3

Empirical Results

The signals approach was applied to the indicators around the dates of the 29 banking and the 87 currency crises. In what follows, we first compare our results for the 15 monthly indicators to those presented in Kaminsky and Reinhart (1999) and reproduced in table 3.1. In addition to presenting our in-sample findings, this exercise allows us to gauge robustness of the signals approach, since the results reported here are derived from a larger sample of countries (25 versus 20.)[1] Moreover, in this chapter we report results for many of the indicators that have been stressed in the financial press surrounding the coverage of the Asian crisis.

The Monthly Indicators: Robustness Check

Tables 3.1 and 3.2 summarize the in-sample performance of the monthly indicators along the lines described in chapter 2 and presented in Kaminsky, Lizondo, and Reinhart (1998) and Kaminsky (1998). Table 3.1 covers banking crises, and table 3.2 presents the results for currency crises. The variables are shown in descending order based on their marginal predictive power. For banking crises, for instance, the real exchange rate has the greatest predictive power and imports the least. For each indicator, the first column of the tables shows the noise-to-signal ratio. An indicator with a noise-to-signal ratio of unity, such as those in the bottom of the

1. The five countries included here that were not a part of the Kaminsky and Reinhart (1999) sample are the Czech Republic, Egypt, Greece, South Africa, and South Korea.

Table 3.1 Ranking the monthly indicators: banking crises

Indicator	Noise-to-signal	Percent of crises accurately called	$P(C \mid S)$	$P(C \mid S) - P(C)$	Rank in Kaminsky (1998)	Difference in rank (+ denotes an improvement)
Real exchange rate	0.35	52	24.0	14.1	1	0
Stock prices	0.46	76	23.4	11.2	3	0
M2 multiplier	0.46	63	18.3	9.0	4	0
Output	0.54	90	17.3	7.2	5	0
Exports	0.68	79	14.3	4.7	7	+1
Real interest rate	0.68	96	16.8	4.2	6	−1
Real interest rate differential	0.73	100	15.6	3.7	8	0
Bank deposits	0.73	64	12.9	3.1	9	0
M2/reserves	0.84	72	11.4	1.7	10	0
Excess real M1 balances	0.88	44	11.0	1.2	13	+2
Domestic credit/nominal GDP	0.89	46	10.9	1.1	11	−1
Reserves	0.92	83	10.7	0.8	12	−1
Terms of trade	1.01	92	11.6	−0.1	14	0
Lending-deposit interest rate	1.48	56	8.3	−3.5	15	0
Imports	1.75	64	6.0	−4.1	16	0

Sources: The authors and Kaminsky (1998).

tables, issues as many false alarms as good signals. The second column shows the percent of crises (for which there were data for that indicator) accurately called, while the third column lists the probability of a crisis conditional on a signal from the indicator, $P(C \mid S)$. The fourth column shows the difference between the conditional and unconditional probabilities, $P(C \mid S) - P(C)$, the fifth column shows the ranking that the indicator received in the previous signals approach analysis, and the last column calculates the difference between its current and previous rank. Hence, a +3 in the last column would mean that the indicator moved up three notches as the sample was enlarged, while a −2 would reflect a decline in its ranking.

The indicators' rankings based on their marginal predictive power are shown under the heading $P(C \mid S) - \mathrm{P}(C)$. The better the indicator, the higher the probability of crisis conditioned on its signaling—that is, the higher the $P(C \mid S)$—and the bigger the gap between the conditional probability ($P(C \mid S)$ and the unconditional probability $P(C)$. The unconditional probability of a banking crisis (not shown) varies slightly from indicator to

