5

An Assessment of Vulnerability: Out-of-Sample Results

As emphasized in chapter 1, predicting the timing of currency and banking crises is likely to remain an elusive task for academics, financial market participants, and policymakers. Recent events, however, have highlighted the importance of improving upon a system of early warnings. In this chapter, we apply the signals approach to several out-of-sample exercises using data for January 1996 through June 1997. Besides providing an assessment of the model's out-of-sample performance, this exercise may shed light on why most analysts did not foresee the Asian crisis.

In the first exercise, we look at measures across countries of crisis vulnerability (e.g., total number of signals, proportion of indicators signaling, and the number of top indicators signaling). But this exercise does not weigh the signals according to the relative track record of the indicators issuing the signal, or it only does so in a very approximate way. The second exercise extends the cross-country analysis by adjusting the threshold for each indicator so as to include more borderline signals in our measure of vulnerability. A third exercise weighs the indicators by the inverse of their noise-to-signal ratio to generate a series of cross-country vulnerability ratings for both currency and banking crises. In yet a fourth exercise, we construct a composite indicator to map the time-varying probability of crisis; we compare its in- and out-of-sample performance to that of a naive forecast and the best of the univariate indicators. Finally, our last exercise focuses on the time-series dimension by mapping out the probability of crises for four Asian countries over the January 1996-December 1997 period.

Needless to say, such exercises are fraught with the traditional Type I and Type II errors. Assume that the null hypothesis is that the economy

is in a state of ''tranquility.'' If a high proportion of indicators are flashing, then one could reject that hypothesis in favor of the alternative—namely, that a crisis is likely in the next 24 months. Yet even though a country may be vulnerable, in the sense that a high proportion of variables are signaling trouble, the crisis may be averted through either good luck, good policies, or credible implicit bailout guarantees. This would be an example of a Type II error (rejecting the null hypothesis when it is true). A recent example of this case is Brazil, in which multiple signals were flashing as early as 1997, but these warning signs did not culminate in a full-fledged crisis until 1999. Alternatively, the crisis may occur without much warning from the indicators; this is a Type I error (failing to reject the null hypothesis when it is false). Borrowing a phrase from Sherlock Holmes, such a situation can be regarded as ''the dog that did not bark in the night'' and could be interpreted as evidence of contagion or multiplicity of equilibriums, an issue that we take up in chapter 6 and one that is particularly relevant for understanding the Indonesian crisis.

Vulnerability and Signals

Table 5.1 shows how our 25 sample countries compare on vulnerability to currency crises over the June 1996-June 1997 period, using several simple measures of vulnerability. The first column shows the total number of signals from among the 15 monthly indicators listed in table 3.1 that ''flashed'' during the period. The next column indicates how many of the 15 indicators sent signals, while the third data column lists the number of ''top five'' indicators sending signals. (For banking crises, these are real exchange rates, stock prices, the money multiplier, output, and exports, and for currency crises, they are real exchange rates, stock prices, exports, M2/reserves, and output.). The next set of columns give the comparable information for the eight annual indicators. In this case, we focus on the ''top three'' indicators. (For banking crises, the share in GDP of short-term capital inflows, current account balance as a share of investment, and the overall budget deficit as a share of GDP, and for currency crises, they are the current account balance as a share of GDP, the current account balance as a share of investment, and the overall budget deficit as a share of GDP.) The last column gives the percentage of the 23 indicators that are signaling. The reason to highlight the number of top indicators signaling is that these are the indicators with the lowest noise-to-signal ratios; hence a signal from these is more meaningful than a signal from a less reliable indicator.

