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Predicting Emerging Market Currency Crashes

Manmohan Kumar, Uma Moorthy and William Perraudin

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Predicting Emerging Market Currency Crashes

Prepared by Manmohan S. Kumar, Uma Moorthy and William Perraudin[1]

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Abstract

This paper assesses 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.

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Author's E-Mail Address: mkumar@imf.org; umoorthy@econ.bbk.ac.uk; wperrauding@econ.bbk.ac.uk

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I. INTRODUCTION

Currency crashes have been the subject of considerable interest following the 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 emerging markets may now be presumed to be immune to the destabilizing fluctuations that affected Indonesia, Korea, Thailand, Russia and others.

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-policy-makers 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 policy-maker and is equally interested in 'successful' and `unsuccessful' speculative attacks. From the standpoint of an investor, manager of foreign reserve positions or a macro policy-maker 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 percent and 10 percent). 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 1994-95 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-' 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.

II. Modeling Exchange Rate Crashes

A. Past Empirical Studies

A substantial literature has now accumulated on the empirical modeling of exchange rate crises.[2] Kaminsky, Lizondo, and Reinhart, 1998 provide a comprehensive survey. This literature comprises three types of analysis.[3] 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 Vanwijnbergen, 1989; Jeanne and Masson, 1997; Cole and Kehoe, 1996; and Sachs, Tornell, and Velasco, 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 signaling models. Examples include Kaminsky, Lizondo, and Reinhart, 1998; Kaminsky and Reinhart, 1999; and Goldstein, Kaminsky, and Reinhart, 2000. In such models, individual variables such as the real effective exchange rate or debt to GDP ratios 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).

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[2] For references on recent theoretical studies, see Flood and Marion, 1997.

[3] 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, 1995; Klein and Marion, 1994; and Otker and Pazarbasioglu, 1994.

Signaling models are often described as being non-parametric approach. In fact, they are parametric with the parameters being the threshold levels for the variables. These models are intuitively appealing and are versatile, but to-date they have been essentially univariate in character. Kaminsky, 1998 suggests a way of combining individual signals to form a composite index for forecasting purposes[4] which would strengthen their power.

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, Rose, and Wyplosz, 1996 employ probit models for industrial countries using quarterly data between 1959 and 1993. They define crises to be increases greater than 25 percent in an index consisting of a weighted average of percentage (i) devaluations in bilateral exchange rates against the US dollar, (ii) falls in reserves, and (iii) increases in interest rates. In contrast, Frankel-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 percent and which (b) exceed the devaluation in the previous year by 10 percent.

One paper which somewhat resembles ours is Berg and Pattillo, 1999. Their paper examines how well two different crisis prediction models (a signaling model like that of Kaminsky, Lizondo, and Reinhart, 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).

B. 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, Rose, and Wyplosz, 1996. In cases where authors do explicitly forecast crises (for example, Kaminsky, Lizondo, and Reinhart, 1998; Frankel and Rose, 1996; Goldstein, Kaminsky, and Reinhart, 2000; Kaminsky, 1998; Berg and Pattillo, 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, Rose, and Wyplosz, 1996; Sachs, Tornell, and Velasco, 1996; Goldstein, Kaminsky, and

[4] 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.

Reinhart, 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.[5] 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 cut-off point which we set to 5 percent or 10 percent 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 out-perform 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.

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 percent (i.e., a doubling of the rate of depreciation) and again employ a crash cutoff parameter, γ_2, of 5 percent or 10 percent.

Our second definition of crash, with the acceleration requirement given in equation (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

[5] For example, Goldstein, Kaminsky, and Reinhart, 2000 define a crisis as a weighted average of changes in the exchange rate and in foreign exchange reserves.

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.[6]

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, Rose, and Wyplosz, 1996; Frankel and Rose, 1996; Berg and Pattillo, 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.[7]

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 do 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, op. cit.,1999 conclude that banking crises, "are not necessarily the immediate causes of 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 crises reflect common causes and these causes are captured in the forecasting variables we include in our models, modeling currency crises alone will not induce biases or reduce forecasting power.

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

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

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

where X is a vector of explanatory variables and β is a vector of parameters.

C. Data

The dataset that we employ runs from the 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 dataset. 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 modeling 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 over-fitting 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.[8]

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 twelve-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.[9] 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 two months exceeds an annualized rate of 100 percent, 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[10] so we include the ratio of official foreign debt to private foreign debt.[11]

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[8] 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.

[9] See Ozkan and Sutherland, 1995.

[10] See Cole and Kehoe, 1996.

[11] 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, Rose, and Wyplosz, 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 three 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,[12] has experienced a crash in the last three months.[13]

Lastly, we include (i) a proxy for the external financial environment in the form of a global liquidity indicator (see the Appendix for a definition), (ii) non-fuel 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 over-reaction effects in exchange rate changes. Kaminsky and Schmukler, 1999 provide evidence of market over-reactions 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.[14] 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 eighteen months. Some of the forecasts come initially from the EIU but are refined and up-dated using the most timely available data by CSFB analysts. If one wishes to implement a practical crash risk model, it seems advisable to employ these forecasts in the way that we do.

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[12] The criterion is that the correlation of export growth in the two countries in the last forty-eight months exceeds 75 percent.

[13] 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 Figures 1 and 2). Hence, the contagion effects we include do not represent post-Asian-crisis data-snooping.

[14] 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.

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 twelve 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 Europe prior to the early 1990s. To cope with this, where gaps occurred part-way through a series, we interpolated observations, again using cubic splines. When gaps occurred either at the beginning or 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: $f(x) \equiv sign\,\{x\} \log(1+|x|)$ 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.

III. Results

A. Crash Definitions

Figure 1 shows the frequency of crashes defined as depreciations exceeding 5 percent, 10 percent and 15 percent 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 percent 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 Figures 2a and 2b, 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 Figure 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 1990's, whereas the 1997-98 Asian crash has consisted of a larger number of unanticipated depreciations.

B. 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 percent and 10 percent crash cutoff points. Using a 15 percent 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 dataset. 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 twelve-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 one month, is significant in the total depreciation regressions and tends to have a positive effect on the crash probability. This is intuitively 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 non-fuel 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 equation 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 datasets resemble those from the estimations based on the whole sample period, though, 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 sub-samples. When the middle third of the data is left out, non-fuel 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 U.S. 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 six 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 counter-intuitive coefficient signs and one statistically significant parameter.