Table 3.2 Ranking the monthly indicators: currency crises

Indicator	Noise-to-signal	Percent of crises accurately called	$P(C\|S)$	$P(C\|S) - P(C)$	Ranking in K & R (1999)	Difference in rank (+ denotes an improvement)
Real exchange rate	0.22	58	62.1	35.2	1	0
Banking crisis	0.32		46.0	17.0	2	0
Stock prices	0.46	66	47.6	18.3	4	+1
Exports	0.51	80	42.4	15.0	3	−1
M2/reserves	0.51	75	42.3	14.9	5	0
Output	0.57	71	43.0	12.5	6	0
Excess real M1 balances	0.57	57	40.1	12.3	7	0
Reserves	0.58	72	38.9	12.2	8	0
M2 multiplier	0.59	72	39.2	11.6	9	0
Domestic credit/nominal GDP	0.68	57	35.6	8.3	10	0
Terms of trade	0.74	77	35.4	6.5	11	0
Real interest rate	0.77	89	32.0	5.5	12	0
Imports	0.87	59	30.1	2.9	14	+1
Real interest rate differential	1.00	86	26.1	−0.1	12	−1
Lending-deposit interest rate	1.32	63	24.4	−4.8	16	+1
Bank deposits	1.32	43	22.3	−5.2	15	−1

K & R = Kaminsky and Reinhart (1999).

Sources: The authors and Kaminsky and Reinhart (1999).

indicator because of differences in data availability, since not all indicators span the entire sample.[2] For some indicators the sample is such that the incidence of banking crises (i.e., their unconditional probability) is as low as 9.8 percent or as high as 12 percent. For currency crises, the unconditional probability is clustered in the 27 to 29 percent range.

Several interesting features stand out from tables 3.1 and 3.2.

First, the ranking of the indicators appears to be quite robust across sample selections, as shown in the last column of table 3.1. In other words, the results from the 25-country sample closely match the results of the 20-country sample. For currency crises, none of the monthly indicators changes in relative performance by more than one position as the sample is enlarged, and for 10 of the indicators, there is no change at all. For

2. As shown in Kaminsky, Lizondo, and Reinhart (1998), the bigger the gap between the conditional probability (P(C|S) and the unconditional probability P(C), the lower the noise-to-signal ratio.

banking crises, the maximum ranking change is two positions and 10 of the monthly indicators show no change in their relative ranking. This is a positive factor for the expected out-of-sample usefulness of the signals approach. Specifically, it suggests that the indicators could well have a similar relative predictive ability for countries that are not included in the sample.[3]

Second, some of the most reliable indicators are the same for banking and currency crises. Deviations of the real exchange rate from trend and stock prices stand out in this regard. Close runners-up are output and exports. A similar statement applies to the least useful indicators; imports and the lending-deposit ratios, for example, do not have any predictive ability for either type of crisis. Several of the low-scoring indicators also carry the weakest or most ambiguous theoretical rationale.[4]

Third, there are some important differences in the ranking of indicators between currency and banking crises. This suggests that currency and banking sector vulnerability takes on different forms. A case in point is the ratio of M2 (in dollars) to foreign exchange reserves, a variable stressed by Calvo and Mendoza (1996) as capturing the extent of unbacked implicit government liabilities. It does quite well (ranks fifth) among the 16 indicators of currency crises, but it is far less useful when it comes to anticipating banking crises. Similarly, the money multiplier, real interest rates, and bank deposits are of little use when it comes to predicting currency crises but do much better in predicting vulnerability to banking crises. This result should not come as a surprise. Both the money multiplier and real interest rates are strongly linked to financial liberalization, which itself helps predict banking crises. As shown in Galbis (1993), real interest rates tend to increase substantially in the wake of financial liberalization. Furthermore, the steep reductions in reserve requirements that usually accompany financial liberalization propel increases in the money multi-

3. We did not included the larger industrial countries (particularly the G-7 countries) in our sample because they have characteristics (such as the ability to borrow in their own currency, a relatively good external-debt servicing history, and high access to private capital markets) that on *a priori* grounds would seem to make their crisis vulnerability different from that of most emerging economies. In addition, data constraints, extremely large structural shifts over time, and difficulties associated with identifying a ''normal'' period led to the decision to exclude China, Russia, and most of the transitional economies from the sample. Finally, we excluded low-income developing countries from the sample because we wanted to concentrate on emerging economies that had (in addition to the requisite data availability) significant involvement with private international capital markets. In the end, however, one can only tell whether our sample selection results in certain biases by doing further robustness checks on alternative samples of countries.