Table 5.1 provides this information for currency crises using the thresholds reported in table 3.2. There is considerable cross-country variation, with the lowest proportion of signals coming from Egypt and the highest

Table 5.1 Signals of currency crises, June 1996-June 1997

	Monthly indicators			Annual indicators			Total
Country	Total signals	Number of indicators signaling	Top indicators signaling	Total signals	Number of indicators signaling	Top indicators signaling	Percentage of indicators signaling
Argentina	35	3	1	2	2	0	22
Bolivia	33	6	2	0	0	0	26
Brazil	37	5	3	0	0	0	22
Chile	34	2	1	1	1	0	13
Colombia	27	5	1	3	3	0	35
Czech Republic	77	10	3	4	2	2	52
Denmark	21	3	1	1	1	0	17
Egypt	14	3	2	0	0	0	13
Finland	74	7	1	2	2	0	39
Greece	32	8	2	3	2	0	43
Indonesia	6	3	1	1	1	0	17
Israel	24	4	1	1	1	0	22
Malaysia	36	9	3	0	0	0	39
Mexico	11	2	0	2	2	0	17
Norway	9	3	0	1	1	0	17
Peru	16	2	0	1	1	0	13
The Philippines	59	8	1	2	2	0	43
South Africa	42	8	3	1	1	0	39
South Korea	32	8	3	3	3	0	48
Spain	44	6	2	1	1	0	30
Sweden	55	5	1	1	1	0	26
Thailand	50	6	3	1	1	1	30
Turkey	22	4	1	3	3	0	30
Uruguay	58	5	0	1	1	0	26
Venezuela	18	5	2	1	1	0	26

from the Czech Republic, which indeed floated following a speculative attack and substantial reserve losses in May 1997.

Table 5.2 repeats the same accounting exercise, but here we include "borderline" signals. Specifically, we enlarged the size of the rejection region by 5 percent for all the indicators. For instance, instead of having a 10 percent threshold for stock prices, we now have a 15 percent threshold. This sensitivity analysis increases the likelihood of making a Type II error (rejecting the null hypothesis of tranquility when you should not) while reducing the probability of a Type I error (not rejecting when you should). Including borderline signals does not seem to generate large shifts in the most and least vulnerable groups. As shown in the last column in table 5.2, borderline signals do not alter the picture at all for some countries (such as Argentina), but they do markedly increase the proportion of indicators signaling, as well as the number of signals, for countries such as South Korea (from 48 to 65 percent) and South Africa (from 39 to 52 percent).

Tables 5.3 and 5.4 report the results for banking crises using the original thresholds and the "borderline" scenario, respectively. The country profiles that emerge are similar to those for currency crises; this may reflect the fact that several of the indicators have common thresholds for currency and banking crises.

While conveying useful information on vulnerability, the preceding analysis does not fully discriminate between the more and less reliable indicators. Kaminsky (1998) shows how to construct a "composite index" to gauge the probability of a crisis conditioned on multiple signals from various indicators; the more reliable indicators receive a higher weight in this composite index. This methodology and its out-of-sample results are described in the remainder of this chapter.

In weighting individual indicators, a good argument can be made for eliminating from our list of potential leading indicators those variables that had a noise-to-signal ratio above unity; this is tantamount to stating that their marginal forecasting ability, $P(C|S) - P(C)$, is zero or less. Applying this criterion to banking crises, the lending-deposit ratio, the terms of trade, government consumption growth, and FDI as a share of GDP should be dropped. For currency crises, the excluded indicators are the domestic-foreign interest rate differential, the lending-deposit ratio, bank deposits, central bank credit to the public sector, and FDI as a share of GDP. For the remaining indicators with noise-to-signal ratios below unity, we weighed the signals by the inverse of the noise-to-signal ratios reported in tables 3.1 through 3.4. For a currency crisis, suppose that both the real exchange rate and imports are issuing a signal. Because the real exchange rate has a very low noise-to-signal ratio (0.22), it would receive a weight of 4.55 (i.e., 1/0.22); in contrast, with a relatively high noise-to-signal ratio (0.87), imports would receive a weight of only 1.49 (i.e., 1/0.87).