C. 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. Figures 3 and 4 contain a selection of such plots for 12 countries chosen from the 5 regions and using the unanticipated depreciation definition of a crash. The plots show estimates of one-month-ahead crash probabilities. 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 percent dependent variable definition, and are scaled up so as to increase the amount of detail visible in the plots.[15]

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 two months. So, "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 Figures 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 dataset 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.

D. 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 percent, 2 percent, 5 percent, 10 percent and 15 percent.[16] 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 percent and 10 percent 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

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[15] 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, expression $1-(1-y)^{12}$. would equal the probability of at least one crash occurring in a twelve 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.

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

similar to the out-of-sample results. If we choose to use a 5 percent crash definition, we find that a 5 percent cutoff point will correctly forecast about 50 percent of the observed crashes as against 75 percent of the observed calms. If we use a more stringent 10 percent crash definition, we find that these figures are reversed, with 75 percent of observed crashes being predicted as against about 50 percent 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 percent 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 cut-off is 5 percent, the total depreciation model correctly predicts crashes 35 percent of the time while the corresponding figure for the unanticipated depreciation model is 48 percent. However, the total depreciation model out-performs the other in several other important cases (e.g., when a 5 percent definition is employed).

We also calculate a summary measure of goodness of fit for crisis prediction based on a suggestion in Brier, 1950 (see Diebold and Lopez, 1995 for a discussion). For both the 5 percent crisis definition and for the 10 percent crisis definition, and for in-sample and out-of sample estimates, we calculate QPS where

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

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

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

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 percent 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.

E. Trading Strategies

Inspection of probability plots such as those in Figures 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[17] 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 one 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 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 sub-sample, and then generated probabilities and calculated trading strategy returns for the remainder of the sample, termed the hold-out sub-sample. We examined three hold-out sub-samples 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 percent.[18] All probabilities were estimated using the 5 percent 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.

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

[18] Increasing the cutoff point say to 3 percent 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.

Looking first at the short strategies, we note that, as one might expect, the results are much better when the whole dataset is used in the estimation.[19] But, it is striking 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 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 a quite 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 dataset 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.

Last, 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 transactions costs. The profit per-trade reported in Table 4 is generally of the order of 50 basis points. This significantly exceeds the round trip transactions 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 one-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

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

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.

IV. 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 Pattillo, 1999 which found that discrete choice models based on monthly data have some explanatory power for exchange rate crises.

In summary, this paper provides a contribution to the literature on determinants of currency crashes by developing and rigorously evaluating a practical set of tools for forecasting these crashes. The analysis in this paper would be useful, in complementing existing models, to macro policy-makers, investors in emerging financial markets, and financial regulators concerned about the currency exposures of the institutions they supervise.

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

	Unanticipated depreciation		Total depreciation	
	5 percent	10 percent	5 percent	10 percent
Constant	-4.03	-5.05	-3.73	-4.73
	(26.85)	(23.20)	(27.04)	(23.90)
Real GDP §	-0.19	-0.21	-0.28	-0.25
	(2.29)	(1.75)	(3.25)	(1.97)
Real effective exchange rate *f*	-0.12	-0.15	0.04	-0.06
	(1.24)	(1.03)	(0.45)	(0.42)
Exports ±	-0.14	0.10	-0.07	0.05
	(1.42)	(0.74)	(0.76)	(0.38)
Foreign direct investment §	-0.04	0.02	-0.07	-0.14
	(0.48)	(0.13)	(0.73)	(1.04)
Portfolio investment §	-0.16	-0.19	-0.20	-0.28
	(1.82)	(1.55)	(2.30)	(2.13)
Foreign exchange reserves ±	-0.49	-0.86	-0.24	-0.55
	(4.26)	(4.36)	(2.37)	(2.98)
Foreign exchange reserves/imports	-0.25	-0.23	-0.16	-0.30
	(2.39)	(1.45)	(1.51)	(1.83)
Official debt/total debt	-0.25	-0.30	-0.20	-0.22
	(2.55)	(2.13)	(2.00)	(1.44)
Budget deficit/GDP	0.01	0.04	-0.04	0.03
	(0.13)	(0.36)	(0.53)	(0.26)
Global liquidity indicator	-0.07	0.14	-0.11	0.02
	(0.70)	(1.07)	(1.00)	(0.10)
Non-fuel commodity prices ±	-0.00	-0.04	-0.03	0.05
	(0.04)	(0.27)	(0.26)	(0.30)
Capital account liberalization	-0.02	-0.02	-0.06	-0.01
	(0.32)	(0.27)	(0.77)	(0.09)
Linear trend	-0.05	-0.11	-0.15	-0.06
	(0.45)	(0.68)	(1.41)	(0.35)
High inflation regime	0.22	0.13	0.13	0.19
	(2.15)	(0.95)	(1.20)	(1.26)
Lagged change	-0.02	-0.01	0.20	0.15
in exchange rate	(0.31)	(0.07)	(3.16)	(1.67)
Contagion	0.23	0.15	-0.12	-0.40
(export growth correlation)	(0.93)	(0.38)	(0.39)	(0.74)
Contagion	0.96	1.32	0.47	0.59
(regional effect)	(5.23)	(5.12)	(2.55)	(2.11)
Log-likelihood	-605.92	-321.94	-594.29	-302.80
Number of crises	160.00	77.00	146.00	65.00
Number of observations	4140.00	4140.00	4140.00	4140.00
Likelihood ratio	142.95	122.31	74.90	63.40

Note: t-statistics appear in parentheses

f Deviation from trend

± Twelve-month percentage change

§ Deviation from trend of twelve-month percentage change

Table 2: Goodness of Fit: Type I and Type II Errors

Unanticipated depreciation

Predictions based on estimation over whole sample period Jan 1985 - Oct 1999

Estimated	5 percent Crisis definition				10 percent Crisis definition			
probability	In-sample		Out-of-sample		In-sample		Out-of-sample	
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

Estimated	5 percent Crisis definition				10 percent Crisis definition			
probability	In-sample		Out-of-sample		In-sample		Out-of-sample	
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

Estimated	5 percent Crisis definition				10 percent Crisis definition			
probability	In-sample		Out-of-sample		In-sample		Out-of-sample	
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

Estimated	5 percent Crisis definition				10 percent Crisis definition			
probability	In-sample		Out-of-sample		In-sample		Out-of-sample	
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

Estimated	5 percent Crisis definition				10 percent Crisis definition			
probability	In-sample		Out-of-sample		In-sample		Out-of-sample	
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

Estimated	5 percent Crisis definition				10 percent Crisis definition			
probability	In-sample		Out-of-sample		In-sample		Out-of-sample	
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

Table 3: Goodness of Fit Statistics – Brier's Quadratic Probability Score

Unanticipated depreciation	5 percent crisis definition		10 percent crisis definition	
	In-sample	Out-of-sample	In-sample	Out-of-sample
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	Percent crisis definition		10 percent crisis definition	
	In-sample	Out-of-sample	In-sample	Out-of-sample
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 $QPS = \frac{2}{T}\sum_{t=1}^{T}(P_t - Q_t)^2$

where Pt = estimated probability of a crisis at time t; $Q_t = 1$ if corresponding observation is a crisis, 0 otherwise.

