ELSEVIER

Journal of Empirical Finance 10 (2003) 427–454

Journal of EMPIRICAL FINANCE

www.elsevier.com/locate/econbase

Predicting emerging market currency crashes

Mohan Kumar[a], Uma Moorthy[b], William Perraudin[b,c,d,*]

[a] IMF, Washington, DC, USA

[b] Department of Economics, Institute for Financial Research, Birkbeck College, 7-15, Gresse Street, W1P 2LL, London, UK

[c] Bank of England, London, UK

[d] CEPR, London, UK

Abstract

We study the extent to which crashes in emerging market currencies are predictable using simple logit models based on lagged macroeconomic and financial data. To evaluate our model, we calculate trading strategies in which an investor goes long or short in the currency depending on whether crash probabilities are low or high. When we estimate the model on part of the data and then use the parameter estimates to generate predictions for the remainder of the sample, we find that substantial profits may be made. Furthermore, the model correctly forecasts major crashes even on an out-of-sample basis.

JEL classification: F31; G14
Keywords: Currency crisis; Exchange rates; Forecasting

1. Introduction

Currency crashes have once again become the subject of considerable interest following the recent crises in Asia, Russia and Brazil. These crises were for the most part unforeseen and affected countries that had for several years been regarded as subjects for emulation by other developing economies. Few developing countries may now be presumed to be immune to the destabilizing fluctuations that have affected Indonesia, Korea, Thailand and others.

* Corresponding author. Department of Economics, Institute for Financial Research, Birkbeck College, 7-15, Gresse Street, W1P 2LL, London, UK. Tel.: +44-207-631-6404; fax: +44-207-631-6416.
E-mail address: wperraudin@econ.bbk.ac.uk (W. Perraudin).

0927-5398/03/$ - see front matter
doi:10.1016/S0927-5398(02)00068-3

Given this background, devising techniques for assessing currency vulnerability and predicting crashes is an important objective. Statistical measures of crisis risk serve several purposes. Macro policymakers are interested in leading indicators of pressure on exchange rate parities; market participants are increasingly concerned to measure and limit their exposure to large exchange rate fluctuations; and financial regulators are keen to understand the exchange rate exposures of the institutions they supervise.

In looking at crises empirically, it is important to be clear exactly how a currency crisis is defined. Much of the relevant empirical literature looks at crisis indices (termed currency pressure indicators) defined as weighted sums of percentage changes in exchange rates, interest rates and foreign currency reserves. Use of such indices is appropriate if one views crises from the standpoint of a macro policymaker and is equally interested in 'successful' and 'unsuccessful' speculative attacks. From the standpoint of an investor, manager of foreign reserve positions or a macro policymaker who cares primarily about 'successful attacks' on the currency, a simpler definition of crisis based on large depreciations is more appropriate.

In the present paper, we look at two crash definitions, namely, (i) large devaluations adjusted for interest rate differentials, and (ii) large devaluations which exceed the devaluation in the previous period by some multiple. To distinguish our approach from that of studies which employ currency pressure indicators, we shall refer to crises defined using either (i) or (ii) as *currency crashes*.

A second feature of our study which differs from much previous research is that we focus on the degree to which currency crashes can be forecast. Most earlier studies have taken a more descriptive approach, relating the occurrence of crises to contemporaneous rather than lagged variables. Studies which have attempted to forecast crises have mostly assessed their results on an 'in-sample' basis. In contrast, in our study, we evaluate forecasts on an explicitly out-of-sample basis, for example, estimating our model on two thirds of the sample and then forecasting crashes in the remaining "hold-out" sample period.

Our approach to forecasting consists of applying logit models to pooled data on 32 developing countries from January 1985 to October 1999. Lagged financial and macroeconomic variables, both global and country-specific, are employed as explanatory variables. Crashes are defined as exchange rate devaluations which exceed specific cutoff levels (5% and 10%). The data used are a mixture of monthly and annual statistics drawn from a wide range of different sources.

We evaluate the performance of our models in several ways. The parameter estimates we obtain are intuitive and statistically significant. The crash probabilities implied by our estimates appear to signal important recent crises including the 1994/1995 Mexican crisis and the 1997 collapse of Asian currencies. This remains the case when we repeat the calculations on an out-of-sample basis. Goodness-of-fit measures including those based on type I and type II crash forecast errors are reasonable when calculated either on an 'in-sample' or an 'out-of-sample' basis.

Perhaps the most interesting check of our model's forecasting performance consists of calculations of profits on trading strategies. The trading strategies consist of going short (long) when the probability of a currency crash is high (low). We implement the trading strategies on an out-of-sample basis by (i) estimating the model parameters using two thirds of the sample, and (ii) calculating crash probabilities for the remaining third of the sample, and (iii) calculating trading strategy returns using the probabilities. The results suggest that fairly substantial profits could have been made using our model.

2. Modelling exchange rate crashes

2.1. Past empirical studies

A substantial literature has now accumulated on the empirical modelling of exchange rate crises.[1] Kaminsky et al. (1998) provide a comprehensive survey. This literature comprises three types of analysis.[2] First, there are case studies of specific devaluation episodes, often employing explicit structural models of balance of payments crises. Notable examples include Blanco and Garber (1986), Cumby and van Wijnbergen (1989), Jeanne and Masson (2000), Cole and Kehoe (1996) and Sachs et al. (1996). These studies are informative about the episodes in question and revealing with regard to structural models proposed by theorists.

Second, various studies have analyzed currency crises using signalling models. Examples include Kaminsky et al. (1998), Kaminsky and Reinhart (1999) and Goldstein et al. (2000). In such models, individual variables such as the real effective exchange rate or debt to GDP levels are deemed to "signal" that a country is potentially in a crisis state when they exceed some threshold. The threshold is then adjusted to balance type I errors (that the model fails to predict crises which actually take place) and type II errors (that the model predicts crises which do not occur).

Signalling models are often described as being nonparametric approach. In fact, they are parametric with the parameters being the threshold levels for the variables. While intuitively appealing, signalling models are essentially univariate in character. Kaminsky (1999) suggests a way of combining individual signals to form a composite index for forecasting purposes[3] but this does not solve all problems. To illustrate, suppose that several of the signalling variables are very closely correlated. They may each have a very high noise-to-signals ratio even though all but one of them add almost nothing to the collective forecasting power. The problem here is that the noise-to-signal weights are themselves based on univariate analysis.

A third type of empirical study (and the one which most closely resembles our own) looks at pooled panel data, employing discrete choice techniques in which macroeconomic and financial data are used to explain discrete crisis events in a range of countries. For example, Eichengreen et al. (1996) employ probit models for industrial countries using quarterly data between 1959 and 1993. They define crises to be increases greater than 25% in an index consisting of a weighted average of percentage (i) devaluations in bilateral

[1] For references on recent theoretical studies, see Flood and Marion (1999).

[2] One might mention a fourth type of study, namely, papers which examine specific features of crisis, such as the role of currency pegs or realignments. See, for example, Flood and Marion (1997), Klein and Marion (1997) and Otker and Pazarbasioglu (1994).

[3] Her approach consists of forming a weighted sum of signal variables in which the weights equal the inverses of the noise-to-signal ratios of the variables.

exchange rates against the US dollar, (ii) falls in reserves, and (iii) increases in interest rates. In contrast, Frankel and Rose (1996) employ probit models on annual developing country data over the period 1971 to 1992, and define crises as devaluations in bilateral exchange rates against the US dollar which are (a) greater than 25% and which (b) exceed the devaluation in the previous year by 10%.

One paper which somewhat resembles ours is Berg and Patillo (1999). Their paper examines how well two different crisis prediction models (a signalling model like that of Kaminsky et al., 1998 and a probit model) would have forecast the 1997 Asian crisis. Their results are consistent with ours in that they find explanatory power for models using monthly data (especially in the case of the probit model). However, the crisis definition they use is based on a measure of currency pressure. They do not focus, as we do, on trading strategies and their out-of-sample evaluations are based on quite small hold-out samples (just the 1997 Asian crisis).

2.2. Logit-based crisis forecasting

Much of the literature described above seeks to explain the origins of currency crises by relating their occurrence to contemporaneous explanatory variables (see, for example, Eichengreen et al., 1996). In cases where authors do explicitly forecast crises (for example, Kaminsky et al., 1998; Frankel and Rose, 1996; Goldstein et al., 2000; Kaminsky, 1999; Berg and Patillo, 1999), they do not compare forecasting performance with naive alternative measures of crisis risk such as interest rate differentials on an out-of-sample basis. In the current research, we focus particularly on the forecastability of currency crashes allowing for interest rate differentials.

Furthermore, we depart from most of the crisis literature (see, for example, Eichengreen et al., 1996; Sachs et al., 1996; Goldstein et al., 2000) in that we investigate crashes defined as large market moves adjusted for interest rate differentials rather than looking at composite indices of exchange rate pressure.[4] Thus, if e_t is the exchange rate vis-à-vis the US dollar and r_t and r_t^* are domestic and foreign (US) interest rates of maturity Δ, we suppose that a crisis takes place if

$$100\left[\frac{e_{t+\Delta}-e_t}{e_t}\right]\left[\frac{1+r_t^*}{1+r_t}\right] > \gamma_1 \tag{1}$$

where γ_1 is a cutoff point which we set to 5% or 10% in our estimations. We refer to this definition as an *unanticipated depreciation crash*. Note that the product on the left-hand side of this inequality is the return that an investor receives if he shorts the domestic currency for the period Δ, investing the proceeds in US bonds of maturity Δ.

By employing the above crisis definition, we are able to assess the degree to which the variables in our model outperform the forecast implicit in market spreads. If one is designing a crisis forecasting model, it is important to look at predictive power over and above the forecast implicit in spreads since a model might appear to perform well while in fact it is simply picking up public information implicit in relative interest rates.

[4] For example, Goldstein et al. (2000) define a crisis as a weighted average of changes in the exchange rate and in foreign exchange reserves.