Table 5.2 Borderline signals of currency crises, June 1996-June 1997

Country	Monthly indicators			Annual indicators			Total
	Total signals	Number of indicators signaling	Top indicators signaling	Total signals	Number of indicators signaling	Top indicators signaling	Percentage of indicators signaling
Argentina	35	3	0	2	2	0	22
Bolivia	33	8	2	0	0	0	35
Brazil	39	7	3	0	0	0	32
Chile	40	5	2	1	1	0	26
Colombia	49	7	3	3	3	0	43
Czech Republic	85	10	3	4	2	2	61
Denmark	28	5	1	2	2	0	30
Egypt	22	3	2	1	1	0	17
Finland	86	8	1	3	2	1	43
Greece	41	8	3	3	3	0	48
Indonesia	9	4	3	1	1	0	22
Israel	37	6	3	1	1	0	30
Malaysia	40	9	3	0	0	0	39
Mexico	24	2	0	2	2	0	17
Norway	31	7	2	1	1	0	35
Peru	26	5	1	2	2	0	30
The Philippines	68	8	3	3	3	0	48
South Africa	63	10	3	2	2	0	52
South Korea	63	11	3	5	4	1	65
Spain	55	7	2	1	1	0	35
Sweden	60	6	1	1	1	0	30
Thailand	54	6	3	1	1	1	30
Turkey	33	5	3	3	3	0	35
Uruguay	71	5	1	1	1	0	26
Venezuela	29	5	2	1	1	0	26

Table 5.3 Signals of banking crises, June 1996-June 1997

	Monthly indicators			Annual indicators			Total
Country	Total signals	Number of indicators signaling	Top indicators signaling	Total signals	Number of indicators signaling	Top indicators signaling	Percentage of indicators signaling
Argentina	36	4	0	1	1	1	22
Bolivia	42	8	2	0	0	0	35
Brazil	39	6	2	0	0	0	26
Chile	34	2	1	1	1	0	13
Colombia	38	5	2	3	3	1	35
Czech Republic	81	10	3	4	2	1	52
Denmark	24	4	0	1	1	0	22
Egypt	18	3	0	0	0	0	13
Finland	77	7	1	3	2	1	39
Greece	39	8	3	2	2	1	43
Indonesia	10	3	2	1	1	1	17
Israel	32	6	3	1	1	0	30
Malaysia	42	9	3	0	0	0	39
Mexico	16	4	1	2	2	0	26
Norway	30	8	2	1	1	0	39
Peru	19	5	1	1	1	0	26
The Philippines	59	8	3	2	2	0	43
South Africa	55	10	3	1	1	0	43
South Korea	42	10	4	3	3	1	57
Spain	51	7	1	1	1	0	35
Sweden	59	5	1	1	1	0	26
Thailand	53	6	2	1	1	1	30
Turkey	27	5	3	2	2	0	30
Uruguay	74	5	1	1	1	0	26
Venezuela	18	4	1	2	2	0	26

Table 5.4 Borderline signals of banking crises, June 1996-June 1997

Country	Monthly indicators			Annual indicators			Total
	Total signals	Number of indicators signaling	Top indicators signaling	Total signals	Number of indicators signaling	Top indicators signaling	Percentage of indicators signaling
Argentina	46	7	1	1	1	1	35
Bolivia	45	8	2	0	0	0	35
Brazil	44	9	3	0	0	0	39
Chile	43	7	3	1	1	0	35
Colombia	70	9	3	3	3	1	52
Czech Republic	87	10	3	4	2	2	52
Denmark	29	6	1	1	1	0	30
Egypt	24	3	0	0	0	0	13
Finland	88	8	1	3	2	1	43
Greece	50	9	4	2	2	1	48
Indonesia	14	4	3	1	1	1	22
Israel	49	8	4	1	1	0	39
Malaysia	49	9	3	0	0	0	39
Mexico	30	5	1	2	2	0	30
Norway	37	8	2	1	1	0	39
Peru	27	6	2	1	1	0	30
The Philippines	73	8	3	2	2	0	43
South Africa	68	10	3	1	1	0	48
South Korea	74	13	5	3	3	1	61
Spain	58	9	2	1	1	0	43
Sweden	66	8	2	1	1	0	39
Thailand	58	9	3	1	1	1	43
Turkey	35	6	3	2	2	0	35
Uruguay	86	6	1	1	1	0	30
Venezuela	34	6	2	2	2	0	35

Table 5.5 Weighting the signals for currency and banking crises in emerging markets, June 1996-June 1997

