted noise to signal ratio. Lower adjusted noise to signal is better because the indicator is less noisy. The second column in Table 2 shows the optimum threshold percentiles that minimize the adjusted noise to signal ratio. The third indicates the percentage of observations correctly called under the signal approach. Again, international reserves tend to have the highest percentage of observations called, followed by terms of trade, and GDP. These are followed by stock market performance and developments in the real exchange rate.

The fourth column in Table 2 shows the good signals as the percentage of possible good signals ranging from 23 percent to 91 percent. This is another measure of the propensity of the indicators to issue good signals. The ratio of the current account to GDP has the highest good signals in terms of all possible good signals whereas the real exchange rate deviation from trend has the lowest measure. The following column gives the percentage bad signals in terms of all possible bad signals. Overall one would like this number to be smaller. The best performer here is terms of trade and the worst is current account/GDP ratio. The sixth column in Table 2 is the adjusted noise to signal ratio, which measures the noisiness of indicators. Clearly, the lower the ratio, the better is the signal. The international reserves have the lowest adjusted noise to signal

⁸ The growth rate of imports, the growth rate of exports, the ratio of current account to GDP, and the terms of trade are indicators that represent the external sector and also indicate trade competitiveness. The ratio of lending rate to the deposit rate and the growth in the M2 multiplier are indicators of financial liberalization. The interest rate differential is the indicator related to capital account and capital mobility. The ratio of domestic credit to GDP represents the wealth effect. Excess money balances and the growth rate of international reserves show the state of monetary policy. The ratio of M2 to international reserves and the ratio of M2 to total reserves represent financial conditions. The stock index represents the equity market. GDP and the real interest rate are indicators for the real sector.

ratio of 0.51, and the real exchange rate deviation has the highest adjusted noise to signal ratio of 1.19. The adjusted noise to signal ratio can also be used as a criterion in the prediction of probability of the crises. It is important to notice that when a signaling device issues signals at random times, the adjusted noise to signal ratio will be equal to unity. Therefore, those indicators with an adjusted noise to signal ratio equal to or higher than unity introduce excessive noise, and so are not helpful in predicting crises. The next two columns show the probability of the crises given signals and the marginal probability of the crises. The deviation of probability of the crises given signal and the probability of the crises is shown in the last column of Table 2. The positive sign in this column indicates the over prediction of the crisis probability, and vice versa. Furthermore, the magnitude indicates the closeness of the probability signaling and the overall probability of the crises. In terms of performance, the variables in Table 2 only marginally improve our understanding of crises and those with a negative sign in the last column should be dropped altogether.⁹

Up to this point, the discussion has focused on the ability to predict crises while producing few false alarms. However, policymakers who want to implement preemptive measures would need to know how leading these indicators are. The results in Table 2 do not distinguish between a signal issued a year prior to a crisis and one issued a quarter prior to a crisis. To examine this issue, we measure the average number of quarters in advance of the crisis when the first signal occurs; this, of course, does not preclude the fact that the indicator may continue to give signals to the entire period immediately preceding the crisis. The results are presented in the third column of Table 3. Indeed, on average, these indicators send the first signal

⁹ We also repeated the signal approach for five individual countries, which are Thailand, Malaysia, Indonesia, Korea, and Philippines respectively. Our results indicate different ranking of indicators across countries; however, most of them share some common characteristics such as the stock market index and the international reserves are among the best indicators, and the real exchange rate deviation shows excessive noise in all countries. These results are available upon request.

anywhere between 5 months to 2.5 years before a crisis erupts. Some of the indicators send signals well above others such as the ratio of current account to GDP, the ratio of M2 to international reserves, and excess money balances. Another desirable feature of the leading indicator is the persistence of the signals. The concept of persistence is another way of looking at the noisiness of the indicators. Persistence is measured by the inverse of the adjusted noise to signal ratio. Our results show that the persistence of the indicators ranges between 3 to 7 months.

