Early warning systems for currency crises

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1. Introduction

In recent years, the frequency of currency crises in developing countries seems to have increased. Moreover, the consequences of these financial crises have probably worsened, not only for the country concerned, but also for other countries in the region, due to increased international trade and capital flows. This has encouraged research on the prediction of currency crises. In this paper, this research is summarised and a new approach to modelling currency crises is proposed.

In order to predict currency crises, it is of course essential to define what a currency crisis is. In the theoretical literature, currency crises are defined only for fixed exchange rate regimes. A crisis is identified as an official devaluation or revaluation, or a flotation of the currency. This definition is probably too strict to be useful for our purposes. Many currency crises involve currencies that are not formally fixed to one currency or a basket of currencies, but are allowed to float within certain margins. Even currencies that are allowed to float freely might be subject to a disruptive depreciation due to a speculative attack. Moreover, a small official devaluation in a tranquil period does not have to be disruptive as it may bring the real exchange rate more into line with fundamentals. Such an action might very well preclude future speculative attacks, and should not be identified as a crisis. For most purposes, the size of the depreciation is what matters, not so much whether this depreciation is caused by an official policy move or otherwise. Therefore, many empirical studies define a currency crisis as a large (either nominal or real) depreciation. Here, the problem arises of deriving the appropriate threshold above which a depreciation should be labelled a crisis. Another issue concerning the definition of a crisis is whether or not to include unsuccessful speculative attacks. Authorities may react to a currency attack by means of direct intervention in the foreign exchange market, or by raising interest rates. These attacks might also be included in the crisis definition as the necessary policy actions might be disruptive for the economy as well. In addition, from an investor's point of view, including unsuccessful speculative attacks might be useful as unsuccessful attacks also indicate vulnerability.

In this paper, a currency crisis indicator, based on monthly nominal exchange rate depreciations relative to the US dollar and depletions of official reserves, is constructed for emerging markets economies. Interest rates are not included in the index as interest rate data for emerging countries are not always available and/or reliable. The main innovation in our modelling approach is that we model the crisis index itself, instead of a zero-one variable representing index values below or above a certain threshold. The proposed model has two regimes – one for tranquil and one for crisis episodes – where the probability of ending up in the crisis regime depends on the economic circumstances. In the crisis regime, both the mean depreciation and the volatility are larger. The modelling technique resembles the one introduced in Vlaar (1998), where a two-regime model was used to predict weekly exchange rate changes within the European Monetary System, but is extended in two respects. First, not only the probability to end up in the crisis regime, but also the mean depreciation and the volatility in this regime are allowed to differ with economic conditions. Second, the model is adjusted to allow for panel data estimation.

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The continuous modelling approach has several advantages. First, by using the index itself, we do not discard information regarding the severity of a crisis. Therefore, large index values have more impact on the model than values just above the (arbitrarily set) crisis threshold. Second, as the continuous crisis variable varies between observations, there is no need to include many crisis episodes in the sample in order to estimate the model. Consequently, we can concentrate on emerging markets without having to include developed countries in the sample as well. Finally, the continuous modelling approach makes it possible to distinguish between variables that have an effect on the probability of a crisis and those that affect the severity of crises.

The rest of this paper is organised as follows. In Section 2, some theoretical background on currency crises is given. Section 3 summarises the main results from the empirical literature. In Section 4, the new modelling approach is described. Section 5 contains the estimation and forecast results, and Section 6 concludes. The Appendix describes the data.

2. Theoretical considerations

As to the reasons for currency crises, the "first generation" models of, for example, Krugman (1979) focus on inconsistencies between an exchange rate commitment and domestic economic fundamentals, such as excess creation of domestic credit, typically prompted by a fiscal imbalance. In these models, currency crises occur because international reserves are gradually depleted. The model fixes the timing of a currency attack such that the remaining reserves before the attack are just enough to satisfy the foreign currency demands of market participants during the attack.

The "second generation" models of, for example, Obstfeld (1986) view currency crises as shifts between multiple monetary equilibria in response to self-fulfilling speculative attacks. Consequently, the timing of the attack can no longer be determined, as it is no longer unique. In these second generation models, currency attacks can take place even though current policy is not inconsistent with the exchange rate commitment. The attacks can nevertheless be successful because the costs of maintaining a currency peg, in the form of high domestic interest rates, rise in response to the attack. In this framework, speculative attacks become more likely if high interest rates become more problematic. One reason for this might be economic slowdown or high unemployment rates. Another might be a weak domestic banking sector (Obstfeld (1995)). Raising interest rates increases short-term funding costs for banks, whereas the higher proceeds from loans might be of little importance to bank profits due to the longer maturity on average of loans relative to deposits and the increased probability of bad loans triggered by the rise in the interest rate.

This is one way banking and currency crises might be related. If there is an implicit government commitment to bail out troubled banks, bank runs might also lead directly to a currency crisis if the increased liquidity which results from the government bailout is inconsistent with the fixed parity (Velasco (1987), Calvo (1998)). The causality between banking and currency crises might also run in the other direction, however, for instance if the domestic banking sector is exposed to exchange rate risk due to short-term foreign lending (Chang and Velasco (1998)). Indeed, Kaminsky and Reinhart (1996) find evidence of both directions, although during most twin crises the banking crisis is preceded by the currency crisis.

3. Empirical literature

Kaminsky et al. (1998) summarise the results of 28 empirical studies on currency crises that have appeared over the last 20 years. Although the studies differ widely in crisis episodes considered and methodologies used, some general conclusions can be drawn. First, in order to explain all currency crises a wide variety of variables is needed. This is because crises can have many different causes. Some variables do seem to have predictive power for many crises, however. In particular, real

exchange rates and international reserves are included in many studies and found significant most of the time. Other variables that seem to do well, although the limited number of studies considering them precludes firm statements, are the domestic inflation rate and domestic credit growth. Current account deficits on the other hand are usually not found to have a significant impact. Rather than replicating the results by Kaminsky et al., we choose to highlight just a few typical studies and to concentrate on emerging market economies. The studies will be categorised by the methodology used.

3.1 The signal approach

The signal approach is primarily a bivariate method. For each variable the average level (or growth) in the period preceding the crises is compared to that in tranquil periods. If the variable behaves differently before a crisis, an extreme value for this variable provides a warning signal. The question of what value should be considered extreme in this context is solved by weighing the percentage of crises predicted against the percentage of false signals. The threshold level can either be the same for all countries, or be based on the country-specific empirical distribution of the variable. Given the warning signals of the individual variables, a composite leading indicator can be constructed as a weighted average of the individual signals.

In this procedure, both the crisis indicator and the explanatory variables are transformed into dummies, namely larger or smaller than a given threshold. This procedure probably gives the best results if there is a clear distinction between crisis episodes and periods of tranquillity. Regarding the crisis indicator, this is probably true if only the most severe crises are above the threshold or if the crisis definition is related to a currency peg. However, in most studies the number of severe currency crises is limited, and less serious depreciations are also labelled as crises. In that case, there is no clear distinction between observations just above and those below the crisis threshold. Concerning the explanatory variables, disregarding the exact value of the variable seems inefficient as, for instance, a current account deficit twice the value of the threshold seems to provide a stronger signal than a deficit just above it. If the individual signals are combined to compute a composite leading indicator, this inefficiency leads to inferior results. Another problem that arises in combining the signals is that the optimal weights for the individual signals cannot easily be assessed if the signals are correlated. If, however, one is primarily interested in finding vulnerabilities, without being particularly interested in exact probabilities, this method may be appropriate since it immediately points to the most important variables. This is particularly helpful for determining appropriate economic policy actions.

Kaminsky et al. (1998) use a signals approach to predict currency crises using monthly data for a sample of 15 developing and five industrial countries during 1970–95. In their study, a currency crisis is defined to occur when a weighted average of monthly percentage nominal depreciations (either with respect to the US dollar or the Deutsche mark) and monthly percentage declines in reserves exceeds its mean by more than three standard deviations for that country.[2] For 15 variables, based on economic priors and data availability, they compare the levels in the 24 months prior to the crises with values in tranquil periods. For each variable, an optimal threshold value is computed, above which the variable gives a signal for a crisis in the coming 24 months. The threshold levels are computed as a percentile of the distribution of the variable *by country* in such a way that the noise-to-signal ratio is optimal. The variables that have most explanatory power are (1) the real exchange rate deviation from a deterministic trend, (2) the occurrence of a banking crisis, (3) the export growth rate, (4) the stock price index growth rate, (5) M2/reserves growth rate, (6) output growth, (7) excess M1 balances, (8) growth of international reserves, (9) M2 multiplier growth, and (10) the growth rate of the domestic credit to GDP ratio.

