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Assessing Early Warning Systems: How Have They Worked in Practice?

ANDREW BERG, EDUARDO BORENSZTEIN, AND CATHERINE PATTILLO*

Since 1999, IMF staff have been tracking several early warning system (EWS) models of currency crisis. The results have been mixed. One of the long-horizon models has performed well relative to pure guesswork and to available non-model-based forecasts, such as agency ratings and private analysts' currency crisis risk scores. The data do not speak clearly on the other long-horizon EWS model. The two short-horizon private sector models generally performed poorly. [JEL F31, F47]

Research on developing early warning system (EWS) models of currency crisis received a strong stimulus in recent years following the Mexican and Asian crises. Both events took the international community somewhat by surprise and thus focused attention on indicators and methods that could assist in the timely identification of highly vulnerable countries. Since the beginning of 1999, IMF staff has been systematically tracking, on an ongoing basis, various models developed in-house and by private institutions, as part of a broader forward-looking vulnerability assessment.

EWS models play a necessarily small part in vulnerability assessment relative to more detailed country-specific analyses. We do not review the IMF's expe-

*Andrew Berg is a Division Chief in the Policy Development and Review Department of the IMF, Eduardo Borensztein from the Research Department of the IMF is currently on leave at the Inter-American Development Bank, and Catherine Pattillo is a Senior Economist in the African Department of the IMF. This paper was largely written in 2002–3, while all three authors were in the Research Department of the IMF. The authors would like to thank the editors of this journal, Francis Diebold, and many IMF staff members, including Paul Cashin and Robert Rennhack, for useful comments, and Manzoor Gill for superb research assistance.

rience with the broader vulnerability assessment process here.[1] The question we are interested in, and to which we return in the conclusion, is whether EWS models have any role to play at all.[2]

This paper looks in detail at the performance of these models in practice to date. We emphasize the distinction between in-sample and out-of-sample prediction. For an EWS model to be a useful tool in monitoring vulnerabilities, it must hold up in real time, after the model has been formulated. We thus focus on the actual forecasts made since 1999, though we also reexamine the run-up to the Asia crisis.

A typical result from our earlier studies was that, while the model forecasts we reexamine here were statistically significant predictors of crises, whether they were economically significant was harder to say. In other words, the forecasts were informative compared with a benchmark of complete random guessing, but it was less clear whether they were useful to an already informed observer. It is reasonable to suppose that comprehensive, country-specific holistic assessments by informed analysts, based on all available qualitative and quantitative information, must be better than inevitably simple EWS models. Indeed the ability to take all the information into account is clearly a huge potential advantage. But there have been no studies on whether such comprehensive assessments are in fact better. We gain perspective on this issue here by comparing EWS model forecasts to non-model-based indicators, such as bond spreads, agency ratings, and risk scores published by analysts.

I. EWS Models

Policy initiatives to monitor indicators of external vulnerability can be traced to the Mexican peso crisis of December 1994. A seminal effort to use a systematic quantitative early warning system to predict currency crises was the "indicators" model of Kaminsky, Lizondo, and Reinhart (1998). The Asia crises of 1997/98 provided further impetus for the effort. Evidence suggested that despite the daunting challenges involved in this sort of exercise, this kind of model had some success in predicting these crises out of sample (Berg and Pattillo, 1999a). It also suggested that a variety of improvements could substantially improve model performance (Berg and Pattillo, 1999b).

In light of this research, IMF staff has implemented various models to predict currency and balance of payments crises since 1999, as described in Berg and others (2000). IMF staff has also tracked various private sector models, including Goldman Sachs' GS-WATCH and Credit Suisse First Boston's Emerging Markets Risk Indicator, and a more recent model, the Deutsche Bank Alarm Clock. Table 1 summarizes the main features of the models under consideration here. It details

[1]Some discussion of the role of EWS models in broader vulnerability assessment can be found in IMF (2002) and in Berg and others (2000).

[2]Predicting currency crises is closely related to predicting exchange rate movements, so any success of EWS models is notable in the context of the extensive literature, starting with Meese and Rogoff (1983), which has shown how difficult it is to predict exchange rates out of sample. Berg and others (2000) discuss this point further in the EWS context.

Table 1. Specification of Early Warning Models

	DCSD[1] (Berg, Borensztein, Pattillo)	Crisis Signals[2] (based on KLR)	GS-WATCH[3] (Goldman Sachs)	EMRI[4] (Credit Suisse First Boston)	DB Alarm Clock[5] (Deutsche Bank)
Crisis Definition	Weighted average of one-month changes in exchange rate and reserves more than 3 (country-specific) standard deviations above country average	Same as DCSD	Weighted average of three-month changes in exchange rate and reserves above country-specific threshold	Depreciation > 5% and at least double preceding month's	Various "trigger points": Depreciation > 10% and Interest rate increase > 25% typical
Horizon	2 years	2 years	3 months	1 month	1 month
Method	Probit regression with rhs variables measured in (country-specific) percentile terms	Weighted (by frequency of correct predictions) average of indicators. Variables measured as 0/1 indicators according to threshold chosen to minimize noise/signal ratio	Logit regression with (most) rhs variables measured as 0/1 indicators based on thresholds found in autoregression with dummy (SETAR)	Logit regression with rhs variables measured in logs, then deviation from mean and standardized	Logit two-equation simultaneous systems on exchange rate and interest rate "events" of different magnitude
Variables	Overvaluation Current account Reserve losses Export growth ST debt/reserves	Overvaluation Current account[6] Reserve losses Export growth	Overvaluation Export growth	Overvaluation Debt/exports	Overvaluation

Reserves/M2 (level)[6]			
Reserves/M2 (growth)	Reserves/M2 (level)	Growth of credit to private sector	
Domestic credit growth			
	Financing requirement		
		Reserves/imports (level)	Industrial production
Money multiplier change		Oil prices	Domestic credit growth
Real interest rate			
Excess M1 balances	Stock market	Stock price growth	Stock market
		GDP growth	
	Political event		
	Global liquidity		
	Contagion	Regional contagion	Devaluation contagion
			Market pressure contagion
			Regional dummies
			Interest rate "event"

Source: Berg and others (2000).
Note: rhs = right-hand-side.
[1]DCSD: Developing Country Studies Division of the IMF (Berg and others, 2000).
[2]KLR: Kaminsky, Lizondo, and Reinhart (1998).
[3]Goldman Sachs: Ades, Masih, and Tenengauzer (1998).
[4]EMRI: Emerging Markets Risk Indicator, Credit Suisse First Boston: Roy and Tudela (2000).
[5]Deutsche Bank: Garber, Lumsdaine, and van der Leij (2000).
[6]Not included in the original KLR model.

the crisis definition employed, the prediction horizon, the method used to generate predictions, and the predictor variables. Appendix I contains a more complete description of the models. Table A.1 shows all the crisis dates for these models since January 1999.[3]

As Table 1 illustrates, the specification of EWS models involves a number of decisions that, while guided in some way by economic theory, are largely empirical and judgmental in nature. Currency crises, for example, are not precisely defined events, but the models must nonetheless define crisis dates in terms of the data. (See Box 1 for a discussion of how the different models implement the currency crisis concept.) The choice of a prediction horizon depends on the objectives of the user. The in-house models adopt a relatively long horizon, which should allow time for policy changes that may prevent the crisis. The time horizon of private sector models is shorter and their criterion for evaluating the accuracy of predictions (frequently, a trading rule) is sometimes different. Nevertheless, it is still informative to consider the predictions from private sector EWS models when assessing vulnerability, especially because those predictions are disseminated widely within the investor community.

The predictive variables in the models are inspired by theories of balance of payments crises but constrained by data availability, but in the end reflect what works best in fitting the data. The choice of statistical method is an essentially empirical decision. Appendix I discusses considerations that apply to these specification choices with special reference to the models tracked in the IMF.

II. The Value Added of EWS Models

Since early 1999 the IMF has been regularly producing forecasts from two EWS models, the Kaminsky-Lizondo-Reinhart (KLR) and the Developing Country Studies Division (DCSD), and monitoring two private sector models, the Goldman Sachs (GS) and Credit Suisse First Boston (CSFB). This section examines the usefulness of these models in providing early warnings of crises.

The evaluation of EWS models requires a benchmark. Typically the question is whether a model provides a statistically and economically significant prediction of crisis. This might appear to be a low standard to meet. Given the difficulties involved in crisis prediction, however, it is ambitious. To forecast crises reliably implies systematically outperforming the market at predicting sudden changes in the exchange rate.

Assessments must focus on out-of-sample performance. Successful in-sample predictions are much easier to achieve than out-of-sample predictions but much less meaningful. First, the diligent analyst may have searched through enough truly unrelated variables until finding some that, by coincidence, happen to be corre-

[3]More recently, other models have been developed at the IMF, such as Mulder, Perrelli, and Rocha (2002) and Abiad (2003). Other recent developments include models designed to predict other sorts of crises, such as Manasse, Roubini, and Schimmelpfennig (2003). For a review of recent developments in this literature, see Abiad (2003).

Box 1. Crisis Definition

The early warning system (EWS) models considered in this paper attempt to predict currency crises, as distinct from other sorts of crises, such as debt and banking crises. Although opinions differ as to what constitutes a currency crisis and when one is observed, the formulation of an EWS model requires a specific quantitative definition (Table 1 briefly describes the crisis definitions for the models discussed in detail in this paper. Table A.1 lists all the crisis dates for the various models for the 1999–2001 period (1999–2002 for DCSD and KLR)).

Models that attempt to predict only successful speculative attacks, such as that of Credit Suisse First Boston (CSFB), define crises solely by sufficiently large changes in the exchange rate over a short period of time. For a private sector institution, predicting sudden large changes in the exchange rate alone may be the main objective. EWS models implemented by the IMF, as well as the Goldman-Sachs (GS) model, attempt to predict both successful and unsuccessful speculative attacks by calculating an "exchange market pressure" index that combines exchange rate and reserve changes.

For the CSFB model, a crisis occurs when the exchange rate moves by more than some threshold amount over a short period of time (see Table 1). For the in-house models, a crisis occurs when the exchange market pressure index is very high relative to its historical average.[1] The GS model also defines a crisis as an index value that is high relative to a country-specific threshold, with the threshold defined so as to separate calm periods from those of unusual volatility. The GS definition tends to produce more frequent crises, often occurring for several consecutive periods, while the Developing Country Studies Division (DCSD) and the Kaminsky-Lizondo-Reinhart (KLR) crises are almost always isolated. Comparing over a common sample of 16 countries from 1996 through mid-2001, the CSFB crisis definition produces 34 crises, the DCSD/KLR definition produces 34 crises, and the GS definition 150 crises, with the latter grouped into 47 distinct episodes of one or more consecutive crisis months.