Table 4: Trading Strategy Statistics for Crisis Probability 2.0 Percent

	Cumulative excess profits				
	Total profit	Profit per trade	t-stat (x100)	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	0.00
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 2.0 percent.
Long strategy
Total profit over funding cost on investing US$1 in market each time that estimated monthly probability falls below 2.0 percent.
Risk premium
This is the CAPM risk premium relevant for the total trading profit calculated using US S&P 500 index.

Table 5: Annual Trading Strategy Profits - Unanticipated Depreciation

Country	Short strategy 1994	1995	1996	1997	1998	1999	Total
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

Country	Long strategy 1994	1995	1996	1997	1998	1999	Total
Hong Kong	0	0	0	0	0	0	0
India	1	-1	0	0	0	0	1
Indoñesia	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 signaled when the estimated monthly crisis probability exceeds 2.0 percent.
Crisis probabilities are calculated using estimates from beginning of sample Jan 1985 - Dec 1993.

Table 6: Estimation on Sample Excluding January 1994 to October 1999

	Unanticipated depreciation 5 percent	Unanticipated depreciation 10 percent	Total depreciation 5 percent	Total depreciation 10 percent
Constant	-3.88	-4.97	-3.60	-4.52
	(21.75)	(18.26)	(22.04)	(19.49)
Real GDP §	-0.20	-0.15	-0.24	-0.16
	(1.80)	(0.89)	(2.14)	(0.91)
Real effective exchange rate *f*	-0.10	-0.11	0.02	-0.08
	(0.87)	(0.61)	(0.17)	(0.42)
Exports ±	-0.20	-0.11	-0.07	-0.15
	(1.75)	(0.64)	(0.56)	(0.83)
Foreign direct investment §	0.03	0.05	-0.10	0.06
	(0.23)	(0.28)	(0.90)	(0.33)
Portfolio investment §	0.06	-0.03	-0.03	-0.04
	(0.46)	(0.16)	(0.26)	(0.20)
Foreign exchange reserves ±.	-0.46	-0.86	-0.24	-0.53
	(3.25)	(3.43)	(1.85)	(2.29)
Foreign exchange reserves/imports	-0.05	0.03	0.02	-0.10
	(0.34)	(0.17)	(0.13)	(0.46)
Official debt/total debt -	0.37	-0.44	-0.33	-0.35
	(3.06)	(2.36)	(2.69)	(1.86)
Budget deficit/GDP	-0.00	0.02	-0.03	0.02
	(0.04)	(0.14)	(0.36)	(0.13)
Global liquidity indicator	0.11	0.36	0.06	0.28
	(1.01)	(2.37)	(0.49)	(1.75)
Non-fuel commodity prices ±.	0.04	-0.12	0.01	0.02
	(0.33)	(0.59)	(0.10)	(0.11)
Capital account liberalization	-0.03	0.04	-0.18	-0.00
	(0.25)	(0.32)	(1.50)	(0.00)
Linear trend	-0.33	-0.36	-0.30	-0.28
	(2.40)	(1.73)	(2.15)	(1.30)
High inflation regime	0.09	0.22	0.08	0.05
	(0.74)	(1.17)	(0.63)	(0.27)
Lagged change	-0.09	-0.13	0.24	0.17
in exchange rate	(0.74)	(0.78)	(2.82)	(1.29)
Contagion	0.51	0.20	0.21	0.17
(export growth correlation)	(1.54)	(0.35)	(0.59)	(0.26)
Contagion	0.52	0.83	0.14	-0.18
(regional effect)	(2.29)	(2.37)	(0.61)	(0.45)
Log-likelihood	-379.26	-191.44	-382.36	-187.48
Number of crises	95.00	42.00	92.00	38.00
Number of observations	2692.00	2692.00	2692.00	2692.00
Likelihood ratio	63.48	49.93	37.33	24.31

Note: t-statistics appear in parentheses.

f Deviation from trend.

± Twelve-month percentage change.

§ Deviation from trend of twelve-month percentage change.

Table 7: Estimation on Sample Excluding January 1990 to December 1994

	Unanticipated Depreciation 5 percent	10 percent	Total depreciation 5 percent	10 percent
Constant	-3.86	-4.45	-3.64	-4.41
	(20.38)	(19.63)	(20.47)	(19.60)
Real GDP §	-0.09	-0.10	-0.19	-0.14
	(0.95)	(0.80)	(1.91)	(1.08)
Real effective exchange rate *f*	-0.23	-0.33	-0.09	-0.23
	(2.04)	(2.17)	(0.76)	(1.47)
Exports ±	-0.23	-0.03	-0.16	-0.00
	(1.85)	(0.23)	(1.33)	(0.02)
Foreign direct investment §	-0.06	-0.04	0.03	-0.15
	(0.58)	(0.28)	(0.23)	(1.08)
Portfolio investment §	-0.08	-0.07	-0.16	-0.14
	(0.85)	(0.58)	(1.47)	(1.00)
Foreign exchange reserves ±	-0.33	-0.27	-0.12	-0.12
	(2.72)	(1.79)	(1.02)	(0.81)
Foreign exchange reserves/imports	-0.21	-0.18	-0.20	-0.26
	(1.71)	(1.16)	(1.55)	(1.58)
Official debt/total debt	-0.24	-0.25	-0.16	-0.15
	(2.07)	(1.61)	(1.33)	(0.94)
Budget deficit/GDP	0.01	-0.02	-0.07	-0.01
	(0.12)	(0.20)	(0.83)	(0.13)
Global liquidity indicator	-0.18	0.10	-0.18	-0.03
	(1.26)	(0.57)	(1.21)	(0.16)
Non-fuel commodity prices ±	0.37	0.72	0.44	0.91
	(2.39)	(3.43)	(2.70)	(3.97)
Capital account liberalization	-0.08	-0.13	-0.05	-0.13
	(1.07)	(1.34)	(0.59)	(1.14)
Linear trend	0.03	-0.00	-0.15	0.04
	(0.26)	(0.00)	(1.12)	(0.22)
High inflation regime	0.61	0.80	0.59	1.00
	(3.94)	(3.70)	(3.44)	(4.02)
Lagged change	0.09	0.07	0.14	0.08
in exchange rate	(1.31)	(0.94)	(2.07)	(0.90)
Contagion	-0.03	-0.34	-0.20	-0.97
(export growth correlation)	(0.11)	(0.94)	(0.67)	(2.05)
Contagion	1.30	1.68	0.81	1.34
(regional effect)	(5.80)	(5.99)	(3.57)	(4.65)
Log-likelihood	-424.86	-277.59	-397.49	-254.73
Number of crises	124.00	73.00	106.00	64.00
Number of observations	2288.00	2288.00	2288.00	2288.00
Likelihood ratio	114.39	91.44	63.29	74.53