	Currency crises		Banking crises	
Country	Weighted signals	Rank	Weighted signals	Rank
Argentina	5.41	16	7.98	10
Bolivia	6.59	12	7.30	13
Brazil	7.57	10	6.08	14
Chile	5.90	15	5.74	16
Colombia	10.59	8	11.87	6
Czech Republic*	15.42	2	17.24	1
Egypt	6.02	14	8.33	9
Greece	14.27	6	14.15	3
Indonesia*	7.54	11	8.33	9
Israel	6.30	13	10.38	8
Malaysia*	12.46	7	7.74	12
Mexico	2.82	19	2.59	19
Peru	2.82	19	5.33	17
The Philippines*	14.40	5	11.52	7
South Africa	16.52	1	12.74	4
South Korea*	14.57	4	14.55	2
Thailand*	14.63	3	12.09	5
Turkey	8.21	9	7.87	11
Uruguay	4.40	18	4.88	18
Venezuela	5.28	17	6.02	15

Note: An asterisk (*) denotes the country had a currency crisis, a banking crisis, or both in 1997-98.

Formally, we construct the following composite indicator,

$$I_t = \sum_{j=1}^{n} S_t^j / \omega^j \tag{5.1}$$

In equation 5.1, it is assumed that there are n indicators. Each indicator has a differentiated ability to forecast crises, and as before, this ability can be summarized by the noise-to-signal ratio, here denoted by ω^j. S_t^j is a dummy variable that is equal to one if the univariate indicator, S^j crosses its critical threshold and is thus signaling a crisis and is zero otherwise. As before, the noise-to-signal ratio is calculated under the assumption that an indicator issues a correct signal if a crisis occurs within the following 24 months. All other signals are considered false alarms.

If *all* 18 good indicators were sending signals, the maximum value that this composite vulnerability index could score is 30.05 for banking crises and 33.23 for currency crisis. This score is a simple sum of the inverse of the noise-to-signal ratios for the good indicators that are retained. However, it is seldom the case that every indicator signals. Table 5.5 presents the composite score of the indicators that are signaling for the 20 emerging

Table 5.6 Vulnerability to financial crises in emerging markets: alternative measures, June 1996-June 1997

Country	Average proportion of indicators signaling both crises	Rank	Average proportion of top eight indicators signaling both crises	Rank	Average of "weighted" signals	Rank
Argentina	29	11	11	5	6.69	14
Bolivia	35	8	22	4	6.94	12
Brazil	36	7	33	3	6.82	13
Chile	31	9	33	3	5.74	17
Colombia	48	4	44	2	11.23	7
Czech Republic*	57	2	56	1	16.33	1
Egypt	15	15	11	5	6.42	15
Greece	48	4	44	2	14.21	4
Indonesia*	22	14	44	2	7.93	11
Israel	35	8	44	2	8.34	9
Malaysia*	39	6	33	3	10.10	8
Peru	30	10	22	4	4.08	19
The Philippines*	46	5	33	3	12.96	6
Mexico	24	13	11	5	2.71	20
South Africa	50	3	33	3	14.63	2
South Korea*	63	1	56	1	14.56	3
Thailand*	35	8	44	2	13.36	5
Turkey	35	8	33	3	8.04	10
Uruguay	28	12	11	5	4.88	18
Venezuela	31	9	22	4	6.02	16

Note: An asterisk (*) denotes the country had a currency crisis, a banking crisis, or both in 1997-98.

economies in our sample; currency and banking crises are treated separately. The first data column provides the relevant value of the index for a currency crisis. The next column shows the country's ordinal ranking for the vulnerability index relative to the remaining 19 countries. South Africa, the Czech Republic, and Thailand emerge as the most vulnerable on the basis of the signals issued and the quality of those signals during January 1996-June 1997.

For banking crises, the comparable exercise ranks the Czech Republic, South Korea, and Greece as the most vulnerable. Perhaps not surprisingly, near the bottom of the list are countries such as Mexico and Venezuela, which are still recovering from their 1994-95 crises.

Thus far, we have treated banking and currency crises separately in our vulnerability rankings. If one wanted to assess the "average" vulnerability to both banking and currency crises, one may want to combine the information contained in these two measures. Table 5.6 provides information on the average proportion of indicators signaling banking

and currency crises, the average proportion of the top eight indicators (monthly and annual) that are signaling, and the average of the ''weighted'' indices reported in table 5.5 for currency and banking crises. The table also ranks the countries, by these three criteria, depending on the degree of ''vulnerability.''