Country-specific threshold levels for the economic variables have the advantage that national elements are taken into account. However, as the same percentile is used for all countries, it also implies that, within sample, all variables signal the same number of crises per country. Although only countries that experienced currency crises are included in the sample, this artefact seems undesirable. The real

[2] Weights, mean depreciations and volatility are calculated separately for high inflation episodes, defined as months preceded by a six month period with more than 150% inflation.

exchange rate is by far the most successful indicator. However, this result might be partly spurious as the deviation of the bilateral real exchange rate from a deterministic trend is used. Consequently, any real overvaluation according to this definition has to lead to either a depreciation or a lower inflation rate at home than in the reference country.

Berg and Pattillo (1998) evaluated their approach with respect to predicting the Asian crisis out of sample, and found mixed results. Most (68%) crises were not signalled in advance, and most (60%) of the signals were false. Nevertheless, the predictions were better than random guesses, both economically and statistically. The results improve slightly (also in-sample) if the current account relative to GDP and the level of the M2/reserves ratio are included. They also compare the ranking of severity of currency crises in 1997 with the ranking of vulnerability according to predicted probabilities of crisis. The composite leading indicator can explain 28% of the variance. If the current account/GDP and M2/reserves ratios are also included, this rises to 36%.

3.2 Limited dependent regressions

In the limited dependent regression models (logit or probit models), the currency crisis indicator is modelled as a zero-one variable, as in the signals approach. The explanatory variables are not transformed into dummy variables however, but are usually included in a linear fashion. The logit or probit functions ensure that the predicted outcome of the model is always between zero and one. The regression approach has several advantages compared with the signals approach. First of all, the prediction of the model is easily interpreted as the probability of a crisis. Moreover, as the method considers the significance of all the variables simultaneously, the additional information of new variables is easily checked. A disadvantage of this approach might be that the impact of an individual variable is less easily detected. Due to the non-linear logit or probit function, the contribution of a particular variable depends on all the other variables as well. A practical problem of using this strategy to model currency crises is that the number of crises is usually limited. Consequently, there are only a few ones in the sample, compared with a large number of zeros, resulting in poor estimation results. In order to increase the number of ones, many studies combine data from industrialised and emerging market economies.

Frankel and Rose (1996) use the probit model to estimate the probability of crisis in an annual sample of 105 developing countries covering 1971–92. A crisis is defined as a depreciation of at least 25%, exceeding the previous year's depreciation by at least 10%. The use of annual data has the advantage that more variables are available, for instance regarding fiscal positions and external debt. Moreover, compared with monthly data, the balance between zeros and ones in the sample is probably better. They find 69 crashes in 780 observations. They present several specifications, and conclude that the probability of crisis increases when output growth is low, domestic credit growth is high, foreign interest rates are high, foreign direct investment as a proportion of total debt is low, reserves are low, or the real exchange rate is overvalued. The results for output growth, the real exchange rate and reserves were not robust across specifications, however. Berg and Pattillo (1998) evaluate the results of Frankel and Rose. Using a cutoff probability of 25% , only 17 out of 69 crises are rightly predicted within sample, whereas 33 out of 711 tranquil periods are wrongly predicted. They argue that one of the reasons for these rather poor results might be that the country group is too diverse. They proceed with a smaller group of larger (emerging) markets over the sample 1970–96. Given results in other studies, the reserves/M2 and reserves/short-term debt ratios are also included as explanatory variables, where only the former shows significant results. For this specification, 38 out of 60 crises and 342 out of 383 tranquil periods are rightly predicted. The out-of-sample results are still disappointing, however. According to the definition of Frankel and Rose, there were no crises in 1997! This clearly indicates one of the problems with yearly data if a crisis takes place around the end of the year. If the ranking of their crisis index in 1997 is compared with the ranking of predicted probabilities of crisis, only 6% of the variance is explained in the original specification. For the modified model the percentage is even lower, 5%. In both cases, the model does not perform significantly better than random guesses.

Berg and Pattillo (1998) also use a probit model to study currency crises. They base themselves on the data and crisis definition of Kaminsky et al (1998), augmented by the current account and the ratio of M2 over reserves, as described above. In their regression model, not only the crises themselves are labelled "one", but also the 23 months prior to the crisis. Economically, this procedure has the advantage that the optimal model is sought that signals a crises two years in advance. Of course, this also means that the origins of a crisis are supposed to be visible two years in advance. Statistically, the procedure strongly improves the balance between the zeros and the ones in their monthly data set. They investigate whether a threshold value for the explanatory variables, as in the signals approach, improves on a linear specification. This turns out not to be the case. The variables that have most explanatory power are (1) the deviation of the real exchange rate from trend, (2) the current account, (3) reserve growth, (4) export growth, and (5) the ratio of M2 to reserves. In the model, not the variables themselves but the percentiles of the country-specific distribution of the variables are included. Using a cutoff probability of 25%, the model signals 48% of crises and 84% of tranquil periods correctly, within sample. Out of sample, the results are even better: 80% of crises and 79% of tranquil periods are correctly called. The prediction of the ranking of crisis severity in 1997 is not very successful. Only 23% of the variance is explained, slightly worse than the signals approach of Kaminsky et al. (1998), though still significantly better than random guesses.

The "Event Risk Indicator" by JP Morgan (1998) is based on a logit regression on monthly observations for 25 industrial or emerging countries over the sample 1980–97. Their crisis indicator is defined as a monthly real depreciation of the key bilateral exchange rate of over 10%. Consequently, this crisis definition excludes unsuccessful speculative attacks. As their basic goal is to find a model that can be used to predict profitable months to invest in weak currencies, this choice is reasonable. They balance the number of crises and tranquil periods in their sample by including only three tranquil periods per country. The explanatory variables for these three periods are calculated as: first, the average value of the variables over the estimation sample (1980–94), excluding the months in which there was a crisis, the month before, and the month after these crises; second, the average plus one standard deviation over the same sample; and third, the average minus one standard deviation. As a consequence, the predictions of the model are not directly interpretable as probabilities of a currency crash. The key factor behind currency crashes is supposed to be lack of competitiveness, included in the model as an overvalued real exchange rate (a dummy variable that can take the values one to four, based on the average value of the real exchange rate in the last two years, relative to the average value in the ten years before). As the model is used to select profitable investment months in weak currencies, predicting the exact timing of a crisis is extremely important. This timing is supposed to depend on two factors. First, the credibility of the government's commitment to defend the exchange rate, which is related to expected economic growth (modelled by means of the three-month rise in stock prices) and the size of foreign exchange reserves (relative to foreign debt). Second, the force of financial contagion, reflected in global risk appetite and local currency crash clustering. Global risk appetite is measured as the correlation between return and risk (reflected in high interest rates and an overvalued currency) over the last three months. Both the one month lagged and the seven months lagged six-month changes in this variable are included, as currency crashes are most likely if risk appetite changes from positive to negative. The local currency crashes variable is computed as a weighted number of currency crashes in the relevant currency block (Deutsche mark or US dollar) in the last six months, where recent crashes are given a higher weight than earlier ones.

The regression results show that the six-month change in risk appetite is the most important explanatory variable, followed by the number of local crashes and the reserves/debt ratio. The real exchange rate is just significant at the 5% level, the six-month change in risk appetite lagged seven months at the 10% level, and the change in stock prices at the 15% level. Using a cutoff level of 40%,[3] 31 out of 37 crises and 69 out of 74 quiet periods are correctly predicted within sample. The model also seems to predict quite well out of sample, as an investment strategy based on the model predictions outperforms a passive, or random, investment strategy on average. According to the authors, the results of the model are most sensitive for the clustering variable, followed by the current

[3] Over the period January 1988 to September 1997, this cutoff point would signal the risk of a crisis 29% of the time.

and lagged changes in risk appetite. Notwithstanding the importance of current sentiment, they also claim that the model signals all the major first crashes, including Mexico (December 1994), the ERM (September 1992), and Thailand (July 1997). This is surprising as only lagged variables are used in the model, and some of these crises came as a complete surprise to the market, thereby precluding the importance of contagion variables.

3.3 Severity of crisis indicators

A third category of models is not directly aimed at predicting the timing of currency crises, but at predicting which countries are going to be hit hardest, given the occurrence of a crisis somewhere in the world. If the timing of currency crises is largely unpredictable, for instance due to the importance of market sentiment, and the behaviour of financial markets during an international crisis is supposed to be different from normal behaviour, this strategy might be most fruitful. The idea is to define a crisis index (for instance based on depreciations and international reserve losses), spanning the whole period during which international markets were under stress, for a cross-section of countries. The differences between countries in the magnitude of this crisis index are subsequently explained by variables representing the economic situation at the onset of the crisis. This can be done by simple cross-section regression analysis. Usually, only one crisis episode is considered at a time, but a panel of crisis episodes can be used as well.

