2

Methodology

Our approach to identifying early warning indicators of financial crises in emerging economies reflects a number of decisions about the appropriate methodology for conducting such an empirical exercise. Key elements of our thinking are summarized in the following guidelines.

General Guidelines

First, finding a systematic pattern in the origin of financial crises means looking beyond the last prominent crisis (or group of crises) to a larger sample. Otherwise there is a risk either that there will be too many potential explanations to discriminate between important and less important factors or that generalizations and lessons will be drawn that do not necessarily apply across a wider body of experience.[1] We try to guard against these risks by looking at a sample of 87 currency crises and 29 banking crises that occurred in a sample of 25 emerging economies and smaller industrial countries over 1970-95.[2]

Several examples help to illustrate the point. Consider the last two major financial crises of the 1990s: the 1994-95 Mexican peso crisis and

1. One can also view "early warning indicators" as a way to discipline or check more "subjective" and "idiosyncratic" assessments of crisis probabilities for particular economies—just as more comprehensive, subjective assessments can act as a check on the quality of early warning indicator projections.

2. Our out-of-sample analysis spans 1996-97. Our criteria for defining a currency and a banking crisis is described later in this chapter.

the 1997-99 Asian financial crisis. Was the peso crisis primarily driven by Mexico's large current account deficit (equal to almost 8 percent of its GDP in 1994) and by the overvaluation of the peso's real exchange rate, or by the maturity and composition of Mexico's external borrowing (too short term and too dependent on portfolio flows), or by the uses to which that foreign borrowing was put (too much for consumption and not enough for investment), or by the already-weakened state of the banking system (the share of nonperforming loans doubled between mid-1990 and mid-1994), or by bad luck (in the form of unfortunate domestic political developments and an upward turn in US international interest rates)? Or was it driven by failure to correct fast enough earlier slippages in monetary and fiscal policies in the face of market nervousness, or by a growing imbalance between the stock of liquid foreign-currency denominated liabilities and the stock of international reserves, or by an expectation on the part of Mexico's creditors that the US government would step in to bail out holders of *tesobonos?*[3]

Analogously, was the Asian financial crisis due to the credit boom experienced by the ASEAN-4 economies (Thailand, Indonesia, Malaysia, and the Philippines), or a concentration of credit in real estate and equities, or large maturity and currency mismatches in the composition of external borrowing, or easy global liquidity conditions, or capital account liberalization cum weak financial sector supervision? Was it the relatively large current account deficits and real exchange rate overvaluations in the run-up to the crisis, a deteriorating quality of investment, increasing competition from China, global overproduction in certain industries important to the crisis countries, or contagion from Thailand?[4] There are simply too many likely suspects to draw generalizations from two episodes—even if they are important ones. To tell, for example, whether a credit boom is a better leading indicator of currency crises than are, say, current account deficits, we need to run a horse race across a larger number of currency crises.[5]

Equally, but operating in the opposite direction, there is a risk of "jumping the gun" by generalizing prematurely about the relative importance of particular indicators from a relatively small set of prominent crises. One example is credit booms—that is, expansions of bank credit that are large relative to the growth of the economy. These have been shown to

3. See Leiderman and Thorne (1996) and Calvo and Goldstein (1996) for an analysis of the Mexican crisis.

4. These alternative explanations of the Asian crisis are discussed in BIS (1998), Corsetti, Pesenti, and Roubini (1998), Goldstein (1998a), Radelet and Sachs (1998), IMF (1997), and World Bank (1998).

5. Some of these explanations, of course, are not mutually exclusive. For example, large current account deficits may be the outcome of financial liberalization and its attendant credit booms.

forerun banking crises in Japan, in several Scandinavian countries, and in Latin America (Gavin and Hausman 1996). Yet when we compare credit booms as a leading indicator of banking crises to other indicators across a larger group of emerging economies and smaller industrial countries, we find that credit booms are outperformed by a variety of other indicators. Put in other words, credit booms have been a very good leading indicator in some prominent banking crises but are not, on average, the best leading indicator in emerging economies more generally. Again, it is helpful to have recourse to a larger sample of crises (in this study nearly 30) to sort out competing hypotheses.

The second guideline is to pay equal attention to banking crises and currency crises. To this point, most of the existing literature on leading indicators of financial crises relates exclusively to currency crises.[6] Yet the costs of banking crises in developing countries appear to be greater than those of currency crises. Furthermore, banking crises appear to be one of the more important factors in generating currency crises, and the determinants and leading indicators of banking crises should be amenable to the same type of quantitative analysis as currency crises are.[7]

Some policymakers have argued that, looking forward, the emphasis in surveillance efforts should be directed to banking sector problems rather than currency crises. The underlying assumption supporting that view is that as more countries adopt regimes of managed floating, currency crises become a relic of the past. We believe this view to be overly optimistic. It is noteworthy that among all the Asian countries that had major currency crises in 1997-98 only Thailand had an "explicit pegged exchange rate" policy. Indonesia, Malaysia, and South Korea were all declared managed floaters, while the Philippines in principle (but not in practice) had a freely floating exchange rate. Among emerging markets, there is widespread "fear of floating," and many of the countries that are classified as floaters have implicit pegs, leaving them vulnerable to the types of currency crises we study in this book.[8]

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6. See Kaminsky, Lizondo, and Reinhart (1998) for a review of this literature. Among the relatively few studies that include or concentrate on banking crises in emerging economies, we would highlight Caprio and Klingebiel (1996a, 1996b), Demirgüç-Kunt and Detragiache (1998), Eichengreen and Rose (1998), Furnam and Stiglitz (1998), Honohan (1997), Gavin and Hausman (1996), Goldstein (1997), Goldstein and Turner (1996), Kaminsky (1998), Kaminsky and Reinhart (1998, 2000), Rojas-Suarez (1998), Rojas-Suarez and Weisbrod (1995), and Sundararajan and Baliño (1991).

