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Safety from Currency Crashes

KENT OSBAND and CAROLINE VAN RIJCKEGHEM*

As part of a proposed two-stage early warning system, we estimate "safety zones" for fundamentals under which currency crashes are unlikely to occur. We depart from traditional regression-based early warning systems and instead estimate the set of fundamentals for which currency crises never occurred and label this environment "safe or near-safe." For a sample of emerging markets from 1985 through 1998, we are able to classify 47 percent of the observed tranquil environments as safe or near-safe on a 12-month horizon, based on criteria in which external debt and reserves feature heavily. Nonparametric tests indicate that environments we identified as safe or near-safe bear less than a 1 percent risk of a currency crash. The results also pass a number of out-of-sample tests. [JEL: F31, F47]

In the past decade a sizable literature on early warning systems of currency crises has developed.[1] A common feature of this literature is that, using probit or logit models, it establishes a one-to-one relationship between the probability of a crash and fundamentals. This paper complements the literature by focusing instead on "safety zones," which identify those fundamentals for which crises never occur.

The motivation for the approach is three-fold. First, the approach yields information on safe or near-safe environments. This is potentially useful on its own; it can act as a guide to risk-averse policymakers and investors and help manage risk by aiding investors in deciding how much capital to set aside against their portfolios. Probit- and logit-based models can also provide this information: for any

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[1]See Eichengreen, Rose, and Wyplosz (1995), Frankel and Rose (1996), Kaminsky, Lizondo, and Reinhart (1998), Berg and Pattillo (1999), and Bussiere and Mulder (1999).

chosen probability of a currency crash, these models can be solved for the required level of fundamentals. In that regard, our approach provides complementary estimates of safe environments.

A second motivation stems from the possibility of multiple equilibria. As a growing literature on self-fulfilling expectations emphasizes (e.g., Obstfeld, 1994; Cole and Kehoe, 1996), a given vector of fundamentals may be consistent with more than one equilibrium. For example, the high interest rates induced by a market expectation of devaluation might themselves influence a government to devalue out of concern for unemployment, budgetary pressures, or banking system soundness. Yet the same government dealing with the same fundamentals but with more optimistic markets might not devalue. Investors with limited information may rationally follow the herd, leading to sudden jumps from one equilibrium to another (Banerjee, 1992; Bikhchandani, Hirshleifer, and Welch, 1992; Calvo and Mendoza, 1996). Fundamentals still play a role, as they tend to determine whether multiple equilibria are possible in the first place: for sufficiently strong fundamentals, a currency may never be attacked (Krugman, 1996; Jeanne, 1997; Flood and Marion, 1998; and Masson, 1998).

A framework based on estimation of safety zones is logically consistent with the existence of multiple equilibria, whereas conventional probit or logit analysis is not necessarily so. If for given fundamentals a crisis could or could not occur, one cannot expect a one-to-one relationship between fundamentals and the probability of a currency crash, as is presumed by probit or logit analysis.[2] This characteristic tends to make crisis prediction based on fundamentals particularly difficult and could explain the rather poor performance of empirical models to date (Berg and Pattillo, 1999).[3] For instance, during the Asian crises, even the best-predicting model—the "signals" approach of Kaminsky, Lizondo, and Reinhart (1998) (KLR)—did not predict well out of sample.[4]

Third, estimates of safety zones can be combined with other early warning systems to improve predictive ability. The identification of safe currencies/episodes, using mainly measures of economic fundamentals, would then constitute the first stage of a two-stage method. One possibility for the second stage would be to estimate crash probabilities for currencies not identified as safe in the first stage, using mainly *financial market variables* (e.g., interest rates and capital flows). If the multiple equilibria view is correct, such a two-stage method can be expected to work better than a fundamentals-only approach. Another possibility is to combine *existing early warning systems* for currency crashes with the first stage output: as we discuss

[2]For elaboration of this point in the context of a model of multiple equilibria, see the full version of this paper, available upon request.

[3]Flood and Marion (1998) provide a potential alternative explanation to multiple equilibria for the poor performance of empirical models, focusing on the role of uncertainty. They argue that the widely used definition of crises by Eichengreen, Rose, and Wyplosz (1995), where crises are defined as observations that are 2 standard deviations greater than the average exchange market pressure index, predisposes the sample towards containing few predictable (i.e., anticipated) crises, because predictable crises tend to be associated with relatively small changes (or even changes in the "wrong" direction) in reserves, exchange rates, and interest rates at the time a peg is abandoned.

[4]KLR called only 25 percent of "precrisis months" correctly, while the rate of false alarms was 63 percent. With fewer false alarms allowed, only 4 percent of these months were called correctly (Berg and Pattillo, 1999).

later, one can improve on virtually any existing early warning system by filtering out safe currencies first. We concentrate on the first stage estimation in this paper.

Our method can be summarized as follows. We identify safe zones by looking at both univariate and composite indicators (unions, linear combinations, and intersections of univariate indicators) involving fundamentals. We next find thresholds for the different indicators such that no crises, which we define as large currency devaluations, have ever been observed for values of the indicator beyond the threshold. In other words, we filter out all environments that appear healthier than the healthiest precrisis environments. To give a simple example, if the highest ratio of reserves to short-term debt for which a crisis has ever been observed within a given period (say a year) is three, we classify as safe all environments where the reserves are more than triple the short-term debt.

One potential challenge to the method is that thresholds can end up being very lax if at least one crisis occurred when the fundamentals were basically sound. In that case, very few observations would be considered safe, causing our method to lose its practicality. A second challenge is that some day a crisis is bound to happen under more favorable fundamentals than in the past, which means that we cannot hope to identify regimes that are 100 percent safe (this is why we use the term "safe or near-safe"); we investigate the likelihood of this happening—that is, we investigate the statistical properties of our estimator, using nonparametric techniques. Our tests turn out to meet these challenges rather well, as we identify a fairly large class of safe or near-safe currency environments. For a sample of 3,755 country-months in emerging markets, nearly half are classified as having a less than 1 percent chance of large (10 percent) devaluation of the local currency on a 12-month horizon. Thus, our approach does appear to have considerable practical merit. We also check our results out of sample for industrial countries and for the Brazilian January 1999 devaluation and find that the model performs well.

The paper is organized as follows. Section I presents our method of identifying safe zones and presents the main statistical properties of our first-stage filters. Section II discusses practical issues in estimation, Section III presents our main results for emerging markets, and Section IV presents out-of-sample results. Section V concludes. In Appendix I, we develop the statistical properties of our proposed filters using nonparametric techniques. In Table A1, we provide crisis dates for our sample of countries. In Table A2, we list the data sources.