Concentrating on the average of the ordinal rankings derived from the weighted signals (last column of table 5.6), we can see that clustered at the top of the list are several of the countries that have had or are still undergoing financial crises; these countries are denoted by an asterisk. This suggests a relatively encouraging out-of-sample performance for the signals approach. The three measures of vulnerability provide similar rankings for most of the ''extreme'' cases, such as the Czech Republic, South Korea, Malaysia, and the Philippines among the countries that have already had crises and South Africa, Colombia, and Greece among those that have not. In the case of Greece, however, there was an orderly devaluation, while in Colombia's case there was both a devaluation (in August 1998) as well as serious banking sector difficulties. For countries such as Thailand and to a lesser degree Indonesia, taking into account the ''quality'' of the indicator that is signaling considerably changes the overall ranking.

The Composite Indicator and Crises Probabilities

While the foregoing exercise allows us to assess the relative propensity to crisis across countries at a point in time—like a snapshot—it does not convey information on the *dynamics* of the process. To assess the extent to which a country is becoming more or less vulnerable to crisis over time, one would need a continuum of such snapshots. To do so, it is convenient to link the composite index to the implied probability of crisis.

Once we construct this composite indicator, we can then proceed—as we did with the individual indicators in chapters 2 and 3—to choose a critical value for the composite indicator so that when the composite indicator crosses this threshold, a crisis is deemed to be imminent.[1] As before, this critical threshold could be chosen so as to minimize the noise-to-signal ratio of the composite indicator. Moreover, we could calculate the probability of a crisis conditional on the composite indicator signaling a crisis (i.e., crossing the critical threshold) as well as the odds of a crisis when the composite indicator is not signaling. However, this procedure would not give us an exhaustive reading of vulnerability as the crisis approaches because it is dichotomous—that is, it will only provide two

1. Meaning, as in the individual indicators, in the subsequent 24 months.

types of information—namely, signal or no signal. We want also to introduce shades of gray in crisis vulnerability.

The idea is to analyze the empirical distribution of the composite indicator jointly with the occurrences of crises and to estimate probabilities of crises conditional on different values of the composite indicator. We would like to evaluate what the odds are of a crisis if none of the individual indicators are signaling (i.e., when the composite indicator takes on a value of zero) or when all the indicators are signaling (that is, when the composite reaches its maximum value). But we would also like to evaluate the intermediate scenarios, which depend on both how many and which of the indicators are signaling. For example, we would like to calculate the probability of a crisis conditioned on knowing that the value of the indicator is in the 9 to 14 range, which as we saw from the cross-section analysis earlier in this chapter was associated with a number of the recent crises (table 5.5).

In practice, we can construct this set of probabilities using the information on the value of the composite indicator for all the countries in the sample together with the information on crises. Probabilities of crises are estimated as follows:

$$P(C \mid \underline{I} < I_t < \bar{I}) = A/(A + B) \tag{5.2}$$

where $\underline{I}$ is the lower bound of the range we are interested in (9 in our earlier example) and I is the upper bound of the range we are interested in (14 in our example). As before, we have the following two-by-two matrix,

	Crisis occurs in the following 24 months	No crisis occurs in the following 24 months
$\underline{I} \leq I_t \leq \bar{I}$	A	B
$I_t \notin [\,\underline{I}\,,\bar{I}\,]$	C	D

These probabilities will be estimated using all the information from all the countries in the sample. Once we estimate these probabilities and use the information on the number of signals being issued at any moment in time, we can construct time-series probabilities of crisis for every country. P_t^m denotes the probability of a crisis for country m in period t.

