NOTES D'ÉTUDES

ET DE RECHERCHE

LEADING INDICATORS OF CURRENCY

CRISES IN EMERGING ECONOMIES

Olivier Burkart and Virginie Coudert

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in Emerging Economies

Olivier Burkart [1] and Virginie Coudert [2]

Abstract

This study identifies common features of currency crises in 15 emerging countries over the period 1980-1998. By analyzing such features, we build an early-warning system aimed at predicting looming crises in probabilistic terms. This work departs from the existing literature in several ways. First, we use quarterly data, in contrast to other studies, which are based on monthly or annual data. This allows us to characterize crises more accurately and also to analyze the behavior of leading indicators as actual crises approach. Second, the overvaluation of currencies is assessed by using real effective exchange rates, instead of the usual bilateral rates. In addition, capital control dummies are included in the set of explanatory variables and contagion indicators are constructed. Finally, we use the Fisher linear discriminant analysis technique. The model yields a relatively good - and unbiased - ratio of correct predictions: four out of five crises are predicted correctly and only one out of five non-crises is predicted as a crisis. **These results compare favorably to those of other models. For early warning systems, there is a fundamental trade-off based on the Bayes' formula in a context of rare events: to a certain extent, one has to choose between a high ratio of good classifications of crises and a low ratio of false alarms.** Furthermore, using Bayes' formula allows us to calculate the posterior probability that a given emerging economy will be in a period of currency crisis within a one-year horizon.

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Leading Indicators of Currency Crises
in Emerging Economies

Olivier Burkart and Virginie Coudert [3]

1. Introduction

Recent years have seen an increase in currency crises affecting a large number of countries, either directly or indirectly. Certain similarities are generally observed in the way these crises unfold: a loss of foreign exchange reserves, a capital outflow, and a sudden depreciation of the currency [4]. If similarities between these economies also exist just before currency crises occur, they could be used to predict these crises. This is the theme of the present study. It is certainly true that each crisis is specific: the debt crises in Latin America of the 1980s are different from the Mexican crisis in 1994, which differs from the crises of South-East Asia in 1997, and even within each of these crisis episodes, every crisis presents some specificity. However, this does not preclude the existence of common features.

Theoretical studies have identified several types of crises (for a recent survey, see Jeanne (1999)). "Speculative attack models" stress the importance of fundamental factors in the triggering of crises (Krugman, 1979). The crises come from expansionary monetary or fiscal policies which are inconsistent with the peg of the exchange rate. This situation results in continuous losses of reserves, which suddenly leads to a devaluation. In this type of model, speculators' behavior is not the source of the crisis, they only accelerate the process. "Escape clause models" introduce strategic considerations based on the consequences that may result from the defense of a peg in speculative attacks (Obstfeld, 1994). Crises may occur because rational speculators expect that governments will not be willing to support these consequences when confronted with a speculative attack. For example, if the level of unemployment is high or the banking system is weak, monetary authorities may hesitate to raise the interest rates to maintain their peg, for the cost of raising interest rate is very high in this case. In these types of models, expectations of crises may be self-fulfilling and there is a possibility of multiple equilibria. Therefore, crises may occur without a worsening of fundamentals and without inconsistent

[4] Kamin (1999) presents evidence in favor of even broader similarities between crisis episodes.

policies. Other recent models have emphasized the role of contagion in the triggering of crises (Gerlach and Smets, 1994), as well as the role of moral hazard, especially after the Asian crisis (Krugman, 1999).

Theoretical work provides some guidance when choosing potential leading indicators, which should reflect fundamentals as well as any variable able to influence the market expectations. However, it does not allow to discriminate between competing indicators nor does it enable their respective weights to be determined. That is why an abundant empirical literature has developed in parallel.

The episode of the Mexican crisis in 1994-1995 and subsequently the Asian crises in 1997 have led to a revival of these empirical studies. Most of them are concerned with the analysis of one or several particular events (single-country or regional studies). However, an increasing number of studies also try to identify features that are common to a large set of crises (see the work carried out at international organizations (e.g. the International Monetary Fund, the World Bank and the Bank for International Settlements), in academic institutions and at central banks (Deutsche Bundesbank, Bank of Canada, Federal Reserve Board, Federal Reserve Bank of New York, Österreichische Nationalbank)). They aim at constructing early-warning systems (EWSs), able to detect crises before they occur. The existing studies can be classified according to different criteria [5]: the countries analyzed (developing, emerging, industrialized), the periodicity of the time series (monthly, annual), the crisis indicator used (exchange rate pressure, actual devaluation), the time horizon of the prediction (several months, one year, two years) and the methods implemented (signal approach, Logit/Probit [6]). These criteria are not always independent. For example, in the case of developing and emerging countries, an actual devaluation seems to be a reasonable concept, whereas it is more difficult to justify using this criterion for industrialized countries.

Kaminsky, Lizondo and Reinhart (1997) systematically analyzed a large set of different possible leading indicators. They can be divided into several categories: indicators linked to the current account (trade balance, growth in exports, terms of trade, real exchange rates, etc.), indicators linked to capital flows (reserves, short-term capital flows, foreign direct investment, etc.), debt indicators (total debt, debt service, short-term debt, etc.), financial indicators (credit expansion, M2, stock price indicators, interest rates, etc.) and macroeconomic indicators (GDP, investment, inflation, public deficit, etc.). The appendix gives the list of the indicators used in this study, i.e. the leading indicators found in the literature which seemed to us potentially the most relevant. Many possible indicators are difficult to quantify (e.g. lax banking supervision, the political background). However, these features seem often (but not always) to be captured indirectly through the available indicators. Kaminsky, Lizondo and Reinhart (1997) identified some leading indicators which seem particularly useful: the amount of foreign exchange reserves, the real exchange rate, domestic credit, credit to the public sector and inflation. There also exist other possible, less important indicators: the trade balance, export performance, the

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[5] One could add to this list the potential leading indicators. However, this is not an easily implementable criterion for distinguishing EWSs.
[6] In addition, Weber (1998) recently proposed a structural VAR approach for industrialized countries.

growth of M2 and GDP, and the public deficit. However, this study does not include the recent Asian crisis. One of the few studies which do analyze this crisis is that of Radelet and Sachs (1998). The authors find that the most significant indicators are: the ratio of short-term debt to reserves (and not total debt to reserves) and the growth of credit to the private sector. Neither the real exchange rate nor the current account is significant.

This paper contributes to the empirical identification of common features in currency crises. It aims at constructing early warning indicators able to predict looming currency crises in probabilistic terms. This study takes stock of what has been achieved so far and gives empirical results for a set of 15 emerging countries over the period 1980:1-1998:4, thus including the Asian crisis. We depart from the existing literature in several ways. First, we work on quarterly data, unlike other studies carried out so far, which use annual or monthly data. This allows us to characterize crises in a more precise manner than is the case in previous work on emerging economies, to consider crisis periods and to answer questions about the way leading indicators behave as crises approach. Second, as contagion and overvaluation of currencies are generally considered to be major factors in triggering currency crises, we include these two effects in EWSs. A possible currency overvaluation is measured by the real effective exchange rate, which seems a more accurate proxy than the bilateral rates usually seen in the literature. Moreover, dummies on restrictions of capital flows have been introduced in the set of explanatory variables. Finally, the study is carried out using the Fisher linear discriminant analysis technique, whereas the existing literature relies on the signal approach or on Logit/Probit analysis.

This analysis gives a scoring of the countries according to the risk of a currency crisis within a 4-quarter horizon. These scores are translated into probabilistic terms using Bayes' formula. We obtain a relatively good ratio of correct predictions with respect to the economies analyzed: four out of five crises are predicted correctly and only one out of five non-crises is predicted as a crisis. These estimations can be considered as unbiased as they are obtained by cross-validation. Moreover, by using quarterly data and defining crisis periods, we can study the behavior of the score as a crisis approaches. This also allows us to analyze how the influence of different indicators changes with the choice of the length of a crisis period.

The rest of the paper is organized as follows. Section 2 describes the main specific features of this work, compared to other EWSs in the literature. Section 3 is devoted to selecting a proper definition of a crisis, which implies the construction of several simultaneous crisis indicators . Section 4 deals with methodological issues concerning discriminant analysis and presents the data. Results are given in section 5. Several scores are proposed, according to the sample retained. Constructing score functions by region improves upon the "global score" obtained on the basis of the whole population and allows a synthetic score to be obtained. Section 6 compares our results to those of other studies. This comparison underlines the existence of a fundamental trade-off in constructing EWSs: predicting many crises correctly vs. giving a few false alarms. This helps shed some light on the skeptical views

sometimes encountered and makes us optimistic about the future role of these models in decision-making.

2. Specific features of our approach

As we intend to use the model regularly for assessing the risk of currency crises, the use of quarterly data appeared to be the best solution. Improving the indicators of overvaluation and introducing contagion also seemed necessary.

2.1. Use of quarterly data

This work is based on quarterly data, whereas the bulk of the studies carried out so far use annual or monthly data. Although an annual periodicity allows easier access to data, it has a number of disadvantages. The indicators used cannot really take into account financial phenomena, such as capital flows and variations in reserves and interest rates, which occur with increasing speed. This seems to be especially true in periods of exchange-rate crisis. Furthermore, annual time series weaken the predictive value of leading indicators. With annual data, the exact timing of a crisis is subject to considerable uncertainty since it is unclear whether it took place at the beginning of the year or at the end. Thus a leading indicator, usually presented as having a lead of one year, can actually have a lead of between one and two years [7].