Note: t-statistics appear in parentheses

f Deviation from trend

± Twelve-month percentage change

§ Deviation from trend of twelve-month percentage change

Table 8: Estimation on Sample Excluding January 1985 to December 1989

	Unanticipated depreciation 5 percent	10 percent	Total depreciation 5 percent	10 percent
Constant	-4.11	-5.07	-3.77	-4.87
	(24.00)	(20.64)	(24.14)	(20.83)
Real GDP §	-0.33	-0.37	-0.39	-0.37
	(3.38)	(2.77)	(4.00)	(2.54)
Real effective exchange rate *f*	0.05	0.03	0.21	0.11
	(0.48)	(0.21)	(1.91)	(0.63)
Exports ±	0.00	0.22	-0.05	0.10
	(0.00)	(1.65)	(0.44)	(0.68)
Foreign direct investment §	0.02	0.12	-0.05	-0.10
	(0.19)	(0.80)	(0.48)	(0.66)
Portfolio investment §	-0.24	-0.28	-0.27	-0.34
	(2.42)	(1.96)	(2.66)	(2.22)
Foreign exchange reserves ±	-0.38	-0.76	-0.17	-0.46
	(3.05)	(3.59)	(1.55)	(2.31)
Foreign exchange reserves/imports	-0.38	-0.41	-0.22	-0.41
	(3.13)	(2.33)	(1.83)	(2.20)
Official debt/total debt	-0.06	-0.24	-0.04	-0.12
	(0.49)	(1.45)	(0.34)	(0.69)
Budget deficit/GDP	-0.17	-0.08	-0.13	-0.08
	(1.46)	(0.50)	(1.30)	(0.47)
Global liquidity indicator	-0.30	-0.10	-0.27	-0.30
	(2.21)	(0.56)	(1.88)	(1.41)
Non-fuel commodity prices ±	-0.13	-0.07	-0.10	-0.06
	(1.06)	(0.46)	(0.84)	(0.32)
Capital account liberalization	-0.00	-0.01	-0.04	0.03
	(0.05)	(0.06)	(0.44)	(0.26)
Linear trend	0.09	-0.12	-0.03	-0.04
	(0.74)	(0.65)	(0.28)	(0.23)
High inflation regime	0.33	0.22	0.19	0.34
	(2.84)	(1.38)	(1.60)	(2.04)
Lagged change	-0.05	0.05	0.20	0.21
in exchange rate	(0.46)	(0.51)	(2.64)	(1.99)
Contagion	0.07	0.08	-0.81	-1.55
(export growth correlation)	(0.24)	(0.16)	(1.81)	(1.49)
Contagion	0.98	1.19	0.52	0.66
(regional effect)	(4.70)	(4.03)	(2.49)	(2.10)
Log-likelihood	-461.62	-251.37	-465.38	-229.71
Number of crises	124.00	62.00	116.00	51.00
Number of observations	3300.00	3300.00	3300.00	3300.00
Likelihood ratio	133.82	112.94	73.86	67.11

Note: t-statistics appear in parentheses.
f Deviation from trend.
± Twelve-month percentage change.
§ Deviation from trend of twelve-month percentage change.

Table 9: Trading Strategy Statistics for Crisis Probability 3.0 Percent

	Cumulative excess profits				
	Total profit (x100)	Profit per trade	t-stat	p-value	Risk premium for total profits
Short strategy					
Unanticipated depreciation					
-estimation on whole sample; trading profit over whole sample	7.48	0.92	3.10	0.00	-0.11
-estimation on data to 12/93; trading profits over hold-o ut sample	4.09	0.85	2.99	0.00	-0.59
-estimation exc. middle of data; trading profits over ho ld-out sample	0.27	0.15	0.35	0.36	-0.00
Total depreciation					
-estimation on whole sample; trading profit over whole sample	6.41	0.65	2.90	0.00	-0.06
-estimation on data to 12/93; trading profits over hold-out sample	4.00	0.80	3.16	0.00	-0.68
-estimation exc. middle of data; trading profits over ho ld-out sample	0.56	0.19	0.38	0.35	-0.08
Long strategy					
Unanticipated depreciation					
-estimation on whole sample; trading profit over whole sample	3.45	0.15	1.26	0.10	-0.18
-estimation on data to 12/93; trading profits over hold-out sample	2.26	0.28	1.46	0.07	-0.13
-estimation exc. middle of data; trading profits over ho ld-out sample	-0.07	-0.01	-0.05	0.52	-0.23
Total depreciation					
-estimation on whole sample; trading profit over whole sample	2.17	0.10	0.76	0.22	-0.07
-estimation on data to 12/93; trading profits over hold-out sample	2.33	0.30	1.45	0.07	-0.07
-estimation exc. middle of data; trading profits over ho ld-out sample	-0.42	-0.05	-0.21	0.58	-0.10

Short strategy.
Total profit over funding cost on shorting markets by US$1 each time that estimated probability exceeds 3.0 percent.
Long strategy.
Total profit over funding cost on investing US$1 in market each time that estimated probability falls below 3.0 percent.
Risk premium
This is the CAPM risk premium relevant for the total trading profit calculated using US S&P 500 index.