Once we construct these time series of crisis probabilities, we can also evaluate the forecasting ability of the composite indicator and compare its track record with that of other indicators, such as our top-ranked univariate indicator, the real exchange rate. To conduct this horse race, we follow Diebold and Rudebusch (1989) and employ the Quadratic Probability Score (QPS) as our metric of goodness of fit. In particular, the QPS evaluates the average closeness of the predicted probabilities and

Table 5.7 Composite indicator and conditional probabilities of financial crises

Value of indicator	Probability of a currency crisis	Probability of a banking crisis
0-1	0.10	0.03
1-2	0.22	0.05
2-3	0.18	0.06
3-4	0.21	0.09
4-5	0.27	0.12
5-7	0.33	0.13
7-9	0.46	0.16
9-12	0.65	0.27
12-15	0.74	0.37
Over 15	0.96	n.a.
Memorandum:		
	Unconditional probability of a currency crisis	**Unconditional probability of a banking crisis**
	0.29	0.10

n.a. = not applicable

Source: Kaminsky (1998).

the observed realizations, as measured by a dummy variable that takes on a value of one when there is a crisis and zero otherwise.[2]

$$QPS^k = 1/T \sum_{t=1}^{T} 2(P_t^k - R_t)^2 \tag{5.3}$$

where $k = 1,2,3$ refers to the indicator P^k, refers to the probability associated with that indicator, and R_t refers to the zero-one realizations. The QPS ranges from zero to two, with a score of zero corresponding to perfect accuracy.

Empirical Results

Table 5.7 reports the conditional probabilities of both currency and banking crises using the composite indicator. One column reports the likelihood of currency crises. When almost none of the indicators are signaling a future crisis, the composite indicator takes on values between zero and two, and the probability of a currency crisis is only about 10 percent. The probability of a currency crisis increases sharply and nonlinearly as signs

2. This approach has also been used to assess the ability of various indicators to anticipate turning points in the business cycle (Diebold and Rudebusch 1989).

Table 5.8 Scoring the forecasts: quadratic probability scores

	Currency crises		Banking crises	
Indicator	Tranquil times	Crisis times	Tranquil times	Crisis times
Naive forecast	0.173	1.008	0.024	1.620
Real exchange rate	0.115	0.979	0.018	1.589
Composite indicator	0.110	0.862	0.024	1.309

Source: Kaminsky (1998).

of vulnerability in the economy increase. Specifically, the probability of a currency crisis reaches almost 100 percent when the composite indicator takes on a value of 15 or above.[3] The right column reports the same evidence for banking crises. As with currency crises, the probabilities of a collapse of the banking sector increase sharply as the economy deteriorates. However, as we found with the univariate indicators, banking crises are harder to anticipate. Even when nearly all the univariate indicators are signaling, the probability of a banking crisis only climbs to about 40 percent.

Table 5.8 turns to the forecasting accuracy of the composite indicator. The left side of the table looks at currency crises, while the right side examines banking crises. The performance of the composite indicator is compared with the performance of the real exchange rate—the best univariate indicator—as well as to the naive forecast based on the unconditional probability of crisis. The score statistics are reported separately for "crisis times" and for "tranquil times;" this provides information on the performance of the leading indicators across regimes. Recall that the closer the score in table 5.8 is to zero, the more accurate is the forecast. The real exchange rate does significantly better in anticipating currency crises than the unconditional forecast of currency crises. More important, the composite indicator performs better—in terms of accuracy—than the real exchange rate, but the larger improvements are obtained when forecasting in crisis times.

As shown on the right side of table 5.8, all indicators score worse when predicting the onset of the banking crises—that is, the 24 months bracketing the beginning of the banking crises. Again, the real exchange rate does better than the unconditional forecast of banking crises in general. For example, the quadratic probability score declines from 0.024 and 1.620 for the naive forecast of currency crises to 0.018 and 1.589 for the real exchange rate forecast during tranquil and crisis times, respectively. The composite indicator outperforms the real exchange rate in forecasting the onset of a banking crisis but is outperformed by the real exchange rate during tranquil times. This is explained by the fact that the real exchange rate issues very few false alarms during tranquil periods.

3. Note we are not using the annual indicators in this exercise.

An Out-of-Sample Application to Southeast Asia

Using the information on the monthly value of the composite indicator and on the conditional probabilities of crises, we can construct a time series of probabilities of crises for our sample countries both in the sample period (from January 1970 to December 1995) and out of it (from January 1996 to December 1997). As an illustration, figure 5.1 reports the time-series probabilities of currency crises for four Southeast Asian economies in the 1990s. The vertical lines in the figures represent the onset of a crisis.