Several authors have worked with monthly data. However, many non-financial variables are not available on a monthly basis. Studies based on monthly data are therefore exposed to the criticism of omitted explanatory variables. In addition, a monthly timeframe introduces the problem of autoregressive effects and possibly complicated lag structures.

By using quarterly data, we are able to overcome these difficulties, or at least alleviate them. We can also consider questions, which would otherwise be out of reach or more difficult to analyze. Is there a monotonic evolution of leading indicators as crises approach? Is it useful to distinguish between different types of indicators for different prediction horizons? For example, structural indicators may be more important for an horizon in excess of one year and financial-flow indicators may become increasingly important as the predictive horizon shrinks (9, 6 or 3 months).

But the use of quarterly data is not without consequences. Several potentially important leading indicators can be constructed only from variables available on an annual basis. This is the case for data on indebtedness (which are taken from the World Bank's debt tables) and also for national accounts or balance of payments data of several countries. The data on external indebtedness published by the Bank for International Settlements (BIS) are semi-annual. Such data must be transformed into quarterly data. This is done by fitting a cubic spline curve to the (semi)annual inputs. we have taken into consideration the nature of the different time series (stocks or flows, end-of-period or mean values).

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[7] See Esquivel and Larraín (1998) for an ad hoc procedure to alleviate this problem with annual data.

The transformation assumes that the indicators evolve smoothly. This seems justified in the case of structural variables which do not vary much - at least with respect to the other variables - and serve mainly to normalize the indicators. Typically, this is done for the GDP of some countries like Bolivia, Brazil, Chile, Columbia, Hungary, Indonesia, Poland or Thailand, as this variable is the denominator of several ratios. Be that as it may, we feel that the gains - the number of identifiable crises, the sharpness of the analysis and finally the quality of the results - largely outweigh the drawbacks.

2.2. Representing contagion phenomena

Contagion effects are the focus of increasing attention in the literature on currency crises (Gerlach and Smets, 1995; see Drazen (1999) for an overview), as well as in policy advice to emerging countries and the investing strategies of international investors [8]. Recent experience has shown that some countries may suffer from contagion effects, in spite of relatively good fundamentals. In some cases, contagion triggers a currency crisis that would not have otherwise occurred; in other cases, the crisis is amplified or simply accompanied. In theory, several channels of contagion can be identified. Suppose that a crisis occurs in an emerging country A, and that its currency suddenly collapses. What would be the effects on another emerging country B?

A first effect appears through price competition. With sticky prices, the goods produced by firms located in country A enjoy a decrease in their prices abroad, boosting their exports, and an increase in prices of their foreign competitors in the home market, making the imports decrease. Therefore, foreign countries suffer from a decrease in their competitiveness, which varies according to the intensity of the competition with A. The loss for a given country B depends on the extent of its bilateral trade with A and also on the competition between A and B on third markets. Usually, the magnitude of the effect is linked to the geographic proximity of the two countries because neighborhood happens to be a good proxy for the intensity of trade. It can be measured by the move in the real effective exchange rate of partner countries.

A second channel comes from a volume effect, because of the sudden fall in country A imports. This fall in imports immediately follows the currency crisis and comes not only from the price effects, but also from the fall in income that is simultaneous to the balance of payments crisis. It is different from the price effect, because even if the relative prices of A and B had not moved, the exports from B to A would have fallen because of the drop in A's GDP and thus the sudden decrease in the demand addressed to the partner country B. The magnitude of the effects depends on the size of B's exports to A relative to its GDP [9].

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[8] On the basis of recent currency crises, the IMF has introduced a contingent credit line (CCL) to allow countries to better protect themselves against the risk of contagion.

[9] Barth and Dinmore (1999) analyze trade prices and volumes during the Asian crisis and conclude that the decline in export prices has strongly eroded export revenues for crisis countries, despite an increase in export volumes.

The third channel relies on financial links. Country A creditors are weakened because of the financial losses experienced in the crisis. Two types of effects may be generated. A direct effect may be observed if an emerging country B, already fragile, is among A's big creditors. Examples of this type of channel are Korean investments in Asia or Brazilian capital invested in GKOs. Indirect effects may occur when creditors (from any country) need to liquidate assets in another emerging market B to face their losses in country A. This effect takes place because of the flight to quality which is observed just after a crisis. Instead of proportionally selling any assets in its portfolio, the creditors would select the most vulnerable emerging country B, which may trigger a crisis in these countries.

Moreover, contagion phenomena can be amplified - or even generated - by expectations. For example, expectations can sustain or amplify a crisis if investors judge the health of the economy of a given country by means of the price and income effects previously considered. However, a crisis can also be generated by expectations, as shown by some of the "escape clause models". In this case, expectations give rise to multiple equilibria that are partly or completely self-fulfilling. Several studies have analyzed some of these contagion channels empirically. Eichengreen, Rose and Wyplosz (1996) show that trade integration is important as an explanatory factor of currency crisis contagion in industrialized countries, while Glick and Rose (1998) show similar evidence for a larger set of countries. Esquivel and Larraín (1998) present indirect evidence for contagion by expectation, and Kruger, Osakwe and Page (1998) conclude in their study that the evidence of regional contagion is strong.

We have constructed a contagion indicator that captures regional contagion. The value of this indicator is equal to the number of countries experiencing a crisis in the preceding quarter in the same region. Therefore, it is equal to n if n countries experienced a currency crisis in the preceding quarter, and 0 otherwise.

2.3. Measuring currency overvaluation

We have tried to improve upon the real exchange rate indicators, which are usually calculated versus the dollar, and sometimes versus the dollar or the mark, because this approach is insufficient to explain the overvaluation phenomena in emerging countries. Recent experience has shown that the fluctuations of the dollar versus all currencies could greatly damage competitiveness in countries whose currencies are pegged to the dollar. For example, just before the Thailand crisis in the first half of 1997, the baht was largely overvalued in effective terms because of its peg to the dollar and the dollar appreciation versus all other currencies since the spring of 1995. This overvaluation is now generally thought of as one of the major factors of the crisis (World Bank 1998; Chinn 1998; Coudert 1999). Considering the Thai real exchange rate alone would have been misleading for it would have largely underestimated the overvaluation.

Therefore, we calculated effective real exchange rates on a broad basis, including 47 partners (OECD and emerging countries). The weights for calculating effective exchange rates are double weights on exports, which correspond to bilateral trade and competition in third markets. They are computed on the basis of the BIS methodology [10]:

$$w_{ij} = \left(\frac{X_i^j}{X_i} \right) \left(\frac{Y_j}{Y_j + \sum_{h=1}^{n} X_h^j} \right) + \sum_{k \neq i, j} \left(\frac{X_i^k}{X_i} \right) \left(\frac{X_i^k}{Y_k + \sum_{h=1}^{n} X_h^k} \right)$$

where X_i^j are exports from country j to country i (of all goods); X_i are total exports of country i; Y_j is the production of country j for its domestic market, defined as the difference between its GDP and its exports; and n is the number of countries. Regarding countries for which bilateral trade data are not available, we constructed proxies based on the bilateral trade relations in their region, as discussed in the appendix. The real effective exchange rate of country j with respect to its n trading partners is defined in the usual way:

$$ERff_j = \prod_{j=1}^{n} \left(\frac{ER_i}{ER_j} \right)^{w_{ij}}$$

where ER_j is the real exchange rate of the currency of country j with respect to the dollar; e_j the exchange rate with respect to the dollar; and $ER_j = (P_j / P_{us}) / e_j$ where P_j is the price in country j, and w_{ij} are the double weights on exports described above.

The real effective exchange rate can be considered a proxy of currency misalignment. If the purchasing power parity hypothesis (PPP) is thought to hold in the long run, real exchange rates should be constant at that horizon. An increase in the level of the real exchange rate above its long-term mean can be used as a proxy for overvaluation.

2.4. Capital controls

Capital controls can play a potentially important role in explaining the absence of currency crises. They may be used in a attempt to protect a fixed exchange rate system against speculative attacks and their consequences on official reserves and interest [11]. Although their long-run efficiency is questionable, they may have a certain impact on the occurrence and the timing of crises. In order to take into account restrictions on capital flows, we have constructed a dummy variable by using and updating an existing database (Cottarelli and Giannini, 1997) [12]. The information given in this database is sufficiently detailed to construct quarterly dummies.

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[10] See Turner et Van't dack (1993).

[11] For a brief survey of theoretical explanations of capital controls, see Johnston and Tamirisa (1998).

[12] The database has been updated by means of information published by the IMF (1996-1998).

3. Defining currency crises

To identify leading indicators, it is necessary to define currency crises precisely. Several approaches exist in the literature. A first approach defines a dichotomous indicator which equals 1 if there is a crisis and 0 otherwise. Another approach privileges a quantitative indicator which can take any real value (e.g. it continuously increases as a crisis approaches or intensifies). Both amount to the construction of a "simultaneous indicator of crisis".

These two kinds of indicators can be constructed on the basis of an indicator for exchange rate pressure or an indicator of devaluation. The studies using exchange rate pressure indicators put the emphasis on the fact that there can be a crisis even if it did not lead to a devaluation. These indicators include exchange rate movements, variations of international reserves and - in the case of industrialized countries - interest rates (as in Eichengreeen, Rose and Wyplosz, 1995). Another strand of research relies on indicators that are mainly based on movements in nominal exchange rates (as in Frankel and Rose, 1996).

We have constructed several different indicators on the basis of those existing in the literature and have compared their results. We have retained simultaneous indicators, which only include relative loss in foreign exchange reserves (*r*) and depreciation of the currency *(e)* [13].