Sachs et al. (1996) use this framework to explain the severity of currency crises during the Mexican crisis of December 1994 (the so-called Tequila effect). They examine data on a cross-section of 20 emerging markets. Their crisis index is defined as a weighted average of the percentage decrease in reserves and the percentage depreciation of the exchange rate, from November 1994 to April 1995. They claim that only countries that were already vulnerable were hit by the Mexican crisis. Only three factors are essential for measuring vulnerability: an overvalued real exchange rate, measured as the real appreciation between the average 1986–89 level and the one over 1990–94; a weak banking system, measured by the four-year growth in credit to the private sector; and low levels of international reserves relative to M2. It turns out that only the combination of weak fundamentals (real overvaluation or weak banks) and relatively low reserves induced a crisis. They also investigate the influence of investment, savings, current accounts, the size of capital inflows, and fiscal policy stances, but these variables do not improve the results. Depending on the window over which the crisis index is calculated, their model can explain 51% to 71% of the variation in the crisis index over the Mexican crisis. Berg and Pattillo (1998) investigate whether the same equation can explain variations in the severity of crises during the Asian crisis. Unfortunately this is not the case. Even the results for the Mexican crisis turn out to be sensitive to minor revisions. Including three more countries changes the coefficients significantly. This sensitivity is probably due to small-sample problems. They estimate a model with seven variables, whereas they have only 20 observations. When the original equation, or slightly modified versions estimated on the Mexican crisis, is applied to the Asian crisis, at most 5% of the rankings are explained. When the same specification is re-estimated with data from the Asian crisis, the coefficients change significantly, and the real exchange rate is no longer significant. This equation can explain 21% of the variance in rankings (within sample). Tornell (1999) challenges these poor results. Using a model very similar to the one in Sachs et al. (1996), he concludes that banking weakness, real appreciation and international liquidity can explain both crises.[4] When estimated on data of the Mexican crisis only, the out-of-sample prediction of the Asian crisis still explains 24% of the variance in ranking. The fact that this result is not robust for minor changes in, for instance, the definition of the explanatory variables, raises serious doubts about the applicability of the model as a prediction device, however.

These problems are again confirmed by Bussière and Mulder (1999). They investigate the factors behind the depth of the 1994 and 1997 crises, and whether these can explain the 1998 Russian crisis.

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[4] Both models include dummy variables for weak verses strong fundamentals (based on the real exchange rate and credit growth), and high verses low reserves. The results are especially sensitive to changes in the definition of the threshold levels for these dummy variables.

For this purpose they estimate a model using a panel of 22 emerging markets for the 1994 and 1997 crises. As explanatory variables they compare those used by Tornell (1999) with the ones included in the early warning system (EWS) model of the IMF (Borenzstein et al. (1999)).[5] The results strongly favour the variables of the latter study. Within sample, the explanatory power of the two models is about the same. Out of sample, however, the ranking of vulnerability according to Tornell's model turns out to be *negatively* correlated with the severity of crises in the aftermath of the Russian moratorium in August 1998. The EWS-based model results in a significant positive correlation (0.56). This model only includes three variables: the four-year growth in the real exchange rate, the current account/GDP ratio, and the short-term debt/reserves ratio, with the latter being by far the most significant. Other variables that were investigated, but found insignificant, are export growth, reserve changes (both are included in the EWS model), credit growth, current account minus foreign direct investment over GDP, M0, M1 or M2 over reserves, and short-term debt over GDP. The one variable that does have a positive impact is the availability of an IMF programme. The presence of an IMF-supported programme significantly reduces the depth of a crisis. From these results, the authors conclude that all three crises are primarily liquidity-driven, as opposed to solvency-driven. Whether the model can also be used to predict the next crisis remains to be seen. One of the problems relates to the availability of data. The authors include the last available observation of the explanatory variables before the starting point of the crises. This practice results in data being included that were not available to the market before the crisis. Especially with respect to short-term debt, the inclusion of the end-June 1997 and end-June 1998 positions is dubious as these figures only became available in November, whereas the crises started in July/August.

Glick and Rose (1998) use cross-sectional data on both industrial and developing countries (161 countries in total) for five different currency crises (1971, 1973, 1992, 1994 and 1997) to explain contagion. The inclusion of a large number of countries reduces the small-sample problem, but at the expense of allowing for more heterogeneity in the sample. The crisis episodes are investigated separately, not as a panel. They find strong evidence that trade linkages explain regional patterns of currency crises for all five periods. Domestic macroeconomic factors do not consistently help in explaining the cross-country incidence of speculative attack.[6] As no regional variable other than trade relations is included in the regressions, it is not clear whether trade relations really *cause* contagion, or whether the trade variable simply picks up the regional preferences of international investors. If the latter phenomenon is indeed dominant, diversifying trade patterns won't shelter countries from regional currency crises.

4. A new approach

The three approaches just discussed all have their disadvantages. The signals and limited dependent approaches define a currency crisis as a discrete event, which is doubtful for marginal crises, and disregards the depth of the crisis. The severity of crisis method only uses crisis observations, thereby completely disregarding the timing of a crisis, and possible information from tranquil periods. In this chapter, we propose a method that combines elements of the limited dependent and severity of crisis methods. As in the latter approach, we model a continuous crisis index, in this case a weighted average of the monthly depreciation of the exchange rate and of the monthly percentage decline in international reserves. In contrast to these models however, we consider not only crisis episodes but all available observations. Thus, it is assumed that tranquil periods also provide information regarding the

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5 This model is based on Berg and Pattillo's (1998) model. The main difference is that the short-term debt/reserves ratio is included instead of the M2/reserves ratio.

6 Only inflation seems to matter during all five crises. Real growth significantly *increased* the severity of all but the 1992 crisis. Other variables included are credit growth (significant in 1994), government budget over GDP (significant in 1971 and 1973), current account over GDP (significant in 1994), and M2 over reserves (some influence in 1973 and 1994). All coefficients widely vary across crisis periods. In a probit regression, none of the macroeconomic variables is significant in any of the five crisis episodes considered.

vulnerability of individual currencies. The fact that vulnerabilities materialise primarily during crises is modelled by means of a model with two regimes, one for normal and one for unexpectedly volatile periods, where the latter regime is characterised by, on average, larger depreciations and extra volatility, which are common to crises. Unlike than with the limited dependent models, the definition of crisis periods is not imposed beforehand, but is the outcome of a stochastic process. The weaker the fundamentals of a country, the higher the probability of entering the volatile regime.

The empirical model can be described by the following six equations:

(1) $$I_{it} = X1_{it}\beta_1 + \lambda_{it}\vartheta_{it} + \varepsilon_{it}$$

(2) $$\varepsilon_{it} \sim (1-\lambda_{it})N(-\lambda_{it}\vartheta_{it}, h_{it}) + \lambda_{it}N((1-\lambda_{it})\vartheta_{it}, h_{it} + \delta_{it})$$

(3) $$h_{it} = X2_{it}\beta_2$$

(4) $$\lambda_{it} = \exp(X3_{it}\beta_3)/(1+\exp(X3_{it}\beta_3))$$

(5) $$\vartheta_{it} = X4_{it}\beta_4$$

(6) $$\delta_{it} = X5_{it}\beta_5$$

The first equation describes the evolution of the crisis indicator (I_{it}) for country *i* at time *t*. It consists of three parts: a linear part for normal periods, a non-linear part related to crisis episodes, and a stochastic error term. The distribution of the error term is described in equation (2). Conditional on being in the normal regime, which has probability $(1-\lambda_{it})$, the innovation is normally distributed with expectation $-\lambda_{it}\vartheta_{it}$ and variance h_{it}, whereas in the volatile regime the mean and variance are higher by ϑ_{it} and δ_{it} respectively. Note that the expectation of the combined process is zero. The volatility in the normal regime is described by equation (3). The probability of entering the volatile regime is estimated in the familiar logit form (equation (4)). Equations (5) and (6) describe, respectively, the additional expected depreciation (ϑ_{it}) and variance (δ_{it}) in the volatile regime. The parameters in this model (the β_is) are estimated by maximum likelihood. In order to ensure that the conditional variances are always positive, β_2 and β_5 and the corresponding economic variables $X2_{it}$ and $X5_{it}$ are restricted to being non-negative.