We also estimate models using a second definition, according to which a crash occurs if

$$100\left[\frac{e_{t+\Delta}-e_t}{e_t}\right] > \gamma_2 \tag{2}$$

$$\left[\frac{e_{t+\Delta}-e_t}{e_t}\right] > (1+\gamma_3)\left[\frac{e_t-e_{t-\Delta}}{e_{t-\Delta}}\right] \tag{3}$$

We call depreciations which satisfy this second definition *total depreciation crashes*. Note that, in our estimates, we take γ_3 to equal 100% (i.e., a doubling of the rate of depreciation) and again employ a crash cutoff parameter, γ_2, of 5% or 10%.

Our second definition of crash, with the acceleration requirement given in Eq. (3), is very close to the crisis definition adopted by Frankel and Rose (1996). They justify the inclusion of an acceleration requirement as a means of eliminating depreciations which represent smooth although rapid declines in the currency. Our rationale is somewhat different. If markets base their expectations of exchange rate movements on the last period's change, then one could regard the requirement of an acceleration in the rate of depreciation as a proxy for a relative interest rate adjustment. The results we obtain using the total devaluation crash definition may therefore be seen as providing a check on those we obtain with explicit interest rate adjustments.[5]

Since our definition of crash implies a dichotomous event (the crash occurs or not), it is natural, if one wishes to forecast crashes, to apply limited dependent-variable methods such as probit or logit. Most prior empirical studies which have employed discrete choice models (see, for example, Eichengreen et al., 1996; Frankel and Rose, 1996; Berg and Patillo, 1999) have used probit models. We use a logit framework. The only difference is that the underlying latent variable which is assumed to generate the discrete event in both logit or probit models has a slightly different distribution, being more fat-tailed in the logit case.[6]

Lastly, one might note that some recent research (see, for example, Kaminsky and Reinhart, 1999) has argued that banking and exchange rate crises may interact. Clearly, the presence of banking sector fragility may affect a monetary authority's room for maneuver in resisting a speculative attack on its currency. We shall not attempt in this study to condition on banking crises in forecasting currency crashes in part because this would reduce the number of countries that we could include in the sample. Kaminsky and Reinhart (1999) argue that banking crises "are not necessarily the immediate causes of

[5] At the start of our sample period, some interest rates may not be entirely market-determined so such a check is advisable.

[6] If $y=1$ when a crash occurs and $y=0$ otherwise, then with the logistic specification, the probabilities that a crash occurs is

$$P(y=1)=\frac{\exp[\beta'X]}{1+\exp[\beta'X]}, \quad P(y=0)=\frac{1}{1+\exp[\beta'X]} \tag{4}$$

where X is a vector of explanatory variables and β is a vector of parameters. In the probit model, $\frac{\exp[\beta'X]}{1+\exp[\beta'X]}$ is replaced with $\Phi(\beta'X)$ where $\Phi(.)$ is the standard normal cumulative distribution function.

currency crises, even in the cases where a frail banking sector outs the nail in the coffin of what was already a defunct fixed exchange rate system. Our results point to common causes, and whether the currency or the banking problems surface first is a matter of circumstance.'' If both types of crisis reflect common causes and these causes are captured in the forecasting variables we include in our models, modelling currency crises alone will not induce biases or reduce forecasting power.

2.3. Data

The data set that we employ runs from January 1985 to October 1999. Finding consistent data further back is difficult since monthly data for many series in the early 1980s are hard to obtain. Even finding data prior to 1990 is a challenge in the case of interest rate data and we made extensive efforts to construct a clean and consistent data set. The sources used were numerous and included international agencies such as the IMF and World Bank, commercial data providers such as DRI, Reuters, Bloomberg and the Economist Intelligence Unit, and, for some countries, direct use of national data publications.

Traditional econometric modelling might suggest that one estimate models with numerous explanatory variables and successively eliminate variables with relatively low t-statistics. However, since we were interested in out-of-sample forecasting and concerned about overfitting the data, we preferred to select explanatory variables based on a priori judgments drawing on economic theory. Those employed in the models that we report below are described in the Data Appendix.[7]

Theoretical studies of balance of payments crises suggest that a crucial variable is the level of foreign exchange reserves. We include reserves both as a 12-month percentage change and as a ratio to imports. Other macroeconomic variables may affect the probability of crisis if they enter a government's objective function and, hence, are likely to influence the probability of exchange rate crises.[8] We, therefore, include such key macro variables as real GDP, the real effective exchange rate, exports, and the ratio of the budget balance to GDP. We also include a dummy variable for high inflation regimes (unity if the percentage change in the level of the CPI over the last 2 months exceeds an annualized rate of 100%, and zero otherwise).

Financial flows and the openness of capital markets are likely to influence how prone countries are to foreign exchange crises. We therefore include foreign direct investment, portfolio investment and a dummy for capital account liberalization (unity if liberalized, zero if not). The nature of a country's debt may also influence the likelihood of a crisis[9] so we include the ratio of official foreign debt to private foreign debt.[10]

[7] We did try the alternative approach of successively eliminating variables with insignificant t-statistics and found, as one might suspect, that the set of variables this yielded was sensitive to the sample period and that the models did not perform well out-of-sample.

[8] See Ozkan and Sutherland (1995).

[9] See Cole and Kehoe (1996).

[10] Other debt ratios such as the ratio of short-term foreign debt to total foreign debt have too many missing observations for us to include them.

Several recent papers (see Eichengreen et al., 1996; Glick and Rose, 1999) have focused on contagion effects within regions or between countries subject to similar shocks (e.g., because they export similar commodities). We therefore incorporate (i) a zero–one dummy which is unity if a country in the same region has experienced a currency crash in the last 3 months and (ii) a zero–one dummy which is unity if a country of which the export growth is closely correlated with that of the country in question,[11] has experienced a crash in the last 3 months.[12]

Lastly, we include (i) a proxy for the external financial environment in the form of a global liquidity indicator (see Appendix C for a definition), (ii) nonfuel commodity prices, (iii) a linear time trend to allow for long-term trends not picked up by other explanatory variables and (iv) lagged monthly changes in the exchange rate. This last variable may pick up momentum or overreaction effects in exchange rate changes. Kaminsky and Schmukler (1999) provide evidence of market overreactions to bad news in currency crises.

Before the data could be used in estimation, two further problems had to be addressed. First, the basic data included series of different frequencies, namely, monthly and annual. To produce data of a consistent frequency, we interpolated the annual data using cubic spline routines so as to construct monthly series.[13] In performing the interpolations, where appropriate, we allowed for the fact that series were flow rather than stock data by cumulating the series, interpolating and then differencing the resulting monthly series.

The use of interpolated data raises questions about timing especially if one uses the model for forecasting purposes. A monthly observation from an interpolated annual series is based in part on the realization for the year in which the month occurs. The argument for performing interpolations in this way is that at any given moment, we possess interim estimates of the annual data over the coming year to 18 months. Some of the forecasts come initially from the EIU but are refined and updated using the most timely available data by CSFB (1998) analysts. If one wishes to implement a practical crash risk model, it seems advisable to employ these forecasts in the way that we do.

The argument against our approach to interpolation is that it does not require in a strict manner that all data be lagged as is the case for the monthly series we employ. To check whether this affected our results, we repeated our estimations and calculations lagging the interpolated annual data by an extra 12 months. The parameter estimates and trading strategy results from these estimations we obtained (and which are available on request from the authors) suggested that our basic conclusions are robust. The parameter values and *t*-statistics are only slightly changed and the profits on trading strategies are similar.

The second problem we encountered in preparing the data was the presence in some series of missing observations. For example, many series were not available for Eastern

[11] The criterion is that the correlation of export growth in the two countries in the last 48 months exceeds 75%.

[12] It is important to note that the contagion effects evident in the recent Asian crisis were present in previous bursts of currency crashes (see, for example, the Tequila effects following the 1994 Mexican crisis or see the histograms provided in Figs. 1 and 2). Hence, the contagion effects we include do not represent post-Asian-crisis data-snooping.

[13] In some econometric applications, interpolating missing variables in this way would distort results. For example, volatility estimates will be systematically lower using interpolated data. In our case, interpolation appears a reasonable approach.

Europe prior to the early 1990s. To cope with this, where gaps occurred partway through a series, we interpolated observations, again using cubic splines. When gaps occurred either at the beginning or at the end of a series, we dropped those observations from our sample.

To reduce the impact on our results of extreme observations, we transformed all continuous (non-dummy) variables using the function: $f(x) \equiv \text{sign}\{x\}\log\,(1+|x|)$ where log(.) is the natural logarithm. $f(x)$ is a convenient transformation to use since it is continuous and monotonically increasing but dampens large positive or negative observations.

Finally, to facilitate the numerical performance of our hill-climbing Maximum Likelihood routines, we standardized all the continuous explanatory variables by subtracting the sample mean and dividing by the standard deviation. One might in principle criticize this step since it means that we are not solely using lagged data in explaining crashes. The effect is unlikely to be great, however, and when we performed out-of-sample exercises, we were always careful in performing the standardizations to use means and standard deviations calculated only from the data used in the estimation.

3. Results

3.1. Crash definitions

Fig. 1 shows the frequency of crashes defined as depreciations exceeding 5%, 10% and 15% for our sample of 32 countries. The period covered is January 1985 to October 1999. The figure provides frequencies for total (i.e., adjusted for acceleration effects) and unanticipated depreciations (i.e., adjusted for interest rate differentials between the relevant domestic currency and the US dollar) which exceed the three cutoff levels.

For all cutoff levels, the number of total depreciation events on average exceeds the number of unanticipated depreciations in the period before 1996. This is most obviously true for the 15% cutoff level. After 1996, unanticipated depreciations predominate. These observations are consistent with our a priori expectation that the total depreciation events include a certain number of fully predictable depreciations associated with rapid domestic inflation. There were probably more of these in the late 1980s and early 1990s than subsequently, as more countries have adopted anti-inflation programmes in recent years.