The indicator of Corsetti, Pesenti and Roubini (1998) is a weighted average between the loss in reserves *r* and the depreciation of the currency *e* , which yields a quantitative indicator:

ind1 = 0.75*e + 0.25*r,

The indicator of Sachs, Tornell and Velasco (1996) is analogous, except that the weight between reserves and exchange rate is inversely proportional to the conditional volatility of the variables. This allows the variation of reserves to be underweighted, for example, in a period when they have been very volatile:

ind2 =(e/V(e)+r/V(r))/(1/Vr(e)+1/V(r)),

where *V* is the conditional variance.

The indicators of Kaminsky, Lizondo and Reinhart (1997) are qualitative indicators based on the Sachs, Tornell and Velasco (1996) indicator described above. If the preceding indicator exceeds a certain threshold, the period is considered a crisis. Otherwise, it is considered a tranquil period. Two different thresholds have been defined, equal to two or three standard deviations, σ *(ind2),* above the mean m *(ind2):*

ind3 = 1 if *ind2> m(ind2) + 3σ(ind2,); ind3 = 0* otherwise.

ind4 = 1 if *ind2> m(ind2) + 2σ(ind2); ind4 = 0* otherwise.

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[13] Both variables are extracted from *IFS*, IMF (see appendix 1 for the exact denomination).

As some Latin American countries in the sample have experienced periods of hyperinflation, the sample is split into two subsets: normal periods and hyperinflationary periods, for which two separate means and variances are calculated.

These indicators suffer from a number of drawbacks (Flood and Marion, 1998): there is no clear-cut way to choose the weights of their components; there are time aggregation problems because the relevant changes in the variables may occur in time intervals that cannot be captured by the periodicity chosen; these indicators may select series of crises that are unpredictable from the perspective of "speculative attack models" (Flood and Marion give examples where some of the crisis indicators point in the wrong direction at the time of the currency crisis).

Several authors prefer to use indicators referring only to exchange rate variations. This choice can be justified if the focus is on "successful" speculative attacks (as in the work of Esquivel and Larraín, 1998) and cases where currency crises culminate in a devaluation - as is typically the case in emerging countries. Different conditions, which are introduced in addition to the exchange rate variation, make it possible to account for periods of hyperinflation.

The Frankel and Rose (1996) simultaneous indicator is a qualitative indicator based only on the depreciation of a currency. A crisis is defined as being when the annual depreciation exceeds 25% (the study was carried out on annual data). In order to take into account hyperinflation, a 25% depreciation is considered to be a crisis if it also exceeds the depreciation of the former period by 10%.

$$ind5 = 1 \text{ if } e> 25\% \text{ and } e>e(-1) +10\% \quad ind5 = 0 \text{ otherwise.}$$

One serious drawback of this approach is the arbitrary threshold set at 25%. Milesi-Ferretti and Razin (1998) elaborated on the previous indicator in order to refine the conditions that strip out the influence of hyperinflation. They propose three types of indicators. For the first one, a period is considered a crisis if the depreciation of the exchange rate is superior to 25% and to the double of the former period's depreciation; moreover, the preceding depreciation must have been less than 40%.

$$ind6 = 1 \text{ if } e> 25\% \text{ and } e>2 e(-1) \text{ and } e(-1)<40\% \quad ind6 = 0 \text{ otherwise.}$$

For the second one, the crisis is defined by a depreciation superior to 15% and to the former one plus 10%; at the same time, the preceding depreciation should have been less than 10%.

$$ind7 = 1 \text{ if } e> 15\% \text{ and } e>e(-1) +10\% \text{ and } e(-1)<10\% \text{ ; } ind7 = 0 \text{ otherwise.}$$

The third one is similar to the second, except that it includes an additional condition of a fixed exchange rate regime in the former period :

$$ind8 = 1 \text{ if } e> 15\% \text{ and } e>e(-1) +10\% \text{ and } e(-1)<10\% \text{ and fixed regime in } t\text{-}1$$

$$ind8 = 0 \text{ otherwise.}$$

These indicators can also be criticized on the grounds that the choice of the thresholds is somewhat arbitrary.

In order to define a simultaneous currency crisis indicator, we have compared and analyzed these different definitions. In general, major crises - like those in Latin America in 1982 or in South-East Asia in 1997 - are well-identified by all indicators. However, a certain number of observations appear as crises for some indicators, but not for others. In general, the indicator of Kaminsky, Lizondo and Reinhart is more selective than other indicators in identifying crises. The heterogeneity of the results led us to compare the indicators on the basis of a chronological analysis (like the one used by Kaminsky and Reinhart, 1996) and to submit them to the judgment of experts on indebtedness issues at the Banque de France [14].

We constructed the indicator:

$ind9 = 1$ if the point is considered as a crisis by Kaminsky and Reinhart (1996) [15]

and 0 otherwise.

We found that *ind7* of Milesi-Ferretti and Razin is very close to *ind9*. As *ind9* is not available for a number of countries, we have merged both indicators:

$ind10 = 1$ if $ind7 = 1$ or $ind9 = 1$; $ind10 = 0$ otherwise.

This new indicator has been analyzed very closely. We checked the points where the component indicators give opposite results, and tried to amend *ind10* in the light of expert judgment. This analysis led us to modify four points that were identified as crises by the statistical indicator *ind7*, but cannot actually be considered as crises by expert judgment: for Mexico in 1985Q3, for Argentina in 1987Q3 and for Peru in 1991Q2 and 1991Q4. In those cases, a currency depreciation higher than 25% is due to hyperinflation rather than to a currency crisis. Finally, we added a crisis for Peru in 1982Q1, which was affected by the debt crisis in Latin America at that moment and for Argentina in 1995Q1 to account for the contagion effect of the "Tequila crisis" on this country [16]. The continuous depreciation of the PEN during this period might account for the fact that, for Peru, it is difficult to identify a particular quarter as a crisis period.

Finally, currency crises that follow each other closely must be treated in a special way. To avoid identifying quarters that refer to the same economic background as separate crises, we have constructed 12-month windows around each crisis.

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[14] We would like to thank C. Eugène (Banque de France, SEDET) for discussing this issue.

[15] We have updated this chronology for East-Asia.

[16] Here we deviate from our crisis definition. Argentina has indeed maintained a fixed rate against the US dollar since April/June 1991 (Rogoff, 1998) and the attack, albeit sizeable, was not successful.

4. Methodological issues

4.1. The data

Our study uses data for 15 emerging countries over the period 1980-1998. Different databases have been used: mostly the "International Financial Statistics" of the IMF, but also the "World Debt Tables" of the World Bank and the "Statistics on External Indebtedness" of the Bank for International Settlements. Some stock price indexes have been fleshed out with Datastream series and some series have been updated with the help of data published by JP Morgan (see the appendix for more details). Two aspects of this data set should be emphasized. First, the database is a panel, i.e. the total number of periods is equal to the sum of the quarters available for each country. Second, the number of periods analyzed varies depending on the leading indicators used, because these indicators are not always available for the whole period. Sufficient data availability for possible leading indicators is thus an initial constraint that we had to take into account in our analysis.

Another issue is the possibility of updating the series with sufficiently recent data. If the model is to be used as an operational tool, series should be available with a very short lag. As this is not the case of the series of IMF or the World Bank, we have used more recent online Datastream series which we connected to series used in our estimation. We have done this work for several of the series finally retained in our leading indicator.

In order to implement the technique of discriminant analysis, it is necessary to have a data set for countries in a currency crisis and for countries that do not experience such a crisis. These two groups of countries are identified by means of the simultaneous crisis indicator presented above *(ind10)*. Table 1 gives the number of crises and non-crises that are identified in this way [17]. The second column of Table 1 shows the importance of the three major crisis episodes: the debt crises of the 1980s, the 1994/1995 "Tequila crisis" (which concerned Mexico and Argentina) and the 1997 South-East Asian crises.

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[17] We prepare such a table for each one of the different crisis definitions.

Table 1
Number of crises and non-crises per year (1981-1998) [18] for 15 emerging countries
(quarterly crisis indicator with one-year window)

Year	Number of crises	% of total	Number of non-crises	% of total
1981	2	7%	39	5%
1982	4	13%	26	4%
1983	4	13%	21	3%
1984	2	7%	28	4%
1985	1	3%	31	4%
1986	2	7%	33	4%
1987	1	3%	39	5%
1988	1	3%	38	5%
1989	2	7%	40	5%
1990	1	3%	45	6%
1991	1	3%	40	5%
1992	1	3%	42	5%
1993	0	0%	60	8%
1994	2	7%	56	7%
1995	1	3%	57	8%
1996	1	3%	59	8%
1997	4	13%	60	8%
1998	0	0%	60	8%
1981-1998	30	3.7% of total number of observations	774	96.3% of total number of observations

The number of crises and their frequency differ from region to region, as shown in table 2.

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[18] The table gives data for the period from 1981 onwards, even though our data set includes data from 1980 onwards. This is because we have used growth variables as potential indicators.

Table 2
Number of crises and non-crises per region (1981-1998)

	Number of crises	% of crises	Number of non-crises	% of non-crises	Crises as % of total
Latin America	16	53%	406	53%	3.7%
Asia	10	33%	248	32%	3.9%
Others (Turkey, Israel, Eastern Europe)	4	13%	120	15%	3.2%
Total	30	100%	774	100%	3.7%

Five sub-samples are defined for every quarter. Each sub-sample groups together all the countries which, in that given quarter, are either in a period of non-crisis or in one of four different "crisis periods", depending upon how close these are to an actual crisis. The following scheme (table 3) gives an example to show how the data are organized.