7. Both Kaminsky and Reinhart (1998) and the IMF (1998c) conclude that the output costs of banking crises in emerging economies typically exceed those for currency crises and that these costs are greater still during what Kaminsky and Reinhart (1999) dubbed "twin crises" (that is, episodes when the country is undergoing simultaneous banking and currency crises). We provide further empirical evidence on this issue in chapter 7.

8. See Calvo and Reinhart (2000) and Reinhart (2000) for a fuller discussion of this issue.

We analyze banking and currency crises separately, as well as exploring the interactions among them. As it turns out, several of the early warning indicators that show the best performance for currency crises also work well in anticipating banking crises. At the same time, there are enough differences regarding the early warning process and in the aftermath of crises to justify treating each in its own right.

A third feature of our approach—and one that differentiates our work from that of many other researchers—is that we employ monthly data to analyze banking crises as well as currency crises.[9] Use of monthly (as opposed to annual data) involves a trade-off. On the minus side, because monthly data on the requisite variables are available for a smaller number of countries than would be the case for annual data, the decision to go with higher frequency data may result in a smaller sample. Yet monthly data permit us to learn much more about the timing of early warning indicators, including differences among indicators in the first arrival and persistence of signals. Indeed, many of the annual indicators that have been used in other empirical studies are only publicly available with a substantial lag, which makes them plausible for a retrospective assessment of the symptoms of crises but ill-suited for the task of providing an early warning. Hence, we conclude that the advantages of monthly data seemed to outweigh the disadvantages.[10] In the end, we were able to assemble monthly data for about two-thirds of our indicator variables; for the remaining third, we had to settle for annual data.

A fourth element of our approach was to include a relatively wide array of potential early warning indicators. We based this decision on a review of broad, recurring themes in the theoretical literature on financial crises. These themes encompass

- asymmetric information and ''bank run'' stories that stress liquidity/currency mismatches and shocks that induce borrowers to run to liquidity or quality,
- inherent instability and bandwagon theories that emphasize excessive credit creation and unsound finance during the expansion phase of the business cycle,
- ''premature'' financial liberalization stories that focus on the perils of liberalization when banking supervision is weak and when an extensive

9. For example, the studies of banking crises in emerging markets by Caprio and Klingebiel (1996a, 1996b), Goldstein and Turner (1996), Honohan (1995), and Sundararajan and Baliño (1991) are primarily qualitative, while the studies by Demirgüç-Kunt and Detragiache (1997), Eichengreen and Rose (1998), and the IMF (1998c) use annual data for their quantitative investigation of the determinants of banking crises.

10. Private-sector ''early warning'' analyses likewise seem to be moving in the direction of using monthly data. See Ades, Masih, and Tenegauzer (1998) and Kumar, Perraudin, and Zinni (1998).

network of explicit and implicit government guarantees produces an asymmetric payoff for increased risk taking,

- first- and second-generation models of the vulnerability of fixed exchange rates to speculative attacks,[11] and
- interactions of various kinds between currency and banking crises.

In operational terms, this eclectic view of the origins of financial crises translates into a set of 25 leading indicator variables that span the real and monetary sectors of the economy, that contain elements of both the current and capital accounts of the balance of payments, that include market variables designed to capture expectations of future events, and that attempt to proxy certain structural changes in the economy (e.g., financial liberalization) that could affect vulnerability to a crisis.

Once a set of potential leading indicators or determinants of banking and currency crises has been selected, a way has to be found both to identify the better performing ones among them and to calculate the probability of a crisis. In most of the existing empirical crisis literature, this is done by estimating a multivariate logit or probit regression model in which the dependent variable (in each year or month) takes the value of one if that period is classified as a crisis and the value of zero if there is no crisis. When such a regression is fitted on a pooled set of country data (i.e., a pooled cross-section of time series), the statistical significance of the estimated regression coefficients should reveal which indicators are "significant" and which are not, and the predicted value of the dependent variable should identify which periods or countries carry a higher or lower probability of a crisis.

A fifth characteristic of our approach is that we use a technique other than regression to evaluate individual indicators and to assess crisis vulnerability across countries and over time. Specifically, we adopt the nonparametric "signals" approach pioneered by Kaminsky and Reinhart (1999).[12] The basic premise of this approach is that the economy behaves differently on the eve of financial crises and that this aberrant behavior has a recurrent systemic pattern. For example, currency crises are usually preceded by an overvaluation of the currency; banking crises tend to follow sharp declines in asset prices. The signals approach is given diagnostic and predictive content by specifying what is meant by an "early" warning, by defining an "optimal threshold" for each indicator, and by choosing one or more diagnostic statistics that measure the probability of experiencing a crisis.

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11. First-generation models stress poor fundamentals as the cause of the currency crises, while second-generation models focus on shifts in market expectations and self-fulfilling speculative attacks. See Flood and Marion (1999) for a recent survey of this literature.