I. Methodology

The filters we use extract low-risk observations by looking for fundamentals X that exceed certain thresholds M, during precrisis periods. Formally, we describe a filter F as a mapping from a set Ω of observations to a subset $F(\Omega)$. Each member of $F(\Omega)$ is called an extraction from Ω under the filter. As noted previously, we are particularly interested in filters that set the thresholds high enough to exclude all precrisis observations, but not any higher.

We apply four types of threshold filters, which we label "ordinary," "multilinear," "union," and "intersection":

- An ordinary filter relies on a single variable X and threshold m. X is signed so that higher values mean stronger fundamentals.

- An intersection filter takes the logical intersection (Boolean "and" condition) of its component filters. It classifies an observation as low risk if and only if every component filter does.
- A multilinear filter forms a new variable Y out of a linear combination of other variables X. Otherwise it works like an ordinary filter.
- A union filter takes the logical union (Boolean "or" condition) of its component filters. It classifies an observation as low risk if and only if at least one component filter does.

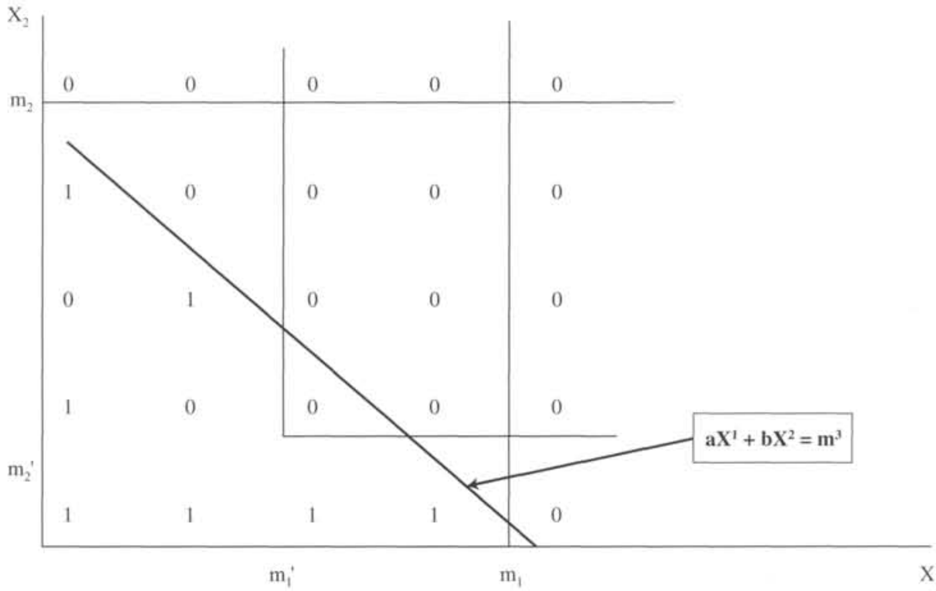
Figure 1 depicts these four types of filters graphically in an example with two indicators, X_1 and X_2. Thresholds are denoted by "m." Zeros represent tranquil periods and ones precrisis periods. We will later define precrisis periods as observations lying within a year of a currency crash. Note how the number of precrisis observations declines to zero as one moves into the Northeastern quadrant of the graph, as fundamentals improve. In the example, nine tranquil observations can be extracted (i.e., classified as "safe") based on the union of two ordinary filters, $X_1>m_1$, $X_2>m_2$. Based on the intersection filter $X_1>m_1'$ and $X_2>m_2'$, an additional six tranquil observations can be classified as safe. Using the multilinear filter $aX_1+bX_2>m_3$, one additional tranquil observation can be extracted. After application of these four filters, three tranquil observations (along with six precrisis observations) remain in the vulnerable zone. A union filter of these four filters labels an observation as safe as long as one of the four filters does so.

As noted in the introduction, we cannot hope to identify completely safe regimes. Thresholds are estimated based on finite samples and could be violated by a future crisis. We develop the statistical properties of our estimator, using nonparametric techniques in Appendix I. That discussion suggests that, as long as observations are independent, individual tests should be based on at least 99 extractions, in order to ensure *with 99 percent confidence* that a currency environment does not lead to crisis within 12 months. Without independence, i.e., in the case of serial correlation of fundamentals, a multiple of this number of extractions is required. The above applies to individual filters. Filters can always be combined into a union of filters, thereby yielding a larger number of extractions. The confidence one has that an observation is safe based on the union of filters depends on the number of individual filters that extract the observation. Confidence will be higher for observations extracted by several filters, lower for those that fail to be extracted by some filters. When an observation is extracted by one filter but not another, confidence is higher when there is a large number of "marginal" extractions by the former and a low number by the latter. Finally, since a larger number of filters in a union can reduce the degree of confidence about whether an extracted observation is safe (because it is more likely at least one filter will not extract the observation), we restrict the number of component filters in our proposed union filter.

II. Practical Issues of Estimation

Let us now turn to practical issues of estimation. In order to have sufficient confidence in our estimates, we tried to estimate the model conservatively. To this end we made a series of ad hoc adjustments:

Figure 1. Delineating Safety



Legend: 0 = tranquil period (i.e., not followed by a crisis)
1 = precrisis period (i.e., followed by a crisis)

- We used only variables with an economically plausible connection with currency crises. We did this by focusing on variables that other papers found to be empirically relevant.
- We gave ordinary filters precedence over multilinear filters, as the former are easier to understand and interpret and less prone to overfitting.
- We restricted multilinear filters to combinations of four variables at a time using a grid of five possible weights, with care taken to span the space relatively evenly and avoid near-duplication. This reduced our search to 369 tests per combination, which our spreadsheets could easily manage.[5] We also checked for robustness to small shifts in weights.
- We restricted intersection filters to combinations of two ordinary filters. To simplify the search we constrained one of the thresholds to equal the average value observed for the variable in question and then adjusted the other threshold to exclude all precrisis observations while also extracting the largest possible number of tranquil periods.
- Most important, we concentrated on finding filters with several hundred extractions and with nearly 100 or more marginal extractions, so that even if the

[5]Looking for multilinear filters amounts to choosing the best slope for separating hyperplanes. Without loss of generality, the highest weight on a variable can always be taken as one. For four parameters selected from a grid of five weights including one, there are 5^4=625 distinct combinations but 4^4=256 do not contain any ones. So the number of distinct combinations containing ones equals 625–256=369. We chose to search evenly in the space of angles. Hence, we chose our five weights as $\{\tan(k\pi/16)\}$ for k=0 to 4, or {0,.20,.41,.67,1}.

preliminary estimates of risks have to be multiplied several times (because independence might not be expected to hold and because we take the union of a number of filters) the chances of a crash remain slim.