When one disaggregates across regions, as we do in Fig. 2a and b, it is plain that the typical pattern involves bursts of crash activity in different regions of the world. Latin America has seen two periods of significant crash activity, in the 1986 to 1988 period and again in 1994 to 1996. The Middle East experienced a small number of crashes around 1990 while Asia has had a period of very serious crash activity in 1997 and 1998. Such bursts of crashes suggest the presence of regional contagion effects. Finally, Africa and Eastern Europe have tended to experience crashes periodically and the histograms in Fig. 2 suggest there is less contagion in these regions.

It is also interesting to note in the regionally disaggregated crash data that Latin America displays a relatively high number of total depreciation crashes with a peak occurring in the early 1990s, whereas the 1997/1998 Asian crash has consisted of a larger number of unanticipated depreciations.

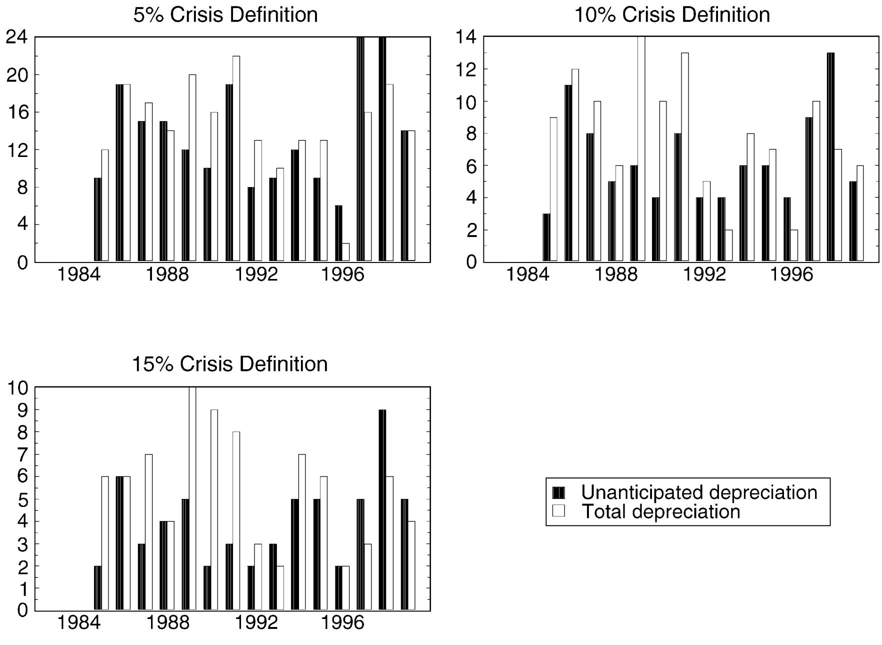


Fig. 1. Total number of crises in each year.

3.2. Logit parameter estimates

To forecast crashes based on total or unanticipated depreciations, we estimated logit models using the lagged explanatory variables described above. We based our definition of crash on 5% and 10% crash cutoff points. Using a 15% cutoff, one obtains so few crashes that reliable inference was difficult. The relatively small number of crashes in the sample for each individual country also precluded use of fixed effect models in which the constants vary across countries. Our approach was therefore to pool data for different time periods and countries.

Table 1 shows Maximum Likelihood estimates of logit models for different cutoff points based on the entire data set. This ran from January 1985 to October 1999. All the models yielded highly significant likelihood ratio statistics suggesting that the right-hand side variables contain substantial explanatory power. The signs of the effects are generally consistent with a priori expectations.

The right-hand side variables, which proved most significant across both dependent variables, are 12-month percentage changes in foreign exchange reserves, real GDP expressed as a deviation from trend and the regional contagion dummy. In addition to the these three variables, reserves as a fraction of imports, portfolio investment, official debt as a proportion of total debt and the lagged exchange rate are significant in at least one of the regressions.

The change in the exchange rate, lagged by 1 month, is significant in the total depreciation regressions and tends to have a positive effect on the crash probability. This is intuitively

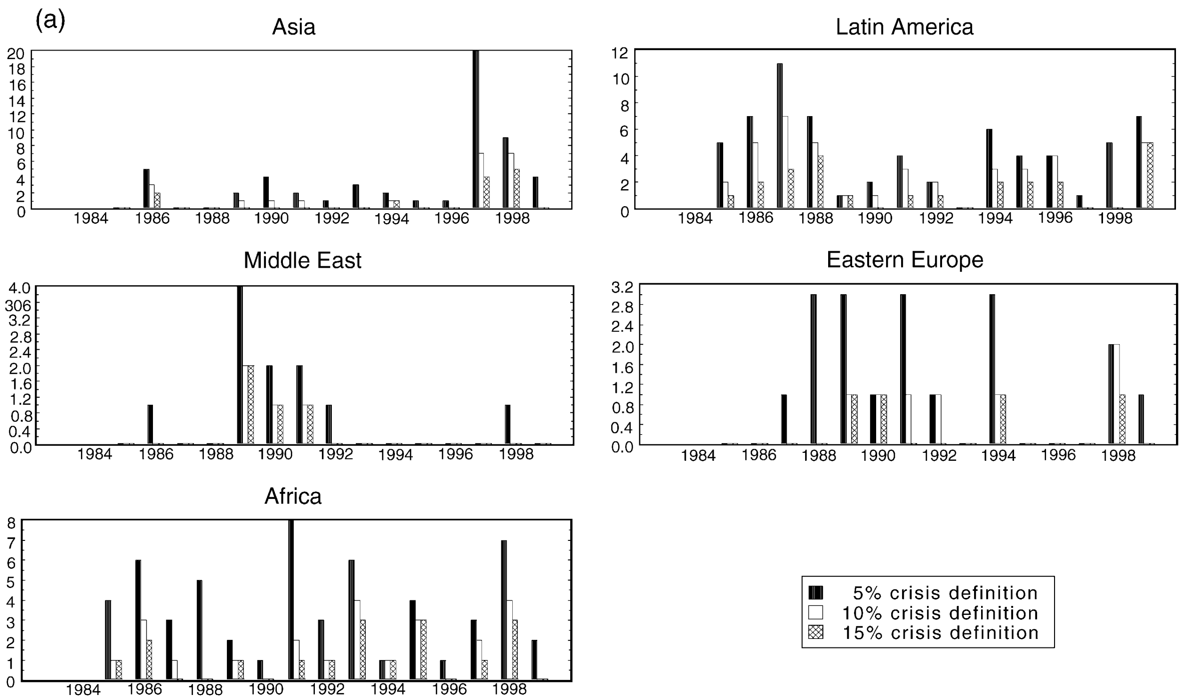


Fig. 2. (a) Unanticipated depreciation: Annual number of crises by region. (b) Total depreciation: Annual number of crises by region.

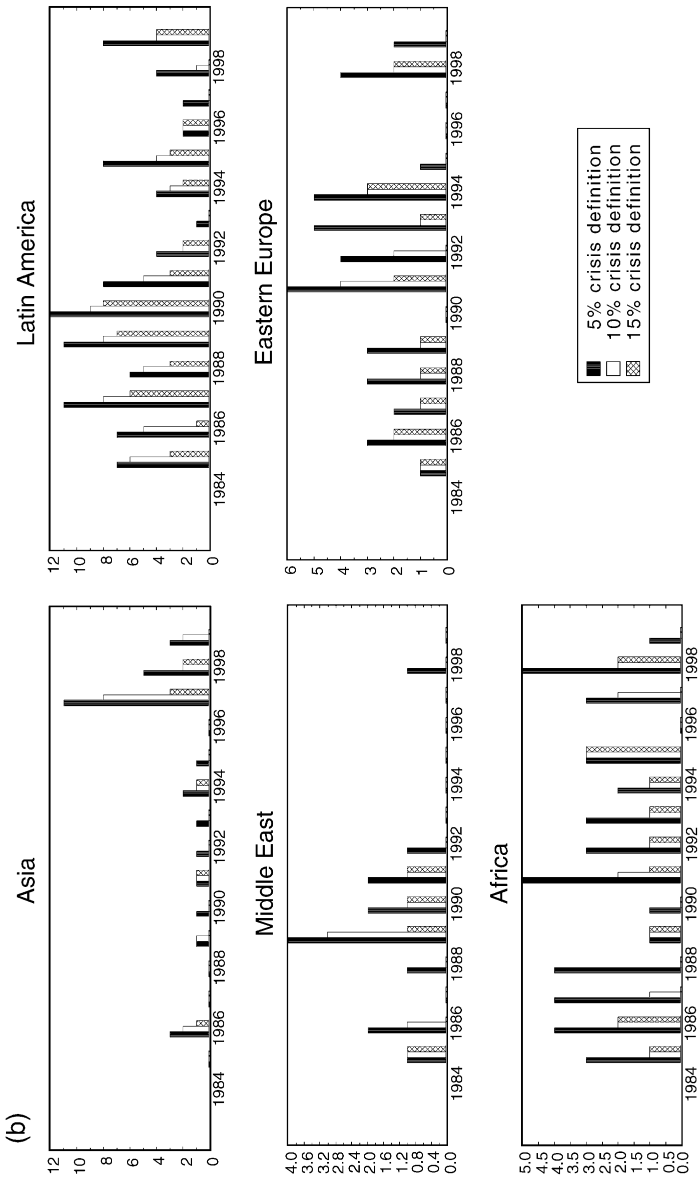


Fig. 2 (*continued*).