Apart from the second equation, economic variables, denoted by $X1_{it}$ to $X5_{it}$, might enter all equations. The interpretation of their influence differs between equations, however. The economic variables in the first equation describe the evolution of the crisis indicator in normal periods. Candidate variables are past changes in exchange rates and international reserves; this enables us to model the positive autocorrelation in these series, and inflation rates and (changes in) the real exchange rate, as many countries allow their currency to depreciate gradually in order to maintain competitiveness. The volatility in normal periods (equation (3)) is explained by its own past, as volatility is correlated through time- and country-specific as well as area-wide past volatility in order to account for international aspects of volatility. Consequently, once a crisis has occurred, volatility is expected to stay high temporarily, even if the probability of entering the volatile regime drops to zero. The fourth equation describing the probability of entering the volatile regime might involve a range of variables that increase the probability of a currency crisis. Variables that are found to be significant in other studies on currency crises could be included in our model via this equation. The additional expected change (ϑ_{it}, equation (5)) and volatility (δ_{it}, equation (6)) in the crisis regime are most likely driven by indicators of current inequalities, such as deviations of the real exchange rate from trend, indicators of contagion, such as the number or depth of crises in neighbouring countries, and liquidity-related variables, which influence the probability to overshoot an equilibrium value due to capital flight.

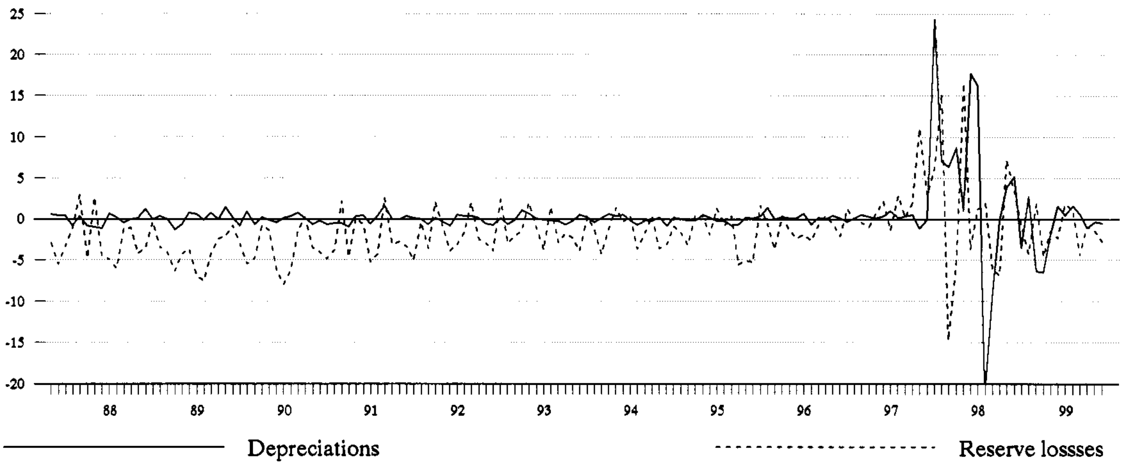
5. Results

5.1 Data

The model is estimated for a panel of monthly observations for 31 emerging or frontier markets, covering the period 1987–96. The starting point of the sample is determined by the availability of short-term debt data, whereas the end point is chosen such that the model could be evaluated out of sample for the Asian crisis. The countries included are: Argentina, Brazil, Chile, Colombia, the Czech Republic, Ecuador, Egypt, Greece, Hungary, India, Indonesia, Israel, Jordan, Korea, Malaysia, Mexico, Morocco, Pakistan, Peru, the Philippines, Poland, Portugal, Russia, Slovakia, South Africa, Sri Lanka, Taiwan, Thailand, Turkey, Venezuela and Zimbabwe. Except for Ecuador, all these countries are included in the emerging market database of the International Financial Corporation (IFC). These countries are likely to be important for international capital transactions. Two countries of the IFC database, namely China and Nigeria, are not included in our study, because of data availability problems, and because of the importance of capital restrictions in these countries. In order to avoid a predominance of high inflation periods, only observations for which inflation in the previous 12 months was less than 50% are included in our study. The effective number of observations further differs by country, and by model specification, due to data availability. Most data are from the IMF’s International Financial Statistics. A detailed description of the data can be found in the Appendix.

The currency crisis index is defined as: 0.8 times the monthly percentage nominal depreciation in US dollar terms plus 0.2 times the monthly percentage decrease in international reserves. These weights are based on the volatility of both components over the entire sample of usable observations. When evaluating the model, a currency crisis will be defined as an index value above 10. Like most empirical studies on emerging markets, we do not include changes in interest rates in our crisis indicator as market interest rates are not available for many countries for a sufficient time period. Contrary to most studies, we use the same weights for depreciations and reserve losses for all countries. We prefer to use this crisis definition as optimal country-specific weights might very well change over the sample, for instance when a currency peg is abolished, or more generally after a currency crisis. This is illustrated for Thailand in Figure 1. Since the Asian crisis, the volatility of reserve changes and, especially, depreciations for the Thai baht have strongly increased. Consequently, the relative volatility of both components has changed. This problem is even more prominent if the sum of the weights differs by country, as is the case if the crisis indicator is defined in terms of the country-specific means and standard deviations of the crisis index, calculated over a pre-crisis period. These indicators signal a new crisis every few months since 1997. Moreover, objective country-specific weights are hard to obtain for currencies with a short history of low inflation, such as that of Argentina or Brazil.

Figure 1 Monthly percentage depreciations and reserve losses Thailand



As explanatory variables, a wide range of variables is considered. In the first instance, all possible candidates are included at the same time. Subsequently, variables that have the wrong sign or are insignificant are excluded. Regarding the time lag for explanatory variables, we included at least a one-month lag for (real) exchange rates, international reserves, inflation rates and the currency regime, two months for GDP, exports, imports, M2 and bank credit, and five months for international debt data. These relatively long time lags reflect the idea that economic variables become especially important if market participants become aware of them. Also, in order to be useful as early warning indicators, long time lags are necessary.

5.2 Estimation results

Table 1 shows the estimation results for the model selected for the 1987–96 period. Three numbers are given for most parameters. The first is the value of the estimated coefficient. As the model contains highly non-linear parts, this value is not always very informative. The second number is a heteroskedasticity-consistent t-value. The last number, between square brackets, gives the average change in the probability that the crisis indicator will exceed 10% if the specific variable is changed one standard deviation in the theoretically dangerous direction. This number gives some idea about the economic relevance of the variables, although it should be noted that no allowance is made for the correlation between the explanatory variables. Moreover, it only gives the average change.

Economic variables do have a significant impact on the crisis index in various ways. In the *linear part*, positive autocorrelation of reserve losses and depreciations is prominent. Moreover, domestic inflation and real overvaluation have a significant direct effect on the crisis index. This is in accordance with the assumption that most countries allow their currency to depreciate gradually, if necessary, in order to remain competitive. Autocorrelation is also important for the *variance*. A quite disturbing result is that the most important factors predicting a crisis are the recent developments in reserves and exchange rates themselves. Nevertheless, other factors matter as well. The influence on the variance of past local volatility, defined as the cross-sectional variance computed over all other countries on the same continent, can be explained by the correlation between exchange rate changes in neighbouring countries, combined with the correlation in volatility over time. Freely floating currencies have a slightly higher volatility in normal periods.

Domestic inflation, an overvalued real exchange rate and reserve losses not only have a direct (linear) effect on the crisis indicator, but they also have an impact through the *probability of entering the volatile regime*. For the probability of a crisis, defined as a crisis index of at least 10, this indirect effect dominates the direct effect. Other variables that have a significant impact on the probability are the import/export ratio, the reserves/M2 ratio, and the annual growth rate in short-term debt over reserves. Consequently, a crisis may be triggered by solvency problems (high import/export ratio or an overvalued currency) as well as liquidity-related problems. Regarding liquidity, note that over the 1987–96 sample, the reserves/M2 ratio is economically and statistically more important than the short-term debt/reserves ratio. The latter variable is, however, very important for explaining the depth of a crisis, as the *additional variance* in the crisis regime is completely dominated by this variable. This result might explain why the influence of the M2/reserves ratio is absent in Bussière and Mulder (1999), as they only investigated the depth of a crisis. The *additional expected depreciation* in the crisis regime is only limited. The only economic variable for which some influence was found is the average depreciation in neighbouring countries in the previous month. This variable reflects contagion effects in currency markets. In the absence of local depreciations in the previous month, the crisis indicator is only expected to grow by an additional 0.21 percentage points in the crisis regime. The main reason is probably that the timing of currency depreciations, or reserve losses, is not easily predictable, otherwise market participants could make arbitrage profits. The influence of uncertainty is much more important.

