8

Summary of Results and Concluding Remarks

In this book we have introduced a set of indicators that, on the basis of both in-sample and out-of-sample tests, appear to be useful for gauging vulnerability to currency and banking crises in emerging economies. The indicators are not precise enough to make fine distinctions in crisis vulnerability across countries and over time, but they can draw some distinctions between the most and least vulnerable groups of countries and recognize large increases in the vulnerability of a given country over time. As such, they have the potential to add value as a "first screen" of vulnerability and as a supplementary tool to other types of analysis of crisis vulnerability. As suggested in chapter 5, we think the indicators would have been useful in anticipating the Asian currency and banking crises.

In this chapter, we summarize our key results. Furthermore, in thinking about future evaluation of such leading indicators of crises, two obvious questions arise: would publication of the indicators erode their usefulness in an early warning system, and are there policy implications associated with the better performing indicators? We discuss each of these questions in turn.

Summary of Findings

Our main empirical findings can be summarized in 12 main points.

First, banking and currency crises in emerging markets do not typically arrive without any warning. **There are recurring patterns of behavior in the period leading up to banking and currency crises.** Reflecting this tendency, the better-performing leading indicators anticipated between 50 and 100 percent of the banking and currency crises that occurred over the 26-year sample period. At the same time, even the best leading indicators send a significant share of false alarms (on the order of one false alarm for every two to five true signals).[1]

Second, using monthly data, **banking crises in emerging economies are more difficult to forecast accurately than are currency crises.** Within the sample, the average noise-to-signal ratio is higher for banking crises than for currency crises, and the model likewise does considerably better out-of-sample in predicting currency crises than banking crises. It is not yet clear why this is so. It may reflect difficulties in accurately dating banking crises—that is, in judging when banking sector distress turns into a crisis and when banking crises end. For example, by our criteria, banking distress in Indonesia and Mexico really began in 1992 (and not in 1997 and 1994, respectively). The absence of high-frequency (monthly or quarterly) data on the institutional characteristics of national banking systems probably also is a factor.

Third, **there is wide variation in performance across leading indicators,** with the best-performing indicators displaying noise-to-signal ratios that are two to three times better than those for the worst-performing ones.[2] In addition, the group of indicators that show the best (in-sample) explanatory power also seem, on average, to send the most persistent and earliest signals. **Warnings of a crisis usually appear 10 to 18 months ahead.**

Fourth, **for currency crises, the best of the monthly indicators were appreciation of the real exchange rate (relative to trend), a banking crisis, a decline in stock prices, a fall in exports, a high ratio of broad money (M2) to international reserves, and a recession. Among the annual indicators, the two best performers were both current account indicators—namely, a large current account deficit relative to both GDP and investment (table 8.1).**

Fifth, **turning to banking crises, the best (in descending order) of the 15 monthly indicators were appreciation of the real exchange rate (relative to trend), a decline in stock prices, a rise in the (M2) money multiplier, a decline in real output, a fall in exports, and a rise in the real interest rate. Among the eight annual indicators tested, the best of**

1. The construction of the noise-to-signal ratio is described in chapter 2.

2. When an indicator has a noise-to-signal ratio above one, crises would be more likely when the indicator was not sending a signal than when it was. Similarly, when an indicator has a conditional probability of less than zero, it means that the probability of a crisis occurring when the indicator is signaling is lower than the *un*conditional probability of a crisis occurring—that is, merely estimating the probability of a crisis according to its historical average. For example, if currency crises occur in a third of the months in the sample, the unconditional probability of a crisis is one-third.

Table 8.1 Currency and banking crises: best-performing indicators

Currency crises	Banking crises
High-frequency indicators	
Real exchange rate	Real exchange rate
Banking crisis	Stock prices
Stock prices	M2 multiplier
Exports	Output
M2/reserves	Exports
Output	Real interest rate on bank deposits
Low-frequency indicators	
Current account balance/GDP	Short-term capital inflows/GDP
Current account balance/investment	Current account balance/investment

the pack were a high ratio of short-term capital inflows to GDP and a large current account deficit relative to investment (table 8.1).

Sixth, **while there is a good deal of overlap between the best-performing leading indicators for banking and currency crises, there is enough of a distinction to warrant treating the two separately.** To highlight two noteworthy differences, the two indicators that serve as proxies for financial liberalization—namely, a rise in the real interest rate and an increase in the money multiplier—turned out to be more important for banking crises than for currency crises, whereas the opposite proved true for the two indicators designed to capture currency/maturity mismatches and excessively expansionary monetary policy—namely, a high ratio of broad (M2) money balances to international reserves and excess M1 money balances, respectively.