Table 3
Definition of a crisis and a non-crisis period,
featuring an indicator that can identify an approaching crisis
(Example of 7 countries for the period 1989q4 to 1992q2)

		1989q4	1990q1	1990q2	1990q3	1990q4	1991q1	1991q2	1991q3	1991q4	1992q1	1992q2
Countries in a crisis period	Country 1									k=4	k=3	k=2
	Country 2	k=1	k=0									
	Country 3						k=4	k=3	k=2	k=1	k=0	
	Country 4				K=4	K=3	k=2	k=1	k=0			
	Country 5					K=4	k=3	k=2	k=1	k=0		
	Country 6						k=4	k=3	k=2	k=1	k=0	
	Country 7	k=2	k=1	k=0								
Countries not in a crisis period		k=5	k=5	k=5	k=5	K=5	k=5	k=5	k=5	k=5	k=5	k=5

with the indicator k as follows:
      k=0   countries in crisis

The areas with a *k*-value different from 5 are periods of crisis. The darker the shading, the closer the crisis. Take the example of country 4, which experiences a crisis in 1991Q3. For this country, the quarter 1990Q2 and the preceding quarters are quarters of non-crisis, and the quarters 1990Q3, 1990Q4, 1991Q1 and 1991Q2 are respectively observed 4 (k=4), 3 (k=3), 2 (k=2) and 1 (k=1) quarter(s) before the actual crises occurred. The four quarters after 1991Q3 are eliminated from the sample as well as the other four following quarters if another crisis was observed within the year. A second example illustrates the structure of information available for a given quarter. Let us take 1991Q4. At that time, a crisis is going to occur within the next quarter in countries 3 and 6 and after four quarters in country 1. Country 5 is in crisis.

The two groups used in the discriminant analysis correspond to this structure. One group is formed by the countries that are not experiencing a crisis, and another group of countries which are four, or fewer quarters ahead of an actual crisis. The first group is hereafter referred to as "tranquil periods" or "non crisis" and the second group as "crisis periods".

The quarter of crisis itself and the four following quarters are eliminated in order to take into account an adjustment period, which could differ from tranquil periods and also from crises.

Therefore, the panel obtained is unbalanced insofar as there may be missing data for some countries. However, since the aim is to identify common patterns across countries, this unbalanced data set is preferable because even incomplete information is useful particularly if it concerns a crisis period which, by definition, is rare.

4.2. Methodological issues for building a score function

We have chosen to use discriminant analysis, which is wide-spread, to identify risk units. One application is the identification of corporate default risk at the Banque de France (Bardos, 1998). We apply the same method to identify currency crises, for it aptly fits the structure of a typical classification problem.

Linear discriminant analysis has several advantages: robustness over time, interpretability, simple probabilistic utilization and easy maintenance (Bardos, 1998). Amemiya (1981) makes a theoretical comparison of qualitative choice models and discriminant analysis. This author also cites studies which suggest a high robustness of discriminant analysis with respect to non-normality. This is also confirmed by Knoke (1982). Logit or Probit analysis could have been used instead, as in most other studies on leading indicators of currency crises. Comparative studies have also shown that the results of the

Logit/Probit approach are often quite close to those obtained by discriminant analysis. However, Logit/Probit analysis is prone to the problem of multicolinearity, whereas this is not systematically an issue in discriminant analysis. Moreover, even if the log-likelihood criterion applied by this approach is warranted by the Cramer-Rao theory (efficiency of the estimates), it is not a function of the model's ability to predict the right response.

Let us first briefly recall the principle of Fisher's classical linear discriminant analysis [19]. If one seeks to classify an observation into one of two populations (corresponding in our case to two groups of countries in each period: the ones that are approaching a crisis and the ones that are experiencing a tranquil period), a rule is to assign observation x (here, a country) into population P_1 if:

$$s(v):=\left(x^1 - x^2\right)'T^{-1}\left(v - \frac{1}{2}\left(x^1 - x^2\right)\right) \geq c$$

and into population P_2 otherwise (x^1 and x^2 are the vector means of two independent samples, T denotes the pooled sample covariance matrix and v is a vector with p components, here the p leading indicators). In order to separate two samples as much as possible, Fisher (1936) proposed the linear discriminant function:

$$LDF(v):=\left(x^1 - x^2\right)'T^{-1}v$$

which is a combination of the p variables. This function has the property that, for any linear combination, say $d'v$, the squared difference between the two sample means (between-samples variance), divided by the pooled estimate of the variance of the difference, is maximized by:

$$d=\left(x^1 - x^2\right)'T^{-1}.$$

This explains why this function is interesting for the analysis of populations with common covariance matrices. The cut-off point c can be chosen in different ways. However, in the case of two populations with normal distributions and equal covariance matrices, there exists a best classification rule, which gives the smallest expected probability of misclassification. This rule corresponds to:

$$c = \ln\frac{p^2}{p^1},$$

where p^n (n=1,2) is the estimated prior probability of an observation coming from population n. p^n can be obtained from the relative sizes of the two populations. The discriminant analysis is implemented with a population that comprises a mixture of, on the one hand, all crisis periods and, on the other, only a sub-sample of tranquil periods. This is necessary because discriminant analysis is more robust to non-multinormality when the ratio of group observation is close to 1 (Scheffe, 1959). This also allows us to test our score functions out-of-sample.

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[19] For more details see Gnanadesikan *et al.* (1989) or McLachlan (1992).

When applying this technique to the present problem, we must respect certain constraints. In addition to those already mentioned (availability and robustness), the score function must be of "good quality", i.e. we retain the score function which gives a high ratio of correct classifications by cross-validation and for which the ratio of correct classifications is simultaneously low for first- and second-order errors (we come back to this point in the next section). Cross-validation is an additional way of reducing the optimistic bias introduced by in-sample evaluation. This method achieves a nearly unbiased estimate at the cost of a relatively large variance (Lachenbruch and Mickey, 1968).

4.3. Initial choice of possible leading indicators

The heterogeneity of the economies in the sample has led us to choose a large set of possible leading indicators; 34 were initially tested (see appendix). Most of them were based on the results of previous studies (in particular Kaminsky, Lizondo and Reinhart, 1998), and some were original, as mentioned above. After this initial choice, we restricted the set to discriminating indicators with the help of a comparative analysis of each indicator's distribution for the two groups of countries. A decile analysis indicates if, for a given potential leading indicator, the values of the crisis countries are (almost) always below or above the corresponding value of the non-crisis countries. This allowed us to further reduce this set and to exclude possible indicators that discriminate in a non-linear way, meaning that there are several intersections between the two groups' decile distributions [20]. The reason is that non-linear discrimination depends on thresholds that are unstable over time and thus do not serve our purpose of a robust predictive score function. This robustness criterion is a second important constraint for the final choice of leading indicators.

The following figures (1, 2, 3, 4 and 5) just show the average values of some relevant indicators as a crisis comes closer. They compare these values with those of "tranquil periods", which is indicated as a straight line.

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[20] We have also tried stepwise selection procedures. They often give very similar results to the above mentioned procedure. In addition, they allow the relative importance of the potential leading indicators (at least for the most important of them) to be assessed, in general correctly.