With the exception of Indonesia, all the Southeast Asian countries showed a severe state of distress, with about 65 percent of the indicators flashing signals during the year preceding the crisis.[4] The onset of these crises occurred as the economies entered a marked slowdown in growth after a prolonged boom in economic activity fueled by rapid credit creation.[5] This dramatic surge in credit is explained, in large measure, by heavy capital inflows and partly by the reform of the financial system; financial liberalization was accompanied by large reductions in reserve requirements. Overall, the explosive growth in these countries came to an end with a real appreciation of the domestic currencies (which are, in differing degrees, tied to the US dollar) and the corresponding loss of export markets. It is noteworthy that during the latter part of this period, there was a substantial appreciation of the dollar vis-à-vis the yen.

Short-term capital inflows to Thailand amounted to 7 to 10 percent of GDP in each of the years 1994 through 1996, with the growth rate of credit to the nonfinancial private sector amounting to more than 23 percent over 1990-95. While output growth rates increased in the early 1990s to almost 9 percent, fueled in part by easy credit, this rapid growth showed signs of coming to an end with the real appreciation of the domestic currency and the corresponding loss of export markets. The annual growth rate of exports fell from a peak of 30 percent per year in 1994 to about 0 in 1996. Financial sector fragilities were also evident, with runs against major banks starting to occur as early as May 1996. Finally, the sharp increase in interest rates in 1997 to defend the baht put the nail in the coffin of the already weak banking sector.[6] Overall, 75 percent of the indicators for which there are available data were exhibiting ''anomalous'' behavior.

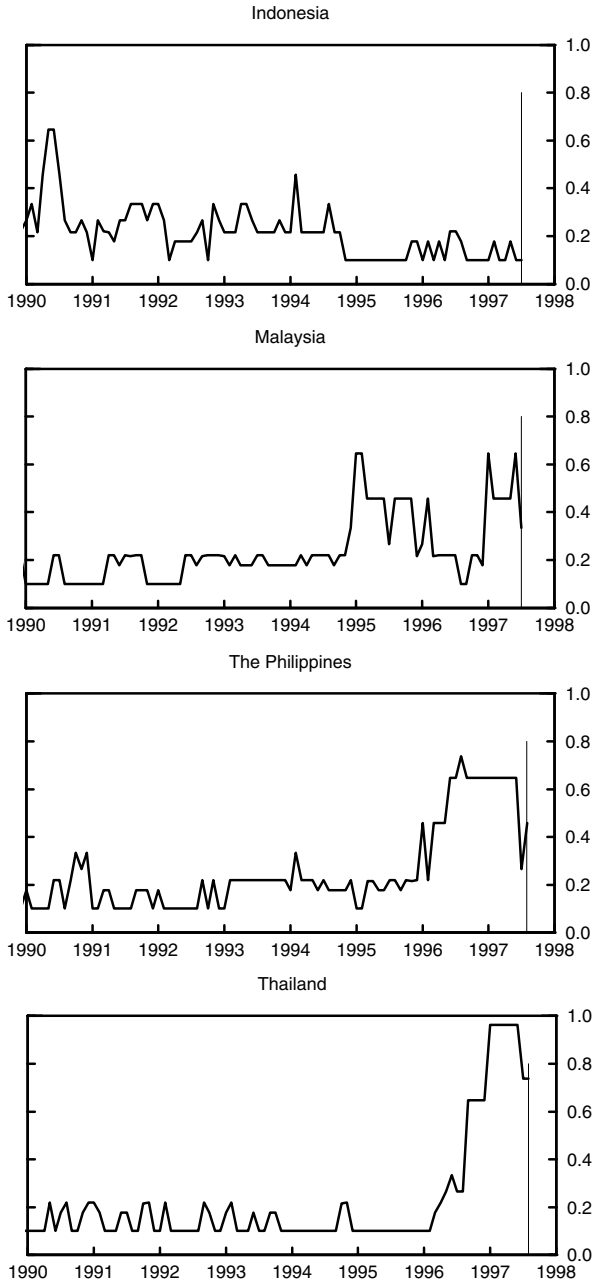
A boom-bust cycle in lending was also evident in the Philippines. As in Thailand, the boom was fueled by capital inflows but also by a dramatic

4. For a more detailed exposition of the incidence of flashing indicators in the run-up to the Asian crisis, see Kaminsky and Reinhart (1999).