So far we have examined the ability of the models to predict the approximate timing of crises for each country. We can also evaluate the cross-sectional success of the models in identifying whether these countries are vulnerable in periods such as the 1997 global financial turmoil. Table 4 represents the results of probit based alternatives. Model 1 is the original model that uses all variables suggested by Kaminsky, Lizondo and Reinhart (1998), and the results show that some of the variables are insignificant.

Model 2 is the result after performing a specification test, namely the Wald test. So far, the multivariate panel probit model is based on the assumption that the intercept terms are constant across countries, which tends to be unrealistic. Model 3 is specified such that each country has a separate dummy variable. The results show that this country dummy is highly significant therefore the intercept tends to be different across countries according to the *fixed effect* model. Model 4 confirms the result of Model 3 even if the ratio of current account to GDP is used instead of the percentage change in this variable. The modification is suggested by Berg and Pattilo (1999) because it is a more common use of current account to GDP in crisis literature than the percentage change of this variable. Our results indicate the improvement of the model prediction due to lower Akaike information criterion (AIC) and higher adjusted pseudo-R². Model 5 uses original variables and includes a country dummy to capture country specific

effects. Model 6 uses variables suggested by Berg and Pattilo (1999) including a country dummy. Our results show that Model 6 tends to be the best fit according to the AIC and adjusted pseudo-R².

It is important to mention that the estimated coefficients do not indicate the increase in the probability of a crisis, given a unit increase in the corresponding variable. The amount of the increase in probability depends on the original probability and the initial values of all the independent variables and their coefficients. Specifically, $\frac{\partial P_i}{\partial x_{ij}} = f(x_i' \beta) \beta_j$ where x_{ij} is the j th element of x_i . The probability of a crisis is

$$(7) \quad P_i = \int_{-\infty}^{x_i' \beta} \frac{1}{\sqrt{2\pi}} \exp\left(-\frac{t^2}{2}\right) dt$$

The predicted probabilities are reported in Table 5.

Table 5 summarizes the probability of the 1997 currency crisis under two different methods. Under the signal approach the probability of the currency crisis ranges from 29 percent to 51 percent, but the probit model shows significantly lower probability. The average probability of the crisis from the pooled samples shows 32.47 percent in the signal approach and 19.48 percent in the probit model. Since the two methods show different results, it is common to ask how good these forecasts are. Given the non-statistical nature of the signal approach, it is somewhat difficult to evaluate its success compared to the alternative probit model. However, we can still measure the sample assessment in three criteria including accuracy, calibration, and resolution. The probit model tends to be very accurate because of low mean square error, low quadratic probability score, and low log probability score. Also, both the signal approach and the probit model have low global square bias, but the probit model has lower global square bias. It is easy to notice that the estimated probabilities from the signal approach are quite higher than

those of the probit model. Comparing the global square bias, small changes in the bias lead to large changes in the estimated crisis probability. Therefore, the estimated probability is very sensitive to the estimation method, but the probit model tends to outperform the signal approach with lower bias. However, there is no significant change in the country's ranking between these methods.

The signal approach generates a variety of different ways to forecast 1997 outcomes. First, we can see which indicators send signals prior to the crisis. The KLR-based forecasts are somewhat successful at ranking countries by severity of crisis. The actual rankings of countries are significantly correlated with the forecasts from the weighted-average of indicator-based probabilities. The weighted probabilities are calculated from good indicators with adjusted noise to signal ratio less than one. The weight is the inverse of the adjusted noise to signal ratio. The average probabilities of the 1997 currency crisis for each country are shown in the first column of Table 5. If we rank countries based on the weighed probabilities of the crisis from high probability to low probability, they are Indonesia, Thailand, Philippines, Malaysia, and Korea, respectively.

Table 6 shows the predicted devaluations and the actual devaluations around the 1997 currency crisis. Calculations are based on the probability of devaluation/regime shifts and the uncovered interest rate parity condition. Let i^d denote the annualized short-term interest rate differential between the home country and the United States, p the probability of devaluation and d the size of devaluation, if it occurs. The quarterly devaluation approximately equals the following relationship: $p \times d = (1 + i^d)^{1/4} - 1$.