Table 1
Estimation on all data: January 1985 to October 1999

	Unanticipated depreciation		Total depreciation	
	5%	10%	5%	10%
Constant	− 4.03 (26.85)	− 5.05 (23.20)	− 3.73 (27.04)	− 4.73 (23.90)
Real GDP[a]	− 0.19 (2.29)	− 0.21 (1.75)	− 0.28 (3.25)	− 0.25 (1.97)
Real effective exchange rate[b]	− 0.12 (1.24)	− 0.15 (1.03)	0.04 (0.45)	− 0.06 (0.42)
Exports[c]	− 0.14 (1.42)	0.10 (0.74)	− 0.07 (0.76)	0.05 (0.38)
Foreign direct investment[a]	− 0.04 (0.48)	0.02 (0.13)	− 0.07 (0.73)	− 0.14 (1.04)
Portfolio investment[a]	− 0.16 (1.82)	− 0.19 (1.55)	− 0.20 (2.30)	− 0.28 (2.13)
Foreign exchange reserves[c]	− 0.49 (4.26)	− 0.86 (4.36)	− 0.24 (2.37)	− 0.55 (2.98)
Foreign exchange reserves/imports	− 0.25 (2.39)	− 0.23 (1.45)	− 0.16 (1.51)	− 0.30 (1.83)
Official debt/total debt	− 0.25 (2.55)	− 0.30 (2.13)	− 0.20 (2.00)	− 0.22 (1.44)
Budget deficit/GDP	0.01 (0.13)	0.04 (0.36)	− 0.04 (0.53)	0.03 (0.26)
Global liquidity indicator	− 0.07 (0.70)	0.14 (1.07)	− 0.11 (1.00)	0.02 (0.10)
Nonfuel commodity prices[c]	− 0.00 (0.04)	− 0.04 (0.27)	− 0.03 (0.26)	0.05 (0.30)
Capital account liberalization	− 0.02 (0.32)	− 0.02 (0.27)	− 0.06 (0.77)	− 0.01 (0.09)
Linear trend	− 0.05 (0.45)	− 0.11 (0.68)	− 0.15 (1.41)	− 0.06 (0.35)
High inflation regime	0.22 (2.15)	0.13 (0.95)	0.13 (1.20)	0.19 (1.26)
Lagged change in exchange rate	− 0.02 (0.31)	− 0.01 (0.07)	0.20 (3.16)	0.15 (1.67)
Contagion (export growth correlation)	0.23 (0.93)	0.15 (0.38)	− 0.12 (0.39)	− 0.40 (0.74)
Contagion (regional effect)	0.96 (5.23)	1.32 (5.12)	0.47 (2.55)	0.59 (2.11)
Log-likelihood	− 605.92	− 321.94	− 594.29	− 302.80
Number of crises	160	77	146	65
Number of observations	4140	4140	4140	4140
Likelihood ratio	142.95	122.31	74.90	63.40

t-statistics appear in parentheses.
[a] Deviation from trend of 12-month percentage change.
[b] Deviation from trend.
[c] Twelve-month percentage change.

reasonable as rapid trend depreciations will generate autocorrelation in crashes in successive months. Variables that one might expect to be highly significant but which proved not to be so, include the degree of capital market liberalization, foreign direct investment and the external environment variables such as global liquidity and nonfuel commodity prices.

It is perhaps striking that the parameter estimates for the unanticipated and total depreciation models are so similar. If our sample included a larger number of countries which had experienced hyperinflations, we would expect to find greater discrepancies [to the extent that the "acceleration" condition in our definition of total depreciation crashes (see Eq. (3)) did not eliminate apparent crashes associated with hyperinflations].

To evaluate the stability of the model and to generate estimates that we can use in out-of-sample evaluation, we re-estimate the models omitting (i) the last third of the data (from January 1994 to October 1999), (ii) the middle third (i.e., the period from January 1990 to December 1994) and finally (iii) the first third (i.e., the period from January 1985 to December 1989). We do not report the parameter estimates from these estimations because of space constraints but they are available upon request from the authors.

The results of the regressions on the shorter data sets resemble those from the estimations based on the whole sample period, although, as expected, significance levels are somewhat lower. The signs of statistically significant parameters do not generally change when the sample period is changed. Foreign exchange reserves, the ratio of official to private debt and the regional contagion dummy remain very significant. Real GDP is less significant when the models are estimated on the subsamples. When the middle third of the data is left out, nonfuel commodity prices and the high inflation dummy appear significant.

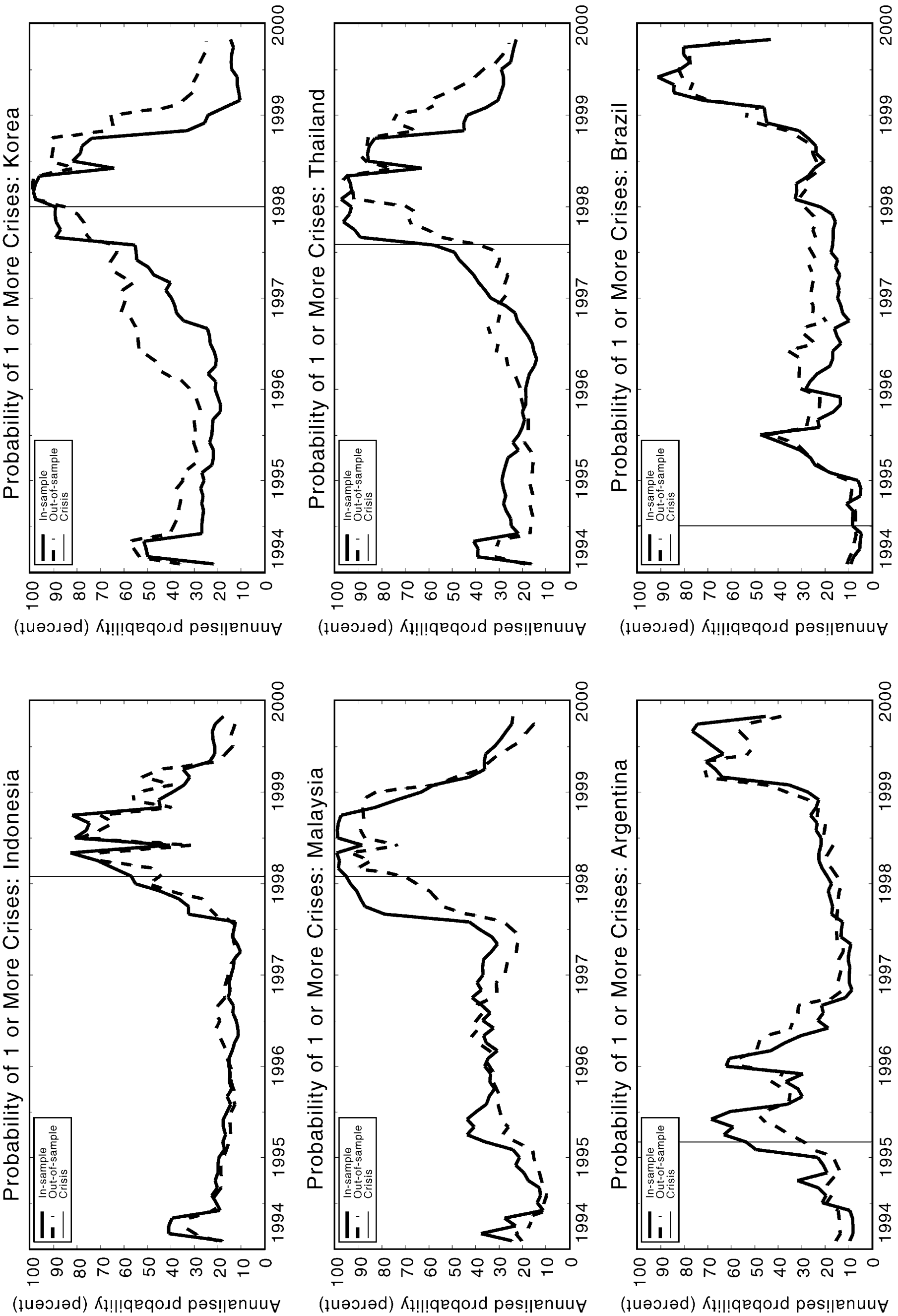
As an experiment, when we had completed our analysis, we ran logit models over our usual total sample period of January 1985 to 1999 including as extra variables the capital flows data published by the US Treasury Department. In principle, one might expect that these data would add significant explanatory power. Since the data are available for only a restricted set of countries, in performing this exercise, we were obliged to omit 6 of our usual 32 countries. The results were generally negative in that including capital inflows and outflows scaled by GDP in models for several different crash threshold, we found mainly counterintuitive coefficient signs and one statistically significant parameter.

To compare the sensitivity of the results to the assumption of a logit versus a probit model, we estimated the Total Depreciation models of Table 1 using a probit specification. The estimated parameters from a logit require scaling before they are comparable to those obtained from a probit estimation. Maddala (1983) suggests multiplying the logit parameters by $\sqrt{3}/\pi$ while Amemiya (1981) suggests that one multiply by 0.625. We found that the latter scaling factor produced closer results. In general, the scaled estimated parameters were broadly similar, especially when the parameters in question had large *t*-statistics. The fact that the parameters were not closer still probably reflects the fact that the crisis events we are modelling are in the tail of the distribution (i.e., there are many more noncrisis periods than crisis periods) so the fat-tailed nature of the logistic distribution will affect the results.

3.3. Probability plots

A convenient although informal way to examine the predictive power of the models is by examining plots of the crash probabilities implied by the estimates. Figs. 3 and 4 contain a selection of such plots for 12 countries chosen from the five regions and using the unanticipated depreciation definition of a crash. The plots show estimates of 1-month-ahead crash probabilities based on the data from January 1985 to November 1997. In each figure, probabilities are plotted for the post-January 1994 period; the solid line shows the crash probability based on a model estimated using the entire data set, while the dotted line represents out-of-sample probabilities based on estimates which omit the last third of the sample (i.e., using data from January 1985 to December 1993). All the probabilities shown use the 5% dependent variable definition, and are scaled up so as to increase the amount of detail visible in the plots.[14]

[14] We annualize the monthly probability, y, by calculating the expression $1-(1-y)^{12}$. If crashes in successive months were independent, binomial events (which although incorrect represents a reasonable approximation), then, $1-(1-y)^{12}$ would equal the probability of at least one crash occurring in a 12-month period. Annualizing in this way permits one to distinguish changes in the probability plots better and also enables one to compare probabilities with interest rate differentials which are typically quoted on an annualized basis.