Table 10: Sub-sample of Countries on all Data: January 1985 to October 1999
with Capital Flows Variables

	Unanticipated Depreciation				Total depreciation			
	5 percent	t-stat	5 percent	t-stat	5 percent	t-stat	10 percent	t-stat
Constant	-3.75	27.93	-4.76	23.77	-4.04	26.79	-5.05	23.21
Real GDP	-0.28	3.28	-0.25	1.91	-0.18	2.20	-0.20	1.57
Real effective exchange rate	0.03	0.29	-0.11	0.74	-0.15	1.66	-0.17	1.18
Exports	-0.08	0.79	0.05	0.37	-0.14	1.57	0.10	0.72
Foreign direct investment	-0.11	1.19	-0.19	1.39	-0.07	0.81	-0.00	0.04
Portfolio investment	-0.17	1.93	-0.24	1.77	-0.14	1.64	-0.18	1.47
Foreign exchange reserves	-0.23	2.22	-0.52	2.83	-0.48	4.12	-0.84	4.28
Foreign exchange reserves/imports	-0.19	1.74	-0.35	2.08	-0.27	2.56	-0.24	1.51
Official debt/total debt	-0.16	1.52	-0.18	1.15	-0.22	2.22	-0.30	2.04
Budget deficit/GDP	0.04	0.52	0.03	0.29	0.01	0.18	0.04	0.37
CAPITAL INFLOWs	-0.04	0.14	0.51	1.22	0.55	1.97	0.39	0.96
CAPITAL OUTFLOWs	0.22	0.74	-0.27	0.63	-0.42	1.41	-0.31	0.75
Global liquidity indicator	-0.12	1.07	0.01	0.08	-0.07	0.72	0.14	1.05
Non-fuel commodity prices	-0.03	0.25	0.04	0.26	-0.01	0.10	-0.05	0.31
Capital account liberalization	-0.07	0.89	-0.02	0.19	-0.03	0.36	-0.02	0.25
Linear trend	-0.14	1.29	-0.06	0.38	-0.05	0.48	-0.11	0.70
High inflation regime	0.08	0.68	0.12	0.73	0.17	1.66	0.11	0.76
Lagged change in exchange rate	0.21	3.25	0.16	1.80	-0.02	0.20	-0.00	0.01
Contagion (export growth)	-0.11	0.38	-0.42	0.76	0.22	0.89	0.11	0.29
Contagion regional	0.49	2.67	0.61	2.19	0.95	5.18	1.32	5.10