The uncovered interest rate parity condition implies that there is no risk premium. The rankings of the predicted devaluation and the actual devaluation are somewhat different, and they

are also different from the ranking of the probability of devaluation that we observed earlier. The predicted devaluations tend to be larger than the actual devaluations. Here, there are some interesting results because one would expect the actual devaluation to be larger than the predicted devaluation due to factors unrelated to economic fundamentals such as risk premiums and speculative pressure. Since our model includes the stock indices that capture part of speculative attack in the model, the results seem to be unexpected. However, this phenomenon can be explained by the implementation of monetary policy to counter the devaluation pressure. As a result, the actual devaluation becomes smaller than the predicted one because it is partly mitigated by preemptive policies.

5. Conclusions

This paper has examined the probability of a currency crisis using two alternative approaches, the signal approach and a multivariate probit model. Both techniques can predict the event with little bias. However, it is hard to judge which method is better because both of these methods have bias less than one percent. The signal approach predicts probability of the crisis 10% - 20% higher than that of the probit model. These probability predictions tend to be sensitive to the method used for estimation, but they share some common characteristics such as the country rankings of the crisis probabilities.

Our results indicate that the signal approach can provide a warning system despite its nonparametric nature. This system is based on monitoring the behavior of a number of indicators and recording the signals issued by these indicators as they move beyond certain threshold levels. A broad variety of indicators detect symptoms that arise in a number of areas. Since a variety of indicators represent different sources of the problem, they would provide the underlying information reflecting the probability of a crisis. The top three indicators that are

useful in anticipating crises include international reserves, stock indices, and GDP, respectively. The average lead time of signals is between three months to seven months, and most indicators send signals in the range of seven months to three years before the actual crisis occurs.

The statistical nature of the probit model allows us to perform specification tests to select variables that significantly contribute to crisis probabilities. The country dummy variables in the probit model are significant and successfully capture country specific effects. However, the probit model cannot provide the inside information about the average lead time and it is difficult to measure the persistence of individual indicators, but the probit model can predict the probability of a crisis like the Asian crisis with little bias.

It is important to mention that there is a significant portion of crisis probabilities that cannot be explained by economic fundamentals. This portion might be driven by non-economic motives such as self-fulfilling expectations, and/or institutional structures. This is in line with Shimpalee and Breuer (2006) who find that worse institutions are associated with bigger contractions in output and corruption, a de facto fixed exchange rate regime, weak government stability, and weak law and order increase the probability of a currency crisis. Nevertheless, our results show that reserve imbalance, the speculative pressure and the problems in the real sector have contributed considerably to the Asian crisis.

We find that excess money balances and the ratio of domestic credit to GDP are significant and have positive correlation with the probability of a crisis. The growth rate of exports and stock indices are significant having a negative relationship with a crisis probability. Interestingly, higher crisis probabilities do not always imply larger devaluations. The predicted devaluation depends not only on the probability of devaluation but also on the interest rate

differences. Overall, the results indicate government policies, the macroeconomic environment, and investor panic/ self fulfilling expectations all play a role in the making of a crisis.

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Table 2. Pooled sample performance of indicators under the signals approach