In order to investigate parameter stability, the same model that was selected for our 1987–96 sample was also estimated for our full sample (May 1987–June 1999), and for the most recent period only (1997–99). Unfortunately, most parameters are not stable. The most notable changes concern the probability of entering the crisis regime. The liquidity-related variables have become much more

Table 1

Estimation results for optimal specification over 1987–96

Estimation sample	1987–96	1987–99	1997–99
$X1_{it}$: *linear expectation*			
Intercept	–1.26 (2.7)	–1.93 (4.2)	–2.81 (2.7)
Quarterly depreciation	0.112 (6.9) [0.22]	0.109 (7.6) [0.23]	0.069 (2.8) [0.32]
Quarterly growth in reserves	–0.011 (3.5) [0.12]	–0.014 (4.5) [0.15]	–0.019 (2.8) [0.18]
Domestic annual inflation	0.015 (3.2) [0.06]	0.013 (3.0) [0.06]	0.019 (1.7) [0.09]
Real exchange rate	0.22 (2.1) [0.02]	0.39 (3.8) [0.03]	0.63 (1.7) [0.08]
$X2_{it}$: *normal variance*			
Intercept	0.28 (3.2)	0.32 (3.2)	0.95 (2.3)
Floating rates	0.51 (1.4)	0.04 (0.1)	0.00 (0.0)
Exchange rate volatility (6 months weighted)	9.45 (4.5) [1.52]	11.70 (6.9) [2.22]	10.45 (5.0) [8.41]
Reserves volatility (6 months weighted)	0.60 (3.9) [2.47]	0.58 (5.2) [2.37]	0.29 (1.9) [0.17]
Average local exchange rate volatility (3mw)	1.17 (2.0) [0.02]	0.44 (0.9) [0.01]	0.00 (0.0) [0.00]
$X3_{it}$: *crisis regime probability*			
Intercept	–9.00 (3.0)	–6.57 (2.2)	–1.19 (0.2)
Real exchange rate	1.42 (2.1) [0.30]	0.99 (1.6) [0.26]	0.35 (0.2) [0.16]
Domestic annual inflation	2.84 (2.2) [0.31]	2.07 (1.9) [0.28]	1.80 (0.6) [0.31]
Import/export ratio	0.62 (3.0) [0.34]	0.25 (1.2) [0.17]	–1.67 (2.4) [–1.03]
Weighted quarterly growth in reserves	–0.86 (2.0) [0.50]	–0.82 (2.5) [0.62]	–0.37 (0.8) [0.27]
Annual growth short-term debt over reserves	0.43 (1.8) [0.24]	0.55 (2.5) [0.40]	1.61 (3.9) [1.74]
Reserves/M2 ratio	–3.50 (2.8) [0.70]	–3.07 (3.0) [0.78]	–4.41 (1.9) [1.71]
$X4_{it}$: *crisis regime additional expectation*			
Intercept	0.21 (0.5)	0.78 (1.6)	2.55 (1.6)
Local average monthly depreciation	0.38 (1.6) [0.18]	0.35 (1.5) [0.18]	0.31 (0.9) [0.38]
$X5_{it}$: *crisis regime additional variance*			
Intercept	0.00 (0.0)	0.00 (0.0)	3.33 (0.4)
Short-term debt/reserves ratio	35.99 (2.1) [1.17]	46.82 (2.7) [1.19]	79.67 (1.6) [0.69]
Number of observations	2,557	3,312	755

Note: Heteroskedasticity-consistent absolute t-values in parentheses. Between square brackets, the increase, measured in percentage points, in the probability of obtaining a crisis indicator value of at least 10, due to a one standard deviation change in the explanatory variable, evaluated over the 1987–96 sample, is shown.

important over the recent period, whereas the influence of solvency-related variables has declined. The import/export ratio in particular changes dramatically, and even becomes significantly negative over the 1997–99 period. The influence of the real exchange rate and inflation also decline, but these effects are somewhat compensated for by a higher direct effect of these variables. Regarding the liquidity variables, the influence of the growth rate of short-term debt to reserves is highly significant. The reserves/M2 ratio also remains significant, however.

Somewhat surprisingly, the influence of contagion seems to have declined over the latter period. Whereas the influence of local depreciations on the additional expected depreciation in the crisis regime has hardly changed, the influence of past local volatility on the variance has declined. Given the worldwide effects of the Asian and Russian crises, this result seems counter-intuitive. One reason for this result might be that, more recently, contagious effects have materialised quicker, that is to say within one month. If that were the case, contagion would not show up in the influence of past depreciations in neighbouring countries, but in the depreciation of the domestic currency. Indeed, the influence of own past exchange rate volatility has increased. In order to investigate the possibility that contemporaneous correlations have increased recently, covariance matrices of normalised residuals of our model were calculated, based on a one-year moving window.[7] Only 12 countries are used for this

[7] The normalised residuals are computed by means of the cumulative distribution function. For each residual, the probability of finding a smaller value than the one observed is calculated. Subsequently, the corresponding normalised

purpose, as data for the other countries were lacking, or excluded because of excessive inflation. Figure 2 shows the cumulative explanatory power of the first three principal components based on these covariance matrices. About 75% of the variance of those 12 crisis indicators can be explained by three common factors. Although the explanatory power of the first three principal components has increased somewhat in recent years, the current level is comparable to the levels of the early 1990s. Therefore, we do not find convincing evidence of increased contagion, other than what can be explained by the variables in our model, over recent years.

Figure 2 Cumulative expanatory power first three principal components nomalised model residuals

5.3 Crisis prediction

Despite the fact that the optimal model for 1987–96 differs from that for 1997–99, it is interesting to see to what extent the model estimated for 1987–96 can be used to predict exchange rate crises in the years thereafter. For that purpose, a currency crisis is defined as a value on the currency crisis indicator of at least 10%. So defined, our sample contains 49 currency crises: 25 before 1997 and 24 thereafter. The total number of crises over the sample for the 31 countries included in the study is somewhat higher, but we only analyse crisis for which we have data on both the indicator and the explanatory variables, and for which inflation over the previous 12 months was less than 50%.

Table 2 shows the predictive power of our model. Success in predicting crises naturally depends on the threshold used to select vulnerable observations. Within sample, if the threshold level is set at 10%, meaning that a warning signal is given whenever the probability of a crisis is at least 10%, 10 out of 25 crises are detected. This comes at the expense of also selecting 111 quiet periods out of 2,532. The large number of tranquil periods selected should not come as a surprise, as our model predicts that the probability of selecting a tranquil period is up to 90%. Indeed, one should not expect to be able to select crisis observations without signalling tranquil periods as well, since this would lead to arbitrage opportunities. If the threshold is lowered to 1%, 23 out of 25 crisis observations are selected, but also about 37% of tranquil periods. At the 0.2% level, all crises are selected. The higher the threshold, the more selective the model. This is reflected in the noise-to-signal ratio, which rises from 11.0% to 65.1% when the threshold is lowered from 10% to 0.2%.

Although the noise-to-signal ratio of our model seems good, one may wonder whether the model is really informative or simply providing information that is already known. More precisely, given the importance of past depreciations and reserve losses in our model, some of the crises we signal are simply continuations of a crisis in the previous period. In order to detect the importance of these repeated crises, we also calculated the predictive power for a restricted sample, where observations for a country are excluded up to two months after a crisis in that country. These results are shown on the

residual is computed by means of the inverse of the standard normal cumulative distribution function (Palm and Vlaar, (1997)). This normalisation procedure has the advantage that the influence of outliers is reduced.

right-hand half of Table 2. Within sample, four crises were continuations of previous ones, and all four are detected at the 10% threshold. However, as 34 out of 39 non-crisis observations that followed a crisis were also signalled as a crisis at the 10% threshold, the noise-to-signal ratios are hardly affected by the truncation.

Table 2
Predictive power crisis index model

	All observations			Excluding 2 months after crisis		
	Crises	Tranquil	Noise/signal	Crises	Tranquil	Noise/signal
			Within sample: May 1987 – December 1996			
Total	25	2532		21	2493	
P10% > 10%	10	111	0.110	6	77	0.108
p10% > 5%	14	308	0.217	10	270	0.227
p10% > 2%	21	608	0.286	17	569	0.282
p10% > 1%	23	913	0.392	19	874	0.387
P10% > 0.5%	24	1315	0.541	20	1276	0.537
P10% > 0.2%	25	1649	0.651	21	1610	0.646
			Out of sample: January 1997 – June 1999			
Total	24	731		16	704	
P10% > 10%	13	39	0.098	5	18	0.082
p10% > 5%	14	73	0.171	6	49	0.186
p10% > 2%	17	151	0.292	9	124	0.313
p10% > 1%	21	227	0.355	13	200	0.350
P10% > 0.5%	23	345	0.492	15	318	0.482
P10% > 0.2%	24	454	0.621	16	427	0.607

Note: The noise-to-signal ratio is defined as the number of bad signals as a share of possible bad signals, divided by the number of good signals as a share of possible good signals.

Out of sample, the results are about as good as within sample. Most of the noise-to-signal ratios are even slightly lower out of sample. Apparently, the fact that not all model parameters are stable over the sample does not affect the predictive power very much. The number of repeated crises is much higher in the forecast period. As in the estimation period, these are all predicted at the 10% threshold level. All in all, the results seem reasonable. At the 1% threshold level 87.5% of crises are detected, at the cost of signalling 33% of the time.