Seventh, while our data on sovereign credit ratings cover only a subsample of crises and relate to only two of the major rating firms (Moody's Investor Services and Institutional Investor), **we find that changes in sovereign credit ratings have performed considerably worse than the better leading indicators of economic fundamentals in anticipating both currency and banking crises in emerging economies.** In addition, we find no empirical support for the view that sovereign rating changes have led financial crises in our sample countries rather than reacting to these crises. In a similar vein, we have found that interest rate spreads (i.e., foreign-domestic real interest rate differentials) are not among the best-performing group of leading indicators. More empirical work needs to be done to determine whether these results are robust to other rating agencies and other samples. Nevertheless, our findings suggest that those who are looking to "market prices" for early warning of crises in emerging economies would therefore be advised to focus on the behavior of real exchange rates and stock prices—not on credit ratings and interest rate spreads.

Eighth, **in most banking and currency crises, a high proportion of the monthly leading indicators—on the order of 50 to 75 percent—reach their signaling thresholds.** Indeed, both in and out of sample, we found that fewer than one-sixth of crises occurred with only five or fewer of the 15 monthly leading indicators flashing. In other words, when an emerging economy is lurching toward a financial crisis, many of the wheels come off simultaneously.

Ninth, **although we have just scratched the surface on testing our leading indicators out of sample, we are encouraged by the initial results—at least for currency crises.** We considered two out-of-sample periods: an 18-month period running from the beginning of 1996 to the end of June 1997 (just before the outbreak of the Asian financial crisis) and a 24-month period running from January 1996 to the end of December 1997. Recall that because the indicators lead crises by anywhere from 10 to 18 months, part of the prediction period will lie outside the out-of-sample observation period.

In each period, we concentrated on the ordinal ranking of countries according to their crisis vulnerability.[3] In chapter 5 we also illustrate for a subset of the countries how one can calculate from this vulnerability index the probability of a crisis for a given country over time. As regards vulnerability to currency crises, the results for the two out-of-sample periods were quite similar. The five most vulnerable countries (in descending order) for the 1996 to mid-1997 period were as follows: South Africa, Czech Republic, Thailand, South Korea, and the Philippines (table 8.2). For the somewhat longer 1996 to end of December 1997 period, the list of the five most vulnerable countries is quite similar, although their ordinal ranking is slightly different: Czech Republic, South Korea, Thailand, South Africa, and Colombia. If the list were extended to the top seven, Malaysia would have been included in both periods.

Perhaps the first question to ask is how many of the countries estimated to be most vulnerable to currency crises in the out-of-sample periods turned out to have undergone such crises? The answer, as shown in the upper panel of table 8.2, is almost all of them. According to our index of exchange market pressure, the Czech Republic, Thailand, South Korea, and the Philippines all experienced currency crises in 1997 (that is, depreciations or reserve losses that pushed the index of exchange market pressure to three standard deviations or more above its mean). Colombia's currency

3. Our preferred measure of vulnerability was an index equal to the weighted average of "good" indicators issuing signals in the out-of-sample period. By "good" indicators, we mean those that had noise-to-signal ratios less than unity during the 1970-95 period. Taking the monthly and annual indicators as a group, there were 18 "good" indicators. We used the inverse of the noise-to-signal ratios as weights for the better indicators. We then ranked each of the 25 countries in the sample according to the computed value of this index. The index is meant to capture the probability of a crisis—not necessarily its severity.

Table 8.2 Country rankings of vulnerability to currency crises for two periods[a]

January 1996-June 1997			January 1996-December 1997		
Country	Rank	Experienced crisis[b]	Country	Rank	Experienced crisis[b]
Most vulnerable					
South Africa	1		Czech Republic	1	*
Czech Republic	2	*	South Korea	2	*
Thailand	3	*	Thailand	3	*
South Korea	4	*	South Africa	4	
Philippines	5	*	Colombia	5	*
Least vulnerable					
Chile	16		Chile	16	
Venezuela	17		Peru	17	
Uruguay	18		Venezuela	18	
Mexico	19		Mexico	19	
Peru	19		Uruguay	20	

a. Weighted index is a sum of the weighted signals flashing at any time during the specified period. Monthly and annual indicators are included. Weights are equal to the inverse noise-to-signal ratios of the respective indicators.

b. An asterisk (*) indicates that the country experienced a crisis during the out-of-sample period.

crisis arrives later, in the summer of 1998. Moreover, while South Africa did not formally make the cut, it could reasonably be classified as a near miss since it experienced a quasi-crisis in June 1998 (a 14 percent devaluation *cum* a 13 percent decline in reserves that pushed the exchange market pressure index 2.7 standard deviations above its mean). Malaysia, which just makes it into the group of the seven most vulnerable, did have a currency crisis in 1997.