Index	Rank	Threshold percent	Correctly called ^a	$A/(A+C)^b$	$B/(B+D)^c$	$B/(B+D) \div A/(A+C)^d$	$P(\text{crisis} \text{signal})^e$	$P(\text{crisis})^f$	$P(\text{crisis} \text{signal}) - P(\text{crisis})$
1. Int. Reserves*	1	17%	68%	0.60	0.31	0.51	0.31	0.18	0.12
2. Imports	17	15%	32%	0.62	0.75	1.21	0.16	0.18	-0.03
3. Exports*	4	10%	58%	0.39	0.28	0.72	0.52	0.44	0.08
4. Terms of trade*	7	11%	67%	0.27	0.24	0.88	0.20	0.18	0.02
5. Real exchange rate dev.*	16	11%	63%	0.23	0.28	1.19	0.16	0.18	-0.02
6. Real interest rate diff.	15	18%	45%	0.56	0.58	1.03	0.18	0.18	0.00
7. Excess money	10	18%	31%	0.90	0.82	0.91	0.20	0.18	0.01
8. Money multiplier of M2	12	16%	35%	0.82	0.76	0.93	0.20	0.18	0.01
9. Domestic credit /GDP	14	20%	38%	0.68	0.69	1.01	0.18	0.18	0.00
10. Real interest rate*	13	10%	49%	0.77	0.74	0.95	0.45	0.44	0.01
11. Lending rate/deposit rate	5	20%	44%	0.76	0.63	0.83	0.21	0.18	0.03
12. M2/Int. Reserves	8	10%	51%	0.87	0.77	0.89	0.47	0.44	0.03
13. GDP*	3	12%	66%	0.40	0.29	0.71	0.24	0.18	0.06
14. STOCK*	2	20%	63%	0.61	0.36	0.59	0.28	0.18	0.09
15. Current Acc./GDP	11	11%	30%	0.91	0.84	0.92	0.20	0.18	0.01
16. M2/ Total Reserves	6	10%	51%	0.89	0.77	0.87	0.47	0.44	0.03
17. Real lending/deposit rate	9	18%	33%	0.88	0.79	0.90	0.20	0.18	0.02

* indicates the threshold below the mean level

^a Percentage of observations correctly called under signal approach.

^b Good signals as percentage of possible good signals; $A/(A+C)$.

^c Bad signals as percentage of possible bad signals; $B/(B+D)$.

^d Adjusted noise-signal ratio; $[B/(B+D)]/[A/(A+C)]$

^e Percentage of signals that were followed by at least one crisis within the subsequent window (24 months) = $A/(A+B)$.

^f The unconditional probability of a crisis; that is, $(A+C)/(A+B+C+D)$.

Table 3. Persistence of signals and average lead time

Index	Persistence	Lead time (quarters)
1. Int. Reserves*	1.95	1.82
2. Imports	0.83	2.82
3. Exports*	1.39	3.35
4. Terms of trade*	1.13	1.71
5. Real exchange rate dev.*	0.84	3.50
6. Real interest rate diff.	0.97	3.90
7. Excess money	1.10	8.00
8. Money multiplier of M2	1.08	4.94
9. Domestic credit /GDP	0.99	3.87
10. Real interest rate*	1.05	7.71
11. Lending rate/deposit rate	1.21	5.08
12. M2/Int. Reserves	1.13	9.36
13. GDP*	1.40	2.60
14. STOCK*	1.69	2.81
15. Current Acc./GDP	1.09	10.30
16. M2/ Total Reserves	1.15	7.71
17. Real lending/deposit rate	1.11	6.19