Figure 1: Total number of Crises in each Year

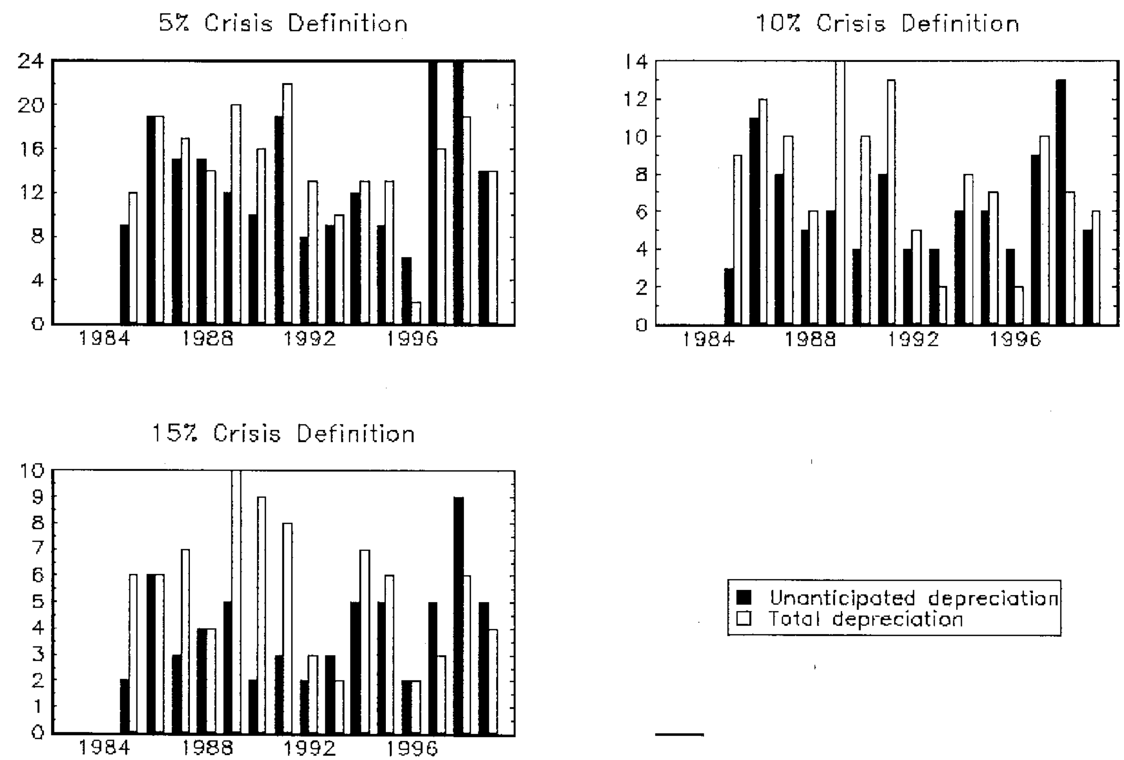


Figure 2a: Unanticipated depreciation
Annual number of Crises by region

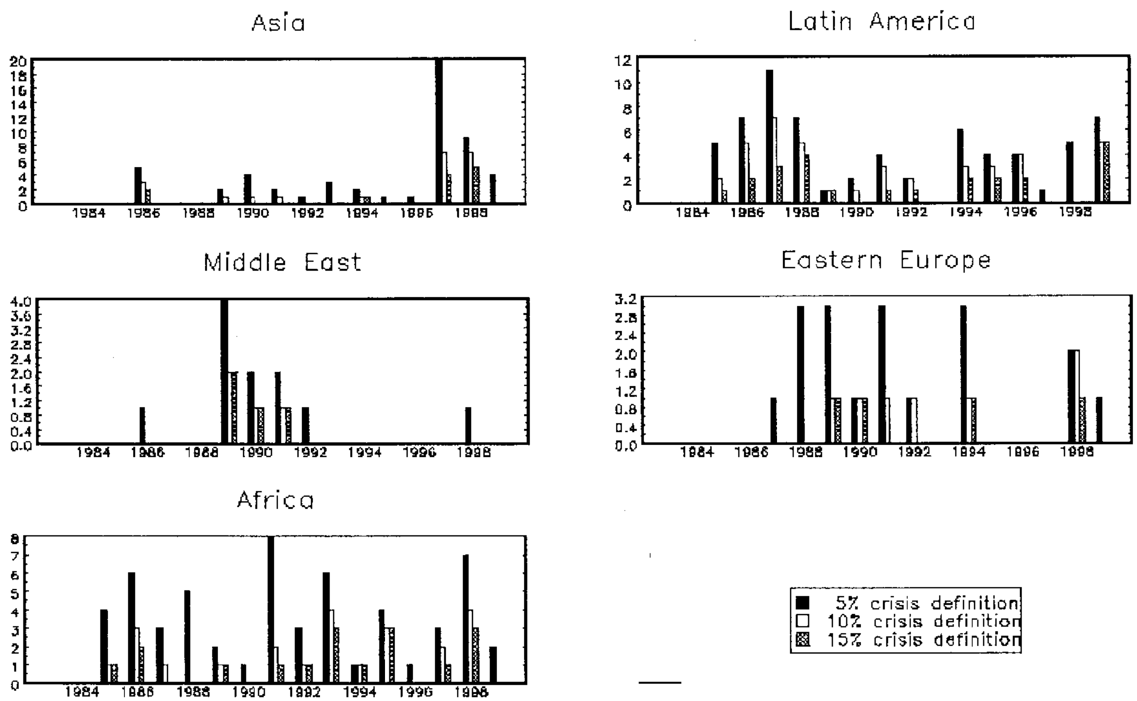


Figure 2b: Total depreciation