12. This approach is described in detail in Kaminsky, Lizondo, and Reinhart (1998).

By requiring the specification of an explicit early warning window, the signals approach forces one to be quite specific about the timing of early warnings. This is not the case for all other approaches. For example, it has been argued that an asymmetric-information approach to financial crises implies that the spread between low- and high-quality bonds will be a good indicator of whether an economy is experiencing a true financial crisis—but there is no presumption that this interest rate spread should be a leading rather than a contemporaneous indicator (Mishkin 1996). Furthermore, the indicator methodology takes a comprehensive approach to the use of information without imposing too many *a priori* restrictions that are difficult to justify.

Finally, we use the signals to rank the probability of crises both across countries and over time. We do so by calculating the weighted number of indicators that have reached their optimal thresholds (that is, are ''flashing''), where the weights (represented by the inverse of the individual noise-to-signal ratios) capture the relative forecasting track record of the individual indicators.[13] Indicators with good track records receive greater weight in the forecast than those with poorer ones. Ceteris paribus, the greater the incidence of flashing indicators, the higher the presumed probability of a banking or currency crisis. For example, if in mid-1997 we were to find that 18 of 25 indicators were flashing for Thailand versus only 5 of 25 for Brazil, we would conclude that Thailand was more vulnerable to a crisis than Brazil. Analogously, if only 10 of 25 indicators were flashing for Thailand in mid-1993, we would conclude that Thailand was less vulnerable in mid-1993 than it was in mid-1997. Thus we can calculate the likelihood of a crisis on the basis of how many indicators are signaling. Furthermore, as will be shown in chapter 5, we can attach a greater weight to the signals of the more reliable indicators. Owing to these features, the signals approach makes it easy computationally to monitor crisis vulnerability. In contrast, the regression-based approaches require estimation of the entire model to calculate crisis probabilities. In addition, because these regression-based models are nonlinear, it becomes difficult to calculate the contribution of individual indicators to crisis probabilities in cases where the variables are far away from their means.[14]

13. While this is one of many potential ''composite'' indicators (i.e., ways of combining the information in the individual indicators), Kaminsky (1998) provides evidence that this weighting scheme shows better in-sample and out-of-sample performance than three alternatives. Also, see chapter 5. One can equivalently evaluate the performance of individual indicators by comparing their conditional probabilities of signaling a crisis.

14. Of course, ease of application is only one of many criteria for choosing among competing crisis-forecasting methodologies. For example, the signals approach also carries the disadvantage that is less amenable to statistical tests of significance. In addition, some of the restrictions it imposes (e.g., that indicators send a signal only when they reach a threshold) may leave out valuable information.

Guideline number six is to employ out-of-sample tests to help gauge the usefulness of leading indicators. The in-sample performance of a model may convey a misleading sense of optimism about how well it will perform out of sample. A good case in point is the experience of the 1970s with structural models of exchange rate determination for the major currencies. While these models fit well in sample, subsequent research indicated that their out-of-sample performance was no better—and often worse—than that of ''naive'' models (such as using the spot rate or the forward rate to predict the next period's exchange rate; see Meese and Rogoff 1983). In this study, we use data from 1970-95 to calculate our optimal thresholds for the indicators, but we save data from 1996 through the end of 1997 to assess the out-of-sample performance of the signals approach, including the ability to identify the countries most affected during the Asian financial crisis.

Our seventh and last guideline is to beware of the limitations of this kind of analysis. Because these exercises concentrate on the macroeconomic environment, they cannot capture political triggers and exogenous events—the Danish referendum on the European Economic and Monetary Union (EMU) in 1992, the Colosio assassination in 1994, or the debacle over Suharto in 1997-98, for instance—which often influence the timing of speculative attacks. In addition, because high-frequency data are not available on most of the institutional characteristics of national banking systems—ranging from the extent of ''connected'' and government-directed lending to the adequacy of bank capital and banking supervision—such exercises cannot be expected to capture some of these longer-term origins of banking crises.[15] Also, because we are not dealing with structural economic models but rather with loose, reduced-form relationships, such leading-indicator exercises do not generate much information on *why* or *how* the indicators affect the probability of a crisis. For example, a finding that exchange rate overvaluation typically precedes a currency crisis does not tell us whether the exchange rate overvaluation results from an exchange rate-based inflation stabilization program or from a surge of private capital inflows.

Nor is the early warning study of financial crises immune from the ''Lucas critique'': that is, if a reliable set of early warning indicators were identified empirically, it is possible that policymakers would henceforth behave differently when these indicators were flashing than they did in the past, thereby transforming these variables into early warning indicators of corrective policy action rather than of financial crisis. While this feedback effect of the indicators on crisis prevention has apparently not yet been strong enough to impair their predictive content, there is no guarantee

15. Indeed, for many countries, detailed data on the state of the banks may not even be available annually.

that this feedback effect will not be stronger in the future (particularly if the empirical evidence in favor of robust early warning indicators was subsequently viewed as more persuasive).

Much like the leading-indicator analysis of business cycles, we are engaging here in a mechanical exercise—albeit one that we think is interesting on a number of fronts. Moreover, this research is still in its infancy, with many of the key empirical contributions coming only in the last two to three years. In areas such as the modeling of contagion and alternative approaches to out-of-sample forecasting, too few ''horse races'' have been run to know which approaches work best. For all of these reasons, we see the leading-indicator analysis of financial crises in emerging economies as one among a number of analytical tools and not as a stand-alone, surefire system for predicting where the next crisis will take place. That being said, we also argue that this approach shows promising signs of generating real value added and that it appears particularly useful as a first screen for gauging the ordinal differences in vulnerability to crises both across countries and over time. A family of estimated conditional crisis probabilities will provide the basis of this ordinal ranking across countries at a point in time or for a given country over time.