Variables

We include variables that are common in the currency crisis literature.[6] Some affect an economy's direct vulnerability to sudden outflows. Others affect the government's willingness to mount an interest rate defense. The variables are as follows:

- Gross international reserves enter in three ways: as a ratio to imports (capturing the traditional concept), as a ratio to a broad money aggregate (Calvo and Mendoza, 1996), and as a ratio to short-term debt (Rodrik and Velasco, 1999).
- The government balance and the growth in domestic credit to the government are standard first-generation variables.
- Growth in domestic credit to the private sector is a proxy for fragility of the banking system as in Sachs, Tornell, and Velasco (1996).
- The four-year growth rate of the real exchange rate, the current account balance, the growth rate of exports, and the three-year growth in the terms of trade are measures affecting competitiveness and current account sustainability.
- Foreign direct investment, portfolio investment, debt service relative to exports, external debt relative to exports, and the share of official debt in total debt are measures affecting the capital account.
- Growth rates of real GDP and industrial production affect nearly every other measure of sustainability.
- A diversified export base helps countries withstand terms of trade and other shocks.[7]

Data Issues

We relied on International Financial Statistics and Global Development Finance as the data are generally standardized and well vetted.[8] Our core data cover the

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[6]See Kaminsky, Lizondo, and Reinhart (1998) for a review of the empirical literature.

[7]We checked whether a country was a fuel or primary commodity exporter, using the WEO 1999 criterion that these categories constitute more than half of export earnings (p. 130). The countries in our sample where this was the case are Nigeria, Zimbabwe, Chile, Peru, and Venezuela.

[8]However, a few problems of data comparability remain. The data on the fiscal deficit is reported in nominal terms without correcting for the impact of inflation on the debt stock (which is really a form of amortization) and hence overstates the fiscal stresses on indebted high-inflation countries (see Blejer and Cheasty, 1993). Also it records central government operations only and hence may understate the stresses on countries with high provincial government deficits. For reserves, we use official gross reserves excluding gold, which understate the stresses on countries with large pledged or otherwise tied-up reserves, such as the 1997 crisis revealed in Asia. For short-term external debt, some countries include debt to the non-bank corporate sector and some do not, and there are other differences as well. For liquid liabilities (used as a denominator for reserves), we used the broad aggregate money plus quasi-money, including foreign exchange deposits, but for some countries a broader or unequally weighted aggregate might be more appropriate. We measure only external debt, not external assets, which is problematic for the creditor countries Hong Kong and Singapore, but fortunately does not affect our analysis because there were no crises in these two countries in the period we cover, so that these countries do not influence the best fundamental in precrisis (i.e., the thresholds).

period 1985–98 for 31 emerging markets.[9] We chose to work with a relatively heterogeneous period in order to be able to span regimes with and without capital mobility. The regimes without capital mobility are regaining relevance because of the introduction of capital controls in some countries and reduced investor appetite for emerging market assets.[10]

We also ensured that the data were available before the forecast observations occur. This is crucial for a genuine early warning system. It means, however, that one cannot interpolate annual data or apply any technique that contaminates the data with future information.[11] Monthly data are unfortunately not available for many variables. To avoid forward-looking interpolation, we used the last available data: quarterly data three months lagged if available and annual data 12 months lagged otherwise.

Crisis Definition

A crisis or currency crash is defined to occur if the monthly depreciation exceeds 10 percent and also exceeds the monthly average depreciation 3–14 months prior to the crisis plus twice the standard deviation of the rate of depreciation over the preceding two years.[12] This definition follows the spirit of Frankel and Rose (1996), though not the letter.[13] It excludes pure "reserves" crises and surges in interest rates that are not associated with large spot FX rate movements—e.g., the "successful defenses" reviewed in Eichengreen, Rose, and Wyplosz (1995).

[9]The countries are Argentina, Brazil, China (from 1992), Chile, Colombia, Ecuador, Egypt, Hong Kong, Hungary (from 1992), India, Indonesia, Israel, Jordan, Kenya, Korea, Malaysia, Mexico, Morocco, Nigeria, Pakistan, Peru, Philippines, Poland (from 1992), Russia (from 1992), Singapore, South Africa, Sri Lanka, Thailand, Turkey, Venezuela, and Zimbabwe.

[10]One related issue of particular concern is the definition of the exchange rate used. IFS reports either the market rate or the official exchange rate (in the case of multiple exchange rate arrangements, usually the principal rate). Which one is reported depends on which series is designated as the most representative by the monetary authorities (Introduction to IFS, September 1999, p. ix). For countries without capital controls, this rate is the market rate. An appendix to the full version of this paper indicates which series was used for countries with capital controls.

[11]If after a crisis the real exchange rate depreciates, growth slows, the current account improves, and short-term debt shrinks, then with hindsight the precrisis levels will tend to look high relative to their longer-term interpolated norms or estimated equilibrium levels. The deviations between actual and "equilibrium" values might then test out to be good leading indicators, but in fact the predictions might simply be "postdictions" based on postcrisis data. To give a concrete example, using Hodrick-Prescott filters to estimate equilibrium GDP or real exchange rates will lead one to conclude that most Southeast Asian economies were significantly overheating before the crises of 1997. However, those particular deviations could not have been observed before the crises erupted. Instead, the low values of output and the real exchange rate after the crisis dragged down the precrisis measures of the equilibrium output and the equilibrium real exchange rate.

[12]We exclude the nearest two months to take into account crises that span several months. For the standard deviation of the exchange rate depreciation we use the exchange rate over the 26th–3rd month prior to the current date.

[13]Frankel and Rose, who use annual data, define a currency "crash" as a nominal depreciation of the currency of at least 25 percent that is also at least a 10 percent increase in the rate of depreciation. Because we use monthly data, we use the much lower 10 percent cutoff for the nominal depreciation rate.

Forecast Horizon

Our forecast horizon is one year. That is, we label environments as "precrisis" if they are followed within one year by a currency crash. The choice of a one-year horizon is only partly arbitrary. A much shorter forecast horizon would be difficult to implement, given the lags in obtaining data.

Sample

Our sample consists of 3,755 monthly observations. These comprise 54 crisis months, 523 precrisis months, and 3,178 tranquil months. In keeping with a tradition in the currency crisis literature, we exclude crises that closely (within 12 months) follow earlier crises. This avoids classifying as precrisis some environments that are more appropriately treated as crisis. Actually we go further and exclude all data occurring less than 12 months after a crisis. We do this, because after a crisis, given data lags, the last available data would in many instances refer to the *precrisis* fundamentals, when really the crisis is triggering a rapid change in fundamentals. Our results should thus be interpreted as answering the question "Is there more than a small chance of crisis within a year, conditional on not having had a crisis in the last year?"