The omission of interest rates in the crisis definitions for most emerging market EWSs, because of poor availability of historical data on market-determined interest rates, is increasingly recognized as a shortcoming in identifying crises. For example, the 1995 attack on the Argentine peso in the wake of the "tequila" effect was the kind of event the models should attempt to predict. However, this failed attack, which was evidenced mainly by a rapid increase in domestic interest rates, is not identified as a crisis by many EWS models. The Deutsche Bank Alarm Clock (DBAC) defines substantial exchange rate depreciations and interest rate increases as separate events but jointly estimates the probability of these two types of events. However, the model uses *International Financial Statistics* (IFS) data on money market interest rates, which are deficient for many emerging economies.

[1]Taking into account whether the crisis index is high relative to its history in a particular country has an advantage relative to defining a crisis by the same absolute cutoff depreciation for all countries. For example, for a country that has had a pegged exchange rate regime and where the rate has remained fixed for some time, a relatively small devaluation might be considered a crisis. The same size depreciation might not constitute a crisis in a country where the exchange rate is flexible and has been more volatile.

Box 1. *(Concluded)*

It is unlikely that any simple formula, however well thought out, will always be successful in picking out crisis periods in the data. One possible improvement would be to combine the results from the quantitative definition with country-specific knowledge about exchange market developments to make some adjustments to the dating of crisis periods. Events that are close calls according to the crisis formula could receive particular scrutiny, and the analyst might judge whether to label some of these as crises. For example, Sri Lanka suffered a reserve loss of about 40 percent during 2000, along with a currency depreciation of nearly 15 percent, culminating in the abandonment of the crawling band exchange rate regime and further currency depreciation in January 2001. Because no single month was sufficiently traumatic, however, the formula employed in the KLR and DCSD models registered a fairly close call, but not a crisis. This episode might have been called a crisis if it had been assessed "by hand."

lated with crises in this particular sample. Such a spurious relationship is not likely to persist in a new sample.[4] Second, even if a true relationship is found in the sample, the next set of crises may be fundamentally different from the last. A model that provides accurate out-of-sample forecasts has thus passed a much tougher test. Of course, only models passing this test are useful for actual crisis prediction. For these reasons, the focus here is on out-of-sample testing.

In this section, several approaches to testing these models are pursued. First, the stage is set by a review of the performance of a model designed prior to the Asia crises, KLR, in predicting those crises. Following earlier work, the model is implemented as it might have been in early 1997 and forecasts are compared with actual outcomes. These predictions are compared with those implied by spreads on dollar-denominated sovereign bonds and sovereign credit ratings as well as the assessments of currency crisis risks produced by country experts from the Economist Intelligence Unit (EIU). These results suggest that the EWS models show promise. The KLR model decisively outperforms all the non-EWS based comparators in this period.

The second part of the section, and the core of the paper, looks at the how the various models that have been monitored at the IMF since early 1999 have performed in this period. First is a detailed analysis of the first set of forecasts officially produced within the IMF, in May 1999. These are compared with the alternative indicators, such as bond spreads, ratings, and analysts' views described above, where possible. We follow with a more systematic examination of how well the models have predicted crises over the full out-of-sample period.

[4]Similarly, models are likely to find an "overvaluation" of the exchange rate before currency crises when the long-run, or equilibrium, exchange rate is calculated, as is usual, as some form of average value over the estimation period that includes the crisis events. Evaluating the out-of-sample performance of the models also avoids any overstatement of the predictive value of the models through this channel.

EWS Models and Alternative Indicators in the Asia Crisis

Berg and others (2000) looked at various measures of performance of a variety of EWS models, focusing in particular on their ability to predict the Asia crises of 1997–98 out of sample.[5] One main conclusion was that the original KLR model, which was designed prior to 1997 and hence without the benefit of hindsight, had substantial predictive power over the Asian episodes. Column 1 of Table 2 shows the ranking of countries according to the risk of currency crisis that KLR would have produced in early 1997. These forecasts are fairly good, with many of the most vulnerable countries in fact being the hardest hit in terms of crisis severity.[6] For example, Korea and Thailand were among the top third of countries in terms of vulnerability, according to the KLR model. Although Brazil and the Philippines, which were not hit particularly hard over this period, were at the top of the vulnerability table, the forecasts are informative overall. Country rank in the predicted vulnerability list is a statistically significant predictor of actual crisis incidence.

One lesson from Berg and others (2000) and other work is that there was clear scope for improvement of those earlier models. A variety of potentially important crisis indicators had not been tested, such as the current account deficit as a share of GDP and the ratio of short-term external debt to GDP. Moreover, regression-based estimation techniques that more fully exploit the information in the data seemed a promising alternative to the "indicator"-based method of the KLR model. A revamped KLR-based model and the DCSD model described in section I were the result of an effort to improve on the original KLR model. Not surprisingly, given the benefit of hindsight, these models perform substantially better in predicting the Asia crises (Column 2 of Table 2 presents results for the DCSD model).

The predictions of EWS models were significantly better than random guesses in predicting the Asia crises, but they were not overwhelmingly accurate. How, in comparison, did the various non-model-based indicators fare over this period? Among these, **sovereign spreads** are a commonly watched indicator of country risk. While the spreads are important indicators of market access, and also market sentiment, they do not fare particularly well as currency crisis predictors over this period. The most affected countries had generally *lower* pre-crisis spreads as of the first quarter of 1997, as shown in the third column of Table 2. The spread averaged 90 basis points in the countries that subsequently suffered a crisis, while it averaged 201 in the other countries.[7]

[5]See also Berg and Pattillo (1999c) on the implications of EWS models for the Asia crisis.

[6]The measure of the severity of crisis for a particular country is the maximum value reached by the exchange market pressure index in 1997, where the index itself is a weighted average of the depreciation of the exchange rate and the loss of international reserves.

[7]Although one could rationalize the low sovereign spreads in the Asian economies on the basis of their relatively low levels of external debt, spreads did increase after October 1997, suggesting that markets may have underestimated risks. The period before the Asian crises was characterized by unusually low spreads for almost all emerging market economies.

Table 2. Risk Assessments Prior to the Asia Crisis Based on KLR, DCSD, Bond Spread, Credit Rating, and the Economist Intelligence Unit (EIU) Forecasts

Country[1]	KLR[2]	DCSD[3]	Spread[4] 1997 Q1	Rating[5] 1997 Q1	EIU 1997 Q1 Currency Risk[6]
Korea, Rep. of	**22**	**24**	**50**	**18**	**22**
Thailand	**20**	**40**	**51**	**25**	**42**
Indonesia	**16**	**32**	**109**	**43**	**38**
Malaysia	**14**	**39**	**37**	**20**	**36**
Zimbabwe	**19**	**n.a.**	**n.a.**	**n.a.**	**58**
Philippines	**34**	**14**	**165**	**55**	**36**
Taiwan Province of China	**23**	**46**	**n.a.**	**n.a.**	**12**
Colombia	**15**	**41**	**129**	**45**	**35**
India	10	21	n.a.	n.a.	35
Brazil	31	15	233	65	51
Turkey	16	18	416	66	56
Venezuela	14	9	n.a.	n.a.	53
Pakistan	20	36	n.a.	68	49
South Africa	19	26	85	48	**39**
Jordan	14	15	n.a.	n.a.	61
Sri Lanka	12	17	n.a.	n.a.	43
Chile	11	14	n.a.	n.a.	17
Bolivia	10	5	n.a.	n.a.	37
Argentina	14	11	265	63	59
Mexico	14	8	231	55	55
Peru	20	26	n.a.	70	51
Uruguay	10	14	135	50	37
Israel	14	24	44	30	46
Average					
Crisis countries	**20**	**34**	**90**	**34**	**35**
Non-crisis countries	15	17	201	57	46
Rank correlation[7]	0.52	0.53	–0.31	–0.49	–0.33

Source: Authors' calculations.

[1]Countries that suffered a crisis in 1997 are in bold. The countries are ordered by severity of crisis.

[2]Probabilities of currency crisis over a 24-month horizon, from average KLR model for 1996.

[3]Probabilities of currency crisis over a 24-month horizon, from average of 1996 DCSD results.

[4]The spread is expressed in basis points. It refers to the difference between the yield on U.S. dollar–denominated foreign government eurobonds and the equivalent maturity U.S. treasury bonds.

[5]Average of S&P and Moody's ratings, each converted to a numerical rating ranging from 100 (S&P SD) to 0 (S&P AAA or Moody's Aaa), following Ferri, Liu, and Stiglitz (1999). A lower number means a better rating (unlike Ferri, Liu, and Stiglitz).

[6]Currency risk: "Scores and ratings assess the risk of a devaluation against the dollar of 20 percent or more in real terms over the two-year forecast period," following EIU.

[7]Countries are ranked according to each indicator as well as according to crisis severity (in both cases a lower number implies a worse actual or predicted crisis). The rank correlation relates these two rankings.

Second, there is some evidence that **sovereign ratings** from agencies such as Moody's and Standard and Poor's (S&P's) have also been poor predictors of recent currency crises.[8] The fourth column of Table 2 shows the sovereign ratings as of the first quarter of 1997, based on a quantitative conversion of Moody's and S&P's ratings, where higher numbers correspond to a better rating. Korea, Malaysia, and Thailand are the highest-rated countries, while Mexico is relatively poorly ranked. Indeed, the average rating in the ten most affected countries was substantially *better* than in the ten least affected countries.

Other non-model-based predictions of currency crises are **surveys of currency market analysts,** such as those prepared by the EIU. The EIU has regularly produced estimates of currency crisis risk, defined as the risk of a 20 percent real depreciation of the currency over the two-year forecast horizon.[9] These estimates derive from the analysis of country experts who consider a broad set of quantitative and qualitative factors, ranging from macroeconomic and financial variables to the strength of the banking system, the quality of economic decision making, and the stability of the political situation. The estimates are available for a large number of countries since 1996. As column 5 of Table 2 shows, these EIU forecasts gave generally positive assessments to the Asian economies that were about to suffer from severe episodes. Indeed, countries with higher risk scores in the second quarter of 1997 were systematically *less* likely to have a crisis during the 1997–98 period.[10]

Along similar lines, there exist surveys of estimates of future exchange rate changes by foreign exchange traders and specialists in financial institutions and multinational corporations. Goldfajn and Valdés (1998) examined the surveys by the *Financial Times Currency Forecaster* and found that such market participants' expectations provided no useful early warning of currency crises in a large sample of emerging markets, or in important cases such as Mexico in 1994 or Thailand in 1997.

To summarize, there is little evidence that "market views," or analysts' views, as expressed in spreads, ratings, and surveys, are reliable crisis predictors, important as they may be in determining market access. This conclusion is illustrated for the case of Korea in Figure 1, which shows DCSD model predictions as well as various other indicators of crisis risk.