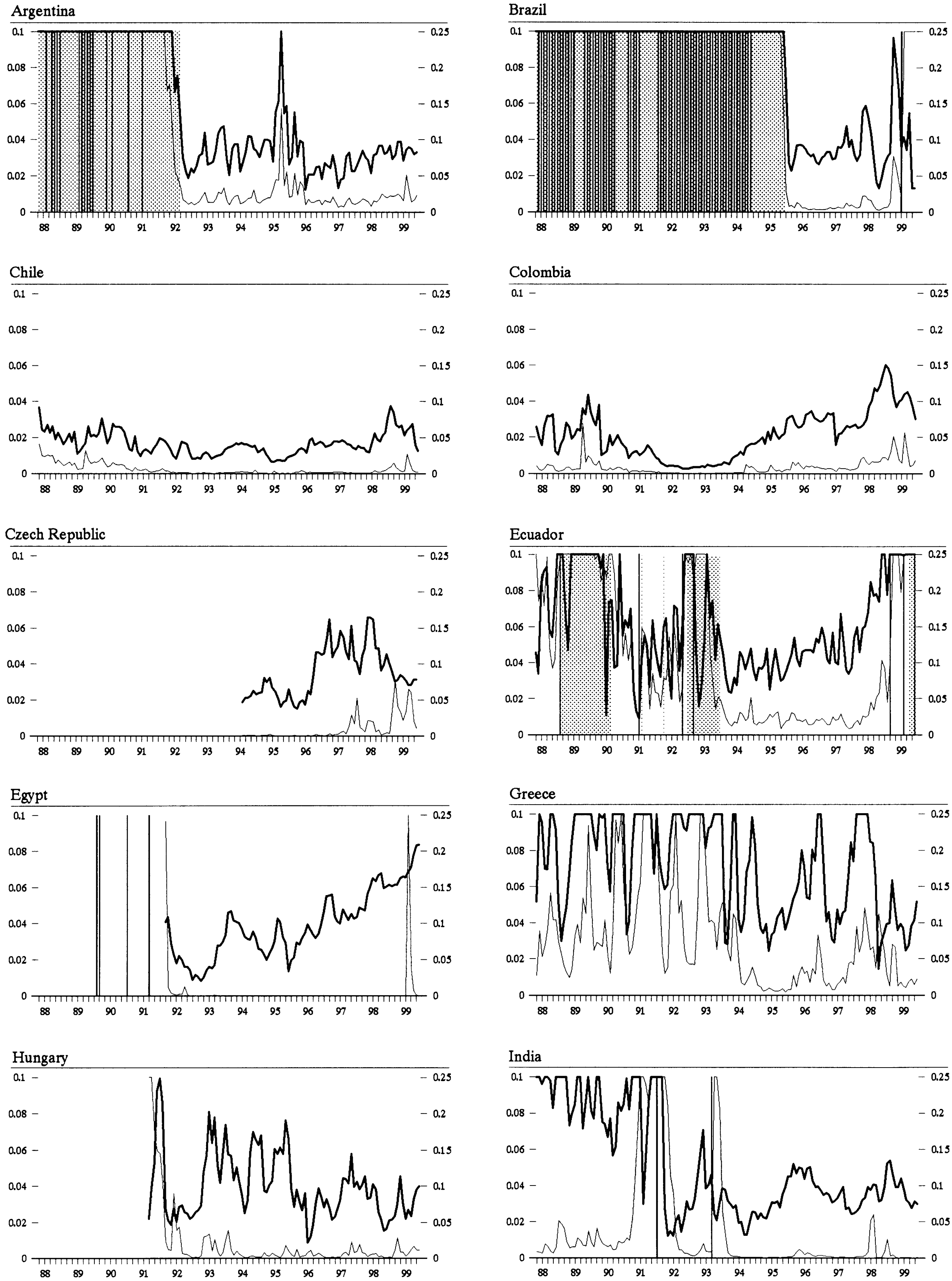
In order to give a better idea of which crises are predicted, Table 3 provides the complete list of crises included in the study. The crises that are best predicted are of course those that immediately followed other crises. Most of the major first crises are detected only at the 1% level. The probability of a crisis in Thailand in July 1997 was only 1.3%, and 1.0% in Russia in August 1998. The Mexican crisis is predicted at the 4.7% level if December 1994 is taken as the crisis date. If the start of this crisis is located at November, during which the crisis indicator was 5.9, the probability of a crisis is 1.4%. The one major crisis that is missed at the 1% level is the recent one in Brazil, for which the probability according to our model was only 0.8%. This is all the more surprising because this was probably the best anticipated crisis ever. One reason for the relatively poor performance of the model for this crisis is the fact that Brazil had increased its foreign reserves in December 1998 by 8.5%. Consequently, the probability of crisis was sharply reduced. Another reason is that the real exchange rate was hardly giving any sign of overvaluation, due to the fact that it was even slightly more overvalued during the reference period (1990). This example clearly shows the advantage of including real appreciation over a fixed period, instead of the level of the real exchange rate. However, as we have shown, we could not find empirical support for that formulation.

Table 3
Characteristics of the currency crises in our sample

Date	Country	Crisis index	Probability of crisis	λ	Annual inflation
8801	Jordan	11.4	3.07	13.4	–1.8
8802	Poland	14.6	5.13	24.6	46.7
8804	Jordan	14.7	22.62	82.3	1.7
8806	Jordan	15.0	32.05	86.1	0.3
8903	Venezuela	121.7	9.01	53.9	43.5
9010	Pakistan	13.3	4.59	27.5	10.6
9101	Ecuador	10.4	0.92	2.3	49.5
9103	Portugal	11.1	2.08	14.9	12.9
9103	Zimbabwe	12.5	2.71	6.7	18.8
9106	Zimbabwe	13.3	19.59	49.0	22.2
9107	India	13.6	17.24	65.3	13.0
9109	Zimbabwe	17.8	35.32	0.0	22.0
9205	Ecuador	11.0	2.69	15.6	49.6
9301	Zimbabwe	12.9	10.82	24.9	46.3
9303	India	11.1	0.33	11.5	5.7
9307	Pakistan	13.9	15.15	61.8	9.6
9309	Pakistan	11.5	20.50	3.4	9.8
9401	Zimbabwe	11.3	1.14	5.7	18.6
9405	Venezuela	35.7	1.38	18.7	48.1
9412	Mexico	53.7	4.69	30.6	6.9
9501	Mexico	11.4	42.21	78.0	7.1
9503	Mexico	18.9	40.38	4.3	14.3
9510	Mexico	11.7	3.11	10.6	43.5
9604	South Africa	14.9	8.14	28.2	6.3
9610	Pakistan	15.7	9.14	45.2	9.8
9707	Philippines	10.8	0.69	19.0	5.7
9707	Thailand	20.7	1.33	14.5	4.4
9708	Indonesia	14.4	1.53	8.3	5.4
9709	Zimbabwe	12.9	10.55	48.1	18.0
9710	Indonesia	11.6	16.63	6.3	7.3
9711	Korea	20.5	2.26	9.9	4.2
9711	Zimbabwe	19.7	12.51	38.4	16.0
9712	Indonesia	23.6	12.16	7.8	8.8
9712	Korea	39.8	20.85	14.8	4.3
9712	Philippines	15.0	5.82	15.8	7.5
9712	Thailand	13.5	11.93	9.6	7.6
9801	Indonesia	96.6	32.55	6.0	10.3
9801	Malaysia	14.9	10.89	7.9	2.9
9801	Thailand	13.2	21.55	6.4	7.6
9805	Indonesia	30.7	25.54	5.7	42.5
9806	Indonesia	33.5	34.73	2.5	49.7
9806	Pakistan	10.3	3.31	15.9	5.6
9806	South Africa	13.5	1.89	11.1	5.1
9808	Mexico	10.6	0.49	7.5	15.4
9808	Russia	29.5	1.01	7.9	5.6
9809	Ecuador	14.0	3.85	28.0	34.2
9809	Russia	81.0	30.36	38.6	9.5
9901	Brazil	55.2	0.82	9.1	1.7
9902	Ecuador	25.0	10.37	24.9	42.3

Note: λ represents the probability of entering the crisis regime of our model. Annual inflation denotes the inflation rate over the 12 months before the crisis.