Note: * indicates the threshold below the mean level

Table 4. Multivariate Panel Probit Model

Variable	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Constant	-2.7797 [-8.6149]	-2.7264 [-8.7207]	-2.6746 [-8.3710]	-2.6269 [-8.2523]	-3.2896 [-7.3031]	-5.4925 [-6.2257]
1. GINTRES	-1.7396 [-1.3485]	-2.0013 [-3.0491]	-2.1937 [-3.1806]	-2.0219 [-2.8997]		
2. GIMPORTS	0.1813 [0.2236]					
3. GEXPORTS	-1.8396 [-1.9948]	-1.6909 [-2.0112]	-1.8867 [-2.1726]	-1.9896 [-2.2655]	-1.8776 [-2.1394]	-1.9854 [-2.161]
4. GTOT	-0.4066 [-0.1332]					
5. GDQT	0.0001 [0.1450]					
6. RDRD	-0.1687 [-6.1793]	-0.1655 [-6.2495]	-0.1690 [-6.3035]	-0.1583 [-5.7895]	-0.1946 [-7.0413]	-0.1589 [-5.5537]
7. EXCESSRM1	0.0077 [1.7474]	0.0084 [1.9618]	0.0090 [2.1015]	0.0092 [2.1310]	0.0097 [2.1942]	0.0081 [1.8446]
8. GM2MB	-2.8493 [-0.7232]					
9. GDCGDP	0.3819 [0.3619]					1.9607 [1.6506]
10. RDR	0.2262 [6.7281]	0.2242 [6.8432]	0.2433 [7.0754]	0.2267 [6.4214]	0.2512 [7.0270]	0.2185 [5.7324]
11. GLRDR	1.1789 [1.4954]		1.3763 [1.7487]	1.3397 [1.6870]	1.2937 [1.6647]	1.4001 [1.6901]
12. GM2INTRES	0.2510 [0.2041]					
13. GGDP	1.7766 [1.2520]	1.4928 [1.7718]	1.9424 [2.2128]	2.0023 [2.2687]	1.5655 [1.8038]	3.9032 [2.4772]
14. GSTOCK	-1.4074 [-1.9519]	-1.2766 [-1.8664]	-1.3906 [-2.0017]	-1.1564 [-1.6509]	-1.6707 [-2.3280]	-1.3729 [-1.8092]
15. CAMAGDP				-0.0969 [-2.1202]		-0.4832 [-3.9146]
16. GM2TOTRES	2.2473 [0.6775]					
17. GCAMAGDP	-0.0991 [-1.0276]				-0.1580 [-1.5964]	
18. CDUMMY			-0.1432 [-2.1724]	-0.1493 [-2.2570]		
19. D1					0.4736 [1.6409]	1.6918 [3.1340]
20. D2					0.2229 [0.6971]	2.6327 [3.2807]
21. D3					0.6414 [2.3651]	2.9401 [3.8048]
22. D4					-0.1117 [-0.3793]	2.1348 [2.7500]
AIC	0.8256	0.7927	0.7846	0.7782	0.8045	0.7465
LR statistic	99.46	95.00	102.33	106.95	100.12	126.02
Prob(LR stat)	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Pseudo R-squared	0.2452	0.2342	0.2523	0.2637	0.2468	0.3107

Variables 1-16 are defined as in Table 2 except a G at the beginning of a variable indicates percentage change instead of the level of that variable. Variable 17 is the growth in the Current Account/GDP ratio. Variable 18 is a country dummy which takes the value 0 for Thailand, 1 for Malaysia, 2 for Indonesia, 3 for Korea, and 4 for the Philippines. Variables 19-22 are separate country dummy variables where $D_i = 1$ for the corresponding country and zero otherwise, where $i = (\text{Thailand, Malaysia, Indonesia, Korea})$. t-statistics are given in parentheses.

Table 5. Average probability of a currency crisis under the signaling and probit models

	Probability (KLR)	Probability (Probit)
All countries	0.3247	0.1948
Thailand	0.3155	0.2101
Malaysia	0.2978	0.1258
Indonesia	0.5156	0.3145
Korea	0.2960	0.1358
Philippines	0.3061	0.1877
MSE	NA	0.1915
QPS	NA	0.2193
LPS	NA	0.3393
GSB	0.0062	0.0001
RES	NA	12.8710
INCORRECT	0.5032	0.1600

Table 6. Predicted devaluation under the uncovered interest parity and actual devaluation

Country	Predicted devaluation (KLR)	Predicted devaluation (probit)	Actual devaluation	Predicted ex. rate (KLR)	Predicted ex. rate (probit)	Actual exchange rate	Ranking
Thailand	0.94	1.41	1.08	50.15	62.31	53.81	4
Malaysia	1.06	2.50	0.76	5.16	8.79	4.41	3
Indonesia	4.02	6.58	2.96	12226.73	18484.87	9662.50	1
Korea	1.52	3.32	0.91	2250.65	3852.43	1701.53	2
Philippines	0.64	1.04	0.62	43.15	53.74	42.66	5