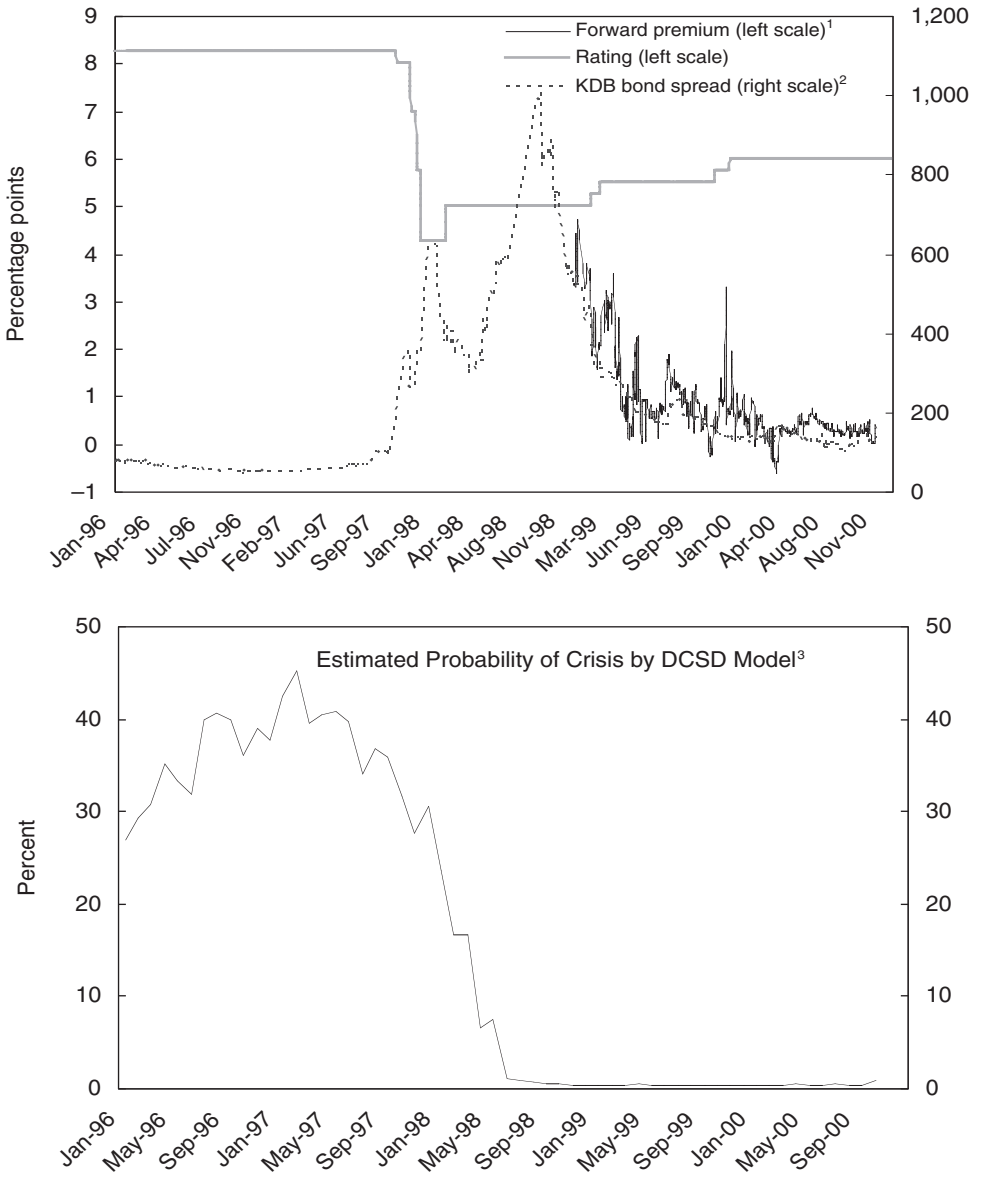
The results of this round of EWS testing were sufficiently promising to suggest the continued implementation of these models on an ongoing basis, along with further research and development. The in-sample results were fairly good. More remarkably, the out-of-sample results were also promising. Here, however,

[8]See Sy (2003) and Reinhart (2002). As with sovereign spreads, it could be argued that these ratings are designed to predict default, not currency crisis. Against this, however, is the fact that currency crises do increase the risk of default and that, because of this, ratings have in fact been downgraded after most currency crises. This suggests that the rating agencies would have likely downgraded the countries had they seen the currency crises coming.

[9]See *Economist Intelligence Unit Currency Risk Handbook,* June 2001.

[10]The Economist Intelligence Unit forecasts are similarly unsuccessful when compared with crises as defined by the EIU itself.

Figure 1. Korea: Forward Exchange Rate Premium, Bond Spread and Probability of an Exchange Rate Crisis Estimated by the DCSD Model, 1996–2000
(*Through November 20, 2000*)



Sources: Bloomberg, JPMorgan, and IMF staff estimates. Berg and others (2000). DCSD stands for Developing Country Studies Division of the IMF in which the model was originally formulated.

[1]The forward premium is defined as the log of the ratio of the 12-month forward rate to the spot exchange rate.

[2]Spread of Korean Development Bank Eurobond over comparable U.S. treasuries.

[3]The probability of a crisis over the next 24 months estimated using the DCSD model.

the results of the DCSD model results must be discounted, since this model benefited from hindsight in its formulation, though only pre–Asia crisis data were used to produce the forecasts.[11] Moreover, it may be that this good Asia-crisis performance was just lucky or, alternatively, that subsequent crisis episodes may have been sufficiently different that these models stopped working. This suggests an examination of the recent performance of the EWS models.

How Well Have the EWS Models Done in Practice Since Their Implementation in January 1999?

We examine this question in two ways. First, we look at the results of the models the first time the forecasts were produced "officially" in a forward-looking exercise, in July 1999.[12] Second, more systemic measures of the "goodness of fit" of the models are examined, emphasizing the comparison of in-sample and out-of-sample model performance, and the trade-off between missing crises and generating false alarms.

The July 1999 forecasts

Table 3 shows the predicted probabilities of crisis for the DCSD and KLR models.[13] Countries that suffered crises are in bold, with the dates of the crisis noted. The KLR, and particularly the DCSD, model did fairly well. Both countries with DCSD probabilities of crisis above 50 percent subsequently had crises, and no crisis country had a probability below 26 percent. Using the models' own definition, there have been only three crises in the roughly two years since July 1999.

As before, it is useful to compare these forecasts with other indicators and estimates. Columns 3, 4, and 5 of Table 3 show spreads on dollar-denominated bonds, sovereign ratings, and the EIU's currency crisis risk scores, all as of the second quarter of 1999. The alternative predictors fared better than prior to the Asia crises but still not well. Spreads are moderately higher, at 549, for the three crisis countries compared with 462 for the others. The average sovereign rating is 56 for the three crisis countries, while it is slightly worse, at 55, for the rest of the countries. The EIU estimates, in contrast, are substantially better here than they were before the Asia crises. For example, the average risk score of the three crisis countries was 59, compared with 42 for the others.[14]

[11]The main benefit from this hindsight was the inclusion of short-term debt and reserves as a predictive variable. The original KLR model had focused on M2/reserves instead. This latter variable also works, though not as well.

[12]Appendix II explains how in-sample and out-of-sample periods are determined for each of the models considered.

[13]The two private sector models monitored at that time, GS and CSFB, forecast only over a one- to three-month horizon. The snapshot of the first "official" July 1999 results is thus not informative. Their performance is examined in the discussion of overall goodness of fit, below.

[14]Using the EIU's own crisis definition, the forecasts perform somewhat worse, with the average risk for the crisis countries below the average for the non-crisis countries.

Table 3. Crisis Probabilities According to Different Models as of July 1999

Country[1]	KLR[2]	DCSD[3]	Spread[4]	Ratings[5]	Economist Intelligence Unit[6]
Colombia (Aug 99)	**42**	**61**	**544**	**45**	**42**
Turkey (Feb 01)	**45**	**50**	**554**	**68**	**58**
Zimbabwe (Aug 00)	**24**	**26**	**n.a.**	**n.a.**	**77**
Bolivia	n.a.	36	n.a.	n.a.	42
Chile	11	36	n.a.	n.a.	29
Venezuela	42	34	n.a.	n.a.	58
Argentina	20	31	471	58	62
Peru	32	26	210	58	35
Uruguay	32	23	216	45	36
Brazil	24	21	451	68	47
Mexico	14	19	296	55	42
Pakistan	n.a.	14	2,270	90	69
Jordan	14	14	n.a.	n.a.	34
South Africa	32	9	141	48	40
India	11	9	n.a.	n.a.	38
Sri Lanka	n.a.	7	n.a.	n.a.	51
Israel	11	6	78	30	30
Thailand	32	4	192	48	41
Philippines	14	3	401	50	28
Malaysia	11	3	174	45	36
Indonesia	32	1	872	78	50
Korea, Rep. of	24	1	238	45	30
Average					
Crisis countries	**37**	**46**	**549**	**56**	**59**
Non-crisis countries	22	16	462	55	42

Source: Authors' calculations.

Note: KLR: Kaminsky, Lizondo, and Reinhart (1998); DCSD: Developing Country Studies Division of the IMF (Berg and others, 2000).

[1]Countries with crises between June 1999 and June 2001 are in bold.

[2]Probabilities of currency crisis over a 24-month horizon, from KLR model. Estimated using data through March 1999, except for Brazil, Jordan, Korea, Mexico, Venezuela, and Zimbabwe (December 1998); Chile and Israel (May 1999); India and Indonesia (January 1999); Malaysia (April 1999); South Africa (February 1999); and Turkey (November 1998).

[3]Probabilities of currency crisis over a 24-month horizon from CSFB model. Estimated through March 1999, except for R.B. de Venezuela (December 1998), Malaysia (January 1999), and Mexico, Thailand, and Indonesia (April 1999).

[4]The spread is expressed in basis points. It refers to the difference between the yield on U.S. dollar–denominated foreign government eurobonds and the equivalent maturity U.S. treasury bonds.

[5]Average of Standard & Poor's (S&P) and Moody's ratings, each converted to a numerical rating ranging from 100 (S&P SD) to 0 (S&P AAA or Moody's Aaa), following Ferri, Liu, and Stiglitz (1999). A lower number means a better rating (unlike Ferri, Liu, and Stiglitz).

[6]Currency risk: "Sources and ratings assess the risk of a devaluation against the dollar of 20 percent or more in real terms over the two-year forecast period," following Economist Intelligence Unit (2001).

The improved performance of the non-model-based indicators compared with before the Asia crisis, combined with the low incidence of crises over the out-of-sample period, suggests that the challenge for the models over this period was more to avoid a large number of false alarms than to call otherwise unforeseen crises.