We also excluded most data from 1998, because at the time we performed the bulk of our tests we did not know whether and where crises would occur in 1999.

III. Findings for Emerging Markets

Using a union (Boolean "or" condition) of nine filters, we were able to classify 47 percent of the 3,178 tranquil observations as associated with very low risk of a currency crash on a 12-month horizon. One filter alone extracted nearly 500 tranquil observations, while the weakest extracted 165. For comparison, note that a filter with no early warning power for currency crashes should on average extract just over six observations from our sample, and the standard deviation should be only 2.5 if the observations are independent.[14] Granted, the means will be much higher for a search among hundreds of possibilities for the best filters on a sample that contains clustered observations. Nevertheless, the chances of seeing random outliers of this magnitude are very small.

Of these nine filters, three are ordinary filters. The first two ordinary filters are the ratio of reserves to short-term debt and the ratio of debt service to exports. They indicate that a country that can easily service its debts out of export proceeds or reserves can also protect its currency. The third ordinary filter examines the share of official debt in total debt. Official debts are likely to be more stable than private debts as donor countries presumably generously issue new debt or roll

[14]Consider a sample consisting of $C+T$ random, independent observations, with C equal to the number of precrisis and T equal to the number of tranquil observations. For any of the last T observations, the probability of outperforming all the previous C would be $1/(C+1)$. It follows that $T/(C+1)$ outperformances would be expected with a standard deviation of $\sqrt{CT}/(C+1)$.

over old debts in difficult times. In other words, all three ordinary filters link currency crashes to difficulties in servicing external debt.

A large number of emerging market environments are safe on the grounds of these variables related to external debt. Nearly one-quarter of all tranquil emerging market environments during 1985–98 had safety margins in either their reserves, exports, or official debt shares that exceeded the best margins ever achieved in precrisis environments. Markets with such high margins would appear able, with over 99 percent confidence, to fend off a local currency crash for at least 12 months.

Five of the high-powered filters involve intersections of ordinary filters. Four of these intersections involve one variable related to external debt and one variable related to some non-debt fundamental expressed as either a growth rate or a share of GDP. The fifth intersection involves a condition on the current account and one requiring diversified exports. The results indicate, again quite plausibly, that current account surpluses, fiscal surpluses, real GDP growth, and FDI can successfully mitigate debt servicing pressures. The most important coupling turned out to be the current account with the debt-to-export ratio. In the sample examined, no emerging market ever experienced a currency crash less than 12 months after simultaneously attaining a better-than-average current account and an external debt of less than 85 percent of exports. What is perhaps more surprising is that nearly 13 percent of all emerging market environments (407 observations) met that criterion in tranquil times. It was the second strongest single filter we uncovered. The related filter, combining a current account balance over 3 percent of GDP with a diversified export structure, is also very powerful, extracting a similar number of observations (386).[15]

Another intersection filter linked the fiscal balance with reserves to short-term debt. Since currencies are often perceived as weakest when fiscal and external financing pressures coincide, an even stronger effect might have been expected. Perhaps this reflects the fact that the nominal fiscal balance is an inadequate measure of fiscal financing pressures (see footnote 8).

The remaining two intersection filters link FDI and real GDP growth respectively with the share of official debt in total debt. FDI, like official financing, tends to be less volatile than other capital flows, and hence is a natural complement to the share of official flows. That growth complements the currency protections of official aid is also hardly surprising. If a country depending heavily on official aid and loans is growing poorly, then the standard policy adjustment entails a devaluation. Conversely, if growth or investment prospects are good, neither official lenders nor private investors are likely to press for devaluation.

[15]While the Boolean "and" condition requiring a diversified export base led to lower extraction thresholds for our filters for several variables, including the budget and current account balance (to 3 percent of GDP), foreign direct investment (to 6 percent of GDP), the debt-export ratio (to 0.4), the change in domestic credit to the private sector as a percent of GDP (to 4 percent), and real exchange rate depreciation (to 50 percent), and excepting the last two variables, all these filters were also associated with extractions over 100 tranquil observations, only the filter involving the current account balance had marginal observations over 50. Hence, only this filter is reported in Table 1.

The last filter is multilinear. We examined 126 four-variable combinations chosen from nine variables: reserves to M2Y, reserves to short-term debt, budget balance, current account balance, debt service to exports, share of official debt in total debt, growth in credit to the private sector, growth in real GDP, and net portfolio investment.[16]

Curiously, the last variable did not significantly enhance the power of any good multilinear filter. The absence of net portfolio investment most likely reflects a combination of poor data quality and instability of portfolio investment on a one-year horizon. An outstanding illustration of the latter is the phenomenal contrast between the huge portfolio inflows into Russia from October 1996 through September 1997 and the huge outflows from October 1997 through September 1998.

All of the other eight variables showed up in at least one multilinear filter extracting 200 or more observations. Nearly always they were coupled with debt ratios, reinforcing our earlier findings. However, the multilinear filters provided relatively few marginal extractions relative to ordinary filters or intersections, so we dropped the multilinear filters given the concerns discussed earlier about overfitting and confidence intervals.

However, one multilinear filter proved more powerful than any other single filter examined. It combines the share of official debt in total debt, debt service to exports, the real growth rate, and reserves to M2Y (which presumably indicates the ability of reserves to resist domestic panic). Here debt is the driving force, as each of the two debt variables carries nearly as much standardized weight as the two non-debt variables combined. This filter extracted 473 observations, or 15 percent of total tranquil observations.

Our findings for emerging markets are summarized in Tables 1 and 2.

How do our findings so far compare with other leading indicators methods? The survey by Berg and Pattillo (1999) reports the "hit" and "false alarm" rates for a number of different methods. Specifically, they report:

- the percent of precrises correctly called, which corresponds to $\frac{A}{A+C}$ in Table 2;
- the percent of calm periods called correctly, which corresponds to $\frac{D}{B+D}$; and
- the percent of false alarms, which corresponds to $\frac{B}{A+B}$.

In general, there is a trade-off between accuracy in calling precrises correctly and false alarms. It is possible to reduce the number of missed precrisis periods by accepting a higher rate of false alarms. In comparing methods, one would like to hold constant one type of error and then compare performance on the other dimension. This would, however, require replication of regression results for other

[16]We excluded the real exchange rate because it performed very poorly as an ordinary filter. This is striking, since several analysts consider this an important risk factor (see, e.g., Dornbusch, Goldfajn, Valdés, 1995, and Sachs, Tornell, and Velasco, 1996). The proximate cause is Nigeria, whose currency crashed in 1992 despite a real exchange rate depreciation of 75 percent over the previous four years. A possibility is that countries heavily dependent on primary commodity exports should be treated on a different scale than other countries, on the grounds that they experience particularly large shocks. This has the empirical attraction of weakening the extraction thresholds for several variables (see footnote 15), but not for the growth in the real exchange rate, where the threshold remains high (a 50 percent depreciation) after removing primary commodity exporters.