Probability of 1 or More Crises: Korea
Probability of 1 or More Crises: Thailand
Probability of 1 or More Crises: Brazil
Probability of 1 or More Crises: Indonesia
Probability of 1 or More Crises: Malaysia
Probability of 1 or More Crises: Argentina
In-sample
Out-of-sample
Crisis
Annualised probability (percent)
1994
1995
1996
1997
1998
1999
2000

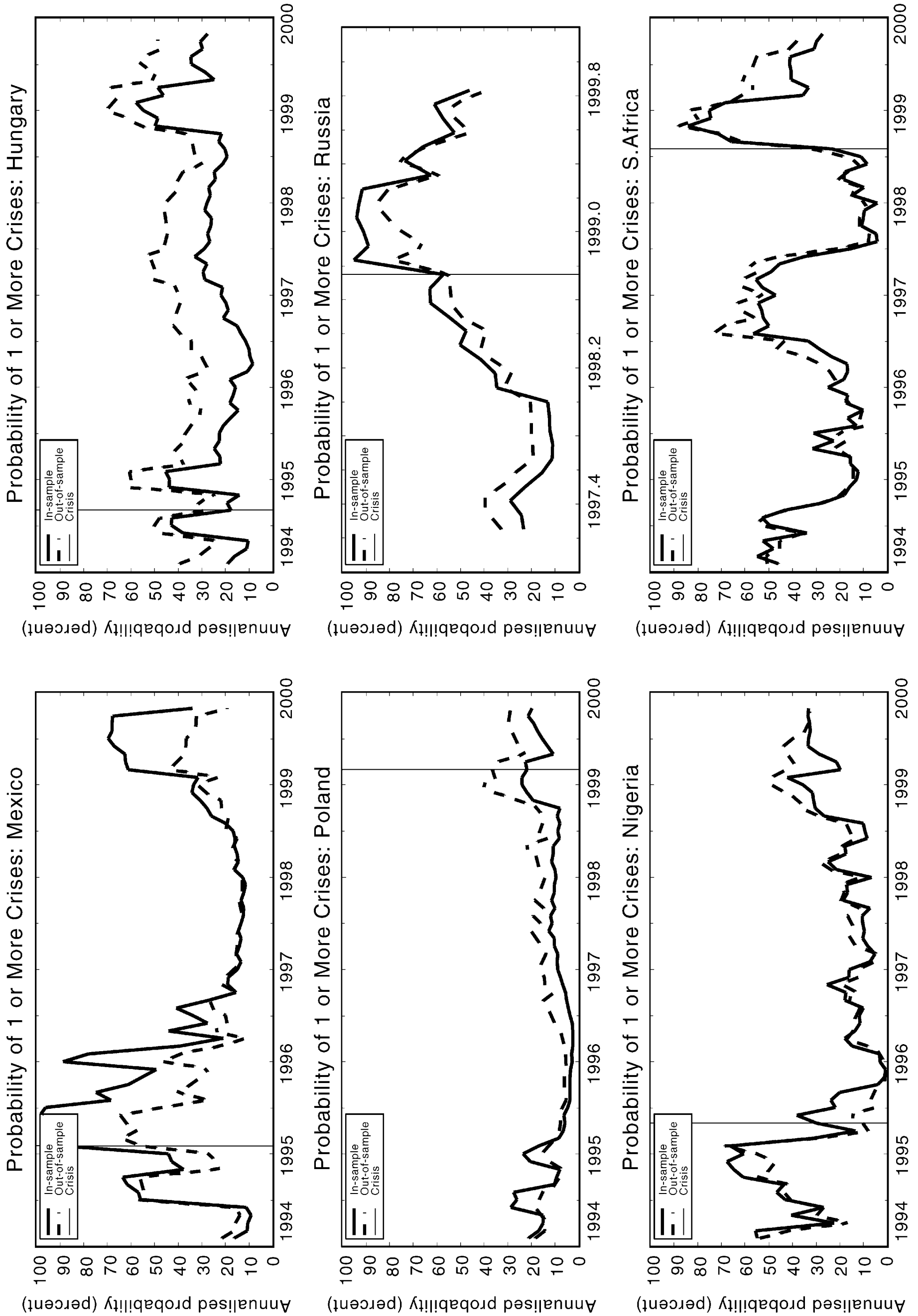


Fig. 3. Crisis probabilities—Unanticipated depreciation.

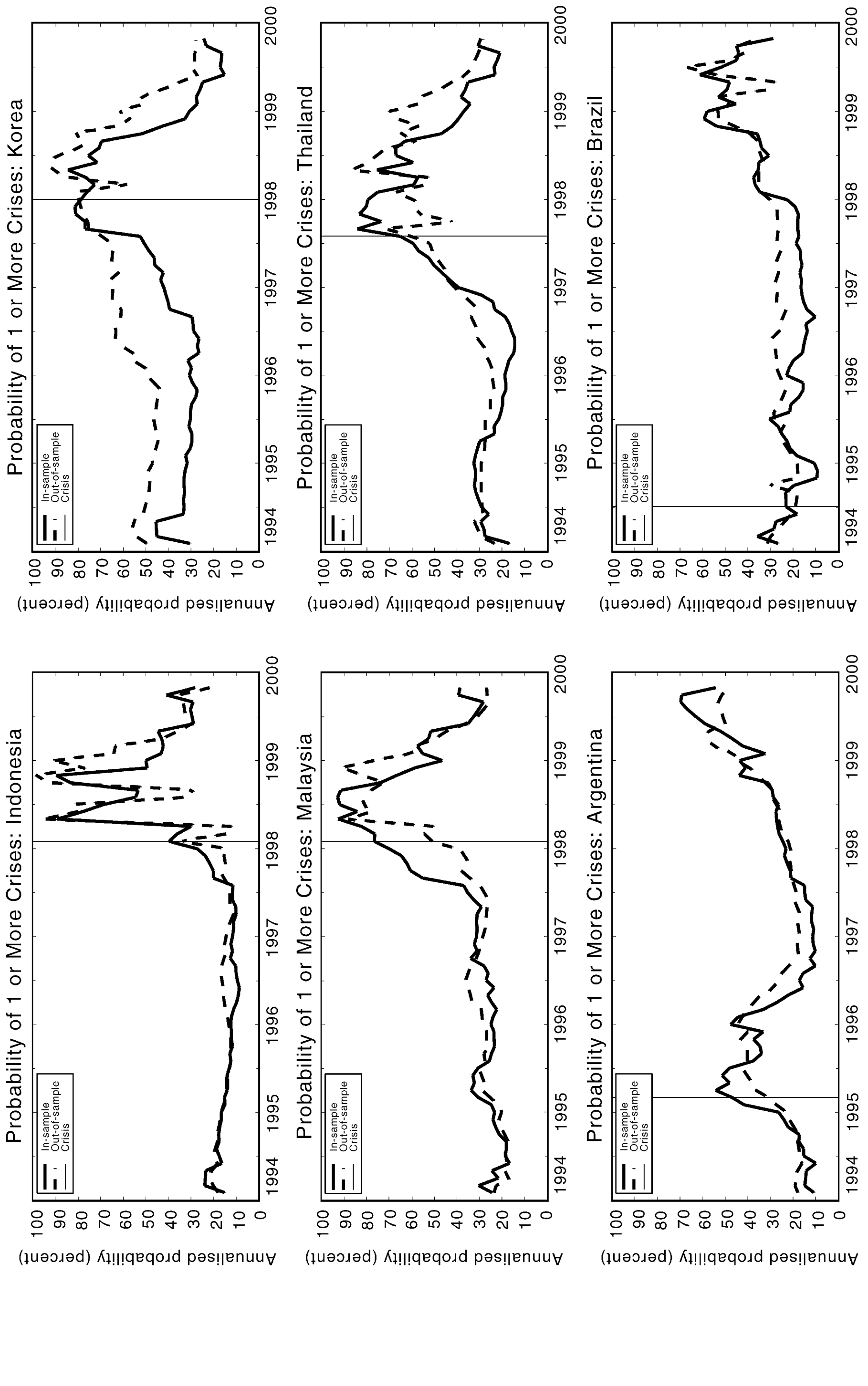


Fig. 4. Crisis probabilities—Total depreciation.