5. This is at odds with the interpretation of these crises provided in Radelet and Sachs (1998), who argue these crises are the byproduct of a financial panic.

6. It is noteworthy that finance companies had been receiving substantial assistance from the central bank during this period.

Figure 5.1 Probability of currency crisis for four Southeast Asian countries, 1990-97



Note: Vertical lines indicate currency crisis date.

Source: Kaminsky (1998).

reduction in reserve requirements, accompanying financial liberalization. Bank credit increased by 44 percent a year during 1995-96. As in Thailand, rapidly expanding credit was an important contributor to the rally in stock and real estate markets, with a fourfold increase in prices in both markets. Foreign currency exposure increased in the Philippines in the 1990s via foreign borrowing to finance domestic lending. Foreign borrowing was concentrated in short maturities. Consumer lending also increased and fueled a surge in consumption, leading to a deterioration of the current account. This deterioration in the external accounts was aggravated by the real exchange rate appreciation of the domestic currency. The loss of competitiveness anticipated a future decline in growth and also contributed to a substantial deterioration of the quality of banks' assets, further reducing the odds of survival of many individual financial institutions. Overall, about 50 percent of the indicators were signaling the increased vulnerability of the economy during the two years before the collapse of the implicit peg in July 1997.[7]

Malaysia shared certain vulnerabilities with Thailand. It too was affected by the slowdown in the region, though to a much smaller degree. It too had large current account deficits during 1990-95, although in 1996 the outlook for the external sector improved somewhat, with the current account to GDP ratio shrinking to -5.3 percent (in Thailand, the current account to GDP ratio in 1996 was roughly -8.0 percent). Moreover, Malaysia, like Thailand, accumulated debt rapidly in the 1990s, with capital inflows fueling a stock and real estate market boom and with asset prices increasing about 300 percent in the early 1990s. Malaysia also suffered from financial sector vulnerabilities (although not to the same extent as Thailand) as a result of the high degree of leveraging in the economy. Indeed, Malaysia had one of the highest ratios of credit-to-GDP in the world, and the banks had a large exposure to the property and equity markets. For Malaysia, about 60 percent of the indicators were showing signs of distress at the onset of the crisis.

Indonesia looked somewhat different. While it too exhibited banking fragilities and while short-term debt easily exceeded available foreign exchange reserves (about 1.7 times the stock of the country's reserves),[8] the current account deficit did not deteriorate as fast (reaching only 3.5 percent of GDP in 1996), the slowdown in growth was not yet evident, and the real exchange rate did not appreciate as much as in the other

7. The Philippines was classified as a managed float in the IMF's exchange rate arrangements classification. Yet even a relatively uninformed bystander could see the large-scale extent of foreign exchange intervention before mid-1997, which kept the Philippine peso's value virtually unchanged against the dollar.

8. The beginning of the banking crisis in Indonesia can be dated to November 1992, when a large bank (Bank Summa) collapsed and triggered runs on three smaller banks. Most state-owned banks also experienced serious difficulties.

countries in the region. Relatively few indicators (less than 20 percent) showed signs of strains in the economy in the months before the crisis. Here, over and beyond all the political uncertainty, as we explain further in chapter 6, a key factor seemed to be contagion from the flurry of financial crises elsewhere in the region—particularly the liquidity squeeze associated with the withdrawal of Japanese banks (the major lenders to the region) in the wake of losses they suffered in the Thai crisis.[9]

To sum up, we have seen in this chapter that the signals approach can draw coarse distinctions, both across countries and over time, in crisis vulnerability during out-of-sample periods (in this case, 1996-97). The approach does reasonably well in anticipating currency crises in most of the Asian crisis countries. At this stage, the model performs much better for currency crises than for banking crises. The evidence presented here also indicates that it is worthwhile to work with a composite index, which outperforms the best of the univariate indicators.

9. The reversal was, in fact, quite pronounced, from capital inflows in the region of $50 billion in 1996 to an outflow of $21 billion in 1997. See Kaminsky and Reinhart (2000) and the next chapter for a discussion on world and regional financial links and their effects on the probability of currency crises.