The distinction between sovereign, or default, risk and currency crisis risk surely plays an important role in explaining the performance of ratings and spreads in some important recent cases—a role that it did not play in the Asia crises. Colombia's crisis in August 1999 involved a drop in the exchange rate as the country abandoned a crawling band exchange rate regime, but there was little subsequent concern about sovereign default. Thus, it is perhaps not surprising that the ratings and spreads do not predict this incident. Conversely, Pakistan suffered a debt crisis but had no currency crisis over the period, and its exceedingly high spreads, which started to widen after the economic sanctions following the nuclear tests in 1998, greatly increase the non-crisis-country average.[15]

Overall goodness of fit since January 1999

A look at the goodness of fit of the models over the entire out-of-sample period provides a more systematic assessment of the models (see Box 2 for details on these measures). The computation of goodness-of-fit measures requires selecting a cutoff probability value, above which the prediction is classified as an "alarm," implying that the model expects a crisis to ensue at some point along the prediction horizon. The threshold probability for an alarm can be chosen to minimize a loss function that weighs two types of errors: failing to predict a crisis and issuing a crisis alarm that does not materialize.

The specification of the loss function implies a decision on how much weight to give to both types of mistakes. The relative weights depend implicitly on the cost imputed to each type of error. From the point of view of an institution concerned with the stability of the international financial system and the well-being of the individual economies that are part of the global system, it would seem that the highest priority would be never to fail to predict a crisis. After all, the very purpose of using EWS models is to prevent currency crises or at least lessen their impact by being able to respond early and in a well-planned fashion. This would argue for choosing a low cutoff probability. In such case, however, the EWS model would be prone to generate a high number of false alarms; namely, crisis predictions that do not materialize. This would impair the credibility of the model and dampen the inclination to take aggressive policy action to prevent a possible crisis. Throughout this chapter, equal weight is placed on the share of alarms that are false and the share of crises that are missed, although the issue could be explored further both in the evaluation and the estimation of the models.[16] From the point

[15]Excluding Pakistan, the average spread for non-crisis countries declines to 312 from 462.

[16]Demirgüc-Kunt and Detragiache (1999), who employ a similar loss-function approach in looking at banking crisis prediction, discuss the relative weights in terms of the costs of policies and regulations to increase the resilience of the banking system versus the costs of rescuing failed institutions.

Box 2. Goodness-of-Fit Measures and Trade-Offs

Early warning systems (EWSs) typically produce a predicted probability of crisis. In evaluating their performance, it would be simple and informative to compare these predicted probabilities with actual crisis probabilities. Because the latter are not directly observable, goodness-of-fit calculations measure how well the predicted probabilities compare with the subsequent incidence of crisis. The first step is to convert predicted probabilities of crisis into alarms; that is, signals that a crisis will ensue within 24 months (assuming that is the model's horizon). An alarm is defined as a predicted probability of crisis above some threshold level (the cutoff threshold). Then each observation (a particular country in a particular month) is categorized as to whether it is an alarm (i.e., whether the predicted probability is above the cutoff threshold) and also according to whether it is an actual pre-crisis month.

The threshold probability for an alarm can be chosen to minimize a "loss function" equal to the weighted sum of false alarms (as a share of total tranquil periods) and missed crises (as a share of total crisis periods). In this paper, equal weight is placed on the share of alarms that are false and the share of crises that are missed. (The former might be thought of as Type 1 errors and the latter as Type 2 errors, if the null hypothesis is no crisis.) A higher weight on missed crises would imply a lower cutoff threshold for calling a crisis, and the model would generate both fewer missed crises and more false alarms. Note that only in-sample information can be used to calculate a threshold for actual forecasting purposes. When using the model out of sample to make predictions, however, there is no guarantee that another threshold would not provide better goodness of fit.

The columns of Table 4 and Table 5 show how the signals from the various models compare with actual outcomes, over various periods. Each number in the goodness-of-fit table represents the number of observations that satisfy the criteria listed in the rows and columns. For example, for the Developing Country Studies Division (DCSD) model (Table 4, column 7) over the January 1999 to December 2000 period, there were a total of 443 tranquil months, and for 90 of them the probability was above the cutoff threshold.

From this table various measures of accuracy can be calculated. For example, the percentage of crises correctly called is equal to the number of observations for which the alarm was sounded and a crisis in fact ensued divided by the total number of actual crises. The footnotes to Table 4 define these various measures.

It is possible that one model might do better when great weight is placed on avoiding false alarms; that is, when cutoff thresholds are relatively high, while another might excel when the optimal cutoff threshold is low. This turns out not generally to be the case for the models examined here. To demonstrate this, figures can be produced that show how the models perform for any cutoff and independent of the loss function chosen. For a given model over a given sample, each candidate cutoff threshold produces a certain percentage of crises correctly called and percentage of false alarms. For example, a cutoff of 0 produces 100 percent crises correctly called but also 100 percent false alarms (as a share of tranquil periods), because the model would predict a crisis every time, while a cutoff of 100 produces 0 percent crises correctly called but 0 percent false alarms, because the model will never predict a crisis. The upper panel of Figure 2 traces all these points for each

Box 2. *(Concluded)*

cutoff between 1 and 100, for the DCSD and the Kaminsky-Lizondo-Reinhart (KLR) models over the in-sample period. Points that are closer to the lower right are unambiguously preferred for any loss function, in that the percentage of crises correctly called is higher while the percentage of false alarms is lower. As shown in the figure, the DCSD model dominates for all cutoff frequencies, in that the DCSD curve lies to the right and below the KLR curve. For any given percentage of crises correctly called, the DCSD model calls fewer false alarms. Figures 3 through 6 show similar results, though they each show one model's in-sample and out-of-sample results.

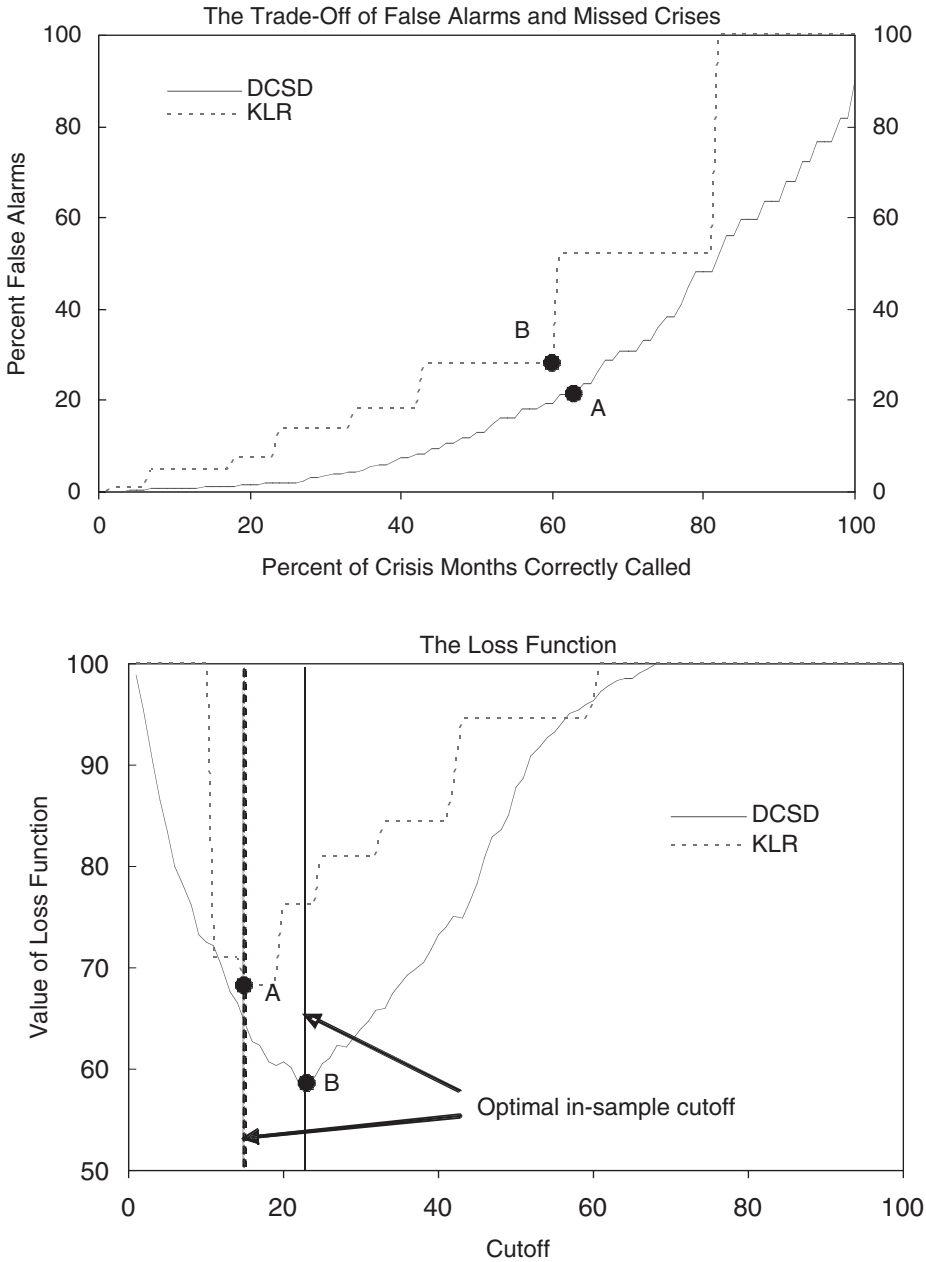
Another way to see how models compare that does not depend on the cutoff is the loss function graph shown in the lower panel of Figure 3. This shows how the models perform for various cutoff thresholds, for a given loss function. To read this figure, note that the loss function is the number of false alarms (in percent of total tranquil periods) plus the number of missed crises (in percent of total pre-crisis periods). A loss function value of 50, for example, implies 20 percentage points fewer false alarms and/or missed crises than a loss function of 70.

An alternative approach would be to apply quadratic probability scores (QPSs) to evaluate goodness-of-fit, as is standard in the literature on evaluation of business cycle forecasts (Diebold and Rudebusch, 1989), which in turn derives from the weather forecast evaluation literature (see Diebold and Lopez, 1996, for a survey of the forecast evaluation literature). In the context of EWS forecast evaluation, the QPS measure, which is an analog of a mean-squared error, was applied by Berg and Pattillo (1999b). A shortcoming of QPSs, however, is that the differences between models are hard to evaluate because there are no probability distributions available for them. It is not possible to tell if one model beats another by a statistically significant margin. Moreover, QPSs do not provide an intuitive interpretation of model performance as do the loss functions used in this paper.

of view of a private investor, although the trade-off between missed crises and false alarms also exists, the evaluation of cost and benefits may be easier, as it is directly related to the returns on different asset positions. In this case, one can suspect a bias toward a loss function that predicts crises more often because, as has been observed, interest differentials are never high enough to offset the impact of a large depreciation that takes place over a very short period.