4. For instance, lending-deposit interest rate spreads could widen in advance of a crisis due to a deterioration in loan quality or a worsening in adverse selection problems. Alternatively, it could be persuasively argued that ahead of financial crises, banks may be forced to offer higher deposit rates, so as to stem capital flight.

plier. Bank runs and deposit withdrawals are at the heart of multiple-equilibriums explanations of banking crises (Diamond and Dybvig 1983) yet figure less prominently in explanations of currency crises.[5]

Lastly, banking crises are even more of a challenge to predict than currency crises. For currency crises, the marginal predictive power of 12 of the 16 indicators (column five) is 5 percent or higher; for the real exchange rate, marginal predictive power goes as high as 35 percent. Indeed 9 of the 16 indicators have marginal predictive power in excess of 10 percent. By way of contrast, for banking crisis 11 of the 15 indicators have marginal predictive power of less than 5 percent, and even the top-ranked macroeconomic indicators have marginal predictive power of less than 15 percent. This relative inability of indicators to anticipate crises in sample may be due to two factors. For one thing, for the earlier part of the sample, banking crises were still relatively rare vis-à-vis currency crises—there is a large discrepancy between the number of currency and banking crises studied here. Detecting recurring patterns becomes more difficult in the smaller sample of banking crises. Also, pinning down the timing of a banking crisis requires a tricky judgment about when banking-sector "distress" turns into a full-fledged crisis. As discussed in chapter 2, the timing of currency crises is more straightforward.

The empirical evidence on the "predictability" of banking crises is still limited to a handful of studies. Some have followed the approach pioneered by Blanco and Garber (1986) for currency crises and have attempted to model the probability of banking crises on the basis of domestic and external fundamentals. These studies have encountered some of the same problems highlighted in table 3.1—specifically, the relatively poor predictive power of the models. Moreover, the results in the studies sometimes conflict with one another. Eichengreen and Rose (1998), for example, find that external conditions, specifically international interest rates, play an important role in predicting banking crises. Real exchange rate overvaluations, growth, and budget deficits have predictive power in their regressions. The composition of external debt also seems to matter. Other variables, including credit growth, they conclude, have little or no predictive ability. In contrast, Demirgüç-Kunt and Detragiache (1998) find no evidence in favor of budget deficits, while real interest rates, credit growth, and M2/reserves figure prominently among their significant regressors. Both studies do find, however, that slower economic growth increases the probability of a banking crisis. In any case, it appears that, to improve upon the ability to predict banking crises, we may need to look beyond macroeconomic indicators—an issue that we take up later.

---

5. However, some recent models (Goldfajn and Valdés 1995) have highlighted the role of bank runs in precipitating currency crises.

Table 3.3 Annual indicators: banking crises

Indicator	Noise-to-signal	Percent of crises accurately called	$P(C \mid S)$	$P(C \mid S) - P(C)$
Short-term capital inflows/GDP	0.38	43	36.8	18.5
Current account balance/ investment	0.38	38	36.1	18.4
Overall budget deficit/GDP	0.47	52	26.9	12.1
Current account balance/GDP	0.50	33	29.3	12.1
Central bank credit to the public sector/GDP	0.52	23	23.8	7.6
Net credit to the public sector/GDP	0.72	15	18.3	4.5
Foreign direct investment/GDP	1.05	24	15.6	−0.6
General government consumption/ GDP	1.44	15	10.0	−3.8

The Annual Indicators: What Works?

Tables 3.3 and 3.4 present evidence on the performance of eight annual indicators that have been prominent in recent discussions of the causes of financial crises. The indicators include the fiscal variables stressed in the Krugman (1979) model of a currency crisis as well as the short-term debt exposure indicators stressed in recent theoretical and empirical explanations of the Asian crisis (Calvo 1998; Calvo and Mendoza 1996; Goldstein 1998b; Radelet and Sachs 1998). As before, the indicators are ranked according to their marginal predictive power. The first column provides information on the noise-to-signal ratio, the second column lists the percent of crises accurately called, the third column provides information on the probability of crisis conditional on signaling, while the last column provides information on the marginal predictive power of the variable.