Putting the Signals Approach to Work

The signals approach described above was first used to analyze the performance of macroeconomic and financial indicators around ''twin crises'' (i.e., the joint occurrences of currency and banking crises) in Kaminsky and Reinhart (1999). We focus on a sample of 25 countries over 1970 to 1995. The out-of-sample performance of the signals approach will be assessed using data for January 1996 through December 1997. These are the countries in our sample:

- **Africa:** South Africa
- **Asia:** Indonesia, Malaysia, the Philippines, South Korea, Thailand
- **Europe and the Middle East:** Czech Republic, Denmark, Egypt, Finland, Greece, Israel, Norway, Spain, Sweden, Turkey
- **Latin America:** Argentina, Bolivia, Brazil, Chile, Colombia, Mexico, Peru, Uruguay, Venezuela

The basic premise of the signals approach is that the economy behaves differently on the eve of financial crises and that this aberrant behavior has a recurrent systematic pattern. This ''anomalous'' pattern, in turn, is manifested in the evolution of a broad array of economic and financial indicators. The empirical evidence provides ample support for this premise.[16] To implement the signals approach, we need to clarify a minimum number of two key concepts which will be used throughout the analysis.

Currency Crisis

A currency crisis is defined as a situation in which an attack on the currency leads to substantial reserve losses, or to a sharp depreciation of the currency—if the speculative attack is ultimately successful—or to both. This definition of currency crisis has the advantage of being comprehensive enough to capture not only speculative attacks on fixed exchange rates (e.g., Thailand's experience before 2 July 1997) but also attacks that force a large devaluation beyond the established rules of a crawling-peg regime or an exchange rate band (e.g., Indonesia's widening of the band before its floatation of the rupiah on 14 August 1997.) Since reserve losses also count, the index also captures unsuccessful speculative attacks (e.g., Argentina's reserve losses in the wake of the Mexican 1994 peso crisis.)

We constructed an index of currency market turbulence as a weighted average of exchange rate changes and reserve changes.[17] Interest rates were excluded, as many emerging markets in our sample had interest rate controls through much of the sample. The index, I, is a weighted average of the rate of change of the exchange rate, $\Delta e/e$, and of reserves, $\Delta R/R$, with weights such that the two components of the index have equal sample volatilities:

$$I = (\Delta e/e) - (\sigma_e/\sigma_R) * (\Delta R/R) \tag{2.1}$$

where σ_e is the standard deviation of the rate of change of the exchange rate and σ_R is the standard deviation of the rate of change of reserves. Since changes in the exchange rate enter with a positive weight and changes in reserves have a negative weight attached, readings of this index that were three standard deviations or more above the mean were cataloged as crises.[18]

For countries in the sample that had hyperinflation, the construction of the index of currency market turbulence was modified. While a 100 percent devaluation may be traumatic for a country with low to moderate inflation, a devaluation of that magnitude is commonplace during hyperinflation. A single index for the countries that had hyperinflation episodes would miss sizable devaluations and reserve losses in the moderate infla-

16. See Kaminsky, Lizondo, and Reinhart (1998) for a survey of this literature.

17. This index is in the spirit of that used by Eichengreen, Rose, and Wyplosz (1996), who also included interest rate increases in their measure of turbulence.

18. Of course, for a study of market turbulence as well as crisis, one may wish to consider readings in this index that are two standard deviations away from the mean.

tion periods because the high-inflation episodes would distort the historic mean. To avoid this, we divided the sample according to whether inflation in the previous six months was higher than 150 percent and then constructed an index for each subsample.[19]

As noted in earlier studies that use the signals approach, the dates of currency crises derived from this index map well onto the dates that would be obtained if one were to define crises by relying exclusively on events, such as the closing of the exchange markets or a change in the exchange rate regime.

Banking Crises

Our dating of banking crises stresses events. This is because on the banking side there are no time series comparable to international reserves and the exchange rate. For instance, in the banking panics of an earlier era large withdrawals of bank deposits could be used to date the crisis. In the wake of deposit insurance, however, bank deposits ceased to be useful for dating banking crises. As Japan's banking crisis highlights, many modern financial crises stem from the asset side of the balance sheet, not from deposit withdrawals. Hence the performance of bank stocks relative to the overall equity market could be an indicator. Yet in many of the developing countries an important share of the banks are not traded publicly. Large increases in bankruptcies or nonperforming loans could also be used to mark the onset of the crisis. Indicators of business failures and nonperforming loans are, however, usually available only at low frequencies, if at all; the latter are also made less informative by banks' desire to hide their problems for as long as possible.

Given these data limitations, we mark the beginning of a banking crisis by two types of events: bank runs that lead to the closure, merging, or takeover by the public sector of one or more financial institutions (as in Venezuela in 1993); and if there are no runs, the closure, merging, takeover, or large-scale government assistance of an important financial institution (or group of institutions) that marks the start of a string of similar outcomes for other financial institutions (as in Thailand in 1997). We rely on existing studies of banking crises and on the financial press; according to these studies the fragility of the banking sector was widespread during these periods.

Our approach to dating the onset of the banking crises is not without drawbacks. It could date the crises "too late" because the financial problems usually begin well before a bank is finally closed or merged. It could also date crises "too early" because the worst of crisis may come later.

19. Similar results are obtained by looking at significant departures in inflation from a 6- and 12-month moving average.