Further information on the out-of-sample performance of the leading indicators of currency crisis can be gleaned by looking for episodes in which, to borrow from Sherlock Holmes, the "dogs were not barking"—that is, by looking to see how often crises occurred among those countries estimated to have relatively low vulnerability. The lower panel of table 8.2 indicates the five countries that were estimated to have relatively low vulnerability to currency crises in 1996-97. As with the high vulnerability group, the ordinal rankings of countries are very similar across the two out-of-sample periods, with Venezuela, Peru, and Uruguay slightly shifting their relative positions in the least vulnerable list. Perhaps an explanation as to why the index of vulnerability is relatively low for some of these countries can be found in the fact that some of these countries were still recovering from earlier crises (Mexico and Venezuela).

But what about Indonesia, which after all suffered the most severe currency crisis (beginning in the summer of 1997) among the sample countries during the out-of-sample period? Why did the model miss it altogether?[4] The explanation probably lies in two areas. First, most of the best-performing (higher weight) leading indicators were not flashing in Indonesia's case. For example, in mid-1997 (just before the outbreak of the Thai crisis), the real effective exchange rate of the Indonesian rupiah was only 4 percent above its long-term average—far below its critical threshold. In a similar vein, neither the decline in stock prices, nor the decline in exports, nor the change in the ratio of M2 money balances to international reserves had hit their threshold values.[5] Second, at least three of the factors important in the Indonesian crisis are not included in our list of indicators: namely, currency/liquidity mismatches on the part of the corporate sector, regional cross-country contagion effects, and political instabilities (in this case associated with the Suharto regime). In this connection, work reported in Kaminsky and Reinhart (2000) and extended in chapter 6 suggests that the withdrawal of a common bank lender (in this case, European and Japanese banks) had a lot to do with contagion in emerging Asia—and Indonesia in particular—after the outbreak of the Thai crisis.

The failure of our leading indicators to anticipate the Indonesian crisis should not, however, obscure the fact that, of the five countries most adversely affected by the Asian crisis (Thailand, South Korea, Indonesia, Malaysia, and the Philippines), the indicators placed three of them (Thailand, South Korea, and the Philippines) in the top vulnerability group and another (Malaysia) in the upper third of the country vulnerability rankings. Given the well-documented failure of private credit ratings and interest rate spreads to anticipate these Asian currency crises (with the possible exception of Thailand), and given that these forecasts are based solely on own-country fundamentals (that is, with no help from contagion variables), this performance on relative-country vulnerabilities is noteworthy. By the same token, the relatively high estimated vulnerability of several of the Asian emerging economies also challenges the oft-heard view that the crisis was driven primarily by investor panic, with little basis in weak country fundamentals.[6]

4. It should be recognized that none of the existing early warning models—including the regression-based models—anticipated the Indonesian crisis.

5. Indonesia's equity prices did suffer a severe decline, but it did not begin until August 1997.

6. Using a very similar approach but a slightly different set of indicators, Kaminsky (1998), who presents a time series of calculated crisis probabilities for the Asian economies, finds results that are in line with those shown in tables 1.6 and 1.7—namely, that estimated currency-crisis vulnerability increased markedly before the 1997 event in Thailand and moderately in Malaysia and the Philippines. Again, no such increase in estimated vulnerability was present for Indonesia. South Korea was not in her sample. Radelet and Sachs (1998) take the opposing view that the crisis in Asia was mainly attributable to investor panic. As discussed in chapter 6, we only find that argument to be convincing in the case of Indonesia.

Table 8.3 Country rankings of vulnerability to banking crises for two periods[a]

January 1996-June 1997			January 1996-December 1997		
Country	Rank	Experienced crisis[b]	Country	Rank	Experienced crisis[b]
Most vulnerable					
Czech Republic	1		Czech Republic	1	
South Korea	2	*	South Korea	2	*
Greece	3		Thailand	3	*
South Africa	4		South Africa	4	
Thailand	5	*	Colombia	5	*
Least vulnerable					
Venezuela	15		Chile	16	
Chile	16		Argentina	17	
Peru	17		Venezuela	18	
Uruguay	18		Peru	19	
Mexico	19		Uruguay	20	

a. Weighted index is a sum of the weighted signals flashing at any time during the specified period. Monthly and annual indicators are included. Weights are equal to the inverse noise-to-signal ratios of the respective indicators.

b. An asterisk (*) indicates that the country experienced a crisis during the out-of-sample period.