A first result is that the in-sample goodness of fit of the models has also been reasonably stable as new data have come in, as Table 4 shows. For example, consider the results for the DCSD model when estimated for Berg and others (2000) in 1998 (column 1) with the same model when used to produce the first set of "official" internal forecasts, produced in July 1999 (column 5). The model's accuracy is actually slightly improved over the longer period. Moreover, the models themselves have remained fairly stable as new data have come in and as the country coverage has changed slightly. For the DCSD model, for example, the values and statistical significance of the coefficients have not changed much.

Figure 2. DCSD[1] and KLR[2] in Sample Forecasts



Notes: See Box 2 for an explanation. Point A corresponds to the cutoff that minimizes the loss function in-sample for the DCSD model. Point B indicates the same point for the KLR model.

[1]Berg and others (2000). DCSD stands for Developing Country Studies Division of the IMF in which the model was originally formulated.

[2]Kaminsky, Lizondo, and Reinhart (1998).

Table 4. Goodness of Fit: DCSD and KLR Models

	Asia Crisis				Recent Experience			
	In sample Dec. 1985 to Apr. 1995		Out of sample May 1995 to Dec. 1996		In sample Dec. 1985 to May 1997		Out of sample Jan. 1999 to Dec. 2000	
	DCSD	KLR	DCSD	KLR	DCSD	KLR	DCSD	KLR
Cutoff[1]	18	15	18	15	23	15	23	15
Value of loss function[2]	59	73	63	76	58	68	90	63
Percent of observations correctly called	73	57	62	57	76	70	72	76
Percent of crises in 24 months correctly called[3]	65	73	84	75	63	60	31	58
Percent of tranquil periods in 24 months correctly called[4]	75	54	53	49	79	72	80	79
False alarms as percent of total alarms[5]	69	78	60	62	64	71	78	65
Probability of crisis given signal[6]	31	22	40	38	37	29	22	35
Probability of crisis given no signal[7]	8	8	10	18	8	10	14	9
Statistical tests of forecasts[8]								
Coefficient in regression of actual on predicted	1.19	1.02	2.13	1.42	1.14	0.87	0.61	1.47
Standard error	0.30	0.25	0.38	0.74	0.18	0.22	0.39	0.52
p-value (coefficient = 0)	0.00	0.00	0.00	0.06	0.00	0.00	0.12	0.01

Table 4. *(Concluded)*

		Predicted[9]		Predicted		Predicted		Predicted		Predicted		Predicted		Predicted		Predicted	
		T	C	T	C	T	C	T	C	T	C	T	C	T	C	T	C
Actual	Tranquil	1,571	533	1,196	1,009	170	151	159	166	1,970	531	1,838	711	353	90	351	92
	Crisis	128	242	108	286	19	101	34	101	180	305	196	291	59	26	36	49

Source: Authors' calculations.

Notes: KLR: Kaminsky, Lizondo, and Reinhart (1998); DCSD: Developing Country Studies Division of the IMF (Berg and others, 2000). See Box 2 for further explanation of items in this table.

[1]This is the cutoff probability above which a forecast is deemed to signal a crisis.

[2]The loss function is equal to the sum of false alarms as a share of total tranquil periods and missed crises as a share of total pre-crisis periods.

[3]This is the number of pre-crisis periods correctly called (observations for which the estimated probability of crisis is above the cutoff probability and a crisis ensues within 24 months) as a share of total pre-crisis periods.

[4]This is the number of tranquil periods correctly called (observations for which the estimated probability of crisis is below the cutoff probability and no crisis ensues within 24 months) as a share of total tranquil periods.

[5]A false alarm is an observation with an estimated probability of crisis above the cutoff (an alarm) not followed by a crisis within 24 months.

[6]This is the number of pre-crisis periods correctly called as a share of total predicted pre-crisis periods (observations for which the estimated probability of crisis is above the cutoff probability).

[7]This is the number of periods in which tranquility is predicted and a crisis actually ensues as a share of total predicted tranquil periods (observations for which the estimated probability of crisis is below the cutoff probability).

[8]Crisis dummy (1 if pre-crisis month, 0 otherwise) is regressed on forecast probabilities, with HAC standard errors. See Box 2 for explanation.

[9]The number in each cell represents the number of observations that are predicted to be (actually are) either tranquil (T) or crisis (C), depending on the column (row).

What about out-of-sample performance? As Appendix II explains, the out-of-sample period for the KLR and DCSD models extends from January 1999 through December 2000, since it is too early to fully judge more recent forecasts. For the private sector GS and CSFB models, which have three-month and one-month horizons, respectively, it is possible to look at goodness of fit through April and August 2001, respectively.

The out-of-sample results vary substantially by model. The KLR model performs better out of sample than in sample, calling 58 percent of pre-crisis months correctly. The forecasts were highly informative: when the crisis probability was below the cutoff, a crisis ensued only 9 percent of the time, compared with 35 percent of the time when the crisis probability was above the cutoff. The DCSD model's performance deteriorated substantially over this sample period, with only 31 percent of pre-crisis months correctly called. The model remained somewhat informative, with crises following above-cutoff signals 22 percent of the time and below-cutoff signals only 14 percent of the time.

Figures 3 and 4 give a more complete picture of the models' performance. The top panel of Figure 3 shows, for example, that the DCSD model has more false alarms out of sample than in sample for all cutoff levels. At the in-sample optimal cutoff, the model has about the same fraction of false alarms but calls many fewer crises correctly. The bottom panel shows that a much higher cutoff (around 50 percent) would have been desirable. It would have avoided many false alarms without increasing the number of missed crises very much. This is reflected in the top panel for the DCSD model, where the out-of-sample curve lies on the in-sample curve in the neighborhood of point C, which corresponds to a cutoff probability of 47 percent.

The out-of-sample period studied in this paper was comparatively calm. According to the specific definition applied in the models, there were two crises per year during the recent period, while the average number of crises per year in the estimation period is almost three. It is perhaps not surprising then that the models tended to predict the crises well in the recent period, but that they also registered a comparatively high number of false alarms; that is, crisis predictions that did not materialize.

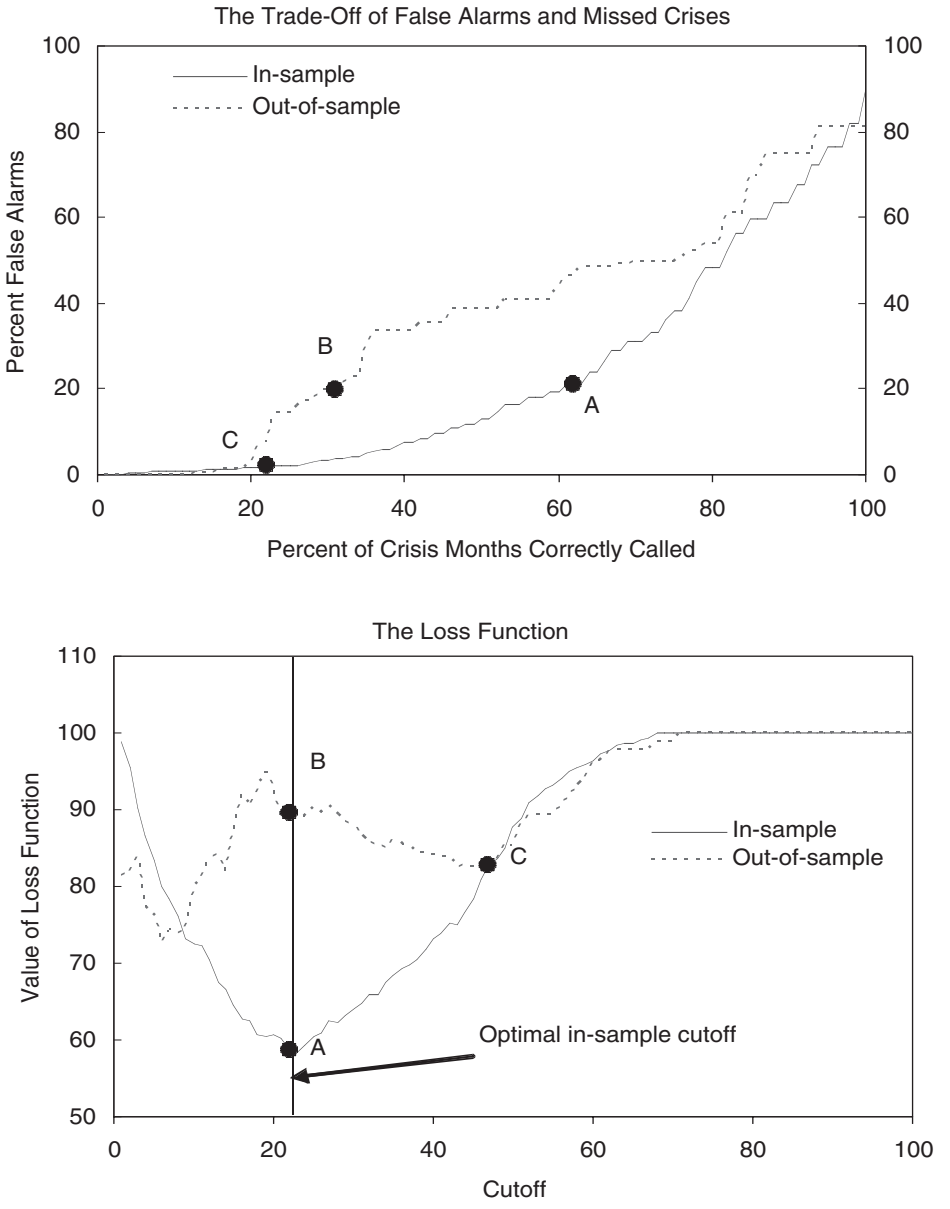
Of course, it is impossible to know until it is too late what the best cutoff probability to call crises is. However, the successful goodness-of-fit performance of the models for *some* cutoffs does imply that the models were able to *rank* the observations reasonably well according to crisis probability, with the higher probabilities assigned to observations that correspond to pre-crisis months.