The top indicator for banking crises is the share of short-term capital inflows to GDP. This is consistent with the results in Eichengreen and Rose (1997) and supports the view that the banking sector becomes particularly vulnerable during cycles of short-term capital inflows. Such short-term inflows are more likely to be intermediated through the domestic banking sector than other types of capital flows, such as foreign direct investment (FDI) and portfolio flows. Indeed, the share of FDI/GDP does poorly as a predictor of banking crises. Two of the fiscal variables—the budget deficit and central bank credit to the public sector—do moderately well,

Table 3.4 Annual indicators: currency crises

Indicator	Noise-to-signal	Percent of crises accurately called	$P(C\|S)$	$P(C\|S) - P(C)$
Current account balance/GDP	0.41	56	43.2	19.5
Current account balance/ investment	0.49	31	39.0	15.1
Overall budget deficit/GDP	0.58	22	36.4	11.5
Short-term capital inflows/ GDP	0.59	29	35.2	10.9
General government consumption/GDP	0.74	15	29.4	5.9
Net credit to the public sector/GDP	0.88	20	26.2	2.4
Central bank credit to the public sector/GDP	0.99	13	23.8	0.1
Foreign direct investment/ GDP	1.00	24	21.7	0.1

while the third—government consumption—does poorly. Hence the role of the public sector in fueling banking crises is somewhat mixed.

Without overinterpreting the results, it is interesting that the composition of the current account matters, in the sense that the current account as a percentage of investment does better in predicting banking crises than the current account as a share of GDP. It may be that investment is more likely to be financed through the international issuance of bonds and stocks or overseas loans, while consumption is more dependent on local bank credit.

Turning to currency crises, the annual indicators that perform best are those measuring current account imbalances. This finding is not representative of the broader empirical literature. As discussed in Kaminsky, Lizondo, and Reinhart (1998), most of the studies that have attempted to explain the *k*-period ahead probability of a currency crisis have had mixed results regarding the current account, with most studies finding it insignificant.

The various fiscal indicators do moderately well in anticipating currency crises, lending some support to Krugman-type models. By contrast with banking crises, the composition of capital inflows appears to have relatively little to add to our understanding of what drives a currency crisis. This result, however, may in part be due to the fact that a large share of

Table 3.5 Short-term debt: selected countries, June 1997 (percent)

Country	Short-term debt/total debt	Short-term debt/reserves
Asia		
Indonesia	24	160
Malaysia	39	55
Philippines	19	66
South Korea	67	300
Thailand	46	107
Latin America		
Argentina	23	108
Brazil	23	69
Chile	25	44
Colombia	19	57
Mexico	16	126

Sources: Bank for International Settlements; *International Financial Statistics*; World Bank.

the currency crises (as opposed to the banking crises) took place in the 1970s in an environment of highly regulated internal and external financial markets, where portfolio flows were negligible.

While our list of indicators is comprehensive, it is by no means exhaustive. The Asian crisis in particular highlighted the importance of currency and maturity mismatches in increasing vulnerability to currency and banking crises. Table 3.5 presents an indicator of the imbalance between liquid liabilities and liquid assets: namely, the ratio of short-term debt to international reserves. All the emerging economies in this group with debt-to-reserves levels in excess of 100 percent in mid-1997 have been casualties of financial turmoil in recent years (even if not all the speculative attacks ultimately succeeded, as in the case of Argentina.) This suggests that variables such as short-term debt to reserves could be a valuable addition to our list of leading indicators of crisis vulnerability.[6]

Do the Indicators Flash Early Enough?

The previous discussion has ranked the indicators according to their ability to anticipate crises while producing few false alarms. Such criteria, however, do not speak to the *lead time* of the signal. From the vantage point of a policymaker or financial market participant who wants to implement preemptive or risk-mitigating measures, it is not a matter of

6. See Calvo and Mendoza (1996) for an early discussion of this issue. We did not use the ratio of short-term debt to reserves as an indicator in our tests because its relevance was highlighted mainly by the Asian crisis and we did not want the out-of-sample tests to be biased by its inclusion. In addition, the data were not available for the early part of our sample.