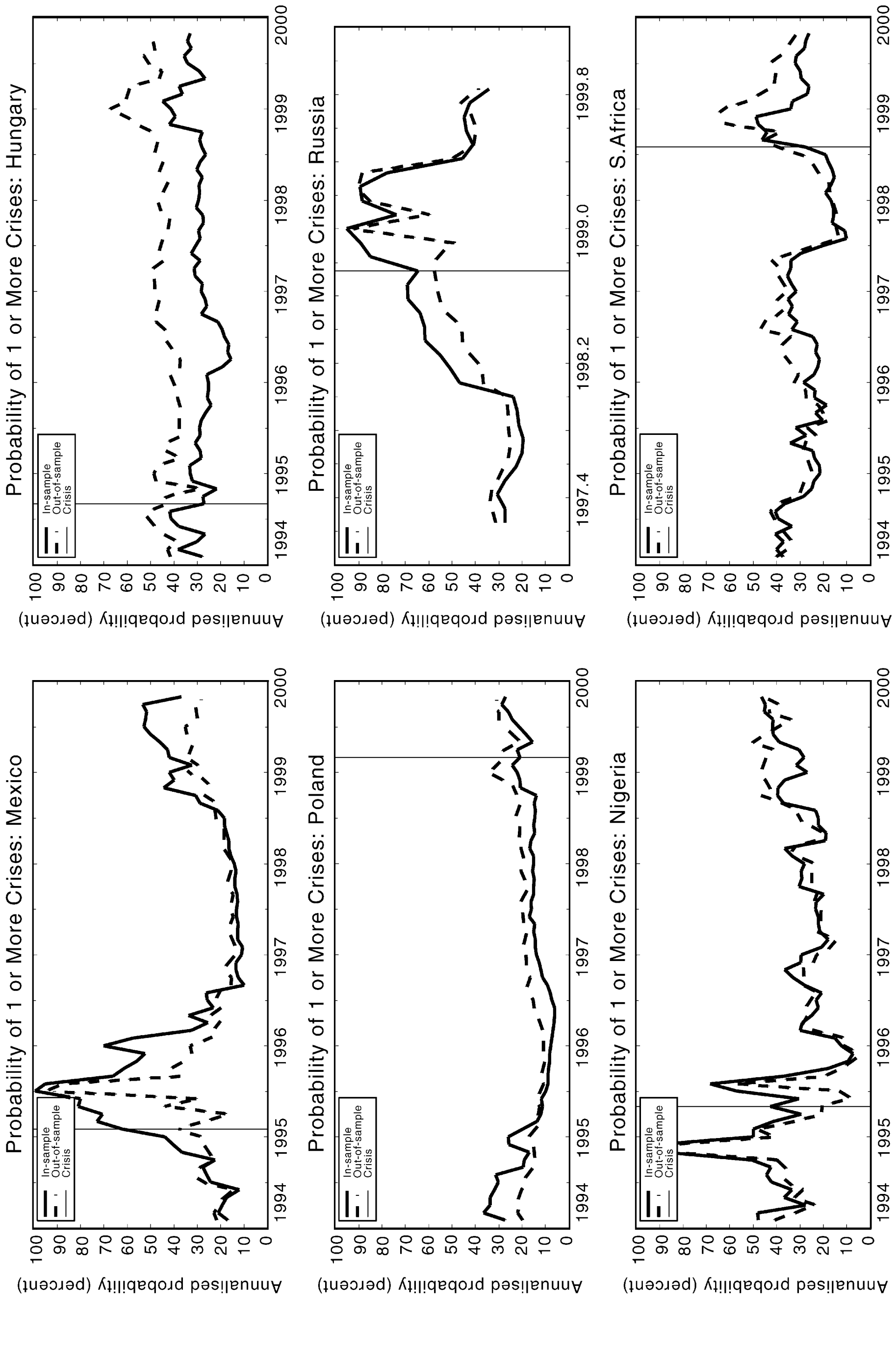


Fig. 4 (*continued*).

We also indicate in the plots (by a solid, vertical line) the date of the largest crash in the post-January 1994 period. One should note that the crash probabilities for each month are calculated using data lagged 2 months. Thus, "up-ticks" in probabilities prior to or coincident with a large crash suggest the model has predictive power.

The probabilities calculated from estimates of the model using both total and unanticipated depreciation crash definitions show increases for the Far East Asian countries in 1997 (see Figs. 3 and 4). They also pick up in a satisfactory way Latin American crashes including Argentina in the early 1990s, Mexico in the mid-1990s, and recent episodes involving Russia and Brazil. Total depreciation probabilities are more stable between the full and the shorter data set than are probabilities for unanticipated depreciation. It is noticeable, for example, that the out-of-sample total depreciation model picks up the Thai crashes in 1997 earlier than does the out-of-sample unanticipated depreciation model.

3.4. Goodness of fit

One way to study the model's predictive power both in- and out-of-sample is to examine the type I and type II errors it produces in crash forecasting. To generate forecasts, we suppose that the model forecasts a crash whenever the monthly forecast of the crash probability exceeds some cutoff point, γ_4. For the cutoff point, we considered the range of values: 1%, 2%, 5%, 10% and 15%.[15] When a low cutoff level is chosen, we will predict crashes when they do not occur (a type II error), whereas for a high cutoff level, we tend to predict periods of calm when a crash took place (type I errors).

Table 2 shows the fractions of correctly and incorrectly forecast crashes and calm periods for unanticipated and total depreciation crashes using 5% and 10% crisis definitions and on an in- and out-of-sample basis. The in-sample results for the entire sample are quite similar for the unanticipated and total depreciation crisis definitions, and are also similar to the out-of-sample results. If we choose to use a 5% crash definition, we find that a 5% cutoff point will correctly forecast about 50% of the observed crashes as against 75% of the observed calms. If we use a more stringent 10% crash definition, we find that these figures are reversed, with 75% of observed crashes being predicted as against about 50% of observed calms.

Comparing the goodness of fit of the unanticipated versus the total depreciation models, it is evident that the former is much better in some cases. For example, in the case of the 10% crisis definition with the hold-out period is the last third of the sample (so the estimation period is January 1985 to December 1993) and when the estimated probability cutoff is 5%, the total depreciation model correctly predicts crashes 35% of the time while the corresponding figure for the unanticipated depreciation model is 48%. However, the total depreciation model outperforms the other in several other important cases (e.g., when a 5% definition is employed).

[15] Note that it made sense to employ small cutoff levels since, in almost all the models, the predicted monthly crash probability only exceeds 10% in a small fraction of cases.

Table 2
Goodness of fit: type I and type II errors

Estimated probability	5% Crisis definition				10% Crisis definition			
	In-sample		Out-of-sample		In-sample		Out-of-sample	
Unanticipated depreciation								
Predictions based on estimation over whole sample period Jan 1985–Oct 1999								
0.01	0	*100*	–	–	15	*95*	–	–
0.02	7	*99*	–	–	44	*76*	–	–
0.05	44	*76*	–	–	81	*51*	–	–
0.10	82	*40*	–	–	95	*26*	–	–
0.15	94	*22*	–	–	98	*15*	–	–
Predictions based on estimation on beginning of sample Jan 1985–Dec 1993								
0.01	0	*100*	0	*100*	12	*89*	15	*94*
0.02	3	*98*	6	*99*	42	*74*	42	*82*
0.05	39	*74*	46	*80*	82	*48*	83	*47*
0.10	82	*32*	83	*42*	96	*19*	95	*31*
0.15	96	*11*	93	*26*	99	*7*	98	*14*
Predictions based on estimation over sample excluding period Jan 1989–Dec 1993								
0.01	2	*99*	1	*99*	8	*99*	12	*87*
0.02	11	*96*	8	*93*	33	*87*	35	*67*
0.05	44	*79*	35	*64*	69	*61*	69	*37*
0.10	73	*54*	69	*35*	89	*36*	85	*19*
0.15	88	*35*	89	*20*	95	*24*	93	*14*
Total depreciation								
Predictions based on estimation over whole sample period Jan 1985–Oct 1999								
0.01	0	*100*	–	–	5	*99*	–	–
0.02	1	*100*	–	–	33	*88*	–	–
0.05	40	*81*	–	–	85	*40*	–	–
0.10	88	*28*	–	–	97	*12*	–	–
0.15	98	*8*	–	–	99	*2*	–	–
Predictions based on estimation on beginning of sample Jan 1985–Dec 1993								
0.01	0	*100*	0	*100*	2	*99*	4	*99*
0.02	2	*100*	1	*100*	29	*88*	30	*81*
0.05	42	*80*	42	*71*	87	*35*	85	*32*
0.10	88	*29*	88	*24*	98	*7*	96	*12*
0.15	98	*7*	97	*8*	100	*1*	99	*4*
Predictions based on estimation over sample excluding period Jan 1989–Dec 1993								
0.01	0	*100*	0	*100*	5	*99*	8	*97*
0.02	2	*99*	1	*99*	25	*91*	30	*81*
0.05	30	*84*	34	*70*	72	*55*	69	*34*
0.10	81	*34*	75	*29*	93	*20*	87	*16*
0.15	97	*9*	90	*11*	98	*7*	95	*9*

Numbers in normal type denote percentage of correctly predicted calm periods, i.e., percentage of observed calms which are correctly predicted.
Numbers in *italic* type denote percentage of correctly predicted crises, i.e., the percentage of observed crises which are correctly predicted.

We also calculate a summary measure of goodness of fit for crisis prediction based on a suggestion by Brier (1950) (see Diebold and Lopez, 1996 for a discussion). For both the 5% crisis definition and for the 10% crisis definition, and for in-sample and out-of-sample estimates, we calculate QPS where

$$\mathrm{QPS} = \frac{1}{T}\left(\sum_{t=1}^{T} 2(P_t - Q_t)^2\right) \tag{5}$$

$$\text{where } P_t = \text{fitted crisis probability} \tag{6}$$

$$Q_t = \begin{cases} 1 & \text{if crisis occurred} \\ 0 & \text{otherwise} \end{cases} \tag{7}$$

Here, T is the sample size and P_t is the estimated crisis probability at time t. Note that QPS is scaled so that it lies between 0 and 2. QPS acts as a rough analogue of MSE, with values of QPS close to 0 indicating greater accuracy of forecast.

The QPS values in Table 3 confirm the good predictive ability of the model. The more stringent 10% crisis definition performs best, as would be expected, and there is broad agreement about the forecasting ability of all the out-of-sample estimations performed.

Table 3
Goodness of fit statistics—Brier's quadratic probability score

	5% Crisis definition		10% Crisis definition	
	In-sample	Out-of-sample	In-sample	Out-of-sample
Unanticipated depreciation				
Predictions based on estimation over whole sample period Jan 1985–Oct 1999	0.32	–	0.15	–
Predictions based on estimation over sample excluding period Jan 1994–Oct 1999	0.28	0.40	0.12	0.20
Predictions based on estimation over sample excluding period Jan 1989–Dec 1993	0.42	0.24	0.24	0.11
Predictions based on estimation over sample excluding period Jan 1985–Dec 1989	0.31	0.37	0.16	0.13
Total depreciation				
Predictions based on estimation over whole sample period Jan 1985–Oct 1999	0.22	–	0.10	–
Predictions based on estimation over sample excluding period Jan 1994–Oct 1999	0.21	0.23	0.08	0.12
Predictions based on estimation over sample excluding period Jan 1989–Dec 1993	0.28	0.20	0.19	0.09
Predictions based on estimation over sample excluding period Jan 1985–Dec 1989	0.22	0.22	0.10	0.10

Brier's quadratic probability score is calculated as $\mathrm{QPS} = \frac{2}{T}\sum_{t=1}^{T}(P_t - Q_t)^2$ where P_t = estimated probability of a crisis at time t; Q_t = 1 if corresponding observation is a crisis, 0 otherwise.