Figure 1 and 2

Overvaluation
Comparison of average values
for different k's

Reserves / M2
Comparison of average values
for different k's

Figure 3 and 4

Reserves / Total debt
Comparison of avreage values for
different k's

Reserves / Imports
Comparison of average values for
different k's
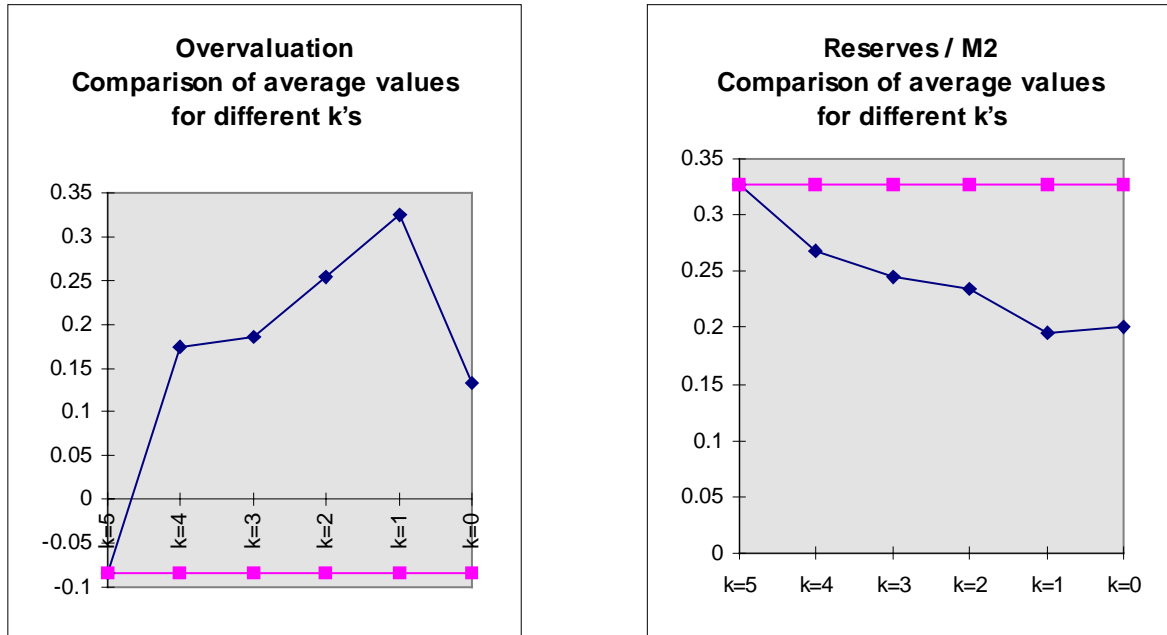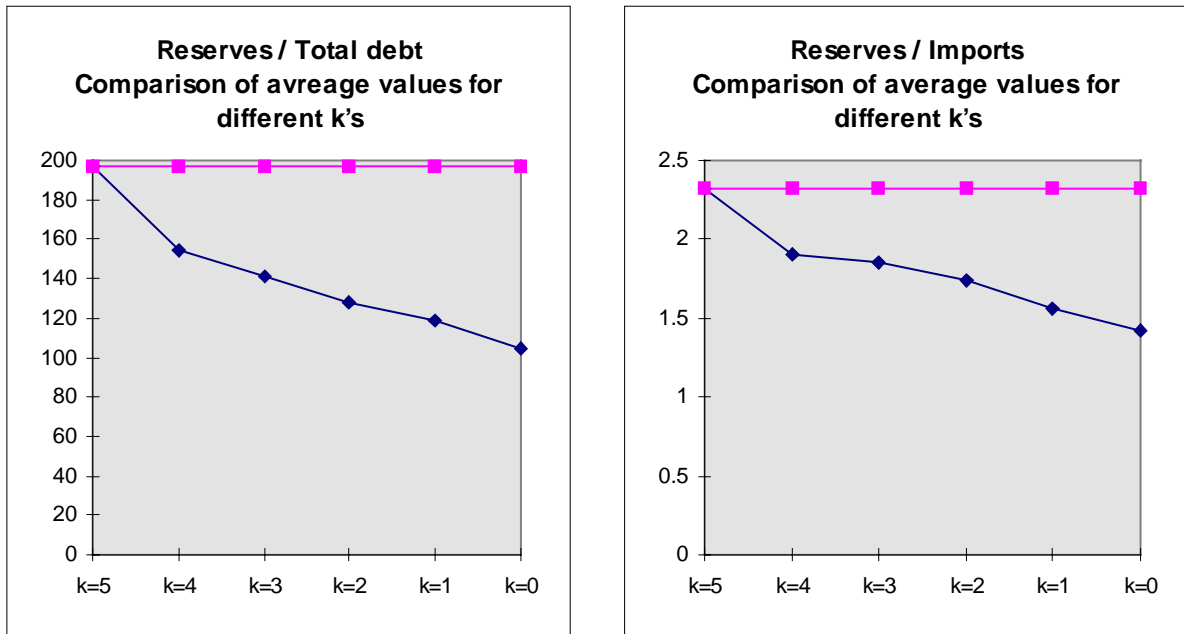
In discriminant analysis, the t-statistics cannot be used to test the significance of the variables figuring in the score function. This is certainly a drawback in comparison with an econometric approach. However, we think that the way we have selected the variables (systematic differences in the variables over the whole - or almost the whole - distribution of the two populations) alleviates this problem and makes the significance of the variables very likely. Another problem is linked to the presence of both

continuous and discrete independent variables. However, the continuous variable coefficients obtained when dropping the discrete variables are not or only slightly changed with respect to those obtained when the discrete variables are present. Thus our framework conforms with the conditions recommended by Knoke (1982) for the use of the LDF if both continuous and discrete variables enter the score function. In addition, the presence of discrete variables increases the ratio of correct classifications. Lastly, we have followed Lachenbruch and Mikey's (1968) recommendation to use their u-method (more commonly known as cross-validation) to determine the error rates if normality is questionable, i.e. when dichotomies are used as explanatory variables.

5. The results

5.1. The "global score"

The following "global score" was obtained. "Global" means that the function of leading indicators is calculated for the whole sample; as opposed to regional scores, which are discussed later and are obtained from regional sub-samples [21]. The signs in brackets correspond to the influence of a positive variation of the indicator on the value of the score.

- (+) reserves / M2
- (+) reserves / total debt
- (-) short-term debt / total debt
- (-) deviation of the real effective exchange rate from its long-term value
- (-) regional contagion indicator
- (-) inflation

These indicators can be grouped together: monetary indicators (1 and 2), a ratio of indebtedness (3), external variables (4 and 5) and a macroeconomic indicator (6). This result is consistent with theoretical explanations. An increase in short-term debt, in inflation or in M2 decreases the value of the score and thus increases the probability of a crisis. In contrast, an increase in reserves or a reduction in total debt improves the score value. An overvalued currency or a high rate of inflation increases the probability of a crisis, as well as the occurrence of crises in the same region. Other indicators are also absent. This does not mean that they are not discriminating. Different score functions were constructed and included other indicators than those given above. However, they yielded rates of correct classification that were not as good as those of the score function given here.

In some respects, these results stand out against those of other studies. For example, Radelet and Sachs (1998), who analyzed the Asian crisis with a Probit model, did not find the real exchange rate overvaluation to be associated with financial crises as we do. This may be due to the larger sample used here. We will come back to this point when presenting the regional score for Asia.

Capital controls do not enter into the score function. This result is consistent with the study by Johnston and Tamirisa (1998), who are skeptical about the effectiveness of capital controls concerning macroeconomic objectives such as those pertaining to currency crises.

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[21] The discriminant analysis was carried out using SAS-PC v 6.12 with a Pentium processor. We also used an add-on elaborated by M. Bardos.

5.2. The quality of the global score

The quality of a score function can be evaluated by its rate of correct classifications, i.e. the number of classifications into each group is divided by the actual number of observations in this group. Here this rate is calculated by cross-validation to choose the best score function in a subsample. It is then applied to the whole population by modifying the cut-off point in order to balance the rates of correct classification of the two error types.

Table 4
Ratio of correct classification corresponding to first and second type errors
(for whole population, 120 crisis periods and 684 periods of non-crisis)

(%)	Prediction of a crisis	Prediction of a non-crisis
Real crisis	79.6	20.4
Real non-crisis	20.4	79.6

The ratios of correct classification give good results (almost 80%) for both classifications (crises and non-crises). In addition, the ratios are satisfactory for the different crisis periods. This means that one can be (almost) equally confident in *ex post* predictions at different time horizons.

5.3. Score values and impending crises

It is interesting to analyze the behavior of leading indicators when a crisis is approaching. This analysis is conducted here by means of the distribution of score values for each type of crisis period (k=1 to 4) and for the periods of non-crisis: minima, maxima and quantiles.

Table 5
Quantiles of score *s* for the types of indicator *k* including those approaching a crisis *

K	Nb	Min	D10	D20	D30	D40	D50	D60	D70	D80	D90	Max
1	47	-3.09	-2.25	-1.54	-1.15	-0.91	-0.64	-0.30	-0.18	-0.00	0.65	0.97
2	23	-2.45	-1.90	-1.72	-1.01	-0.65	-0.46	-0.29	-0.04	0.17	0.69	1.30
3	23	-3.89	-1.99	-1.87	-1.74	-0.63	-0.38	-0.20	-0.07	0.20	0.58	1.47
4	25	-2.43	-1.88	-1.63	-1.14	-0.57	-0.40	-0.21	0.15	0.30	1.14	2.05
5	1221	-4.27	-0.91	-0.22	0.10	0.34	0.59	0.88	1.17	1.48	1.89	2.93

* The notation should be obvious: for example D50 corresponds to the median.

The table shows the expected regularity. The monotonic increase of these values from the minimum to the maximum comes from the calculation of the quantiles. The interesting point is the distribution of the score values within each column. The values should be high in the last line (non-crisis) and they should decrease monotonically when moving upwards. This is indeed what they are doing in most cases. One exception is the minimum value of the non-crisis line, but this one is unique. Some irregularity comes from the worst periods of crisis for each crisis period (columns D10, D20, D30). In these cases, the leading indicators reach very bad values three quarters before the actual crisis. These features may be thought to be specific to the score considered here. In fact, they are not. Using different score functions gives similar results: for the worst cases (left-hand columns), the irregularities persist. This suggests that, in these cases, the crisis mechanism is difficult to capture using a synthetic indicator. It also indicates that four quarters ahead may be the best horizon for predicting a currency crisis because the score becomes non-monotonic for the quarters closer to a crisis. This point will be further analyzed and confirmed in the next section.

5.4. Different lengths of crisis periods

So far the crisis period has been defined with a length of 4 quarters, meaning that the forecast horizon was one year. In this sub-section, this definition is questioned in order to see if another duration might produce different results. More precisely, two phenomena may occur. First, another duration may give better or worse results with the same or similar leading indicators. Second, it may result in a different kind of leading indicators. Typically we expect financial variables (for example, M2/GDP, credit/GDP, growth of domestic credit, stock price index, short-term debt/total debt, etc.) and liquidity indicators (reserves/imports, reserves/M2, etc.) to be more important when the period is short, say 1 quarter, and fundamental indicators (like debt ratios) to dominate an analysis carried out with a longer crisis period. In the following, the previous analysis (based on 4 quarters of crisis) is compared with results obtained with one-quarter crises.

First, the leading indicators identified in the previous score remain important for this shorter period length:

- (+) reserves / M2

- (+) reserves / total debt

- (+) reserves / imports

- (-) short-term debt / total debt

- (-) currency misalignment

In the score function with the best ratio of correct classifications, one additional variable appeared: the ratio of reserves to imports. However, this variable was also one of the important variables in the one-year analysis, even though it did not appear in the best score function. This seems to indicate that, in a

global analysis, currency misalignment as well as debt and reserve ratios are predominant in reflecting vulnerability to currency crises.