Table 3.6 How leading are the signals? (average number of months from when the first signal is issued to the crisis month)

Indicator	Currency crisis	Banking crisis
Bank deposits	15	8
Beginning of banking crisis	19	n.a.
Domestic credit/GDP	12	7
Domestic-foreign interest rate differential	14	16
Excess M1 balances	15	6
Exports	15	16
Imports	16	11
Lending-deposit interest rate ratio	13	6
M2 multiplier	16	12
M2/reserves	13	14
Output	16	13
Real exchange rate	17	10
Real interest rate	17	16
Reserves	15	10
Stock prices	14	12
Terms of trade	15	18

n.a. = not applicable

indifference whether an indicator sends a signal well before the crisis occurs or if the signal is given only when the crisis is imminent. Consider for example, the Conference Board's composite indices of business cycle activity for the United States, which are published on a monthly basis. Both financial market participants and policymakers alike find the leading-indicator composite index more valuable than the coincident and lagging indices. Market participants incorporate this information in their investment decisions, while policymakers give it weight in their policy reactions. Over the years, US monetary policy has become increasingly forward-looking and hence preemptive rather than reactive. One could argue that this transition was facilitated by an improvement in our understanding of the business cycle and early signs of its turning points.

In what follows, we tabulate for each of the monthly indicators the average number of months before the crisis when the first signal occurs. This, of course, does not preclude the indicator from giving signals through the entire period immediately preceding the crisis. Indeed, for the more reliable indicators, signals tend to become increasingly persistent ahead of crises. For the low-frequency (annual) indicators, lead time is not much of an issue since some of these are published with a considerable lag and hence tend to be of less use from an early warning standpoint.

Table 3.6 presents the lead times for our monthly indicators—both for currency and banking crises. In the case of currency crises, the most striking observation is that, on average, all the indicators send the first signal anywhere between a year and 18 months before the crisis erupts, with banking-sector problems (our second-ranked indicator) offering the

Table 3.7 Microeconomic indicators: banking crises

Indicator	Percentage of crises accurately called	Noise-to-signal
Bank lending-deposit interest rate spread	73	0.28
Interbank debt growth	80	0.35
Interest rate on deposits	80	0.47
Rate of growth on loans	58	0.72
Net profits to income	60	1.14
Operating costs to assets	40	1.59
Change in banks' equity prices	7	2.00
Risk-weighted capital-to-asset ratio	7	2.86

Source: Rojas-Suarez (1998).

longest lead time—namely, 19 months. The average lead time for these early signals is 15 months for currency crises. All the indicators considered are therefore best regarded as leading rather than coincident, which is consistent with the spirit of an "early warning system." For banking crises, there is a greater dispersion in the lead time across indicators, and the average lead time is also lower (about 11 months). Furthermore, most of the indicators signal at about the same time, thus the signaling is cumulative and all the more compelling. Thus, on the basis of these preliminary results, there does appear to be adequate lead time for pre-emptive policy actions to avert crises.

Microeconomic Indicators: Selective Evidence

If, as the previous discussion suggests, banking crises are more difficult to predict on the basis of macroeconomic indicators than currency crises, it appears that the analysis of banking crises may benefit from including a variety of microeconomic indicators of bank health. Gonzales-Hermosillo et al (1997) and Rojas-Suarez (1998) provide some insights in this direction. Rojas-Suarez uses bank-specific data from Colombia, Mexico, and Venezuela and applies the "signals" methodology to this data to glean which items in bank balance sheets are most useful in predicting banking distress.

Her results are summarized in table 3.7. They do indeed suggest that bank-specific information could make an important contribution in assessing the vulnerability of the banking sector in emerging markets. More "traditional" indicators, such as liquidity ratios and bank capitalization, turn out to be less useful indicators in Rojas-Suarez's tests, in large part because they are "noisy" and likely to send many false alarms while missing many of the problem spots. At the other end, bank spreads and the interest rate that banks offer on deposits appear to systematically identify the weak banks.

One possible explanation for why interest rate spreads at the micro level may be more useful indicators of banking crisis than aggregate spreads is that the latter may reflect mainly cross-country differences in the extent of banking competition. In contrast, micro spreads are more likely to be more informative about a bank's risk taking, as all banks within a country are apt to face a more common competitive environment.

Goldstein (1998b) stresses bank exposure to the property sector as an indicator in the context of banking crises. He notes that in many of the affected Asian countries, estimates of the share of bank lending to the property sector exceeded 25 percent. Banking sector external exposure, measured in terms of foreign liabilities as a percentage of foreign assets, also appears to be a worthy addition to the list of sectoral or microeconomic indicators of banking-sector problems.