Annual number of Crises by region

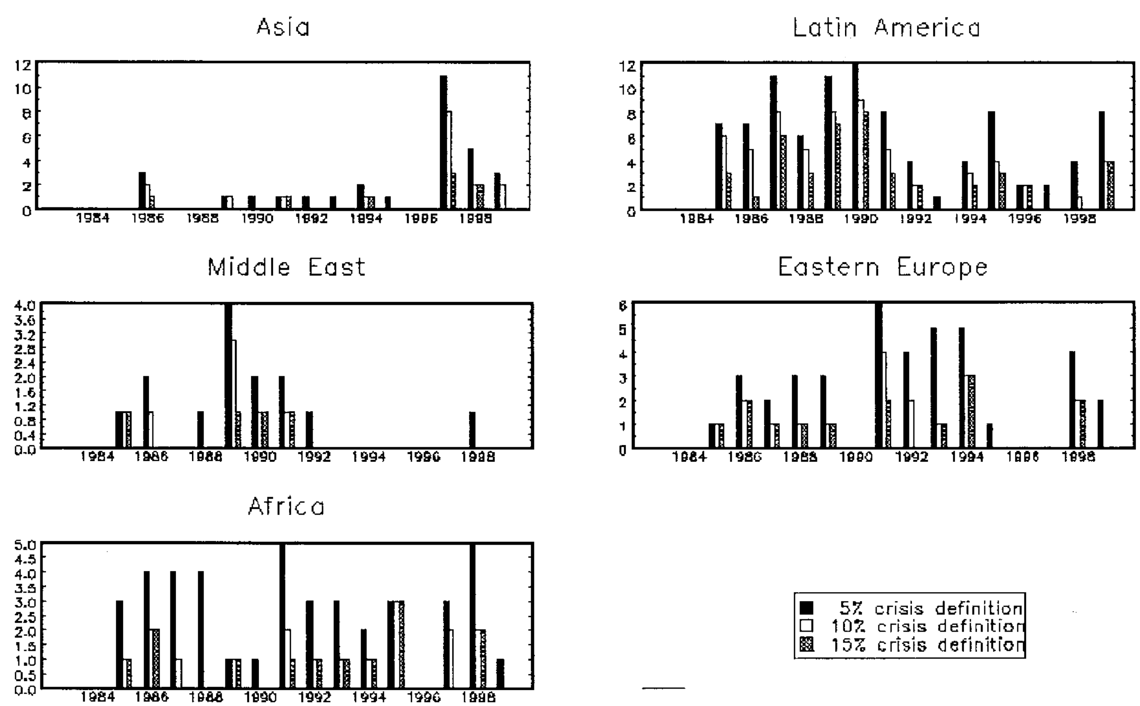


Figure 3: Crisis Probabilities – Unanticipated Depreciation

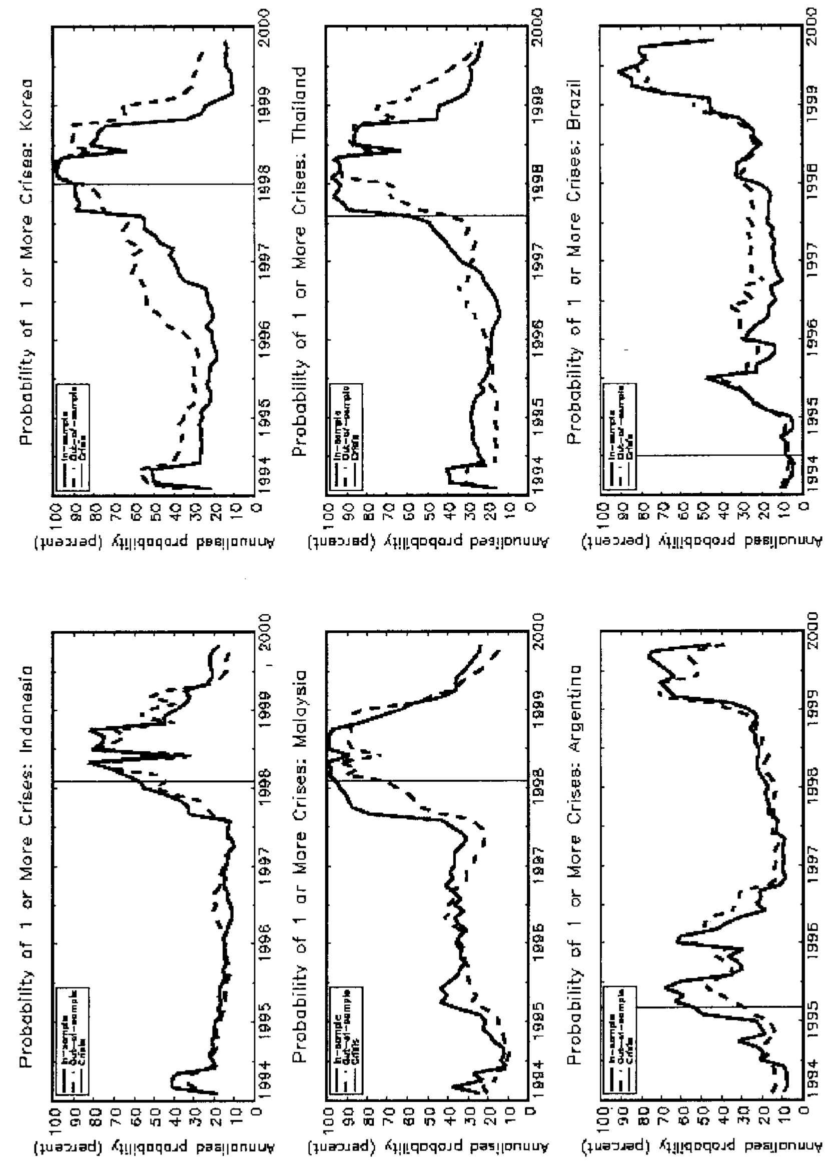


Figure 3: Crisis Probabilities – Unanticipated Depreciation (contd.)