Second, for the 1-quarter horizon, the ratios of correct classification for the first-order and second-order error types were not as good as those for the one-year length. This result can be understood in the light of the graphs in the preceding subsection. In particular, the deterioration of the reserve ratios was almost continuous. As these ratios are important for the 1-quarter length, it is not surprising that the quality of the results is worse. This is logical because the already-bad ratios of the quarters preceding the quarter before the actual crisis are now considered as features of the "healthy" non-crisis periods.

In conclusion, we note that shortening the crisis period does not improve the predictive power of the score function - at least with our set of leading indicators. The one-year crisis period seems to be the most appropriate in our framework.

5.5. Posterior probabilities of currency crises

Bayes' formula allows the calculation of posterior probabilities of currency crises. For this, two sets of information are needed: first, the conditional probability of a country being in crisis (or a period of non-crisis) if the score value falls within a certain interval; second, the prior probability of a currency crisis, estimated using the quarterly rate of crisis [22].

$$P\left[crise / s_1 < score < s_2\right] = \frac{P(crise) \cdot P\left[s_1 < score < s_2 / crise\right]}{P(crise) \cdot P\left[s_1 < score < s_2 / crise\right] + (1 - P(crise)) \cdot P\left[\left[s_1 < score < s_2 / non\ crise\right]\right]}$$

Here we adopt the rule that a country is considered as exposed to currency risk when the posterior probability corresponding to the interval of its score value is much higher than the prior probability of a currency crisis.

Because of the homogeneity of risk zones, we give the posterior probabilities for intervals with different lengths. The risk coefficient is the ratio between the posterior probability and the prior probability. It gives a simple measure of the deviation between the two and makes it possible to compare different scores (as we will see later).

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[22] This latter value is obtained from the prior probability of a crisis in any given quarter. It is calculated by dividing the total number of crises by the total number of periods (here 3.7%). The prior probability at the four-quarter horizon is approximated by multiplying this figure by 4 (here 14.8%).

Table 6
Posterior probability of a currency crisis within one year
and risk coefficient for whole population

Intervals	Probabilities of a crisis within 1 year	Risk coefficient
$s < -1{,}97$	0.66	4.8
$-1.97 <= s < -1.15$	0.55	3.9
$-1.15 <= s < -0.50$	0.27	1.9
$-0.50 <= s < -0.23$	0.23	1.6
$-0.23 <= s < 0.15$	0.15	1.1
$0.15 <= s < 0.35$	0.08	0.6
$0.35 <= s < 1.31$	0.05	0.4
$1.31 <= s$	0.02	0.2

The risk coefficient measures the intensity of the risk of a currency crisis. The higher this risk, the higher the risk coefficient. A value close to 1 indicates a neutral zone where the prior probability and the posterior probability have approximately the same value.

5.6. Regional and synthetic scores

The above analysis can be conducted in several ways. The sample may be split by region, by country or by time period and score functions may be constructed accordingly. A regional breakdown seems the most appropriate. Regional differences in currency crises represent an issue that has already been explored in a short paper by Kaminsky and Reinhart (1998). They present some statistics on the basis of their work on EWSs and show that there are significant differences in volatility, as well as in the number of anomalous values of leading indicators before a crisis in Asia, in Latin America and in other countries. According to these results, the regions should exhibit different score functions, each of which would perform better than the global score function previously established.

We have thus constructed two functions for Latin America and for Asia. The score function for Latin America gives the following results:

- (+) reserves / M2

- (+) reserves / total debt

- (+) reserves / imports

- (-) deviation of the real effective exchange rate from its long-term value

- (-) inflation

This score function indicates that a traditional indicator like the ratio of reserves to imports is specific to Latin American countries.

The score function for Asia exhibits the following leading indicators:

- (+) reserves / M2

- (-) short-term debt / total debt

- (-) deviation of the real effective exchange rate from its long-term value

- (-) growth rate of real domestic credit

- (-) exports + imports / GDP

The presence of real domestic credit growth in the score function confirms the result of Radelet and Sachs (1998). Other identified indicators are in line with the common interpretations of the Asian crises (short-term debt/total debt). Recent internal guidelines for IMF staff recommended the monitoring of the ratio short-term debt/reserves [23], which has some similarity with the ratio short-term debt/total debt appearing in our Asian score. The sign of the openness indicator means that a more open economy is more likely to experience a currency crisis. This result confirms the findings of Berg and Pattillo (1998). But note that the link between openness and currency crises is specific to the Asian countries.

The regional contagion indicator no longer appears in either of these two score functions. This might indicate the existence of common structural problems specific to the countries of each region. These problems seem to be captured by the country specific variables of each score function: reserves/imports for Latin America, and growth rate of real domestic credit, openness indicator and interest rate difference for Asia.

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[23] See Bussière and Mulder (1999).

Table 7
Posterior probability of a currency crisis within one year
and risk coefficient for Latin America

Intervals	Probabilities of a crisis within 1 year	Risk coefficient
s < -1.47	0.81	4.0
-1.47 <= s < -0.76	0.65	3.2
-0.76 <= s < -0.43	0.29	1.5
-0.43 <= s < 0.05	0.17	0.9
0.05 <= s < 0.98	0.14	0.7
0.98 <= s < 1.22	0.09	0.5
1.23 <= s	0.04	0.2

Table 8
Posterior probability of a currency crisis within one year
and risk coefficient for Asia

Intervals	Probabilities of a crisis within 1 year	Risk coefficient
s < -3,25	0.59	4.2
-3.25 <= s < -2.10	0.47	3.4
-2.10 <= s < -0.20	0.28	2.0
-0.20 <= s < 0.40	0.14	1.0
0.40 <= s < 1.02	0.08	0.6
1.02 <= s < 1.70	0.02	0.1
1.70 <= s	0.01	0.1

Concerning the crisis in South-East Asia, our score functions perform well. They identify in advance the crises in Thailand, Malaysia and the Philippines. Only the Indonesian crisis failed to be predicted. This difficulty of predicting the Indonesian crisis was already noticed with other models (Berg and Pattillo, 1998). The only country for which the results in terms of correct classifications are bad is Argentina. But in the light of this country's chronic economic problems during the 1980s and 1990s, this underperformance is not that surprising. The results are satisfactory for the rest of the Latin American countries and for the countries of the other regions. Even though the posterior probabilities are different for the global, Latin American and Asian scores, the range of their risk coefficients is close.

Possible differences between time periods were not analyzed because our period is already relatively short, i.e. "only" 18 years. Schnatz (1998) estimated the period after 1985 in contrast to the period 1970-1997. He finds hardly any difference in the set of leading indicators in comparison with estimations over the entire period and concludes that progressive economic globalization has not really modified the structural forces that determine currency crises.

Finally, for each country, the three previous scores (global, Asian and Latin American) were used to choose the one with the best rate of symmetric correct classifications. The results of this synthetic score function are given in the synoptic table in the following section.

6. Comparison with the results contained in the literature

It is difficult to compare existing empirical studies on currency crisis prediction. However, an effort has been made recently to evaluate the main approaches within a common framework. Berg and Pattillo (1999) analyzed several models and compared their performance with the one of their own contribution. Their conclusion is slightly disappointing insofar as the answer to the question about the predictability of currency crises is summarized in short by: "Yes, but not very well" [24]. Even if this answer may be considered as optimistic compared with earlier, quite negative conclusions (Goldfajin and Valdés, 1997), it seems to confirm the somewhat mixed feelings about this issue shared by a larger audience [25].

In the following, we will follow the approach of Berg and Pattillo (1999) and compare the results of our model to the work done elsewhere. Such an exercise is necessarily limited by the difficulties of an exact comparison, but it conveys some general lessons about the ability of EWSs to predict currency crises.

First, let us recall the models analyzed by Berg and Pattillo and their main properties (additional characteristics are given later in a synoptic table) [26]:

1. Kaminky, Lizondo and Reinhart, (1998). This model (hereafter, KLR) uses a signal approach with 15 leading indicators, i.e. if an indicator passes a certain threshold determined by a quantile of its empirical distribution, the possibility of a crisis is signaled. The "optimal" set of thresholds is calculated as that which minimizes the noise-to-signal ratio (false signals/correct signals). Counting the number of right signals and false alarms allows the authors to calculate the probability of a crisis corresponding to a signal. The final model uses a weighted mean of these indicators with weights corresponding to the inverse of its noise-to-signal ratio.

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[24] To be precise, the authors' conclusion refers to the ability of the main models to predict the Asian crisis.

[25] "Investment banks and academic economists are building complicated models to predict currency crashes. Don't expect them to work" (*The Economist*, August 1st, 1998, p.65).

[26] These approaches are currently used by the Developing Country Studies Division of the IMF to develop an early warning system (see Borensztein et alii, 1999).

2. Augmented KLR. Berg and Pattillo have added two indicators to the above model: the current account and the ratio M2/reserves.

3. First Probit-based alternative model. On the basis of the KLR model, the authors estimate a Probit model with variables that pass a threshold. They find that the probability of a crisis depends on the following variables: real exchange rate deviation, current account, reserve growth, export growth, level and growth rate of the ratio M2/reserves.

4. Second Probit-based alternative model. The same variables appear in the model, but they intervene in a linear way and not by passing a threshold.

5. Third Probit-based alternative model. Here the variables are supposed to influence the probability of a crisis in a piece-wise linear way.

6. Frankel and Rose (1996). These authors proposed one of the first systematic studies of currency crises with a very large set of countries. Berg and Pattillo have reestimated this model over the period 1970-1992.