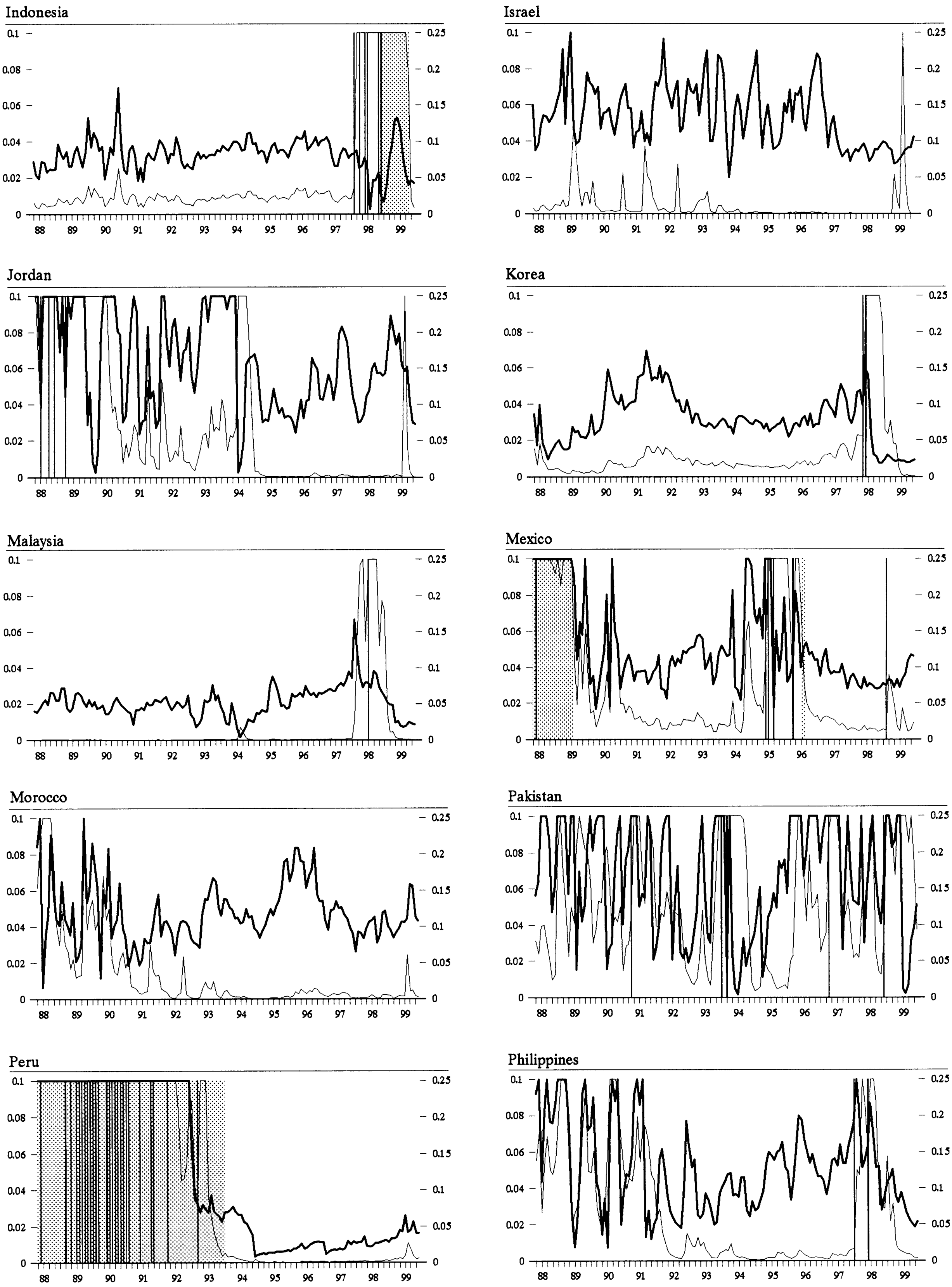
Figure 3 Crisis indicators for various countries



Probability of crisis (left scale) Lambda (right scale)

Note: Bars denote crises; Shaded areas depict periods with inflation higher than 50% annually.

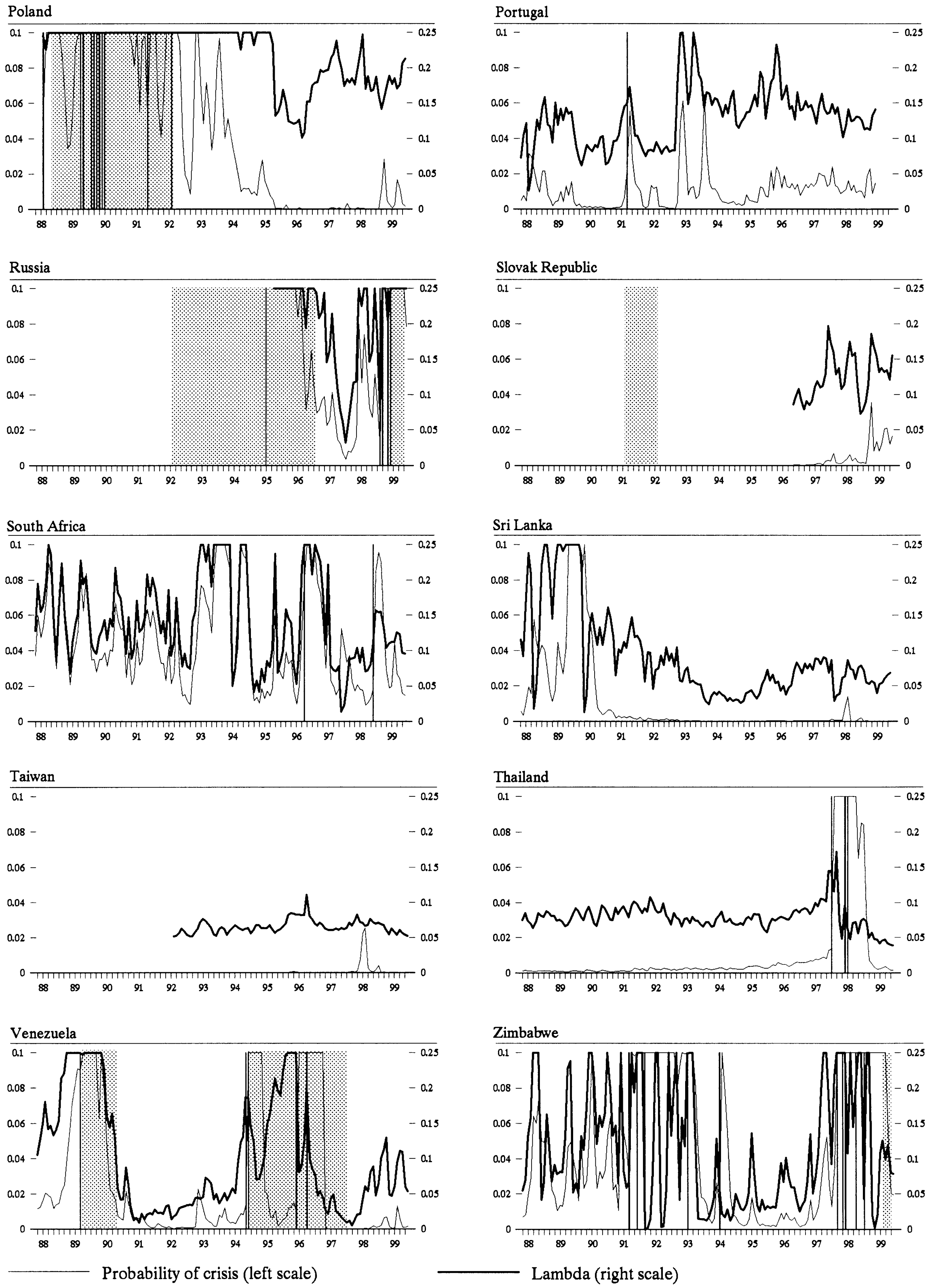
Figure 3 Crisis indicators for various countries (continued)



Probability of crisis (left scale) Lambda (right scale)

Note: Bars denote crises; Shaded areas depict periods with inflation higher than 50% annually.

Figure 3 Crisis indicators for various countries (continued)



Note: Bars denote crises; Shaded areas depict periods with inflation higher than 50% annually.

Apart from the probability of crisis, which incorporates all elements of our model, Table 3 also shows the probability of entering the crisis regime (λ). The main reason for showing both is that the probability of crisis is dominated by current volatility, whereas λ signals vulnerabilities due to economic conditions. Consequently, this crisis indicator might be better suited to signalling first crises. Once a currency is in crisis, λ is likely to fall as the real exchange rate, and possibly the trade balance, improve. Despite this lower λ the probability of crisis will remain high due to the lagged volatility effect. The average value of λ over the estimation sample turned out to be 12.7%. During most crises, λ was much higher. However, even for some of the first crises, for instance the one in Brazil in January 1999, it was lower than the average value. This is probably due to country-specific effects, for instance an overvalued real exchange rate in 1990, the relative importance of trade for the current account, or differences in measurement.