3.5. Trading strategies

Inspection of probability plots such as those in Figs. 3 and 4 suggested that the model is reasonably accurate in predicting crashes. To obtain a more conclusive evaluation of the model's performance, especially out of sample, we calculated a series of trading strategies based on forecasts generated by the model.

In the first set of strategies, which we term short strategies, we took the following approach. Whenever the crash probability for one of the 19 most liquid emerging market currencies[16] exceeded a given cutoff point, γ_5, we would borrow the equivalent of \$1 in the corresponding currency for a month, convert into US dollars, and invest in a dollar deposit. After a month, the position would be closed and any profit or loss added to an account held in dollars. The contents of the latter account were then compounded up by the dollar interest rate month by month but the funds were not reinvested in any way in the emerging market currencies. (The fact that profits are not reinvested makes the strategy relatively conservative).

As a second exercise, we calculated a series of long strategies in which, whenever the crash probability for one of our 19 liquid currencies falls below some cutoff, γ_5, \$1 is borrowed in US dollars and is invested for 1 month in a deposit denominated in the corresponding currency. At the end of the month, any profit or loss is transferred to a US dollar account which is then compounded up at the US interest rate until the end of the trading strategy.

We calculated the trading strategy returns on both an in- and an out-of-sample basis. By in-sample, we mean that we estimate model parameters using the whole sample and then generate crash probabilities and trading strategy returns for the whole sample. By out-of-sample, we mean we estimated the model parameters on a subsample, and then generated probabilities and calculated trading strategy returns for the remainder of the sample, termed the hold-out subsample. We examined three hold-out subsamples in total, the first, middle and last thirds of the entire sample.

Table 4 shows the dollar profits yielded by the above short and long strategies. For both short and long, we calculated profits for a (monthly) probability cutoff γ_5 of 2%.[17] All probabilities were estimated using the 5% crash definition for calculating the dependent variable. As a measure of the statistical significance, we report t-statistics and associated p-values. One may regard the profit numbers as sums of profits on individual trades and hence work out an appropriate t-statistic assuming independence across observations. The latter might be questioned given that, cross-sectionally at least, the crashes are probably not independent. Nevertheless, it is probably an unreasonable approximation.

Looking first at the short strategies, we note that, as one might expect, the results are much better when the whole data set is used in the estimation.[18] However, it is striking

[16] We chose the 19 currencies because their money markets were sufficiently developed by the start of our trading strategy period that transaction costs could be regarded as very small.

[17] Increasing the cutoff point say to 3% did not materially affect the profits generated by the different trading strategies. Omitted due to space constraints, these further calculations are available on request from the authors.

[18] In this case, however, any profits obtained could in part be indications of overfitting. It is still interesting to report them, however, if only to see how much the distinction between in- and out-of-sample matters.

Table 4
Trading strategy statistics for crisis probability 2.00%

	Cumulative excess profits				
	Total profit	Profit per trade (× 100)	t-statistics	p-value	Risk premium for total profit
Short strategy					
Unanticipated depreciation					
• estimation on whole sample; trading profit over whole sample	8.55	0.66	3.64	0.00	−0.11
• estimation on data to 12/93; trading profits over hold-out sample	4.72	0.66	2.91	0.00	−0.71
• estimation exc. middle of data; trading profits over hold-out sample	0.17	0.05	0.17	0.43	−0.00
• estimation exc. beginning of data; trading profits over hold-out sample	1.86	0.88	1.82	0.03	0.01
Total depreciation					
• estimation on whole sample; trading profit over whole sample	7.71	0.45	2.66	0.00	−0.10
• estimation on data to 12/93; trading profits over hold-out sample	3.90	0.46	3.36	0.00	−0.75
• estimation exc. middle of data; trading profits over hold-out sample	0.79	0.15	0.48	0.32	0.13
• estimation exc. beginning of data; trading profits over hold-out sample	2.30	0.70	1.78	0.04	0.03
Long strategy					
Unanticipated depreciation					
• estimation on whole sample; trading profit over whole sample	4.25	0.32	2.74	0.00	−0.11
• estimation on data to 12/93; trading profits over hold-out sample	1.73	0.35	2.08	0.02	−0.07
• estimation exc. middle of data; trading profits over hold-out sample	0.85	0.15	0.62	0.27	−0.21
• estimation exc. beginning of data; trading profits over hold-out sample	−0.29	−0.08	−0.52	0.70	−0.01
Total depreciation					
• estimation on whole sample; trading profit over whole sample	2.97	0.33	3.98	0.00	−0.05
• estimation on data to 12/93; trading profits over hold-out sample	0.99	0.27	1.26	0.10	−0.07
• estimation exc. middle of data; trading profits over hold-out sample	0.83	0.22	2.38	0.01	−0.07
• estimation exc. beginning of data; trading profits over hold-out sample	0.13	0.05	0.42	0.34	0.01

Short strategy: total profit over funding cost on shorting markets by US$1 each time that estimated monthly probability exceeds 2.00%.
Long strategy: total profit over funding cost on investing US$1 in market each time that estimated monthly probability falls below 2.00%.
Risk premium: this is the CAPM risk premium relevant for the total trading profit calculated using US S&P 500 index.

that the out-of-sample trading strategies also in many cases yield substantial and statistically significant profits. Trading strategies based on unanticipated depreciation models generally yield more than those based on total depreciation models. Again, this is

Table 5
Annual trading strategy profits—Unanticipated depreciation

Country	1994	1995	1996	1997	1998	1999	Total
Short strategy							
Hong Kong	0	0	0	− 2	− 4	− 1	− 6
India	− 0	2	− 3	9	5	0	12
Indonesia	− 0	0	0	67	57	8	133
Korea	− 6	− 6	5	62	− 30	− 2	24
Malaysia	1	− 1	− 3	39	− 1	− 1	36
Pakistan	0	8	10	1	8	1	27
Philippines	0	0	0	10	− 3	− 2	5
Singapore	0	0	0	14	1	4	18
Sri Lanka	0	0	− 0	2	4	0	6
Argentina	0	− 6	− 1	0	− 2	− 2	− 11
Brazil	0	− 19	− 12	− 10	− 13	36	− 17
Ecuador	− 6	− 6	− 8	1	16	42	39
Mexico	14	49	− 11	0	2	− 10	44
Israel	0	0	− 4	0	− 2	− 3	− 8
Hungary	− 3	5	1	7	0	0	10
Poland	0	0	0	0	− 8	10	2
Russia	0	0	0	− 5	115	− 15	95
Turkey	47	3	− 0	4	− 3	0	52
Kenya	0	20	− 1	− 7	− 14	14	12
Total	48	49	− 55	193	130	79	472
Long strategy							
Hong Kong	0	0	0	0	0	0	0
India	1	− 1	0	0	0	0	1
Indonesia	3	5	8	− 2	0	20	34
Korea	0	0	0	0	0	0	0
Malaysia	8	0	0	0	0	− 0	8
Pakistan	2	2	0	0	2	0	6
Philippines	18	− 6	4	− 22	0	− 2	− 9
Singapore	8	1	− 1	− 5	0	− 1	2
Sri Lanka	7	− 2	2	− 1	− 2	0	3
Argentina	3	0	1	2	1	0	7
Brazil	71	6	1	0	0	0	77
Ecuador	7	0	0	0	0	0	7
Mexico	− 4	0	4	6	− 10	0	− 4
Israel	4	5	1	0	− 11	1	− 1
Hungary	0	0	0	0	0	0	0
Poland	11	16	1	− 9	5	0	24
Russia	0	0	0	2	0	0	2
Turkey	0	12	− 7	− 7	8	0	6
Kenya	0	6	11	− 9	0	0	8
Total	138	44	47	− 43	− 6	17	173

A crisis is signalled when the estimated monthly crisis probability exceeds 2.00%.
Crisis probabilities are calculated using estimates from beginning of sample Jan 1985 – Dec 1993.

not surprising since one is then using forecasts which are more closely linked to a profit opportunity.

The maximum out-of-sample short strategy profit (corresponding to a hold-out sample consisting of the last third of the sample) of 4.72 is highly significant, having a *t*-statistic of 2.91. It is interesting that the corresponding long strategy also generates quite a large profit of 1.73 profit (with a *t*-statistic of 2.08). If the profits simply reflected a sample selection bias in that we had chosen to study the period of the Asian crisis knowing that there were many large depreciations in this sample, we would not expect to be able to generate the profits trading long.

The out-of-sample trading strategies based on hold-out samples consisting of the first and second thirds of the data set yield more mixed results. In all except one case, positive profits are obtained, however. The short strategy yields (marginally) statistically significant profits when the hold-out period is the first third of the sample, and the long strategy is significant when the hold-out period is the middle third of the sample and the total depreciation model is employed.

Lastly, Table 4 also provides the average profit obtained from individual transactions. It is important to consider these since low levels of expected profits might be offset by transaction costs. The profit per-trade reported in Table 4 are generally of the order of 50 basis points. This significantly exceeds the roundtrip transaction costs one might expect in the 19 quite liquid markets which we use in our trading strategy calculations.

CAPM risk adjustments for the total profits on the trading strategies reported in Table 4 appear in the right-hand column of the table. Since our analysis is from the point of view of a dollar investor, we choose as the reference portfolio S&P 500 index. The risk adjustments for the total profits on each strategy equal the sum of a CAPM beta times the price of risk (the mean return on the S&P minus the mean 1-month US Treasury bill interest rate) summed over all the risky trades included in the trading strategy. As may be seen, the strategies often resemble returns on negative beta assets since the risk adjustments are negative and generally they are very small in size compared to the mean profits.