Turning to banking crises, the ordinal rankings of country vulnerability again are quite similar across the two out-of-sample periods, although the correspondence is slightly lower than was the case for currency crises: four of the five countries estimated to be most vulnerable to banking crises are the same across the two periods. Specifically, for the 1996 to mid-1997 period, the five most vulnerable countries (again in descending order) were Czech Republic, South Korea, Greece, South Africa, and Thailand (table 8.3). When the out-of-sample period is extended through the end of 1997, Greece drops out of the top five and is replaced by Colombia.

As with the vulnerability rankings for currency crises, it is useful to ask which of the countries estimated to be most vulnerable to banking crises actually suffered that fate during the out-of-sample periods. As suggested earlier, this is intrinsically a tougher question to answer for banking crises than for currency crises because the identification and dating of crises are subject to wider margins of error. Recall also that because our 24-month early warning window for banking crises covers both the 12-month period preceding the beginning of the crisis as well as the 12-month period following the onset, successful predictions would include some crises that began toward the end of 1995 and some that started no later than early 1998 (as well as those that began in 1996 or 1997).

With these caveats in mind, the picture painted by table 8.3 can be summarized as follows. Of the five countries estimated to be most vulnerable during January 1996 to the end of June 1997, two experienced banking crises that fall in our prediction window. Specifically, we consider South Korea's banking crisis to have begun in January 1997, with the loan losses stemming from the bankruptcy of Hanbo Steel. In a similar vein, we date Thailand's banking crisis as starting in May 1996, when the Ministry of Finance took control of Bangkok Bank of Finance (following a run on deposits). A third member of the most vulnerable group, the Czech Republic, also experienced a banking crisis although the timing is not clear-cut. The start of the Czech crisis could be dated in August 1996, reflecting the closure of Kreditni Banka; alternatively, one could also defend a much earlier starting date, namely September 1993, when Kreditni was initially placed under supervision.[7] Some researchers (e.g., Kaminsky and Reinhart 1999) also classify Malaysia and the Philippines as having registered banking crises in 1997. The results for the longer out-of-sample period, shown in the upper panel of table 8.3, are quite similar: the same three countries (South Korea, Thailand, and Czech Republic) make up the list of successful banking-crisis predictions. For the more recent sample, Colombia is also added to the list of successful predictions. In April 1998 the bailout by Banco de la Republica of several finance companies facing severe difficulties with mounting losses in their loan portfolios intensified in earnest, and banking sector problems deepened throughout 1998-99.

What about the group of countries estimated to be least vulnerable to banking crises? As seen in the lower panel of table 8.3, four of the five countries in this category are common to both sample periods: Uruguay, Venezuela, Peru, and Chile. Mexico appears only in the shorter period, while Argentina makes the least vulnerable list only in the longer period. For all five of the countries estimated to be least vulnerable, no banking crisis appears to have taken place during the out-of-sample periods. As was the case with the forecasting of currency crises, Indonesia (which is ranked 11 or 12, depending on the sample chosen) emerges as a major misclassification, although timing problems somewhat cloud the issue. Many observers would regard the severity of Indonesia's financial sector problems in 1997 as constituting a ''new'' banking crisis; others might argue that these difficulties constituted a continuation of the banking problems that began in 1992 with the collapse of Bank Summa. In any case, it is clear that the model was not picking up the increase in Indonesia's vulnerability in 1997. Mexico presents another timing problem. Mexico remained in the throes of a banking crisis throughout the out-of-sample period and thus could be classified as highly vulnerable. At the same time, most studies (e.g., Demirgüç-Kunt and Detragiache 1998; IMF 1998b) regard the Mexican banking crisis as having started at least as early as

7. The Czech banking crisis was not included in our in-sample test, and hence the model is not calibrated to account for this crisis.

1994. Here, too, the model seems to have difficulty in identifying changes in vulnerability when they occur in the context of continuing banking problems.