Table 1. Filters for (Near-) Safety from Currency Crashes

Filters	Extractions[1]	Marginal Extractions[2]
Ordinary Filters		
Reserves/short term external debt > 343%	377	125
Debt service/exports < 6.7%	303	52
Official/total external debt > 87.5%	243	111
Intersection Filters		
Reserves/short term debt > average and budget balance/GDP > 1.41%	188	115
Official/total external debt > average and real growth of GDP > 7.9%	165	99
Current account/GDP > average and external debt/exports < 85.5%	407	84
Current account/GDP > 2.8% and diversified exports	386	93
Foreign direct investment/GDP > average and official/total external debt > 64.3%	177	70
Multilinear Filters[3]		
Odtd + dsxm +.41 rm2 +.66 grgdp > 1.78	473	91
Union Filters		
Total	1,502	—

[1]Number of tranquil months satisfying the condition, out of 3,178 total tranquil months.
[2]Number of tranquil months satisfying the condition but no other condition in the table.
[3]All variables are standardized by subtracting their global means and dividing by their standard deviation: odtd = official/total external debt, dsxm = –debt service/exports, rm2 = gross reserves/M2Y, and grgdp = growth in real GDP.

methods, something that is outside the scope of this paper. Here we only place our hit and false alarm rates in the context of those calculated by Berg and Pattillo. Table 3 reports these ratios. Ratios are not strictly comparable across methods because of differences in sample and crisis definition; however, these differences are sufficiently small so as to make the comparison informative.[17]

In our analysis, the percent of precrisis periods correctly called is 100 percent. This is of course by design, since we never label a precrisis as safe. The price to pay for this, as Table 3 shows, is the high rate of false alarms, if "unsafe or unknown" is interpreted to mean "likely to result in crisis." Hence our method scores better in one dimension, but worse in another, and is especially useful to those interested in ensuring safety from a currency crash.

In addition, our method can be used to improve the performance of most other methods. Just apply the two methods jointly using the following rule: label an environment as safe if either method claims it is safe; otherwise forecast a crisis. Provided our method identifies at least one tranquil period missed by the other

[17]Based on reestimation of the Kaminsky and others and Frankel and Rose regressions for somewhat different samples (23 emerging markets in 1970–95 and 41 emerging markets in 1970–96, respectively). Our sample covers 31 emerging markets over the period 1985–98. A crisis in Kaminsky and others is defined with respect to exchange market pressure, including changes in reserves, whereas in Frankel and Rose and in this paper a crisis is defined solely with respect to movements in the exchange rate.

Table 2. Classification of Estimates

Predicted	Actual: Crisis within 1 year	Actual: No Crisis
Unsafe or unknown	523 (A)	1,676 (B)
Safe or near-safe	0 (C)	1,502 (D)

Table 3. Comparative In-Sample Accuracy

	Percentage of Precrisis Periods Correctly Called[1]	Percentage of Calm Periods Correctly Called	Ratio of False to Total Alarms
Our estimates	100	47	76
Kaminsky and others[1]	41	85	63
Frankel and Rose[1]	43	92	54

Sources: Berg and Pattillo (1999), Tables A2, column 1 for Kaminsky and others (1998) and Table 4, model 1 for Frankel and Rose (1996), and this paper for our estimates.

[1]Based on a 25 percent "cutoff probability" (i.e., a crisis is forecast when the probability predicted from a probit regression exceeds 25 percent).

method, the joint method will outperform the other method, for it will yield fewer false alarms and miss no more (or less) precrises.

Further improvements are possible if our method is used as a first-stage sieve, with other crisis detection methods applied in the second stage to the residual. The focus on a more distilled, crisis-rich sample cannot reduce the in-sample forecasting accuracy (since retaining the results from the undistilled sample is always an option) and most likely will significantly improve it. Of course, it is unlikely that the percentages of false alarms and crises missed will both be shaved to single digits. Significant errors are inevitable in the presence of large shocks, or if outcomes are determined largely by autonomous, self-fulfilling expectations.

Given the importance of market expectations and their volatility, we suspect that second-stage estimation would benefit from shortening the time horizon to quarterly or even monthly and including more market variables. Shortening the time horizon will also modestly expand the list of environments judged to be safe. For example, an observation that is safe on a 12-month horizon is also safe for the next nine months on a three-month horizon (e.g., if a country is judged safe for 12 months in January, it will be safe on a three-month basis for February through September). In our data, 56 percent of observations were judged safe on a three-month horizon, versus 47 percent on a 12-month horizon. If desired, one could introduce a mezzanine stage that uses fundamental-based filters to identify additional safe environments on a three-month horizon.

IV. Out-of-Sample Tests

We performed two out-of-sample checks. The first used data for Brazil in 1998 and found that these environments would not have been falsely classified as safe. The second used historical data for 22 developed markets (all the industrial countries covered by IFS except for Luxemburg) from 1970 through 1998.[18] Unfortunately, it was difficult to find comparable data for developed markets on pivotal external debt measures, so that not all the filters in Table 1 could be checked.[19] Nevertheless, the available data do suggest quite strongly that few if any precrises in developed countries would have been classified as safe. The findings are explained in more detail below.

Two sets of checks were performed for Brazil and for industrial countries. First, filters in Table 1 were checked, data permitting. Second, all possible ordinary filters were checked. The results indicate that the filters in Table 1 would not have misclassified Brazil's precrisis period or any developed country precrisis period as safe. Nor would any of the ordinary filters have classified Brazil as safe (Table 4). Finally, only one of the ordinary filters would have mistakenly classified a developed country precrisis period as safe (Table 4). The one exception is foreign direct investment, where the New Zealand large depreciation in December 1985 occurred at a time that FDI was above the threshold for safety set based on the emerging market sample (FDI was 6.8 percent of GDP, compared with a threshold of 5.6 percent of GDP). FDI was not included in our preferred set of 9 filters in Table 1 in the first place, because of a small number of extractions, so this is not really problematic, in the sense that our system would have classified New Zealand as vulnerable in that period. The results also mean that the best fundamentals under which developed countries experienced crises were nearly always less demanding than those for developing countries.[20]

Perhaps this reflects more homogeneity in developed countries than in developing countries, so that the latter experience crises under a wider variety of conditions. Alternatively, perhaps an ideal list of fundamentals should modify variables or include variables like governance, economic diversification, and the depth of domestic capital markets, where developing countries tend to lag developed countries.