To address this issue we also indicate when the banking crisis hits its peak, defined as the period with the heaviest government intervention and/or bank closures.

Identifying the end of a banking crisis is one of the more difficult unresolved problems in the empirical crisis literature—that is, there is no consensus on what the criteria ought to be for declaring the crisis to be over (e.g., resumption of normal bank lending behavior, or a marked decrease in the share of nonperforming loans, or an end to bank closures and large-scale government assistance). In our discussion of the aftermath of crises in chapter 7, however, the end of a banking crisis is understood to be its resolution (i.e., the end of heavy government financial intervention), not when bank balance sheets cease to deteriorate.

Other empirical studies on banking crises have focused on annual data and provide no information on the month or quarter in which banking sector problems surface. Hence it is not possible to compare the exact dates with our own analysis. We can, however, compare the dating of the year of the crisis. In most cases, our dates for the beginning of crises correspond with those found in other studies, but there are several instances where our starting date is a year earlier than theirs. Tables 2.1 and 2.2 list the currency and banking crisis dates, respectively, for the 25 countries in our sample.

The Indicators

In addition to the 15 early warning indicators originally considered in Kaminsky and Reinhart (1999), we evaluate the ability of nine additional indicators that figure prominently in both the theoretical literature on banking and currency crises and in the popular discussion of these events.

The indicators used in Kaminsky and Reinhart (1999) were international reserves (in US dollars), imports (in US dollars), exports (in US dollars), the terms of trade (defined as the unit value of exports over the unit value of imports), deviations of the real exchange rate from trend (in percentage terms),[20] the differential between foreign (US or German) and domestic real interest rates on deposits (monthly rates, deflated using consumer prices and measured in percentage points), "excess" real M1 balances, the money multiplier (of M2), the ratio of domestic credit to GDP, the real interest rate on deposits (monthly rates, deflated using consumer prices and measured in percentage points), the ratio of (nominal) lending

20. The real exchange rate is defined on a bilateral basis with respect to the German mark for the European countries in the sample and with respect to the US dollar for all other countries. The real exchange rate index is defined such that *an increase* in the index denotes a real *depreciation.*

Table 2.1 Currency crisis starting dates

Country	Currency crisis
Argentina	June 1975
	February 1981*
	July 1982
	September 1986*
	April 1989
	February 1990
Bolivia	November 1982
	November 1983
	September 1985
Brazil	February 1983
	November 1986*
	July 1989
	November 1990
	October 1991
Chile	December 1971
	August 1972
	October 1973
	December 1974
	January 1976
	August 1982*
	September 1984
Colombia	March 1983*
	February 1985*
Czech Republic	May 1997
Denmark	May 1971
	June 1973
	November 1979
	August 1993
Egypt	January 1979
	August 1989
	June 1990
Finland	June 1973
	October 1982
	November 1991*
	September 1992*
Greece	May 1976
	November 1980
	July 1984
Indonesia	November 1978
	April 1983
	September 1986
	August 1997
Israel	November 1974
	November 1977
	October 1983*
	July 1984
Malaysia	July 1975
	August 1997*

(continued next page)

Table 2.1 (continued)

Country	Currency crisis
Mexico	September 1976
	February 1982*
	December 1982*
	December 1994*
Norway	June 1973
	February 1978
	May 1986*
	December 1992
Peru	June 1976
	October 1987
The Philippines	February 1970
	October 1983*
	June 1984
	July 1997*
South Africa	September 1975
	July 1981
	July 1984
	May 1996
South Korea	June 1971
	December 1974
	January 1980
	October 1997
Spain	February 1976
	July 1977*
	December 1982
	February 1986
	September 1992
	May 1993
Sweden	August 1977
	September 1981
	October 1982
	November 1992*
Thailand	November 1978*
	July 1981
	November 1984
	July 1997*
Turkey	August 1970
	January 1980
	March 1994*
Uruguay	December 1971*
	October 1982*
Venezuela	February 1984
	December 1986
	March 1989
	May 1994*
	December 1995

* = twin crises

Table 2.2 Banking crisis starting dates

Country	**K & R** (1999) **and G, K, & R** (beginning)	**C & K** (1996)	**IMF** (1996 and 1998a & b)
Argentina	March 1980	1980	1980
	May 1985	1985	1985
			1989
	December 1994	1995	1995
Bolivia	October 1987	1986	n.a.
Brazil	November 1985		1990
	December 1994	1994	1994
Chile			1976
	September 1981		1981
Colombia	July 1982	1982	1982
	April 1998		
Czech Republic	1994	n.a.	n.a.
Denmark	March 1987	n.a.	1988
Egypt	January 1980	1980	1981
	January 1990	1990	1990
Finland	September 1991	1991	1991
Greece	1991	n.a.	n.a.
Indonesia	November 1992	1994	1992
			1997
Israel	October 1983	1977	1983
Malaysia	July 1985	1985	1985
	September 1997		

(continued next page)

to deposit interest rates,[21] the stock of commercial banks' deposits (in nominal terms), the ratio of broad money (converted into foreign currency) to gross international reserves, an index of output, and an index of equity prices (in US dollars). All these series are monthly. For greater detail, see the appendix. The links between particular early warning indicators and underlying theories of exchange rate and banking crises are discussed in some detail in earlier papers (e.g., Kaminsky and Reinhart 1999).