Looking at both the high and low vulnerability groups, it is clear that the early warning model is less successful out of sample in anticipating banking crises than it is in anticipating currency crises. The problem is not so much that the model misses many banking crises that do occur but rather that it generates too many false positives or ''noise,''—that is, it predicts more cases of banking crisis vulnerability than actually occur. In this connection, it is worth noting that we classify only five or six episodes as meeting our criteria for a banking crisis during the out-of-sample period (that is, the period running roughly from late 1995 to early 1998). This list comprises South Korea, Thailand, the Czech Republic, Indonesia, and Malaysia.[8] Of these five crisis cases, three of the countries concerned (South Korea, Thailand, and the Czech Republic) were members of our ''most vulnerable'' group.[9] This might be considered fair performance. Difficulties in forecasting Asian banking crises in 1997 seem to be common to the leading forecasting models—be they signals approach models or regression-based models. For example, Demirgüç-Kunt and Detragiache (1998), using a multivariate logit model, report that the conditional probabilities for banking crises in the five most adversely affected Asian economies were actually below the unconditional crisis probabilities (Furman and Stiglitz 1998). Similarly, Kaminsky (1998) finds that estimated crisis probabilities were rising sharply in the case of the Thai banking crisis and moderately in the case of the Philippines, but not for either Malaysia or Indonesia.

We conducted a number of experiments, which are described in chapter 5, to help gauge the robustness of our results on the ordinal ranking of country vulnerability to currency and banking crises. In one exercise, instead of basing the ordinal vulnerability rankings exclusively on weights derived from the noise-to-signal ratios, we looked at both the proportion of indicators signaling a crisis and the proportion of the top eight indicators signaling a crisis. In another exercise, we looked at various indicators signaling both banking and currency crises and calculated ''average'' vulnerability to banking and currency crises combined. And in yet another set of exercises, we liberalized the optimal thresholds for each of the indicators by 5 percent, thereby making it less likely that we would miss crises that were unfolding, albeit at the cost of predicting crises that never

8. The Malaysian crisis would probably best be regarded as beginning in March 1998, when the central bank announced losses at Sime Bank and elsewhere and when Malaysian President Datuk Seri Mahathir bin Mohamad pledged state funds to prop up weak institutions.

9. Malaysia was ranked fourteenth (out of 25 countries) in the shorter period and tenth in the longer one.

occurred. While these robustness exercises not surprisingly generated some changes in the ordinal rankings, perhaps the most important finding was that the same "core" set of vulnerable countries—the Czech Republic, South Korea, South Africa, Greece, Colombia, Thailand, the Philippines, and Malaysia—consistently remained in the top tier of the vulnerability list. It is also noteworthy that none of these sensitivity exercises anticipated the Indonesian crisis.

All in all, **we regard the out-of-sample performance of the signals approach as encouraging—particularly as regards anticipating currency crises in the Asian crisis countries.**[10] With the exception of Indonesia, the model did well in identifying the countries with relatively high vulnerability. In addition, the model gave strong signals for Brazil, the Czech Republic, South Africa, and Colombia, which also experienced crises (or turbulence) outside the Asian region. The results for banking crises were less impressive. While we would not place much confidence in the precise estimated ordering of vulnerability across countries, we think the signals approach looks promising for making distinctions between the vulnerability of countries near the top of the list and those near the bottom—that is, it may be useful as a "first screen," which can then be followed by more in-depth country analysis.

Some others are pessimistic about both the potential and actual out-of-sample performance of signals-based leading-indicator models of currency crises, including their track record in anticipating the Asian financial crisis.[11] They argue that when such models do perform seemingly well, it is often because they rely on "black box" simple contagion variables (for example, the number of crises that have occurred in the previous period), that the methodology embedded in the signals approach is biased toward overpredicting crises in countries with good histories and this explains its successes in predicting currency crises in Asia, and that both in-sample and out-of-sample performance would be better if the good indicator variables were entered linearly (rather than sending a signal only when the indicator crossed its threshold) and if the weights on the individual indicators were estimated by a regression (rather than selected from an iterative noise-to-signal test one at a time). These critics also argue that the correlation between the severity of observed currency crises and crisis vulnerability predicted by the signals approach was low (at least in 1996) and that (also in 1996) there did not seem to be a marked distinction between the calculated currency crisis vulnerabilities of several

10. This is consistent with the results of a recent IMF study (Berg and Pattillo 1999), which found that the signals model of Kaminsky, Lizondo, and Reinhart (1998) did a better job of predicting the Asian crisis than the models of Frankel and Rose (1996) and of Sachs, Tornell, and Velasco (1996).

11. See Berg and Pattillo (1999), *The Economist* (1998), Furman and Stiglitz (1998), IMF (1998c), and Wyplosz (1997, 1998).

noncrisis countries (particularly Argentina and Mexico) and the Asian crisis countries (Thailand and Indonesia). Further, they find that leading-indicator models have poor in-sample performance in forecasting currency crises for developing countries, especially in emitting Type II errors (false positives) and that publication of a vulnerability index could precipitate a crisis. We do not find these criticisms to be persuasive.