[18]Our developed country sample consists of 7,656 monthly observations. These comprise 37 crisis months, 416 precrisis months, and 6,412 tranquil months. Thus the incidence of crises was about half the level for emerging markets. Data were collected for 20 different variables on the same basis as for emerging markets.

[19]Data are not readily available for external debt, short-term external debt, debt-service, or the share of official debt. While gross external debt can be derived from the International Investment Position for a number of countries, the concept requires modification for comparability with our developing country data on gross debt. Developed countries (both sovereigns and citizens) tend to owe huge external debts, whose shares of GDP far exceed those of emerging markets. However, developed countries also have huge foreign assets. Net assets might be more suitable for international comparisons. One possible reconciliation is to derive gross external debt from the International Investment Position, subtract similarly derived external assets, and compare against gross debt less reserves for emerging markets. However, this neglects the stock of flight capital from emerging markets.

[20]While this implies that virtually no crisis is missed, it also means that many more environments are classified as vulnerable than experience crisis (a high rate of "false alarms").

Table 4. Threshold for Never Observing a Crisis Within a Year Under Ordinary Filters

Variable	Industrial Countries 1970–98	Emerging Markets 1985–98	Brazil (max in 1998)
rm2	>0.54	>0.85	0.32
grm2	>0.33	>0.41	0.05
rm	>11.0	>18.5	14.1
grm	> 6.7	>10.4	4.1
rstd	...	>3.43	2.00
grstd	...	>1.40	0.42
dsx	...	<6.72	57.4
tdex	...	<0.40	2.92
odtd	...	>0.87	0.15
gtot	>0.49	>0.55	0.04
gx	>2.49	>4.43	0.18
grer	>0.33	>0.75	...
cagdp	>0.03	>0.17	–0.008
gcagdp	>0.05	>0.12	0.04
npig	>0.11	>0.31	0.07
gnpig	>0.09	>0.32	0.05
fdig	>0.068	>0.056	0.035
dcpg	<0.13	<0.02	0.26
gdpcg	<–0.05	<–0.06	–0.02
gbgd	>0.01	>0.05	–0.003
ggbgd	>0.10	>0.10	0.006
grgdp	>0.13	>0.14	0.03
gindp	>0.23	>0.46	0.04

rm2 = gross reserves/M2Y; rm = reserves/imports of goods and services; rstd = gross reserves/short-term debt; dsx = debt service/exports; tdex = debt/exports; odtd = official/total external debt; gtot = three-year growth in terms of trade; gx = growth of exports of goods and services; grer = four-year growth of real effective exchange rate; cagdp = current account/gdp; npig = net portfolio investment (as a percentage of GDP); fdig = foreign direct investment; dcpg = domestic credit to the private sector (as a percentage of GDP); gbgdp = budget balance/gdp; grgdp = growth in real GDP; gindp = growth in industrial production. A "g" in front of a variable refers to the one-year change in the variable.

V. Conclusion and Suggestions for Further Research

This paper develops the first stage of a proposed two-stage early warning system of currency crashes. The first stage identifies environments with such strong fundamentals that they face little or no risk of currency crash on a 12-month horizon. We use a simple technique. For variables, intersections of variables, and linear combinations of variables thought to influence currency safety, it identifies the "healthiest" values ever experienced in a precrisis environment. Levels that exceed these thresholds are deemed safe or near-safe. Applying this filtering technique to a sample of emerging markets from 1985 through 1998, we classify 47 percent of the observed environments as safe or near-safe on a 12-month horizon.

This filtering technique has some obvious shortcomings, most notably that the samples may not be representative of the future. For example, suppose the threshold foreign exchange reserves needed to prevent a crisis keep rising as capital markets get more sophisticated. Then our approach could mistakenly classify some vulnerable regimes as safe. However, this shortcoming arises in virtually all empirical work.

One perceived shortcoming is the reliance on extreme observations to set safety thresholds: to economists schooled on normal approximations to central tendencies, extreme values may seem to be very unpredictable. In reality, extreme value distributions tend to converge to a class of distributions with identifiable parameters and confidence intervals. Using a simple nonparametric approach, we inferred that the emerging markets environments we identified as safe or near-safe bore less than a 1 percent risk of a currency crash on a 12-month horizon. In practice, our method also appears highly reliable. Out-of-sample tests on 20 developed countries since 1970 and the January 1999 Brazilian crisis found no single instance of mislabeling a precrisis environment as safe based on our proposed nine filters.

Looking ahead, we can expect to increase the power of our filters to extract safe observations by exploring intersections (Boolean "and" conditions) of *more than two* ordinary filters using genetic algorithms to set thresholds. Next, to derive better confidence intervals, it would be useful to estimate parametric forms for the best values of fundamentals observed in precrisis and also test for possible time trends. Alternatively, further out-of-sample testing could be carried out by re-estimating the model based on an earlier period (say, with a cutoff in 1994) and checking whether the filters perform well for the subsequent period. Perhaps more important, however, is the application of probit or logit techniques to the environments not identified as safe or near-safe. Preliminary work suggests that prediction values improve on more concentrated samples, especially when more market variables are included as a proxy for expectations.

Appendix I. Confidence Intervals

In this appendix we derive the degree of confidence associated with the various kinds of filters.

Ordinary Filters

We begin with a simple but powerful nonparametric test. Let the observed sample contain C "precrisis" environments that experienced crashes within 12 months and T "tranquil" environments that did not. Suppose that S tranquil environments passed the following safety check: their fundamentals, measured using a given index, bettered the best level achieved in a precrisis environment. Then the probability that an out-of-sample observation leads to crisis within 12 months, given that it passed the safety check (i.e., is extracted by the filter), is:

$$\Pr(precrisis / pass) = \frac{C}{(C+1)S} \cong \frac{1}{S} \tag{1}$$

This can be demonstrated as follows. Bayes' rule indicates that the probability in question equals:

$$\Pr(precrisis/pass) = \frac{\Pr(pass/precrisis) \cdot \Pr(precrisis)}{\Pr(pass)} \tag{2}$$

First note that the probability Pr(*pass/precrisis*) that the next precrisis observation will outscore all the preceding C precrisis observations equals the probability that any randomly chosen observation from a sample of $C + 1$ observations will be the best performer. Ruling out ties (as seems proper for real-valued fundamentals), that probability is $\frac{1}{C+1}$. Next note that Pr(*precrisis*) $= \frac{C}{C+T}$ and Pr(*pass*) $= \frac{S}{C+T}$ assuming that the sample is representative of the whole. Result (1) follows after simple algebra.

For large C, (1) is just slightly less than $1/S$. For 99 percent confidence that a currency environment does not lead to crisis within 12 months, look for filters that yield 100 or more extractions (passes) for tranquil environments without extracting precrisis environments.