Turning to the nine "new" indicators introduced here, four of them are expressed as a share of GDP. These are the current account balance, short-term capital inflows, foreign direct investment, and the overall bud-

21. This definition of the spread between lending and deposit rates is preferable to using merely the difference between nominal lending and deposit rates because inflation affects this difference and thus the measure would be distorted in the periods of high inflation. An alternative would have been to use the difference between *real* lending and deposit rates.

Table 2.2 (continued)

Country	**K & R** (1999) **and G, K, & R** (beginning)	**C & K** (1996)	**IMF** (1996 and 1998a & b)
Mexico	September 1982	1981	1982
	October 1992	1995	1994
Norway	November 1988	1987	1987
Peru	March 1983	n.a.	1983
Philippines	January 1981	1981	1981
	July 1997		
South Africa	December 1977	1977	1980
South Korea	January 1986	n.a.	1983
	July 1997		1997
Spain	November 1978	1977	1977
Sweden	November 1991	1991	1990
Thailand	March 1979	1983	1983
	May 1996		1997
Turkey			1982
	January 1991	1992	1991
		1994	1994
Uruguay	March 1971		
	March 1981	1981	1981
Venezuela		1980	1980
	October 1993	1994	1993

n.a. = not applicable
K & R = Kaminsky and Reinhart (1999)
G, K, & R = Goldstein, Kaminsky, and Reinhart
C & K = Caprio and Klingebiel (1996b)

get deficit. In addition, we look at the growth rates in the following variables (the first three as shares in GDP and the fourth as a share of investment): general government consumption, central bank credit to the public sector, net credit to the public sector, and the current account balance. The latter measure of the current account was motivated by the view, particularly popular in the wake of the 1994-95 Mexican peso crisis, that large current account deficits are more of a concern if they stem from low saving as opposed to high levels of investment. Recent events in Asia—a region noted for its exceptionally high levels of domestic saving and its even higher levels of investment—have led to a reassessment of that view. We also look at two measures of sovereign credit ratings. As most of the new indicators are not available at monthly or quarterly frequencies, annual data were used.

Table 2.3 provides a list of the indicators we examine in this book, their periodicity, and the transformation used. In chapter 4, we examine the

Table 2.3 Selected leading indicators of banking and currency crises

Indicator	Transformation	Data frequency
Real output	12-month growth rate	Monthly
Equity prices	12-month growth rate	Monthly
International reserves	12-month growth rate	Monthly
Domestic/foreign real interest rate differential	Level	Monthly
Excess real M1 balances	Level	Monthly
M2/ international reserves	12-month growth rate	Monthly
Bank deposits	12-month growth rate	Monthly
M2 multiplier	12-month growth rate	Monthly
Domestic credit/GDP	12-month growth rate	Monthly
Real interest rate on deposits	Level	Monthly
Ratio of lending interest rate to deposit interest rate	Level	Monthly
Real exchange rate	Deviation from trend	Monthly
Exports	12-month growth rate	Monthly
Imports	12-month growth rate	Monthly
Terms of trade	12-month growth rate	Monthly
Moody's sovereign credit ratings	1-month change	Monthly
Institutional Investor sovereign credit ratings	Semiannual change	Semiannual
General government consumption/GDP	Annual growth rate	Annual
Overall budget deficit/GDP	Level	Annual
Net credit to the public sector/GDP	Level	Annual
Central bank credit to public sector/GDP	Level	Annual
Short-term capital inflows/GDP	Level	Annual
Foreign direct investment/GDP	Level	Annual
Current account imbalance/GDP	Level	Annual
Current account imbalance/investment	Level	Annual

track record of sovereign credit ratings when it comes to "predicting" financial crises. Specifically, we examine the performance of the Institutional Investor and Moody's ratings.

As noted, in most cases we focus on 12-month changes in the variables. This transformation has several appealing features. First, it eliminates the nonstationarity problem of the variables in levels. It also makes the indicators more comparable across countries and across time. Some of the indicators have a strong seasonal pattern, which the 12-month transformation corrects for. For some indicators, such as equity prices, one could contemplate using a measure of under- or overvaluation. However, the empirical performance of most asset pricing models is not strong enough to justify such an exercise.

For the monthly variables (with the exception of the deviation of the real exchange rate from trend, the "excess" of real M1 balances, and the three variables based on interest rates), the indicator on a given month was defined as the percentage change in the level of the variable with respect to its level a year earlier. This filter has several attractive features: it reduces the "noisiness" of working with monthly data, it facilitates cross-country comparisons, and it ensures the variables are stationary with well-defined moments.

Turning to credit ratings, Institutional Investor constructs an index that rises with increasing country creditworthiness and ranges from 0 to 100; this index is published twice a year and is released in March and September.[22] Hence we work with the six-month percentage change in this rating index. For Moody's Investor services, monthly changes in the sovereign ratings are used. A downgrade takes on the value of minus one; no change in the rating takes on a value of zero, and an upgrade takes on the value of one. Since Moody's ratings take on values from 1 to 16, we also worked with changes in the ratings that took into account the magnitude of the change. This issue will be discussed in greater detail in chapter 4.

The Signaling Window

Let us call a signal (yet to be precisely defined) a departure from ''normal'' behavior in an indicator.[23] For example, an unusually large decline in exports or output may signal a future currency or banking crisis. If an indicator sends a signal that is followed by a crisis within a plausible time frame we call it a good signal. If the signal is not followed by a crisis within that interval, we call it a false signal, or noise. The signaling window for currency crises is set *a priori* at 24 months preceding the crisis. If, for instance, an unusually large decline in exports were to occur 28 months before the crisis, the signal would fall outside the signaling window and would be labeled a false alarm.