In Table 5, we disaggregate a typical set of trading strategy profits so as to reveal the source of the profits under unanticipated depreciation. We find, as expected, that an important source of short-strategy profits obtained in the out-of-sample period is the Far Eastern economies in 1997 and 1998. Mexico was also a source of profit in 1994 and 1995, as was Turkey in 1994. Interestingly, however, the single largest source of short-strategy trading profits is the Russian crisis of 1998. Turning to the disaggregated, long-strategy profits also shown in Table 5, we find that the greatest part of the profits are due to Brazil and Poland in the early part of the period studied and to Indonesia in 1999.

4. Conclusion

This paper has investigated the forecastability of crashes in emerging market currencies using lagged information on macroeconomic and financial variables. It extends and complements the existing literature in a number of important ways, including in the specification of the models and especially in evaluating their out-of-sample performance by specifying and running trading strategies.

Crashes are defined as large movements in currencies either adjusting or not for relative interest rate differentials. We find that simple logit forecasting models have significant explanatory power when estimated on two thirds of the sample and then used to predict crashes in the remaining third.

We evaluate the performance of our models (i) through goodness-of-fit measures, (ii) by examining the behavior of estimated crash probabilities in the period prior to large crashes and (iii) by calculating in- and out-of-sample trading strategies based on going long or short in the currency according to whether the crisis predictions are low or high.

The trading strategies suggest that statistically significant and economically substantial profits could have been made. It is particularly interesting that in the last third of the sample, a period in which many emerging market currencies experienced substantial devaluations, profits could be made by going long when crisis probabilities were low.

More broadly, our findings confirm the results of earlier studies which suggested that the most important explanatory variables for crashes are declining reserves and exports, and weakening real activity. Contagion has an important role in explaining the incidence of crash, both as a regional factor and through export growth correlations. Although our focus on trading strategies differs from theirs, our results are consistent with the findings of the recent study by Berg and Patillo (1999), which found that discrete choice models based on monthly data have some explanatory power for exchange rate crises.

In summary, our study has contributed to the literature on determinants of currency crashes, and developed and evaluated rigorously a practical set of tools for forecasting these crashes. The analysis in this paper would be useful in complementing existing models to macro policymakers, investors in emerging financial markets and financial regulators concerned at the currency exposures of the institutions they supervise.

Acknowledgements

We thank Vincenzo Zinni for valuable research support. We are grateful for comments from an anonymous referee and from Giancarlo Corsetti, Andreas Fischer, Giles Keating, Paul Mizen, Paolo Pesenti, Axel Weber, Jonathan Wilmott, participants in seminars at the BIS, the Bank of England, the February 1998 CEPR conference and the May 1998 CEPR/World Bank conference, and staff of CSFB.

Appendix A. Countries in estimation sample

Asia: China, Hongkong, India, Indonesia, Korea, Malaysia, Pakistan, Philippines, Singapore, Sri Lanka, Thailand.

Latin America: Argentina, Brazil, Chile, Columbia, Ecuador, Mexico, Peru, Venezuela.

Middle East: Egypt, Israel, Jordan, Kuwait.

Eastern Europe: Hungary, Poland, Russia, Turkey.

Africa: Kenya, Morocco, Nigeria, South Africa, Zimbabwe.

Appendix B. Countries in trading strategy sample

Asia: Hongkong, India, Indonesia, Korea, Malaysia, Pakistan, Philippines, Singapore, Sri Lanka.

Latin America: Argentina, Brazil, Ecuador, Mexico.

Middle East: Israel.

Eastern Europe: Hungary, Poland, Russia, Turkey.

Africa: Kenya.

Appendix C. Variables used in estimation

Acronyms in bold type refer to abbreviations of variable names.

The trend of a data series is calculated as the mean of the cumulative sum of the series, i.e., the trend in any month is the mean over all previous observations to the beginning of the series.

1. *Real GDP* (**GDP**): Real GDP in domestic currency; deviation from trend of 12-month percentage changes; annual data interpolated by cubic splines.
2. *Real effective exchange rate* (**ER**): Deviation from trend; monthly data.
3. *Exports* (**EXP**): Total exports in millions of US$; 12-month percentage change; monthly data.
4. *Foreign direct investment* (**FDI**): Net foreign direct investment in millions of US$; deviation from trend; annual data interpolated by cubic splines.
5. *Portfolio investment* (**PINV**): Net portfolio investment in millions of US$; deviation from trend; annual data interpolated by cubic splines.
6. *Foreign exchange reserves* (**FXR**): Foreign exchange reserves, excluding gold, in millions of US$; 12-month percentage change; monthly data.
7. *Foreign exchange reserves/imports* (**FX/IM**): Ratio of foreign exchange reserves to imports; monthly data. Total imports in millions of US$; 12-month percentage change; monthly data.
8. *Official debt/total debt* (**ODBT**): Ratio of official medium- and long-term debt to total medium- and long-term debt; annual data interpolated by cubic splines.
9. *Budget deficit/GDP* (**BUDG**): Government budget deficit as percentage of GDP; annual data interpolated by cubic splines.
10. *Global liquidity indicator*: Global variable based on real interest rate and excess M3 in OECD countries; 12-month percentage change; monthly data.
11. *Commodity prices*: Global nonfuel commodity price index; 12-month percentage change; monthly data.
12. *Capital account liberalization*: Dummy variable set to 1 if country's economy is liberalized, 0 otherwise.
13. *Linear trend*
14. *High inflation regime*: Dummy variable set to 1 if the annualized rate of acceleration of bimonthly inflation exceeds 100%, 0 otherwise.

15. *Lagged exchange rate* (**LAG**): One-month percentage change in nominal exchange rate; monthly data.
16. *Contagion (export growth correlation)* (**CTG1**): Dummy variable set to 1 if the correlation in export growth between each pair of countries exceeds 0.75 and if a crisis occurred in one of them within the last 3 months; 0 otherwise.
17. *Contagion (regional effect)*: Dummy variable set to 1 if any country in the region suffered a crisis within the last 3 months; 0 otherwise.

References

Amemiya, T., 1981. Qualitative response models: a survey. Journal of Economic Literature 19, 483–536.

Berg, A., Patillo, C., 1999. Predicting currency crises: the indicators approach and an alternative. Journal of Money and Finance 18, 561–586.

Blanco, H., Garber, P.M., 1986. Recurrent devaluations and speculative attacks on the Mexican peso. Journal of Political Economy 94, 148–166.

Brier, G., 1950. Verification of forecasts expressed in terms of probability. Monthly Weather Review, 1–3.

Cole, H.L., Kehoe, T.J., 1996. A self-fulfilling model of Mexico's 1994–95 debt crisis. Journal of International Economics 41, 309–330.

CSFB, 1998. Emerging markets risk indicator. Analytic Manual. Credit Suisse First Boston, London. May.

Cumby, R., van Wijnbergen, S., 1989. Financial policy and speculative runs with a crawling peg—Argentina 1979–1981. Journal of International Economics 17, 111–127.

Diebold, F.X., Lopez, J.A., 1996. Forecast evaluation and combination. In: Maddala, G.S., Rao, C.R. (Eds.), Statistical Methods of Finance, Handbook of Statistics Series, vol. 14. Elsevier, North-Holland, Amsterdam, New York, pp. 241–268.

Eichengreen, B., Rose, A.K., Wyplosz, C., 1996. Exchange market mayhem: the antecedents and aftermath of speculative attacks. Economic Policy 21, 249–312.

Flood, R.P., Marion, N.P., 1997. The size and timing of devaluations in capital-controlled economies. Journal of Development Economics 54 (1), 123–147.

Flood, R.P., Marion, N.P., 1999. Perspectives on the recent currency crisis literature. International Journal of Finance and Economics 4 (1), 1–26.

Frankel, J., Rose, A., 1996. Currency crashes in emerging markets: an empirical treatment. Journal of International Economics 41 (3–4), 351–366.

Glick, R., Rose, A.K., 1999. Contagion and trade: why are currency crises regional? Journal of International Money and Finance 18, 603–617.

Goldstein, M., Kaminsky, G.L., Reinhart, C.M., 2000. Assessing Financial Vulnerability: An Early Warning System for Emerging Markets. Institute for International Economics, Washington, DC.

Jeanne, O., Masson, P., 2000. Currency crises, sunspots, and Markov-switching regimes. Journal of International Economics 50 (2), 327–350.

Kaminsky, G.L., 1999. Currency and banking crises: the early warnings of distress. Working paper WP/99/178, International Monetary Fund, Washington, DC.

Kaminsky, G.L., Reinhart, C.M., 1999. The twin crises: the causes of banking and balance-of-payments problems. American Economic Review 89 (3).

Kaminsky, G.L., Schmukler, S.L., 1999. What triggers market jitters? A chronicle of the Asian crisis. Journal of International Money and Finance 18, 537–560.

Kaminsky, G., Lizondo, S., Reinhart, C.M., 1998. Leading indicators of currency crises. International Monetary Fund Staff Papers 45, 1–48.

Klein, M.W., Marion, N.P., 1997. Explaining the duration of exchange rate pegs. Journal of Development Economics 54 (2), 387–404.

Maddala, G., 1983. Limited Dependent and Qualitative Variables in Econometrics. Econometric Society Monographs. Cambridge Univ. Press, Cambridge, UK.

Otker, I., Pazarbasioglu, C., 1994. Exchange market pressures and speculative capital flows in selected European countries. Working paper WP/94/21, International Monetary Fund, Washington, DC.
Ozkan, F.G., Sutherland, A., 1995. Policy measures to avoid a currency crisis. Economic Journal 105, 510–519.
Sachs, J.D., Tornell, A., Velasco, A., 1996. Financial crises in emerging markets: the lessons from 1996. Brookings Papers on Economic Activity, 147–215.