Nonparametric techniques can also be used to generate confidence intervals. Suppose that the conditional probability of a crash within 12 months, given an extraction—that is, the true value Pr(*precrisis/pass*) rather than the estimated value (1)—is really R. Assuming that Pr(*precrisis*) and Pr(*pass/precrisis*) remain $\frac{C}{C+T}$ and $\frac{1}{C+1}$, respectively, (1) can be rearranged to show that:

$$\Pr(pass) = \frac{C}{(C+1)(C+T)R} \cong \frac{1}{(C+T)R}$$

Hence

$$Q \equiv \Pr(pass/tranquil) = \frac{\Pr(tranquil/pass)\Pr(pass)}{\Pr(tranquil)} \cong \frac{\frac{1-R}{(C+T)R}}{\frac{T}{C+T}} = \frac{1-R}{RT} \tag{3}$$

If each of the T tranquil observations is independent with a probability Q of passing, the total number of passes will be distributed binomially with mean QT and variance $(1 - Q)QT$. We can then use this to calculate the odds that S or more passes occur.

For large T, we can use the normal approximation to the binomial to facilitate the calculations and determine the maximal $R \equiv$ Pr(*precrisis/pass*) compatible with a specified degree of confidence.

To illustrate the calculations, suppose that $C = 500$, $T = 3000$, and $S = 100$, so that our point estimate of R is 1 percent. To generate 100 outperformances (passes) with at least 99.9 percent confidence (i.e., for 100 to lie within 3 standard deviations of the mean), Q must exceed the maximum solution of $3000Q + 3\sqrt{3000Q(1-Q)} = 99$ or 2.48 percent. Substitution into (3) indicates that we can have 99.9 percent confidence that S is less than 1.33 percent. If $S = 200$, then our point estimate of R is 0.5 percent and we can have 99.9 percent confidence that R is less than 0.61 percent. In practice, in our estimations S is never much below 200, and for a number of measures reaches more than double that level. This leads us to conclude that the environments we identify as safe or near-safe bear less than a 1 percent risk of a currency crash, subject to the qualifications described in the remainder of this section.

Compared with most normal approximations to central tendencies, these confidence intervals are remarkably tight. They reflect the low probability of extreme events, which in turn makes multiples of these events even rarer. Critical to our calculations of confidence intervals, however, is the assumption that the events are independent. With even moderately positive correlations across observations the probability of multiple events would be much higher and hence the confidence intervals wider. This is a problem for us because fundamentals for nearby months in a given country are indeed likely to be strongly positively correlated.

We do not know how much wider the confidence intervals will be. However, to get an idea of the order of magnitude, suppose we assume that fundamentals for a given country in a given quarter are perfectly correlated (e.g., constant within a quarter) but all other correlations are zero. Then we can reestimate our confidence intervals dividing C, T, and S by 3. What used to be a S of 100 now corresponds to a point estimate for R of 2.98 percent and 99.9 percent confidence that R is less than 4.75 percent. What used to be a S of 200 now corresponds to a point estimate for R of 1.48 percent and 99.9 percent confidence that R is less than 2.10 percent. So in this case our confidence gets eroded quite a bit, although by conventional econometric standards it remains very respectable.

So far we have generated confidence intervals using a single value—the best fundamental recorded in precrisis—as a pivot. What if the best fundamental in precrisis is very close to the next-best fundamentals, or conversely is very far from the next-best fundamentals? It would seem reasonable to adjust our estimate of Pr(pass/precrisis) (that is, the odds that the next precrisis sets a new record for fundamentals) upward in the former case and downward in the latter. But how much of an adjustment should we make? We offer a whirlwind tour of how extreme value distributions could be used to refine our estimates of these confidence intervals in the full version of the paper.

Union Filters

While our preceding results for ordinary filters generalize without difficulty to multilinear filters and intersections of ordinary or multilinear filters, union filters demand extra attention. It is nearly always possible to increase the total number of extractions by adding a filter to the union. Hence, the broader is the union of filters used as an early warning system, the more likely an observation will be labeled as safe. However, the degree of confidence associated with the label will not be the same for all extractions from the union. Confidence will be highest for observations that all filters (and hence their intersection) classify as safe. Conversely, confidence will be dampened in extractions that most other strong filters fail to classify as safe.

To establish new confidence intervals, we shall again employ a nonparametric approach. Consider an observation extracted by a first filter but not a second. Denoting the extractions from the first filter as $pass_1$ and the non-extractions from the second filter as $fail_2$, Bayes' rule shows that:

$$\Pr(precrisis / pass_1 \cap fail_2) = \frac{\Pr(pass_1 \cap fail_2 \cap precrisis)}{\Pr(pass_1 \cap fail_2 \cap precrisis) + \Pr(pass_1 \cap fail_2 \cap tranquil)} \tag{4}$$

We can readily estimate $\Pr(pass_1 \cap fail_2 \cap tranquil)$ from relative frequencies as $\frac{N}{C+T}$, where N is the number of tranquil observations extracted by the first filter and not the second. Moreover, we know from earlier discussion that:

$$\begin{aligned}
&\Pr(pass_1 \cap fail_2 \cap precrisis) \\
&= \Pr(fail_2 / pass_1 \cap precrisis) \cdot \Pr(pass_1 \cap precrisis) \\
&\leq \Pr(pass_1 \cap precrisis) \\
&= \Pr(pass_1 / precrisis) \cdot \Pr(precrisis) \\
&= \frac{1}{C+1} \cdot \frac{C}{C+T} < \frac{1}{C+T}
\end{aligned}$$

Hence, the probability (4) of mislabeling is less than $\frac{1}{N}$. Indeed it could be considerably less depending on $\Pr(fail_2 / pass_1 \cap precrisis)$. Unfortunately, this probability cannot be

estimated reliably from available data as the conditioning event occurs on average less than once per $C + T$ observations.