Alternative signaling windows (18 months and 12 months) were considered as part of our sensitivity analysis. While the results for the 18-month window yielded similar results to those reported in this book, the 12-month window proved to be too restrictive. Specifically, several of the indicators we use here, including real exchange rates and credit cycles, signaled relatively early (consistent with a protracted cycle), and the shorter 12-month window penalized those early signals by labeling them as false alarms.

For banking crises, we employ a different signaling window. Namely, any signal given in the 12 months preceding the beginning of the crisis or the 12 months following the beginning of the crisis is labeled a good signal. The more protracted nature of banking crises and the high incidence of denial by both bankers and policymakers that there are problems in the banking sector motivate the more forgiving signaling window for banking crises.

22. Since there are two readings of this index per year, in a typical year, say 1995, we would have the percentage change in the rating from September 1994 to March 1995, from March 1995 to September 1995, and the change from September 1995 to March 1996.

23. Of course, normal behavior may change over time, hence, this approach, like other commonly used alternatives (such as logit or probit) is not free from Lucas-critique limitations. For further discussion of this issue, see Kaminsky and Reinhart (1999).

The Threshold

Suppose we wish to test the null or maintained hypothesis that the economy is in a ''state of tranquility'' versus the alternative hypothesis that a crisis will occur sometime in the next 24 months. Suppose that we wish to test this hypothesis on an indicator-by-indicator basis. As in any hypothesis test, this calls for selecting a threshold or critical value that divides the probability distribution of that indicator into a region that is considered normal or probable under the null hypothesis and a region that is considered aberrant or unlikely under the null hypothesis—the rejection region. If the observed outcome for a particular variable falls into the rejection region, that variable is said to be sending a signal.

To select the optimal threshold for each indicator, we allowed the size of the rejection region to oscillate between 1 percent and 20 percent. For each choice, the noise-to-signal ratio was tabulated and the ''optimal'' set of thresholds was defined as the one that minimized the noise-to-signal ratio—that is, the ratio of false signals to good signals.[24]

Table 2.4 lists the thresholds for all the indicators for both currency and banking crises. For instance, the threshold for short-term capital flows as a percentage of GDP is 85 percent. This conveys two kinds of information. First, it indicates that 15 percent of all the observations in our sample (for this variable) are considered signals. Second, it highlights that the rejection region is located at the upper tail of the frequency distribution, meaning that a high ratio of short-term capital inflows to GDP will lead to a rejection of the null hypothesis of tranquility in favor of the alternative hypothesis that a crisis is brewing.

While the threshold or percentile that defines the size of the rejection region is uniform across countries for each indicator, the corresponding country-specific values are allowed to differ. Consider the following illustration. There are two countries, one which has received little or no short-term capital inflow (as a percentage of GDP) during the entire sample, while the second received substantially larger amounts (also as a share of GDP). The 85th percentile of the frequency distribution for the low capital importer may be as small as a half a percent of GDP and any increase beyond that would be considered a signal. Meanwhile, the country where the norm was a higher volume of capital inflows is likely to have a higher critical value; hence only values above, say 3 percent of GDP, would be considered signals.

24. For variables such as international reserves, exports, the terms of trade, deviations of the real exchange rate from trend, commercial bank deposits, output, and the stock market index, for which a decline in the indicator increases the probability of a crisis, the threshold is below the mean of the indicator. For the other variables, the threshold is above the mean of the indicator.

Table 2.4 Optimal thresholds (percentile)

Indicator	Currency crisis	Banking crisis
Bank deposits	15	20
Central bank credit to the public sector	90	90
Credit rating (Institutional Investor)	11	11
Current account balance/GDP	20	14
Current account balance/investment	15	10
Domestic credit/GDP	88	90
Interest rate differential	89	81
Excess M1 balances	89	88
Exports	10	10
Foreign direct investment/GDP	16	12
General government consumption/GDP	90	88
Imports	90	80
Lending-deposit interest rate ratio	88	87
M2 multiplier	89	90
M2/reserves	90	90
Net credit to the public sector/GDP	88	80
Output	10	14
Overall budget deficit/GDP	10	14
Real exchange rate[a]	10	10
Real interest rate	88	80
Reserves	10	20
Short-term capital inflows/GDP	85	89
Stock prices	15	10
Terms of trade	10	19

a. An increase in the index denotes a real depreciation.

Table 2.5 illustrates the "custom tailoring" of the optimal threshold by showing the country-specific critical values for export growth and annual stock returns for Malaysia, Mexico, and Sweden. A 25 percent decline in stock prices would be considered a signal of a future currency crisis in Malaysia and Sweden but not in Mexico, with the latter's far greater historical volatility.[25]

Figure 2.1 provides another illustration of the country-specific nature of the optimal threshold calculations. It shows for the entire sample our measure of the extent of overvaluation in the real exchange rate for Mexico. The horizontal line is the country-specific threshold, and a reading below this line (recall that a decline represents an appreciation) represents a signal. The shaded areas are the 24 months before the crisis, or the signaling window. Around 1982 the shaded area is wider due to the fact that there was a "double dip," with two crises registering. If the indicator crossed the horizontal line and no crisis ensued in the following 24 months,

25. Indeed, as shown in Kaminsky and Reinhart (1998), the volatility pattern for these three countries is representative of the broader historical regional pattern. The wild gyrations in financial markets in Asia in 1997-99, however, may be unraveling those historic patterns.