In order to allow country-specific differences to be visualised, and to enable us to say something about the lead time of these indicators, Figure 3 shows both the probability of crisis and λ for the countries included in this study.[8] For most first crisis episodes, λ rose in the years before the crisis. Clear examples of this are Malaysia, Thailand and the Philippines, and to a lesser extent Korea during the Asian crisis, Mexico before the 1994 crisis, Ecuador before 1998 and Venezuela before 1989 and 1994. The level of λ is less informative, as there are clear differences between countries. Once the crisis has erupted, the probability of further crises strongly increases, whereas λ is reduced. In view of these results, the predictive properties shown in Table 2 can probably be improved if (changes in) λ are taken into account as well.

Finally, what does our model say about the next crisis? In the light of the developments in λ, the clearest example of increased vulnerability is probably given for Egypt. Indeed, rumours about a forthcoming devaluation of the Egyptian pound are widespread. Furthermore, several Latin American countries (Ecuador, Colombia, Peru, Venezuela and possibly Argentina) are clearly vulnerable, whereas the Asian countries seem to have stabilised.

6. Conclusion

In this paper, a new method is introduced to predict currency crises. The method models a monthly continuous crisis index, based on depreciations and reserve losses, using observations of both crisis periods and quiet periods. The fact that during currency crises the behaviour of market participants differs from under normal circumstances is studied using an econometric model with two regimes, one for troubled, volatile episodes, and one for normal periods. The model is capable of separating the variables that influence the probability of a currency crisis from those that have an impact on the depth of a crisis. In our model, the probability of crisis is directly related to the probability of entering the volatile regime. Relevant variables turn out to be the real exchange rate, the inflation rate, the growth of the short-term debt/reserves ratio, growth in reserves, the reserves/M2 ratio and the import/export ratio. Variables influencing the depth of a crisis have, in our model, a significant impact on the extra expected depreciation and extra volatility in the crisis regime. Local depreciations and the short-term debt/reserves ratio turn out to be the crucial variables here. The most important factors for explaining the current month's crisis index are, however, recent changes in the exchange rates and reserves themselves.

Several differences are noticeable, when comparing results for 1987–96 with those for 1997–99. The main difference between the two periods is that the short-term debt/reserves ratio has become much more important lately, whereas the import/export ratio seems to have lost its explanatory power. This indicates that recent crises were probably more liquidity-driven than previous ones. No clear evidence is found for increased contagion effects. The influence of local depreciations in previous months

[8] Turkey is not included as the its annual inflation rate was below 50% only before 1988. Missing values for economic variables included in the model were replaced with last known values in order to avoid discontinuous lines. The probability of crisis and λ are bounded from above at 10% and 25% respectively.

seems to have declined somewhat, whereas the contemporaneous correlations of the normalised residuals of our model rose only slightly. This result seems surprising given the worldwide impact of the Asian crisis. However, the domino effects of this crisis, as well as the large impact on the world economy, might also be explained by the fact that these countries are much more open and more developed than most previous targets of currency attacks. Consequently, large initial depreciations immediately affected the economic growth potential for neighbouring countries, as they were competing to a large extent on the same markets, and relied on exports for their growth.

The model is reasonably successful in predicting currency crises, including out of sample. If the threshold above which the model gives a warning signal for an impending crisis is set at 1%, 21 out of 24 crises are predicted out of sample. However, this comes at the cost of also giving a warning signal 35% of the time when no crisis is about to occur. The clearest signals are provided for crises that followed other crises. First crises are better detected by changes in the probability of entering the crisis regime (λ). These provide a good summary of changes in the economic vulnerability of currencies. As the link between vulnerabilities and currency crises is far from perfect, however, one cannot expect to detect all currency crises with the help of just one econometric model.

Appendix: Data sources

General: The countries included in this study are: Argentina, Brazil, Chile, Colombia, the Czech Republic, Ecuador, Egypt, Greece, Hungary, India, Indonesia, Israel, Jordan, Korea, Malaysia, Mexico, Morocco, Pakistan, Peru, the Philippines, Poland, Portugal, Russia, Slovakia, South Africa, Sri Lanka, Taiwan, Thailand, Turkey, Venezuela and Zimbabwe. The database consists of monthly observations for the period January 1970 to June 1999. Observations for countries with an annual inflation rate above 50% in the previous month are excluded from the estimation and evaluation procedures. Most data come from the August 1999 International Financial Statistics CD-ROM of the IMF. Additional data are from Datastream or taken from the internet. For Taiwan, which is not an IMF member, most data come from the Directorate General of Budgeting and Accounting Statistics (DGBAS). All explanatory variables are lagged at least one month, and more if the publication lag of the data is likely to be longer. In order to limit the influence of large reserve changes or nominal exchange rates, explanatory variables involving these two variables are bounded to their mean plus or minus five standard deviations. Local variables are calculated over usable observations of the included countries per continent (Asia, Latin America, Europe, or Africa plus the Middle East), excluding the country concerned. Global variables are calculated over the usable observations of all included countries, again excluding the country concerned. Whenever a weighted average of variable X over i months is used, it is calculated as:

$$X_{Wi} = \sum_{j=0}^{i-1}(i-j)X_{t-j} / \sum_{j=1}^{i} j \, .$$

Exchange rates: line ae of the IFS, end-of-period local currency per US dollar, except for Taiwan (London exchange market). As explanatory variable, the variable is lagged in our model at least one month.

International reserves: line 1..ld of the IFS, international reserves excluding gold in millions of US dollars, except for South Africa, for which total reserves including gold (line 1..sf) are used. For Taiwan, official reserves in US dollars, provided by DGBAS. As explanatory variable, the variable is lagged in our model at least one month.

Currency crisis index: 0.8 * monthly percentage depreciation + 0.2 * monthly percentage reserve losses. In the estimation process, this variable is bounded at 50%, in order to limit the influence of an extreme observation (Venezuela, March 1989).

Consumer price index: line 64 of the IFS. For Taiwan, the urban CPI provided by DGBAS is used. As explanatory variable, the variable is lagged in our model at least one month.

Real exchange rates: CPI-based trade-weighted real exchange rates. Three different sources are used: the measure of JP Morgan for Argentina, Brazil, Chile, Colombia, Ecuador, Greece, India, Indonesia, Korea, Malaysia, Mexico, Morocco, Pakistan, Peru, the Philippines, South Africa, Taiwan, Thailand, Turkey and Venezuela; the IFS measure (line rece) for Hungary, Israel, Poland, Portugal, Russia and Slovakia; and own calculations based on trade weights with Japan, the European Union and the United States for the Czech Republic, Egypt, Jordan, Sri Lanka and Zimbabwe. For our own calculations, period average US dollar exchange rates (line af of IFS) and CPIs of Japan, Germany, the United States and the countries concerned are used. The trade weights are from various issues of the Direction of Trade Statistics. As explanatory variable, the variable is lagged in our model at least one month.

M2: Sum of lines 34 and 35 of the IFS. For Hungary, monthly observations provided by the National Bank of Hungary are used. For Taiwan, monthly figures are from DGBAS. As explanatory variable, the variable is lagged in our model at least two months.

Credit: line 32d of the IFS, domestic credit to private sector. For Taiwan, domestic credit to private sector collected by DGBAS; for Hungary, monthly consumer credit from the National Bank of Hungary. As explanatory variable, the variable is lagged in our model at least two months.

Short-term foreign debt and total foreign debt: BIS database. Semiannual reports of foreign lending of BIS reporting banks by country and remaining maturity. Short-term debt is defined as debt with a

remaining maturity of less than one year. As explanatory variables, these variables are lagged in our model at least five months as there is a five-month publication lag. This means using the end-December positions for the months May to October of the next year, and the end-June positions for the months November to April.

Exports and imports: lines 70..d and 71..d of the IFS, exports and imports in millions of US dollars. As explanatory variables, the variables are lagged in our model at least two months.

Gross domestic product: line 99b of the IFS, GDP in current prices. This quarterly series is transformed into a monthly series, using CPI and industrial production (line 66 of the IFS) as indicators. The quarterly GDP series for Taiwan is from DGBAS. If the IFS database did not provide monthly industrial production series, other sources were used as well. The alternative sources for industrial production are: OECD (Hungary, Poland, Portugal and Russia), Macroeconomica (Argentina), Lopes Filho & Associates (Brazil), National Statistical Service of Greece, Biro Pusat Statistik (Indonesia), Statistics South Africa, DGBAS (Taiwan), Bank of Thailand, State Institute of Statistics (Turkey) and Veneconomia (Venezuela). As explanatory variable, the variable is lagged in our model at least two months.

Exchange rate regime: Annual report on exchange arrangements and exchange restrictions, IMF, various issues.

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