How statistically good (in the case of KLR) or bad (in the case of DCSD) are these results? Table 4 also shows the results of regressing the actual value of the crisis variable on the model's predicted probability of crisis for various models and sample periods. Thus, we run a regression of the form

$$c24_{it} = \alpha + \beta * PredProb_{it} + \varepsilon_{it},$$

where $c24_{it} = 1$ if there is a crisis in the 24 months after period t (for country i) and 0 otherwise. $PredProb_{it}$ is the predicted crisis probability for period t and country

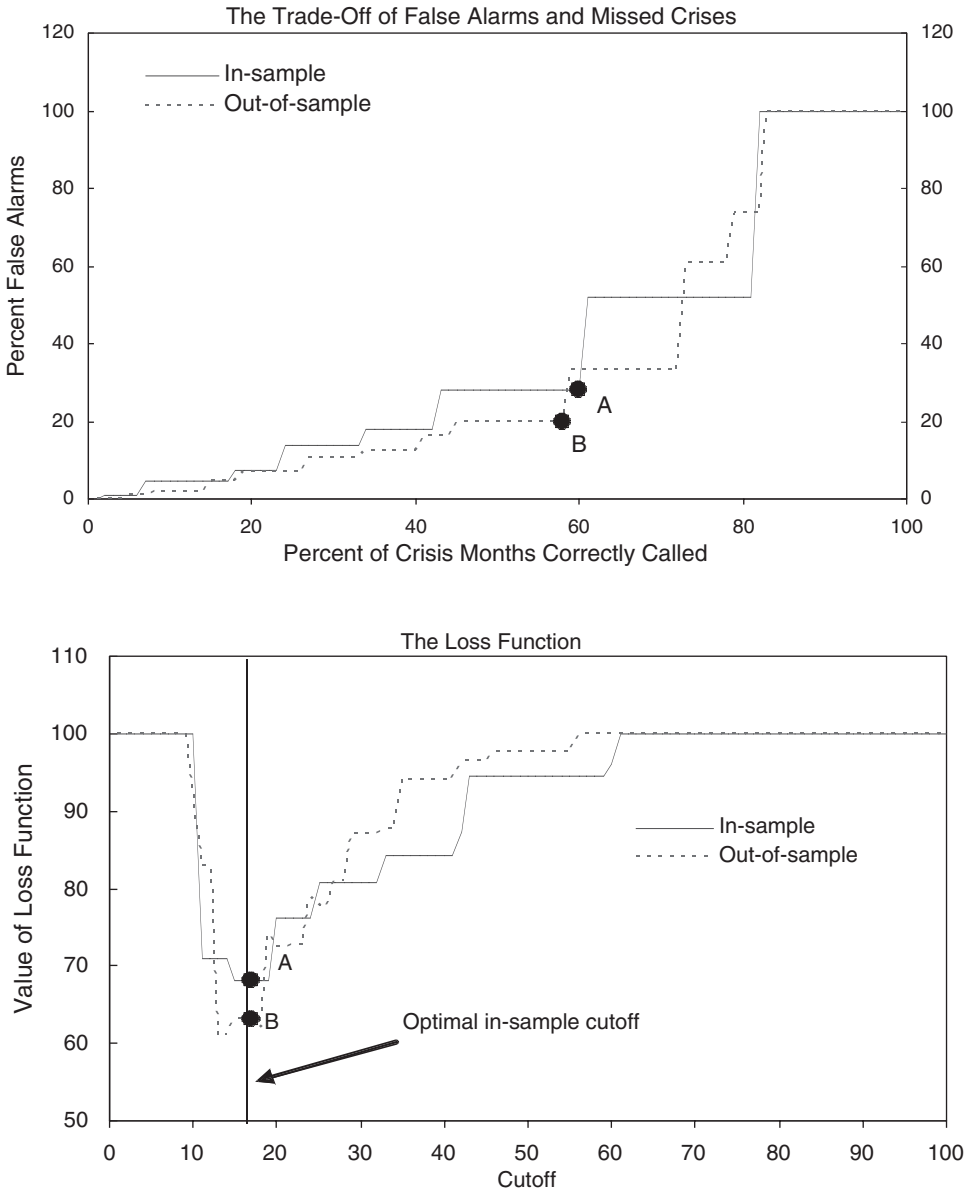
Figure 3. DCSD[1] Forecasts



Notes: See Box 2 for an explanation. Point A corresponds to the cutoff that minimizes the loss function in sample. Point B indicates the out-of-sample results corresponding to the same cutoff. Point C corresponds to a cutoff of 47 percent.

[1]Berg and others (2000). DCSD stands for Developing Country Studies Division of the IMF, the Division in which the model was originally formulated.

Figure 4. KLR[1] Forecasts



Notes: See Box 2 for an expanation. Point A corresponds to the cutoff that minimizes the loss function in-sample. Point B indicates the out-of-sample results corresponding to the same cutoff.

[1]Kaminsky, Lizondo, and Reinhart (1998).

i. For informative forecasts, β should be significant; a coefficient of 1 implies that they are unbiased.[17]

The regression results confirm the strong out-of-sample KLR forecasts and suggest that the data are not revealing for the DCSD model. First, the strong KLR and DCSD in-sample results are clear. The estimated β is always statistically different from 0 and a value of 1 cannot be rejected. Turning to the recent out-of-sample period, the KLR model's forecasts are highly significant, while the hypothesis that the true β is 1 cannot be rejected. The DCSD forecasts are not significant at the traditional confidence levels, with a p-value for $\beta = 0$ of 12 percent. However, the data are more consistent with the hypothesis that the forecasts are accurate than that they are useless: the p-value for $\beta = 1$ is 31 percent.

As suggested by the fact that neither the hypothesis that $\beta = 0$ nor that $\beta = 1$ can be decisively rejected, the tests lack power. This in turn reflects the small amount of information in the out-of-sample period. We illustrate this lack of power by carrying out the following simulation exercise. We suppose that, in fact, the crisis probabilities in the out-of-sample period result from a process that is exactly as described by the DCSD model, and use the DCSD model to generate "data" on which to test the value of the coefficient β. The "data" we create imply that $\beta = 1$ and any remaining errors are a result of noise inherent in the data-generating process—the forecasts are as good as they could be. We then simulate the data-generating process implied by the estimated DCSD model 500 times, creating 500 sets of out-of-sample observations and associated model forecasts. We ask how often these ideal forecasts would look as bad as those actually produced by the DCSD model using the true out-of-sample data. The answer is that for these ideal forecasts, the hypothesis that $\beta = 0$ would *not* be rejected 28 percent of the time.

Neither of the short-horizon private sector models performs well (Table 5 and Figures 5 and 6).[18] Even though in-sample goodness of fit was adequate, the

[17]We estimate this regression using ordinary least squares (OLS) with heteroskedasticity- and autocorrelation-corrected (HAC) standard errors. This solves two sorts of problems. First, the *c24* and *PredProb* variables are highly serially correlated, which causes the OLS standard errors to be incorrect. Monte Carlo exercises suggest that in our setup, the OLS standard errors are substantial underestimates but that a HAC correction largely solves this problem. Second, the *c24* variable is qualitative, resulting in a heteroskedastic ϵ, as is well known from the "linear probability" literature. The usual solution is to run a probit or logit regression. Here, though, the relationship between *PredProb* and *c24* will be linear under either the null (with $\beta = 0$) or the alternative (with $\beta = 1$). The heteroskedasticity is of known form, suggesting the use of feasible generalized least squares estimators (FGLS). However, some observations will produce negative variances. The usual solution is to apply some ad hoc adjustment to these observations, such as dropping them. Our own experience and some Monte Carlo exercises confirm much earlier conclusions that these procedures are unsatisfactory, and suggest that OLS with HAC standard errors produces reasonable results with only a small loss of efficiency compared with Generalized Least Squares (GLS). (See Judge and others (1982) on the linear probability model.) Berg and Coke (2004) discuss similar problems in the estimation of EWS models themselves. Harding and Pagan (2003) address related issues in a different context.

[18]Each model's own definition of crisis is used to evaluate its performance. See Box 1 on crisis definitions.

Table 5. Goodness of Fit: Short-Horizon Models

	In Sample		Out of Sample	
	GS Jan. 1996 to Dec. 1998	CSFB Jan. 1994 to Jul. 2000	GS Jan. 1999 to Apr. 2001	CSFB Aug. 2000 to Aug. 2001
Cutoff[1]	10	35	10	35
Value of loss function[2]	66	58	97	88
Percent of observations correctly called	66	76	50	83
Percent of crises correctly called[3]	66	65	54	27
Percent of tranquil periods correctly called[4]	66	76	50	85
False alarms as percent of total alarms[5]	74	92	87	96
Probability of crisis given signal[6]	26	8	14	4
Probability of crisis given no signal[7]	8	2	12	2
Statistical tests of forecasts[8]				
Coefficient in regression of actual on predicted	1.41	0.17	0.56	0.06
Standard error	0.42	0.03	0.41	0.06
p-value (coefficient<=0)	0.00	0.00	0.17	0.29

Table 5. *(Concluded)*

		Predicted[9]		Predicted		Predicted		Predicted	
		Tranquil	Crisis	Tranquil	Crisis	Tranquil	Crisis	Tranquil	Crisis
Actual	Tranquil	540	279	1,951	618	325	332	361	65
	Crisis	50	98	29	54	45	52	8	3

Source: Authors' calculations.

Notes: GS: Goldman Sachs (Ades, Masih, and Tenengauzer, 1998); CSFB: Credit Suisse First Boston (Roy and Tudela, 2000). See Box 2 for further explanation of items in this table.

[1]This is the cutoff probability above which a forecast is deemed to signal a crisis.

[2]The loss function is equal to the sum of false alarms as a share of total tranquil periods and missed crises as a share of total pre-crisis periods.

[3]This is the number of pre-crisis periods correctly called (observations for which the estimated probability of crisis is above the cutoff probability and a crisis ensues in 3 months (GS), or 1 month (CSFB)) as a share of total pre-crisis periods.

[4]This is the number of tranquil periods correctly called (observations for which the estimated probability of crisis is below the cutoff probability and no crisis ensues in 3 months (GS), or 1 month (CSFB)) as a share of total tranquil periods.

[5]A false alarm is an observation with an estimated probability of crisis above the cutoff (an alarm) not followed by a crisis in 3 months (GS), or 1 month (CSFB).