7. Frankel and Rose reestimated. This is the same model as the preceding one but estimated with revised variables over the period 1970-1996.

In addition, several other models have since been built with the aim of predicting currency crises.

8. Milesi-Ferretti and Razin (1998). Extending and refining the work of Frankel and Rose (1996), this Probit model finds, for different specifications (reserves/imports or reserves/M2), that the following variables are significant: current account balance, overvaluation, terms of trade index, US interest rate, reserves ratio.

9. Esquivel and Larraín (1998). Their significant explanatory variables are: real exchange rate misalignments, current account/GDP, seignoriage/GDP, M2/reserves, terms-of-trade shock, regional contagion.

10. Schnatz (1998, 1999) [27]. This author presents two approaches (signal and Logit) both with country-specific thresholds. The signal model is similar to KLR, but with a crisis window of only one year. The fixed effect Logit model underlines the importance of the following variables: real exchange rate misalignment, growth of domestic credit, export growth, inflation differential (with US), reserves/M2, US interest rate and current account.

11. Deutsche Bundesbank (1999). The fixed effect Logit model computed by the German central bank finds the following leading indicators: real exchange rate misalignment, growth of exports, credit growth, inflation differential (US), reserves/M2, current account, US interest rate.

We have not included the work of Sachs, Tornell and Velasco (1997) in this comparison because the focus of their study is too specific: it tries to make predictions for the aftermath of the Mexican crisis on

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[27] We would like to thank B. Schnatz for providing us with statistics on the explanatory power of his models.

the basis of average values of indicators over the period 1990-1994. For the same reason we excluded the work of Bussière and Mulder (1999)and the Probit model of Kruger, Osakwe and Page (1998) [28],, which covers 19 developing and emerging countries for the period 1977-1993 and gives as explanatory variables: real exchange rate misalignment, M2/reserves, banks' claims on the private sector/GDP, regional contagion.

Table 9 gives a synoptic view of the explanatory power of the main EWSs [29]. However, results are not directly comparable, for the samples on which they computed are different, as are the periodicity and the forecasting horizon. The first four columns of the table may be considered as conditional probabilities, linked by Bayes' formula. For example, the ratio of false alarms is such that:

% of false alarms = Prob(non crisis/crisis predicted) = 1 - Prob(crisis/crisis predicted)

= 1 - (Prob(crisis) Prob(crisis/crisis predicted)/Prob(crisis predicted)

where *Prob(crisis)* is the prior probability of a crisis in the sample and:

Prob(crisis predicted)=

Prob(crisis).Prob(crisis predicted/crisis)+(1-Prob(crisis)).Prob(crisis predicted/non crisis).

In terms of the notation of table 9, this is equivalent to:

$$\% \ of \ false \ alarms = 1 - posterior \ probability = 1 - \frac{prior \ probability * \% \ of \ correctly \ predicted \ crisis}{total \ probability}$$

where

$$total \ probability := prior \ probability * \% \ of \ correctly \ predicted \ crisis$$
$$+ (1 - prior \ probability) * (1 - \% \ of \ correctly \ predicted \ non - crisis).$$

We also give the adjusted noise-to-signal ratio whose expected value is close to 1 in the case of a random process, whereas it converges on 0 with the increasing quality of the model. Because the different models are not strictly comparable, we also present briefly the main features of each model.

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[28] This model has not been included in our synoptic table because the authors do not give rates of correct classification.

[29] The results of models 3 to 9 have been taken from Berg and Pattillo (1999).

Table 9: Results of different models (1)

	% of correctly predicted crises	% of correctly predicted non-crises	% of false alarms (2)	Prior probability (3)	Noise/good signals ratio (4)	Periodicity	Horizon of prediction (5)	Number and type of countries	Refinements	Period analyzed	Method used
1 KLR*	41	85	63	0.180	0.366	Monthly	24 months	5 developed +	country	1970:1-95:12	Signal
KLR**	9	98	44	0.220	0.222			15 emerging	specific		
2 KLR improved by the IMF *	46	81	65	0.175	0.413	Monthly	24 months	23 emerging	country	1970:1-95:12	Signal
KLR improved by the IMF **	9	99	30	0.205	0.111				specific		
3 Alternative IMF model 1*	44	89	57	0.158	0.250	Monthly	24 months	23 emerging	-	1970:1-95:12	Probit
Alternative IMF model 1**	16	99	29	0.130	0.063						
4 Alternative IMF model 2*	48	84	63	0.160	0.333	Monthly	24 months	23 emerging	country	1970:1-95:12	Probit
Alternative IMF model 2**	7	100	11	0.0011	0.000				specific		
5 Alternative IMF model 3*	47	87	59	0.160	0.277	Monthly	24 months	23 emerging	-	1970:1-95:12	Probit
Alternative IMF model 3**	19	98	34	0.160	0.105						
6 Frankel and Rose 1*	25	95	66	0.095	0.200	annual	2 years	105 emerging	-	1971-1992	Probit
Frankel and Rose 1**	7	99	44	0.152	0.143			+ developing			
7 Frankel and Rose 2*	36	95	54	0.105	0.139	annual	2 years	105 emerging	-	1971-1996	Probit
Frankel and Rose 2**	9	99	44	0.120	0.111			+ developing			
8 Milesi-Ferretti and Razin (res/imp)**	36.6	99.3	16.6	0.087	0.188	annual	1-2 year	39 emerging	-	1970-1996	Probit
Milesi-Ferretti and Razin (res/M2)**	34.8	99.1	20.0	0.100	0.270						
9 Esquivel and Larraín***	70.3	76.6	60.0	0.182	0.326	annual	1 year	15 developed	-	1975-1996	Probit with
Esquivel and Larraín ****	54.1	90.0	45.5	0.182	0.203			+ 15 emerging			random effects
10 Schnatz 1	52.2	88.1	55.7	0.158	0.231	Monthly	12 months	25 emerging	country	1970:1-97:6	Signal
Schnatz 2	48.4	88.7	51.7	0.186	0.250				specific		Fixed eff Logit
11 Deutsche Bundesbank	39.8	90.3	56.0	0.160	0.245	Monthly	12 months	12 emerging	country specific	1970:1-97:6	Fixed eff Logit
12 Global model 1 (6)	79.6	79.6	58.7	0.148	0.250	Quarterly	4 quarters	15 emerging	-	1980Q1-98Q4	Discriminant
Global model 2	50.0	91.9	48.2	0.148	0.162						analysis
Global model 3	8.4	99.1	37.0	0.148	0.111						

(1) The results of the different models are not directly comparable because of the differences of samples, periodicity and horizon.

(2) Number of false alarms over number of predicted crises. A false alarm is defined as a signal value indicating a crisis, but not followed by a crisis.

(3) When not directly available in the papers, these values have been calculated on the basis of the three preceding columns.

(4) (Number of false alarms/number of non-crises)/(number of correctly predicted crises/number of crises). (5) The horizon of the prediction corresponds to the crisis window.

(6) Global model 1 = model presented in this paper with equal ratios of correctly predicted crises and non-crises; global model 2: same with % of false alarms close to 50%; Global model 3: same with lowest % of false alarms close to 50%.

* Crises threshold fixed at 25%, i.e. there is a crisis if prob (crises)>25%; ** Crises threshold fixed at 50%, i.e. there is a crisis if prob (crises)>50%; ***Threshold at 20%; **** Threshold at 30%.

In this table, using Bayes' formula to assess the results of EWSs in a common framework highlights the existence of a fundamental trade-off between the percentage of correct crisis predictions and the number of false alarms. Choosing a high percentage of correct crisis predictions implies a high proportion of false alarms, and choosing a low percentage of false alarms goes with a low percentage of correct crisis predictions.

The literature on EWSs has adopted four different attitudes concerning this trade-off:

1) Berg and Pattillo (1999) seem to privilege the percentage of false alarms. This is the reason for the touch of skepticism which characterizes their generally positive attitude about the reliability of the predictions referred to in our introductory section. This also explains why they systematically try to find the threshold value that gives the lowest percentage of false alarms - at the cost of a sometimes extremely low (high) percentage of correct crisis (non-crisis) predictions. However, this criterion may undervalue the true quality of the model. It corresponds to the logic of a dichotomous approach, but neglects the fact that a wrong signal is not necessarily equivalent to the absence of danger of a currency crisis. A wrong signal simply means that, at a given point in time, the economic process did not lead to a devaluation [30], and this may be true even if the danger of a currency crisis was real.

2) In the view of Esquivel and Larraín (1998), one option is to select a threshold value so as to maximize the total number of correct predictions.

3) Esquivel and Larraín (1998) also emphasized another method, which is to choose the threshold that maximizes the average of the first three columns in the synoptic table (this choice corresponds to their threshold value of 30%).

4) Another method has been proposed by Demirgüç-Kunt and Detragiache (1999) [31]. They tailored the monitoring system by means of a loss function so that it fits the decision-maker's preferences. For example, if the decision-maker wants to use the system to determine which cases warrant further analysis, he or she would prefer to have a low number of crisis identification failures, and a fair number of false alarms may be acceptable. However, if the objective were to put pressure on national authorities, false alarms would be given more weight.

Our experience tells us that, if the first four columns of synoptic table 7 are intimately interrelated, the rates of correct predictions depend on the overall modeling process and their values are relatively robust to a change of the country sample. However, this is not true for the prior probability, which is easier to modify than the percentages of correct predictions and thus can influence the percentage of false alarms (to a certain extent) by deleting or adding one or several countries. This prompts us to propose an

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[30] This is clearly true when applying their criterion to our definition of a crisis (devaluation). However, the argument basically applies also when a pressure indicator is used (see also Borensztein et alii, 1999).