Table 2.5 Examples of country-specific thresholds: currency crises

Country	Critical value for exports (12-month percentage change)	Critical value for stock prices (12-month percentage change)
Malaysia	− 9.05	−15.20
Mexico	−13.10	−38.30
Sweden	−11.25	−20.78

as it did in early 1992, it is counted as a false alarm. In the remainder of this section we will define these concepts more precisely.

Signals, Noise, and Crises Probabilities

A concise summary of the possible outcomes is presented in the following two-by-two matrix (for a currency crisis).

	Crisis occurs in the following 24 months	No crisis occurs in the following 24 months
Signal	A	B
No signal	C	D

A perfect indicator would only have entries in cells A and D. Hence, with this matrix we can define several useful concepts that we will use to evaluate the performance of each indicator.

If one lacked any information on the performance of the indicators, it is still possible to calculate, for a given sample, the *unconditional probability of crisis*,

$$P(C) = (A + C)/(A + B + C + D) \tag{2.2}$$

If an indicator sends a signal and that indicator has a reliable track record, then it can be expected that the *probability of a crisis, conditional on a signal, P(C/S),* is greater than the unconditional probability. Where

$$P(C|S) = A/(A + B) \tag{2.3}$$

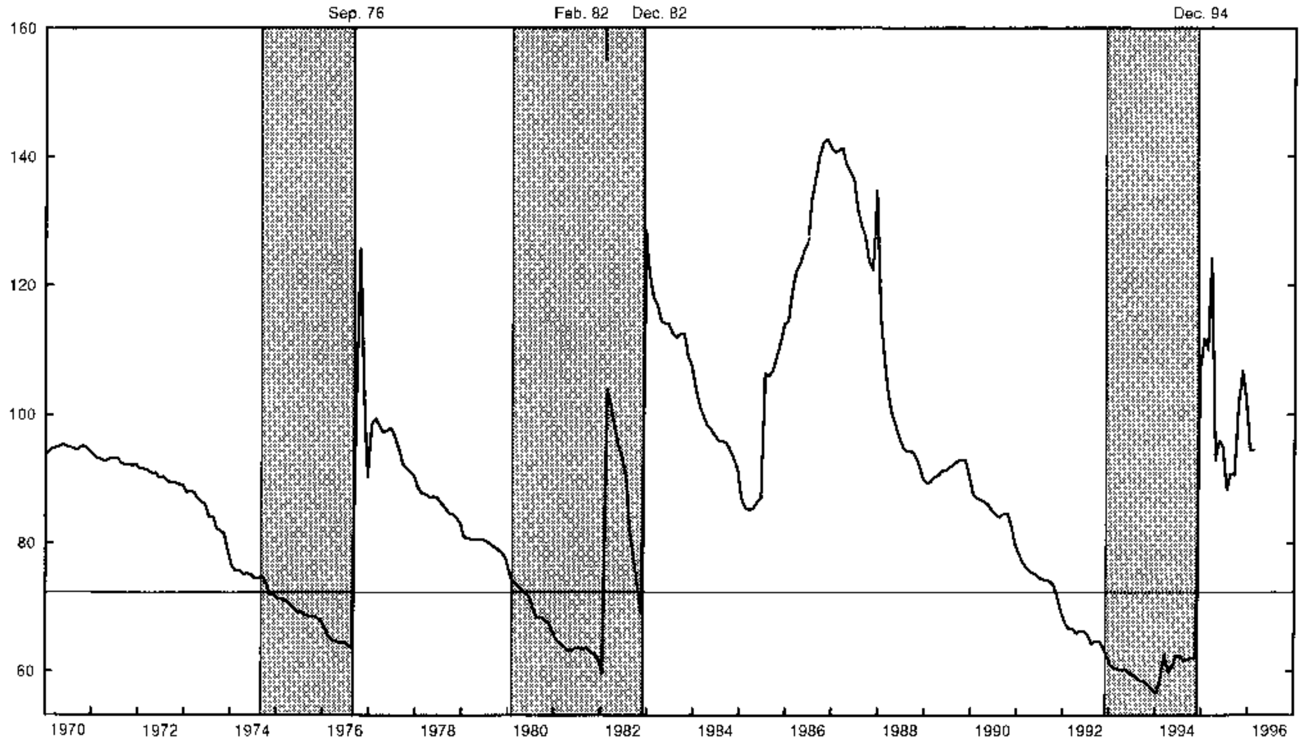
Formally,

$$P(C|S) - P(C) > 0 \tag{2.4}$$

The intuition is clear: if the indicator is not "noisy" (prone to sending false alarms), then there are relatively few entries in cell B and $P(C|S) \approx 1$. This is one of the criteria that we will use to rank the indicators in the following chapters.

Figure 2.1 Mexico: real exchange rate, 1970-96

average of the sample = 100



We can also define the noise-to-signal ratio, N/S, as

$$N/S = [B/(B + D)]/[A/(A + C)] \tag{2.5}$$

It may be the case that an indicator has relatively few false alarms in its track record. This could be the result of the indicator issuing signals relatively rarely. In this case, there is also the danger that the indicator misses the crisis altogether (it does not signal and there is a crisis). In this case, we also wish to calculate for each indicator the *proportion of crises accurately called,*

$$PC = C/(A + C). \tag{2.6}$$

In the next chapter, we employ these concepts to provide evidence on the relative merits of a broad range of indicators in anticipating crises.