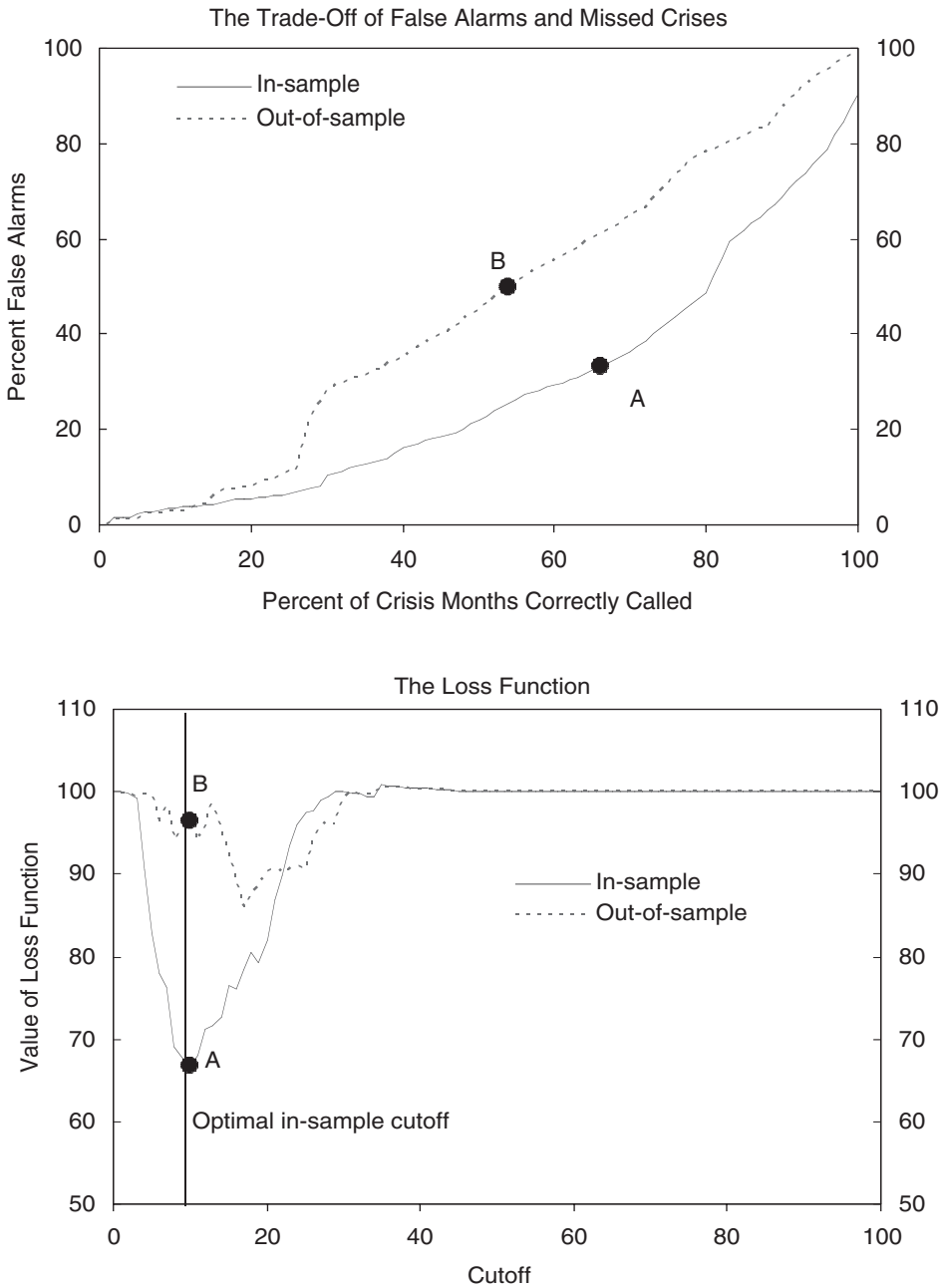
[6]This is the number of pre-crisis periods correctly called as a share of total predicted pre-crisis periods (observations for which the estimated probability of crisis is above the cutoff probability).

[7]This is the number of periods in which tranquility is predicted and a crisis actually ensues as a share of total predicted tranquil periods (observations for which the estimated probability of crisis is below the cutoff probability).

[8]Crisis dummy (1 if pre-crisis month, 0 otherwise) is regressed on forecast probabilities, with HAC standard errors. See Box 2 for explanation.

[9]The number in each cell represents the number of observations that are predicted to be (actually are) either tranquil or crisis, depending on the column (row).

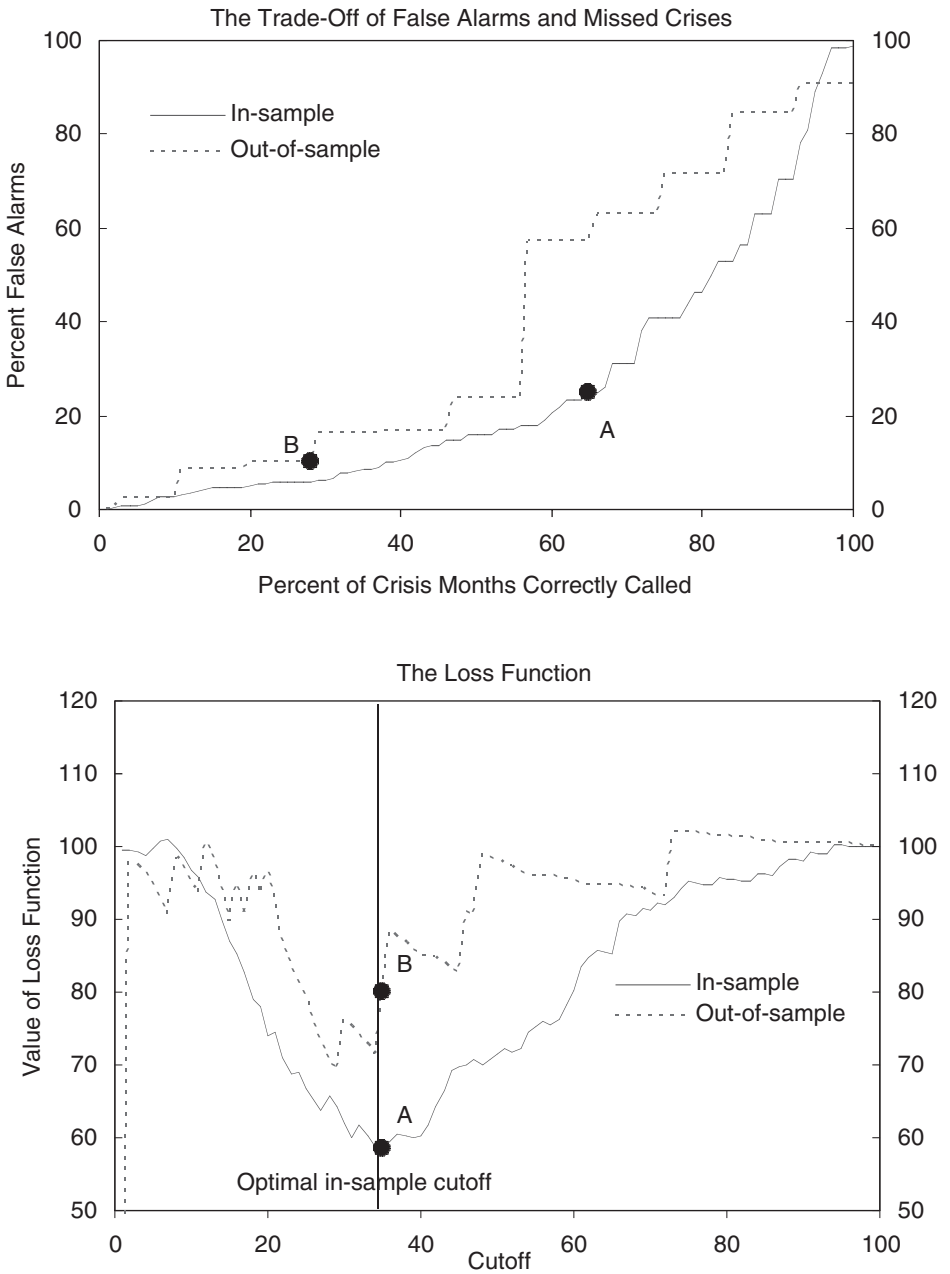
Figure 5. GS[1] Model Forecasts



Notes: See Box 1 for an explanation. Point A corresponds to the cutoff that minimizes the loss function in-sample. Point B indicates the out-of-sample results corresponding to this same cutoff.

[1]Goldman-Sachs (Ades, Masih, and Tenengauzer, 1998) and authors' calculations.

Figure 6. CSFB[1] Model Forecasts



Notes: See Box 1 for an explanation. Point A corresponds to the cutoff that minimizes the loss function in-sample. Point B indicates the out-of-sample results corresponding to this same cutoff.

[1]Credit Suisse First Boston (Roy and Tudela, 2000) and authors' calculations.

models' out-of-sample forecasts deteriorate sharply.[19] The statistical tests reflect this, in that the forecasts are not significant predictors of actual crisis incidence out of sample. Again, the data are not completely definitive, particularly for the GS model. Here, the *p*-value for the hypothesis that the forecasts should be given no weight is 0.17, while the *p*-value that the forecasts are unbiased predictors of crisis risk is 0.28.

All these results should be interpreted cautiously. The number of crises actually observed has been limited. This translates into a small effective sample size.[20] In this context, small changes in sample can make a large difference in the goodness-of-fit indicators yielded by the models. A previous version of this paper found that the DCSD model forecasts performed as well in the January to June 1999 to out-of-sample period as they did in sample.

The private sector models set out to accomplish a distinctly different task than DCSD or KLR did; namely, to predict the timing of a crisis with precision. The adoption of a shorter horizon may make prediction easier, since signs of crisis may emerge more clearly right before a crisis. On the other hand, the exact timing of a currency crisis may be more difficult to predict than vulnerability over an interval of time as wide as two years, in part because of the possibility of multiple equilibria and a resulting difficulty in predicting the timing of speculative attacks. In any case, the comparison of the short-horizon models and the long-horizon models is not direct and must be treated with caution.[21]

A final and necessary qualification is that the terms "false alarm" and "missed crisis" should not be taken too literally. An alarm is considered false if no crisis in fact ensues. However, this signal may have been appropriate. First, the crisis definitions employed may fail to classify some events as crises that we might well want a model to warn about. Second, a warning may be followed by policy adjustment or luck that causes the crisis to be avoided; the warning might nonetheless have been useful. Indeed, an examination of the 90 observations that generated false

[19]This assessment is based on this paper's metric for evaluating performance. CSFB's own method uses a different loss function to choose a cutoff, putting more weight on missed crises. In effect, their objective is to minimize false alarms, subject to achieving a certain share of correctly called crises. Also note that CSFB uses the probabilities in a more complex way to generate various levels of risk warnings for clients, based on changes in the probabilities over the most recent one to six months. We have not evaluated how well this system does in predicting crises.

[20]To put this problem another way, the pre-crisis observations and the predicted probabilities are highly serially correlated; adjusting for this factor greatly increases the standard errors in the model. This also implies that adding observations through extending the time dimension of the out-of-sample period is not as helpful as the increase in the number of total observations would suggest.

[21]In addition, there are some differences in the way the out-of-sample forecasts were generated. Those for the GS model come directly from contemporary monthly publications, so they necessarily reflect incomplete data that had to be supplemented with estimates for various predictive variables. For example, the January 1999 crisis probability (for April 1999) uses GS estimates of data as of January 1999. The CSFB estimates, in contrast, may use revised predictive variables, although it is not clear how substantial the revisions are. This issue is somewhat less serious for the DCSD and KLR models because they forecast over much longer horizons. The July 1999 forecasts, for example, made use of data available only through April for many series, but because the forecast horizon is so long, the use of such data did not make the forecasts obsolete.

alarms in the January 1999 to December 2000 period in the DCSD model suggests that half of them (46) can be readily classified in one or the other of these cases.[22]

III. Summary and Conclusions

Since the beginning of 1999, IMF staff has been systematically tracking, on an ongoing basis, various models developed in-house and by private institutions, as part of its broader forward-looking vulnerability assessment. This paper looks in detail at the performance of these models in practice.