In the two studies (Berg and Pattillo 1999; Furman and Stiglitz 1998) that have explicitly run out-of-sample horse races between the Kaminsky-Reinhart signals model and two other regression-based models of currency crises (Frankel and Rose 1996; Sachs, Tornell, and Velasco 1997), both concluded that the signals approach does better.

Wyplosz (1998) bases his pessimistic conclusions on the in-sample performance of leading-indicator models of currency crises in developing countries using the Frankel and Rose (1996) model—not the Kaminsky-Reinhart signals approach. Using an abbreviated search technique for the optimal threshold for various indicators, Wyplosz finds that (using a 5 percent threshold) 62 of 86 currency crises are detected, while the model signals wrongly—that is, emits false positives—in 43 percent of the crises. Our results are more favorable than Wyplosz's for developing-country currency crises (in-sample). Out of sample, we find that the false positives problem is more serious for the banking crises than for currency crises.

While we present some new results on cross-country contagion in chapter 6, the out-of-sample results—both in earlier Kaminsky-Reinhart studies and in this book—do not rely at all on cross-country contagion; instead, they reflect only own-country fundamentals.

There is (at least to our knowledge) no empirical evidence to support the view that imposing a common absolute threshold for indicator variables would produce better in-sample and out-of-sample performance than our procedure of imposing a common percentile threshold and allowing the absolute threshold to differ across countries. Nor, as we have argued earlier, does it seem more reasonable on *a priori* grounds to impose the one-size-fits-all restriction on countries with different histories—quite the contrary. As for the alleged influence of our procedure in the context of forecasting the Asian financial crisis, one would have thought that if this bias were large, it might have led to a very successful prediction of crises in the Asian countries, yet some of these same critics find that the signals approach does very poorly in forecasting currency crises in these countries.

While more work is clearly needed to assess the robustness of the results to different out-of-sample periods (since these differ and seem to generate different outcomes across studies), we do *not* find that there was little distinction in estimated currency-crisis vulnerabilities between most of the Asian crisis countries, on the one hand, and some other (Latin American) noncrisis countries, on the other. As indicated earlier, we found that Thailand, the Philippines, and Malaysia had *higher* estimated currency-crisis probabilities in 1996-97 than did Argentina and Mexico—not the other way around. Thailand was near the top of our vulnerability list—not near the bottom. Also, it is not obvious that out-of-sample comparisons based on the severity of crises are more meaningful than those (as above) that concentrate on the crisis/no crisis distinction.

In short, just as we emphasized that it is important not to oversell the potential of early warning models to predict crises in emerging economies, we think some of the critics are too quick to dismiss the usefulness of these models because of a mixed out-of-sample performance based on runs from a single period. We should also keep in mind the apparent inability of non-model-based forecasts to foresee the Asian crisis. In our view, much more empirical work will need to be done before we can draw reliable conclusions on the out-of-sample performance of the signals approach.

Examining a somewhat more limited sample (20) of small developed and emerging economies over the 1970-98 period, we looked for patterns in the cross-country contagion of currency crises. Following Eichengreen, Rose, and Wyplosz (1996), we define contagion as a case in which the presence of a crisis elsewhere increases the probability of crisis at home, even when the fundamentals have been taken into account. We considered four channels through which shocks can be transmitted across borders: two dealt with trade links (bilateral trade flows and trade competition in third-country markets) and two channels addressed financial links (correlation of asset returns in global portfolios and reliance on a common bank lender). We also demonstrated how these four contagion channels could be combined and weighted appropriately to form a "contagion vulnerability index."

This exercise led us to our tenth main finding: that **cross-country contagion adds significantly to own-country fundamentals in furthering an understanding of emerging market vulnerability to financial crises and that (at least historically) contagion has operated more along regional than global lines.** According to our contagion vulnerability index, Brazil, Argentina, and the Philippines had high vulnerability to the 1994 Mexican peso crisis; Malaysia, South Korea, and Indonesia had high vulnerability to the 1997 Thai crisis; and Argentina, Chile, and Uruguay had high vulnerability to the 1999 Brazilian crisis. Although it is difficult to separate financial contagion channels from trade channels (since countries linked in trade also are linked in finance) we concluded that withdrawal of a common bank lender (particularly Japanese banks) and high correlation of asset returns were important in the contagion in Asia in 1997-98.