[31] Their paper is about banking crises instead of currency crises. However the problem they face is similar to the one discussed here.

additional criterion for judging the quality of an EWS, namely the extent of the symmetric percentages of correct crisis and non-crisis predictions [32].

In our view, it seems unnecessary to judge the results of EWSs on a single criterion because the final appreciation always depends on the use of the model and on the objective pursued. The presentation of the results should include two criteria corresponding to the opposite ends of the trade-off: balancing the rates of correct classification for crises and tranquil periods [33], and minimizing the percentage of false alarms [34]. An intermediate criterion may be added, such as a threshold close to 50% for false alarms or Esquivel and Larraín's proposal of the threshold that maximizes the average of the percentages of correct predictions (for crises and non-crises) and the percentage of false alarms. These are the three criteria we have retained to present our results in table 9. In this perspective, the results of our model seem to compare favorably with those of the other models.

Finally, it should be noticed that the extent of the percentages of correct predictions and the severity of the above trade-off depend not only on the choice of variables, countries, period analyzed and method used for prediction, but also on the quality of the data. This is a serious difficulty for EWSs. However, it may diminish in the coming years in particular due to the information system being developed at the IMF (cf. the IMF initiative on the Information Notice System (Desruelle and Zanello, 1997)).

7. Conclusion

In summary, this study has led to the following results. The use of quarterly data and the definition of crisis periods enables an improvement in the quality of early-warning systems (sharpness of the analysis, increase of the number of crises available, high ratio of correct classifications). The behavior of the score value is satisfactory when a currency crisis is approaching. A short predictive horizon (1 quarter) gives neither different nor better results than a 4-quarter horizon. Our study confirms that there are regional aspects of currency crises. There exists a fundamental trade-off in EWSs, based on the use of Bayes' formula in the context of rare events: to a certain extent, a decision-maker has to choose between a high ratio of good classifications of crises and a low ratio of false alarms.

Several extensions are possible. First, the set of countries could be enlarged. Second, it would be interesting to use a common framework (countries, periodicity, variables, etc.) in order to compare the results obtained by different statistical methods, in particular discriminant analysis and panel

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[32] With the discriminant analysis technique, the final use of the model has a direct influence on the score function. This is because this technique allows the function to be tailored to the objective pursued and the choice of a different score function according to the importance given to the first and second error types. This is different from a modification of the threshold value alone.

[33] This case does not constitute the extreme end of the trade-off in a proper sense which would rather consist in a high percentage of correctly predicted crises. However, from a pragmatic point of view, symmetric correct predictions seem to yield already relatively high percentages of false alarms and going beyond these may render the model inappropriate for practical purposes.

[34] With an upper limit for the percentage of correct non-crises predictions of 99%.

econometrics (Logit, Probit). Existing comparative studies seem to indicate that these methods give mostly similar results, but this remains to be checked in the present case. It would also be interesting to assess the performance of EWSs vis-à-vis the predictions of informed observers (e.g. rating agencies). However, in the absence of appropriate data, it is difficult to analyze this question. More work on the exact timing of currency crises is also desirable. Assessing the probability of a crisis at a given time horizon can only be a first step in this direction. There are two obvious reasons for the difficulty in analyzing this problem: first, the focus of present studies is on common features, whereas the exact timing of a currency crisis is also dependent on country-specific characteristics; second, speculative behavior, which is difficult to capture using empirical studies, becomes important when a crisis is on the brink of erupting. These two points are also serious obstacles for studies analyzing the depth of currency crises.

Concerning the use of the model as an EWS, some words of caution are in order. First, it is clear that prediction exercises can create a feedback effect which invalidates the prediction. Such effects depend on the existence and the speed of adjustment mechanisms. If it turns out that the crisis predictions of EWSs are invalidated because they are published, this might not be one of their worst achievements. A second point concerns the fact that an observed statistical regularity may tend to collapse once pressure is placed on it for control purposes. For example, in the case where leading indicators are made public, a country may be tempted by "window dressing". If this turns out to be true for EWSs, it is important to choose leading indicators in a way that makes them less prone to manipulation – if that is possible –, or to use the predictions privately in order to alleviate this effect. Finally, it is important to bear in mind that EWSs are instruments aimed only at assisting decision-makers. Their results should be supplemented by other forms of country risk analysis.

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Appendix 1.
The database

List of countries

Countries other than those in the list below have not been included, either because of our final focus, i.e. building an EWS for emerging countries or because of missing/dubious-quality data (e.g. Russia)

Latin America : Argentina, Bolivia, Brazil, Chile, Colombia, Mexico, Peru
Asia: Indonesia, Malaysia , Philippines, Thailand
Europe: Turkey
Africa: South Africa
Eastern Europe: Hungary, Poland

List of variables

The following series come from the IMF's "International Financial Statistics" (the IMF code is given in the middle column).

- Exchange rate		against the dollar
- Market rate	rf	
- Exchange reserves		in dollars
- Total reserves less gold	1ld	
- Foreign reserves	1dd	
- Central bank account		in domestic currency
- Foreign assets	11	
- Monetary base	14	
- External liabilities	16c	
- Bank accounts		in domestic currency
- Domestic credit	32	
- Liabilities on the private sector	32d	
- Money	34	
- Quasi-money	35	
- Interest rates and prices		
- Market rates	60, 60b, 60c	
- Stock price index	62 or 62a	
- Consumption price index	64	
- International transactions:		
- Exports	70	in domestic currency
- Imports	71	in domestic currency
- Exports	70..d	in dollars
- Imports	71..d	in dollars

- Unit value of exports	74	index
- Unit value of imports	75	
- Export prices	76	
- Import prices	76x	

- Balance of payments: in dollars

- Trade balance	78acd
- Current account	78ald
- Exports of goods	78aad
- Imports of goods	78abd
- Capital account	78bcd
- Account of financial operations	78bjd
- Foreign direct investment	78bed
- Portfolio investment	78bgd
- Errors and omissions	78cad

- Public finance: in domestic currency

- Deficit or surplus	80
- Public debt	88
- internal	88a
- external	89a
- in domestic currency	88b
-in foreign currency	89b

- National accounts: in domestic currency

- Investment	93, 93c or 93e or 93e.c
- GDP	99b.. or 99 b.c
- Real GDP	99b.p, 99b.r, 99bpp

The debt ratio series come from the "World Debt Tables" of the World Bank. These series have an annual periodicity and thus had to be converted into quarterly data.

Alternative series on indebtedness come from the "Statistics on External Indebtedness" of the Bank for International Settlements.

Some stock price indexes have been taken from Datastream and some series have been updated for the most recent period using data published by JP Morgan.

Appendix 2.
List of ratios used

Financial ratios
- M2 / GDP
- credit / GDP
- reserves / M2
- growth of domestic credit
- growth of liabilities on the private sector
- reserves / imports

Debt variables and payment behavior
- total debt / GDP
- non-guaranteed external bank claims + non-bank credits / GDP
- debt service / GDP
- debt service / total debt
- short-term debt / total debt
- total debt / exports
- debt service / exports
- interest payments / exports
- public debt / total debt
- foreign direct investment / total debt
- concessional debt / total debt
- multilateral debt / total debt
- reserves / total debt

External variables
- current account / GDP
- exports / GDP
- imports / GDP
- exports+imports / GDP
- terms of trade
- overvaluation of the real effective exchange rate

Macroeconomic indicators
- inflation
- public deficit / GDP
- investment / GDP
- growth rate of the ratio investment / GDP
- growth rate of real GDP
- difference with respect to the US interest rate
- capital controls
- indicator of regional contagion

Appendix 3.
Calculating real effective exchange rates

The matrix of double weights used for calculating the real effective exchange rates has been constructed by F. Marchand (Banque de France, SAMI) with bilateral trade figures extracted from CHELEM, the CEPII trade database. The calculations involve 47 countries, including OECD and emerging countries.

- South Africa
- Morocco
- Nigeria
- Tunisia   (price series only begin in 1987)
- Argentina
- Brazil
- Chile
- Colombia
- Mexico
- Peru
- Venezuela
- Korea
- Hong Kong   (price series only begin in 1990)
- India
- Indonesia
- Malaysia
- Pakistan
- Philippines
- Singapore
- Thailand
- Turkey
- Israel
- Hungary
- Poland
- Czech Republic

Tunisia and Hong Kong have been excluded from the calculation for the other countries because their price series are not long enough to allow the computation of a real exchange rate. It is however possible to calculate a real effective exchange rate for these countries. A similar reasoning applies to the Czech Republic.

For Bolivia, no statistics on bilateral trade are available. Therefore, we have used the structure of trade relations of the region that these countries belong to.

Appendix 4.
List of simultaneous indicators after 4 quarter window

Latin America:

Argentina,	81Q2, 87Q3, 89Q2, 95Q1
Bolivia,	82Q1, 85Q3
Brazil,	83Q1, 87Q1, 89Q3, 90Q4, (99Q1)
Chile,	82Q2, 84Q3
Colombia,	83Q1, 85Q2
Mexico,	82Q1, 85Q3, 94Q4
Peru	82Q1, 87Q4, 91Q2

Asia:

Indonesia,	83Q2, 86Q3, 97Q3
Malaysia,	97Q3
Philippines,	83Q4, 97Q3
Thailand	81Q3, 84Q4, 97Q3

Europe:

Turkey	88Q1, 91Q1, 94Q1

Africa:

South Africa	96Q2

Eastern Europe:

Hungary,	-
Poland,	-

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