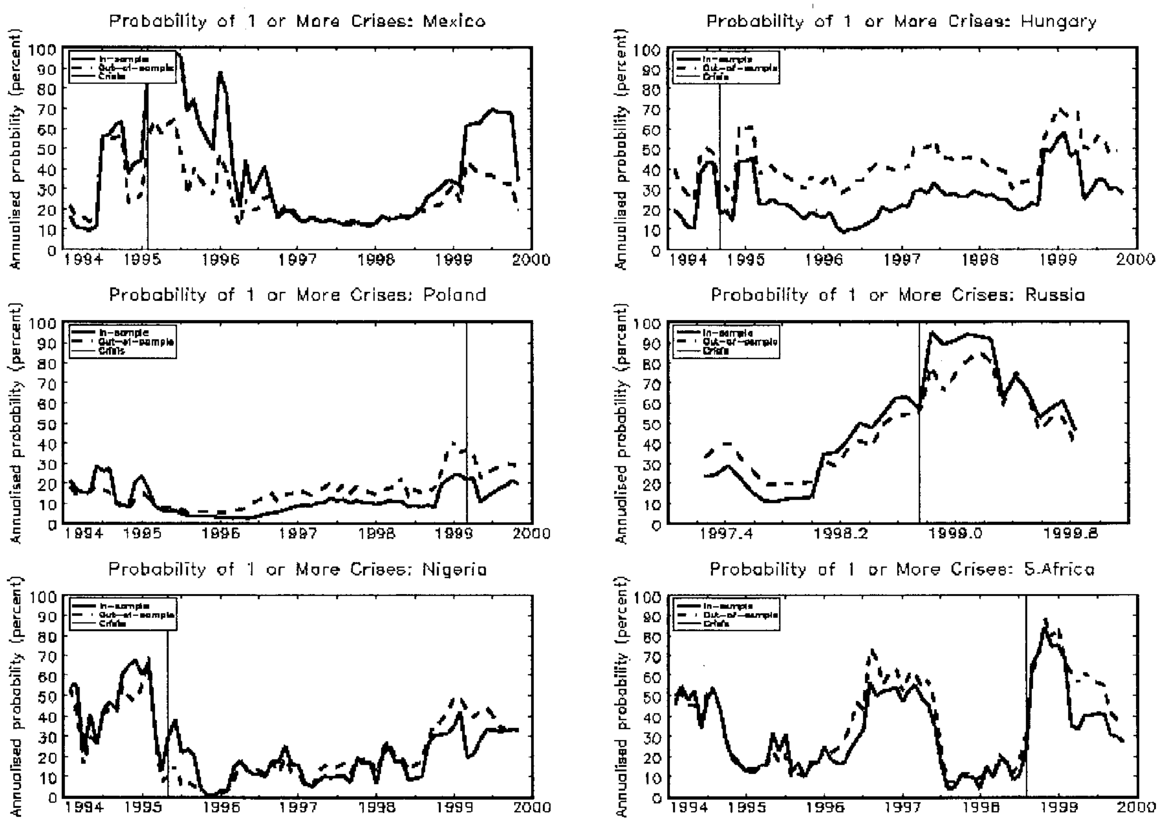


Figure 4: Crisis Probabilities – Total Depreciation

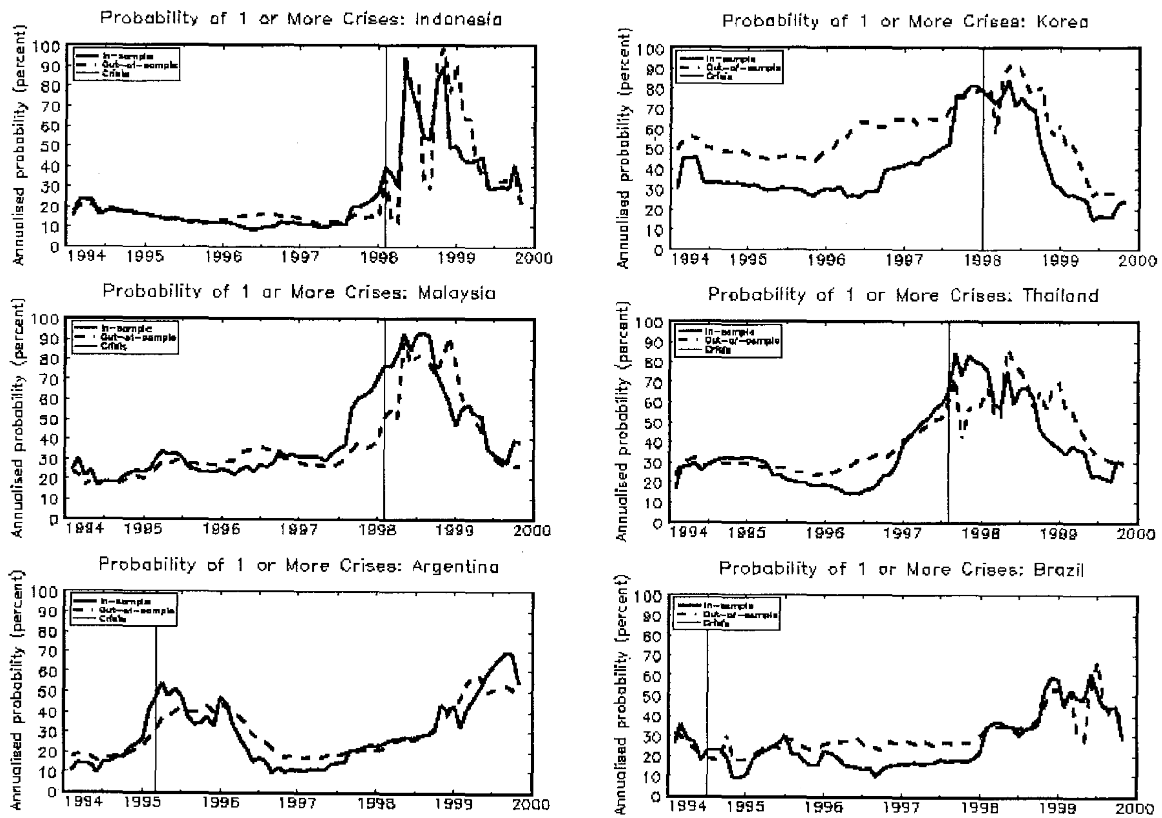
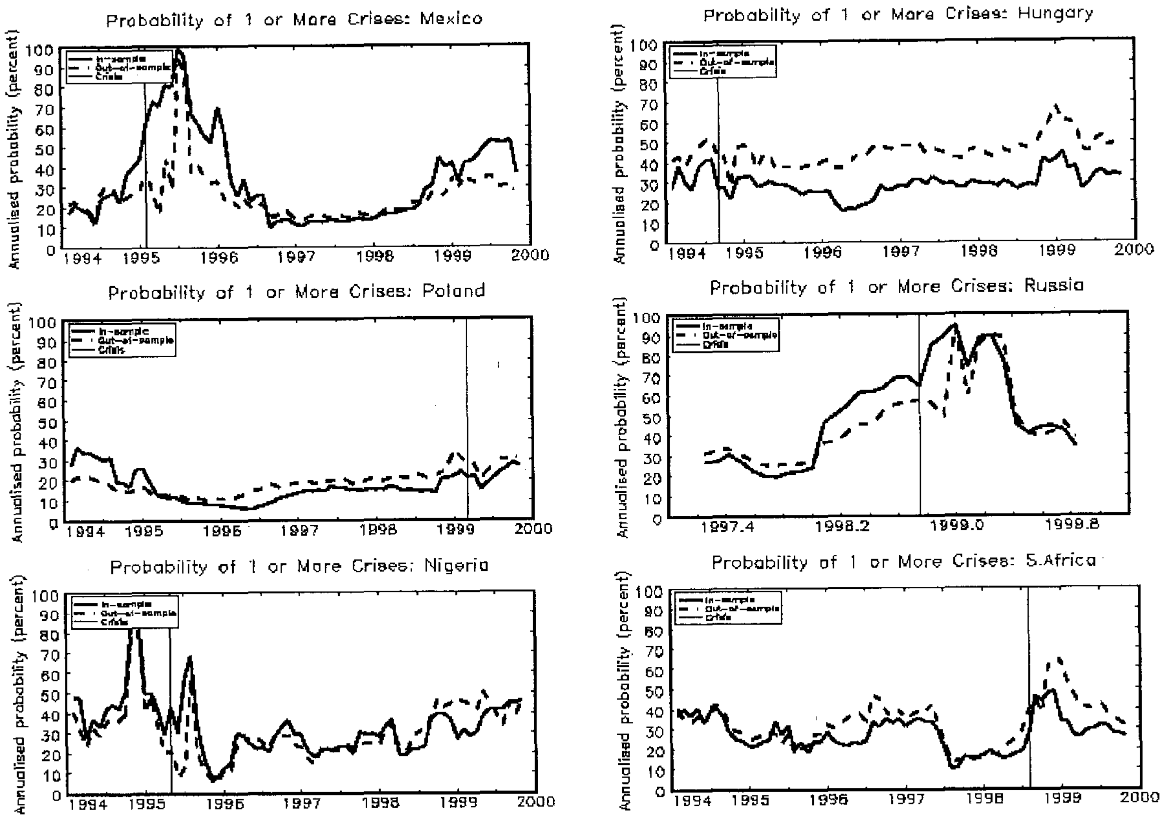


Figure 4: Crisis Probabilities — Total Depreciation (contd.)



Data

Countries in Estimation Sample
Africa: Kenya, Morocco, Nigeria, South Africa, and Zimbabwe.
Asia: China, Hong Kong, India, Indonesia, Korea, Malaysia, Pakistan, Philippines, Singapore, Sri Lanka, and Thailand.
Eastern Europe: Hungary, Poland, Russia, and Turkey.
Latin America: Argentina, Brazil, Chile, Columbia, Ecuador, Mexico, Peru, and Venezuela.
Middle East: Egypt, Israel, Jordan, and Kuwait.

Countries in Trading Strategy Sample
Africa: Kenya.
Asia: Hong Kong, India, Indonesia, Korea, Malaysia, Pakistan, Philippines, Singapore, and Sri Lanka.
Eastern Europe: Hungary, Poland, Russia, Turkey,
Latin America: Argentina, Brazil, Ecuador, and Mexico.
Middles East: Israel.

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 twelve-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 million of US$; twelve-month percentage change; monthly data.
4. *Foreign direct investment* **FDI** Net foreign direct investment in millions of US$; deviation from trend; annual data interpolated by cubic splines.
5. *Portfolio investment* **PINV** Net portfolio investment in millions of US$; deviation from trend; annual data interpolated by cubic splines.
6. *Foreign exchange reserves* **FXR** Foreign exchange reserves, excluding gold, in millions of US$; twelve-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$; twelve-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; twelve-month percentage change; monthly data.
11. *Commodity prices* Global non-fuel commodity price index; twelve-month percentage change; monthly data.

12. *Capital Account liberalization* Dummy variable set to 1 if country's economy is liberalized, 0 otherwise.
13. *Liner trend.*
14. *High inflation regime* Dummy variable set to 1 if the annualized rate of acceleration of bimonthly inflation exceeds 100 percent, 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 three months; 0 otherwise.
17. *Contagion (regional effect)* Dummy variable set to 1 if any country in the region suffered a crisis within the last three months; 0 otherwise.

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