Eleventh, in addition to studying the antecedents of crises we also drew on our data base for information on the aftermath of crises—with particular attention to the speed with which emerging economies return to "normal" after a currency or banking crises. We defined normal in two alternative ways: first, as a period of "tranquility" that excludes not only the crisis years but also the two- to three-year windows before and after the crisis, and second, as the average of the two years just preceding crises.[12]

One of our most robust findings was that the deleterious effects on economic activity are more lingering for banking crises than for currency crises.[13] For example, whereas it took about two years for economic growth to return to the average of the two precrisis years after a currency crisis, that recovery was not evident even three years after a banking crisis. One possible explanation for this difference is that, whereas a currency crisis sharply reduces external sources of funding, a banking crisis curtails access to both external and domestic sources of finance for households and firms—that is, the "credit crunch" is more severe in the wake of banking crises. This more sluggish recovery pattern for banking crises was also evident for exports, imports, and stock prices. For instance, whereas exports recover relatively quickly (eight months) and ahead of the rest of the economy following currency crises, they continue to sink for two years following the onset of a banking crisis. Two other dimensions of the protracted nature of banking crises are that it takes about three to four years for a banking crisis to be resolved and it takes on the order of a year and half between the onset of a banking crisis and its peak. All of this highlights the challenge faced by the Asian crisis countries in sustaining their recoveries: not only did the most affected countries in emerging Asia suffer from currency crises that were accompanied by banking crises (what Kaminsky and Reinhart 1999 dub "twin crises"), but the banking crises themselves are very severe.

Our analysis of the aftermath of crises does not lend support to the notion that devaluations in emerging economies generate deflation. Instead, we find that devaluations are inflationary, that the pass-through to prices is incomplete (hence, devaluations lead to real depreciations), and that it takes between two and three years after a devaluation for inflation to return to the average of the two precrisis years.

Last but not least, **we offer a number of suggestions for improving early warning models of currency and banking crises.** In our view, four directions for future research merit priority.

As hinted above, more work needs to be done to determine the out-of-sample forecasting properties of these models—be it signals approach models or regression-based logit or probit models. In particular, it would be useful to know how robust "who's next" country rankings of vulnera-

12. More specifically, the "tranquil" period excludes the 24 months before and after currency crises and the 24 months before and 36 months after banking crises.

13. In the cases where currency and banking crises coincide, the postcrisis performance would show up in both the averages for currency and banking crises. See chapter 7 for details.

bility are in the face of changes in the forecasting period, different composite indicators, different definitions and transformations of the indicator variables (e.g., alternative definitions of the effective real exchange rate or of real exchange rate "misalignments," and alternative ways of dating banking crises or selecting the early warning "window"), and the restrictions imposed in the different models (e.g., imposing thresholds versus allowing indicators to enter linearly, imposing absolute thresholds versus common percentile ones). It may turn out, as suggested by Berg and Pattillo (1999), that combining certain features of the signals approach and the regression-based models would improve forecasting (e.g., using the signals approach to select the good indicators and then estimating the weights and crisis probabilities using a regression-based format).

We think there is scope to bring other indicators into these horse races. For example, Kaminsky (1998) has found that the share of short-term debt in total foreign debt, as well as a proxy for capital flight (by residents of emerging economies), do quite well in anticipating currency and banking crises within the sample. Looking at the run-up to the Asian financial crisis, Furman and Stiglitz (1998) likewise make a good case for including the ratio of short-term external debt to international reserves as an indicator in future early warning exercises. If monthly data could be obtained both on real property prices and on the exposure of the banking system to property, those too could prove very helpful.

A plausible extension would be to bring institutional characteristics of weak banking systems into the forecasting of banking crises. There is a strong presumption that the following all matter for vulnerability to banking crises: weak accounting, provisioning, and legal frameworks; policy-directed lending; the ownership structure of the banking system (government ownership, foreign ownership, and so on); the incidence of connected lending; the extent of diversification; the quality of banking supervision; and the incentive-compatibility of the official safety net. Yet it is only very recently that any of these factors have begun to enter the empirical literature.[14]

The main constraint on making use of these institutional characteristics is that one cannot get high-frequency measurements of them. Indeed, for some of these characteristics (e.g., the share of government ownership), it has proved difficult to get even annual data that is less than two or three years old. This means that such variables have to be introduced as zero-one dummy variables in a time-series context. There would be more scope to take advantage of such factors in cross-section work—that is, in explaining cross-country differences in the incidence of banking crises over long periods.