For lack of a clearly more plausible alternative, let us make the simplifying assumption that the first and second tests are just as correlated on precrisis environments as on tranquil environments. We can then simplify (4) as follows. Let I be an indicator variable taking the value 1 if the event occurs and 0 otherwise. Denoting the probability of the event by p, I has a mean p and variance $p - p^2$. It follows from the definition of correlation ρ that:

$$\Pr(event_1 \cap event_2) = p_1 p_2 + \rho\sqrt{p_1 - p_1^2}\sqrt{p_2 - p_2^2} \tag{5}$$

Since $\Pr(pass_1 / precrisis) = 1 - \Pr(fail_2 / precrisis) = \frac{1}{C+1}$, application of (5) shows that:

$$\Pr(pass_1 \cap fail_2 / precrisis) = \frac{C}{(C+1)^2} + \rho\sqrt{\frac{C}{(C+1)^2}}\sqrt{\frac{C}{(C+1)^2}} = \frac{C(1+\rho)}{(C+1)^2} \tag{6}$$

Similarly, letting $Q = \frac{S}{T}$ denote Pr(*pass/tranquil*), we find that:

$$\Pr(pass_1 \cap fail_2 / tranquil) = \frac{N}{T} = \tau_1(1 - Q_2) + \rho\sqrt{Q_1 - Q_1^2}\sqrt{Q_2 - Q_2^2} \tag{7}$$

Substituting (6) into (4) with $\Pr(precrisis) = \frac{C}{C+T}$, taking the limit for large C and N, and then using (7) to substitute for ρ establishes that:

$$\Pr(precrisis / pass_1 \cap fail_2) \cap \frac{1+\rho}{N}$$

$$= \frac{\sqrt{Q_1 - Q_1^2}\sqrt{Q_2 - Q_2^2} + \frac{N}{T} - Q_1(1 - Q_2)}{n\sqrt{Q_1 - Q_1^2}\sqrt{Q_2 - Q_2^2}} \tag{8}$$

When $Q_2=Q_1=Q$, so that the two filters give equal numbers of extractions, (8) simplifies to:

$$\Pr(precrisis / pass_1 \cap fail_2) \cap \frac{1}{QT(1-Q)} = \frac{1}{S(1-Q)} \tag{8'}$$

so that, independent of the correlation, the risk is multiplied by roughly $(1 - Q)^{-1}$ relative to the estimate $1/S$ using the first filter only. This is a modest correction for most of the filters we use.

However, if we take a union of many filters, then the effective Q_2 tends to significantly exceed Q_1 and the risk adjustment is much greater. Fortunately, the ρ between a pass on the first test and failure on all of the others tends to be negative, which is another way of saying that measures of safety tend to be positively correlated. Hence, failure on the second filter dampens confidence less than the information on marginal extractions N would suggest (see equation (8)).

Table A1. Crisis Dates[1]

Emerging Markets

Argentina	Apr 85	May 85	Jun 85	Apr 89	
Brazil	Jan 86	Feb 86	Feb 87	Jul 89	Dec 89
	Jan 90	Feb 90	Dec 93	Jan 94	Mar 94
Chile	Jul 85				
China	Jan 94				
Ecuador	Dec 85	Nov 91	Sep 98		
Egypt	Aug 89				
India	Jul 91	Mar 93			
Indonesia	Sep 86	Aug 97			
Israel	Mar 91				
Jordan	Oct 88				
Kenya	Mar 93	Aug 97			
Korea	Nov 97				
Malaysia	Aug 97				
Mexico	Jul 85	Dec 87	Dec 94	Aug 98	
Nigeria	Jun 86	Jan 89	Jul 91		
Peru	Feb 85	Oct 87	Aug 90		
Philippines	Feb 86	Sep 97			
Russia	Aug 98				
South Africa	Jun 98				
Thailand	Jul 97				
Turkey	Mar 86	Mar 91	Jan 94		
Venezuela	Dec 86	Mar 89	Oct 92	May 94	Dec 95
Zimbabwe	Aug 85	Aug 91	Nov 97		

Industrial Countries

Australia	Sep 74	Nov 76	Mar 83	Feb 85	Jul 86	Feb 89
Canada	Feb 73					
Finland	Oct 82	Sep 92				
Greece	Feb 73	Jan 83	Oct 85	Mar 98		
Iceland	Dec 72	Sep 74	Feb 78	Jan 82		
Iceland	Nov 84	May 88	Jun 93			
Ireland	Feb 93					
Italy	Sep 92					
New Zealand	Aug 75	Jul 84	Dec 85	Oct 87		
Portugal	Feb 77	Jun 82				
Spain	Feb 76	Jul 77	Jul 93			
Sweden	Aug 77	Oct 82	Nov 92			
Switzerland	Nov 78					
United Kingdom	Sep 92					
United States	Feb 73					

[1]A currency crash is defined as a 10 percent devaluation, which also exceeds the monthly average devaluation 3–14 months prior to the crisis plus twice the standard deviation of the rate of depreciation over the preceding two years. Excludes crises that fall within 12 months of earlier crises.

Table A2. Data Sources and Description

Definition	IFS or GDF code	Frequency	Mean[1]
portfolio investment, assets (US$)	78bfdzf	Q,A	
portfolio investment, liab (US$)	78bgdzf	Q,A	
net portfolio investment/GDP			0.011
fdi, economy (US$)	78bedzf	Q,A	
foreign direct investment/GDP			0.018
current account (US$)	78aldzf	Q,A	
current account/GDP			–0.014
government budget balance	80...zf	M,Q,A	
budget balance/GDP			–0.027
M1	34...zf	M	
quasi-money (local currency and FX time deposits)	35...zf	M	
money plus quasimoney (M2Y)	35l..zf	M	
reserves/M2Y			0.260
domestic credit to the private sector	32d..zf	M	
domestic credit to the private sector/GDP			0.329
change in domestic credit to the private sector/GDP			0.011
reserves minus gold (US$)	.1l.dzf	M	
industrial production	66...zf or 66..izf	M	
annual growth in industrial production			0.060
exports (US$)	70..dzf	M	
growth in exports			0.115
imports (US$)	71..dzf	M	
reserves/imports			4.560
real effective exchange rate	..reczf	M	
Four-year growth in the real effective exchange rate[2]			–0.047
export prices	74...zf or 74..dzf	Q,M	
import prices	75...zf or 75..dzf	Q,M	
Three-year growth in terms of trade (export prices/import prices)			–0.006
real gdp	99b.rzf or 99b.pzf	A	
real gdp annual growth rate			0.042
short-term debt outstanding (US$)	DTDODDSTCCD	A	
reserves/short-term debt			1.520
public and publicly guaranteed, official creditors (US$)	DTDODOFFTCD	A	
public and publicly guaranteed, total (US$)	DTDODDPPGCD	A	
official debt/total debt			0.464
debt service/exports of goods and services	DTTDSDECTE_1	A	0.237
total debt/exports of goods and services	DTDODDECTE_1	A	2.039
gdp	99b.czf or 99b..zf	A	
foreign exchange rate, end of period, per US$	..ae.zf	M	
foreign exchange rate, average, per US$	..RF.zf	M	
foreign exchange rate, end of period in SDR (industrial countries)	..aa.zf	M	

[1]For emerging markets; based on available data for 1985–98, except for China, Eastern Europe, and FSU, where the data cover 1992–98.

[2]Positive sign refers to depreciation.

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