14. See, for example, Demirgüç-Kunt and Detragiache (1998), who introduce law enforcement and deposit-insurance variables into their banking crisis model.

Lastly, we think the ongoing work on modeling the nature of cross-country contagion of crises should be extended. One of the lessons of the last few major crises (that is, the Mexican crisis and the Asian/global financial crisis) is that the channels of cross-country contagion are more numerous and complicated than we thought earlier. Each of these factors seem to play a part in contagion: trade links (bilateral and third party), perceived similarities in macroeconomic and financial vulnerability, the dynamics of competitive devaluations, induced effects on primary commodity prices, financial links operating via withdrawal of a common bank or mutual fund lender, liquidity and margin-call effects operating via the regulatory framework, and perceived changes in the rescheduling *cum* capital-account convertibility regime (such as took place after the Russian unilateral rescheduling/default in August 1998 and the Malaysian imposition of wide-ranging capital controls). We need to find ways to incorporate more of these channels of contagion in our forecasting models.

Would the Publication of the Indicators Erode Their Early Warning Role?

It is sometimes argued that if the indices of crisis vulnerability were made publicly available on a timely basis, such publication could prompt a self-fulfilling run on a country's currency or its banks. Alternatively, it is sometimes asserted that if countries really paid heed to the message of the indicators and took preemptive action, then the indicators would lose predictive power. This latter outcome would, of course, be highly desirable. While neither of these arguments can be dismissed lightly, we would regard both as exaggerated.

The conditions for generating this type of self-fulfilling runs are likely to be relatively rare. As we have stressed throughout this book, the signals approach is useful in identifying cases of high vulnerability to crises. Explaining the precise timing of the crises remains an elusive goal. To the extent that timing matters and that investment decisions are made under uncertainty, there is little reason to expect that moderate increases in the extent of vulnerability are likely to be sufficient to prompt a speculative attack. As argued earlier, negative announcements of the readings in the leading indicator index of business cycles—which have been published for many years—do not cause a recession, although investors certainly take these readings into account.

By the same token, we think it unlikely that publication would cause the indicators to lose most of their predictive ability. This could certainly occur if preemptive policy was an everytime, everywhere phenomenon and if such preemptive policies were in fact successful in staving off crises. These are strong assumptions. All too often, policymakers are inclined to ignore distress signals on the grounds that, this time, the situation is really different or that there are overriding political objectives against corrective action. Furthermore, even if the signals are heeded and corrective policy actions are taken, they may not be sufficient to prevent the crisis. If the feedback from the indicators to corrective policy action were strong and consistent, we would not have been able to identify useful indicators in the first place. Of course, one could always speculate that future policymakers will be wiser than their predecessors, but that remains to be seen.

Do the Better Performing Indicators Carry Policy Implications?

The empirical evidence presented in this book can be seen as supporting the case for including leading indicators in the analytical tool kit for diagnosing crisis vulnerability. But can one go farther and draw policy implications from the performance of the better univariate indicators?

One should recall that the signals approach outlined in this book and in earlier works by Kaminsky and Reinhart looks for empirical regularities in the behavior of macroeconomic and financial variables in the run-up to currency and banking crises. We thus cannot fully identify from this exercise the channels by which policies affect economic outcomes.

For some of the indicators, the results have clear implications for macroeconomic and exchange rate policies; for others there is no obvious link. For example, the performance of M2/reserves as an indicator of currency crises is suggestive of the desirability of avoiding large discrepancies between liquid liabilities and liquid assets. In this regard, the policy implication would be to encourage emerging market countries to maintain high liquidity ratios, prearranged lines of credit, and an ample stock of reserves. Much of the behavior of other indicators, notably rising real interest rates and money multipliers, are associated with financial liberalization. Indeed, the reliability of these indicators in anticipating banking crises may warn against hasty liberalizations. On the other hand, real exchange rate overvaluations are an important indicator of both currency and banking crises, but the burning policy question that remains unanswered is how emerging market countries can avoid these costly periodic overvaluations. Real exchange rate targeting has been tried by countries as diverse as Brazil, Chile, Indonesia, and Colombia, but the outcomes were quite dissimilar—particularly as regards their consequences for inflation.[15] In the case of some other indicators, such as stock prices, the policy implications are even less obvious.

In short, while we regard the empirical work on early warning indicators as consistent with many stories of the origins of currency and banking crises, one has to be careful not to overinterpret the results, as alternative explanations of crises often yield observationally equivalent implications.

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15. Calvo, Reinhart and Végh (1995) present empirical evidence on this issue.