We have monitored two long-horizon in-house models (DCSD and KLR) and two short-horizon private sector models (GS and CSFB) since 1999. This paper has analyzed the forecasts made between January 1999 and December 2000 by the 24-month-horizon DCSD and KLR models, between January 1999 and April 2001 by the GS model, and between April 2000 and June 2001 by the CSFB model. These forecasts were "pure" out-of-sample forecasts in that no information about actual outcomes was used in the forecasts or, more generally, in the development or estimation of the models themselves.

The results are mixed. The forecasts of the KLR model are statistically and economically significant predictors of actual crises. The forecast accuracy in the out-of-sample period is only slightly inferior to the accuracy in the estimation period. The DCSD model performs substantially worse out of sample than in sample. The forecasts are still somewhat informative, however, and the hypothesis that the forecasts are unbiased and informative is more likely (p-value = 0.31) than the hypothesis that the model's forecasts were useless (p-value = 0.12). The ambiguous statistical results reflect the fact that the out-of-sample period contains 528 observations but only eight crises; the latter number is important in determining the amount of information in the data.[23]

On the whole, the short-horizon private sector models we examined performed poorly out of sample, despite stellar in-sample performance. Both sets of crisis predictions were largely uninformative—the probability of a crisis was about the same whether the forecast probability was above a cutoff threshold or not.

At least for the KLR model and the DCSD model, the forecasts were statistically significant predictors of crisis (only at the 12 percent level for the latter). This means that they are likely better than could have been produced throwing darts at a a suitable target. How do they compare, though, to the more challenging benchmark of alternative forecasts? Here we have compared them with bond spreads, agency ratings, and, perhaps most relevant for IMF work, overall currency crisis risk scores published by analysts. We find that during the Asia crisis, these alternative indicators fared very poorly, much worse than the DCSD and

[22]The countries involved in these 46 observations of technically false, but still useful, alarms are Argentina, Chile (before July 1999), Pakistan, Turkey, Uruguay, and República Bolivariana de Venezuela.

[23]The serial correlation in the data also reduces the effective amount of information, as discussed in note 17. An earlier version of this paper analyzed data through end-1999 and found that the DCSD model performed as well out of sample as in sample. This dependence of the results on the sample is captured by the low power of the tests.

KLR EWS models. During the recent period, the non-model forecasts performed somewhat better, though still generally not as well as the models.

Overall, these results reinforce the view that EWS models are not accurate enough to be used as the sole method to anticipate crises. However, they can contribute to the analysis of vulnerability in conjunction with more traditional surveillance methods and other indicators. It is worth underlining the relatively high standard to which these models are being held. It is plausible to suppose that comprehensive assessments by informed analysts, based on all available qualitative and quantitative information, must be better than the inevitably simple EWS models. But the evidence we have examined with respect to this question is not encouraging concerning these more comprehensive assessments.

The advantage of EWS models lies in their objective, systematic nature. The models process data in a mechanical way and are not clouded by conventional misperceptions or biases based on past experiences. For example, as shown in Section II, Korea, a country with one of the most successful economic records in recent years, was showing some serious signs of vulnerability to an external crisis in 1996–97, according to EWS models. However, possibly because of that successful record, analysts and markets did not signal any increase in risk prior to the December 1997 currency crisis.

Over the Asia crisis periods, the best EWS models did dramatically better than non-model-based predictors, such as spreads, ratings, and assessments of informed analysts. Over the more recent period, the performance of some of these alternative predictors improved somewhat, so that the relative superiority of the models declined. This suggests that recent crises have simply not been the surprises that the Asia crises were, either because they were easier to predict or because analysts' sensitivity was heightened. In general, most analysts foresaw important risks in the crisis countries in question. The expected strength of the EWS models is in identifying important crisis risks that other forms of analysis do not expose, while avoiding an excessive number of false alarms that would dilute the credibility of the crisis signals. The crises of 1999–2002 have not, fortunately, afforded this opportunity.

Looking at events of the past few years, it is clear that several developments are under way that are changing the landscape for currency crisis prediction models. First, we have observed a resurgence of crises in which sovereign and domestic debt dynamics play a central role. Debt and currency crises are related but distinct: most debt crises are associated with currency crises, but the reverse is not true. Recent work has, appropriately, focused on predicting these sorts of crises.[24]

A second trend is the increased importance of floating exchange rates in emerging markets. Over the past decade, in large part in the aftermath of currency crises, there has been a sharp increase in the number of emerging market countries in which the capital account is broadly open, the de jure exchange rate regime is floating, and there is substantial de facto flexibility as well. Ten years ago, perhaps

[24]Detragiache and Spilimbergo (2001) and Manasse, Roubini, and Schimmelpfennig (2003) look at determinants of debt crises. Hemming, Kell, and Schimmelpfennig (2003) look at fiscal vulnerabilities in emerging market economies. Sy (2003) emphasizes that debt and currency crises are distinct events.

only South Africa fit these characteristics among large developing countries. Now many, including Brazil, Chile, Colombia, Korea, Mexico, Poland, and Thailand, have joined the ranks. This sort of arrangement, often augmented by an inflation-targeting monetary policy, is indeed now more the rule than the exception for such countries. Going forward, what does this imply for currency crisis models?

In principle, a sharp depreciation of the exchange rate can happen under a floating exchange rate regime as much as under any other regime. Although floating rate regimes would help to avoid situations of extreme overvaluation, particularly those driven by policy inconsistencies, the economies could still be vulnerable to sudden changes in market sentiment, unsustainable levels of debt, and financial sector weaknesses, among other factors. Moreover, regimes that are broadly floating may, under speculative attack, evolve toward de facto pegs as policymakers resist the downward pressure on the currency. In fact, according to the IMF's de jure classification, there is no evidence that floating rates have been more resistant to currency crises.[25] We draw no firm conclusions here. We suspect, though, that painful currency crises will remain a feature of emerging markets for the foreseeable future.

APPENDIX I

Description of Early Warning System (EWS) Models and Specification Issues

Models Implemented at the IMF

Kaminsky-Lizondo-Reinhart (KLR) model

Perhaps the most prominent model for predicting currency crises proposed before the Asia crisis is the indicators approach of Kaminsky, Lizondo, and Reinhart (1998) (KLR), who monitor a large set of monthly indicators that signal a crisis whenever they cross a certain threshold. The model attempts to predict the probability of a crisis within the next 24 months, where a crisis occurs when there are extreme changes in a weighted average of the monthly exchange rate depreciation and reserve loss. A variable-by-variable approach is chosen so that a surveillance system based on the method would provide assessments of which variables are "out of line." In addition to overvaluation, the current account, reserve losses, and export growth, the model also includes reserves to broad money as a measure of reserve adequacy and several monetary variables, such as domestic credit growth, real interest rates, and excess M1 balances.[26] The information from the separate variables is combined, using each variable's forecasting track record, to produce a composite measure of the probability of crisis (Kaminsky, 1999). IMF staff has implemented a version of the KLR model, supplemented with several additional variables.

[25]A more complete analysis should correct for the influence of other factors that contribute to currency crises and would consider de facto classifications such as those of Levy-Yeyati and Sturzenegger (2001) and Reinhart and Rogoff (2004).

[26]Goldstein, Kaminsky, and Reinhart (2000) add some new indicators and update the KLR model. They find that the best monthly indicators for predicting a currency crisis were real exchange rate appreciation, a banking crisis, a decline in equity prices, a fall in exports, a high ratio of broad money to reserves, and a recession, while the best annual indicators were a large current account deficit relative to both GDP and investment.

Developing Country Studies Division (DCSD) model

The current structure of the DCSD model has been influenced by the path of its development. Its origins were a project testing the out-of-sample performance of the KLR and other models in predicting the Asian crisis. Later work tested the usefulness of interpreting predictive variables in terms of discrete thresholds, the crossing of which signals a crisis (Berg and Pattillo, 1999a and 1999b). Using the same crisis definition and prediction horizon as KLR, but embedding the KLR approach into a multivariate probit regression, the authors found that a better simple assumption is that the probability of crisis goes up linearly with changes in the predictive variables. The variables are measured in percentile form; that is, relative to their own history.

The resulting "linear" probit model in that paper was composed of five variables: real exchange rate deviations from trend, the current account to GDP ratio, export growth, reserve growth, and the level of M2 to reserves. This set of predictor variables was the result of starting with an extensive set of KLR variables, plus our additions, and selecting the most important variables through a specification search process.

Because the role of short-term debt in weak financial systems was brought to the forefront by the Asian crises, a measure of short-term debt to reserves was added to the model (Berg and others, 2000). It was found to be highly significant, while the ratio of M2 to reserves lost its significance and was dropped from the model, resulting in the current five-variable DCSD model.[27]

Policy Development and Review (PDR) model

A third EWS model recently developed by the IMF is the PDR model. This EWS adds balance sheet variables and proxies for standards to the DCSD model (Mulder, Perrelli, and Rocha, 2002). The following variables have been deemed important in predicting the probability of a crisis: at the corporate level, leveraged financing and a high ratio of short-term debt to working capital; balance sheet indicators of bank and corporate debt to foreign banks as a share of exports; and a legal regime variable proxying shareholder rights.

The corporate sector data are available only on an annual basis and with a significant lag. These variables are often slow moving, however, so they can still contribute to forecasting accuracy. More up-to-date data, as well as a larger and more stable underlying sample of corporations, would increase the analytical and forecasting usefulness of the model.

Private Sector Models

The interest of investment banks in developing EWSs as tools for advising their clients has fluctuated, based on what is "in fashion" and whether crises are in the daily headlines. Following the Asian crisis, most major banks developed in-house models attempting to predict currency crashes. These models were designed either for explicit use in advising on foreign currency trading strategies, or, more generally, to assess values and risks in emerging market currencies and supplement economic forecasts provided to investors. Since that time, a number of these systems have ceased operation: Lehman Brothers has abandoned its Currency Jump Probability model; Citicorp no longer implements its Early Warning System for anticipating balance-of-payments crises in Latin America; and JPMorgan has substituted a simple weighted vulnerability index for its Event Risk Indicator model. However, as volatility in emerging markets ratcheted up again in late 2000 and in 2001, a number of new private models were brought out. For example, Deutsche

[27]The model uses mainly monthly data, but also some quarterly or, for some countries, annual data. These latter series are interpolated or extrapolated to generate monthly crisis predictions.

Bank introduced its Deutsche Bank Alarm Clock (DBAC) and Morgan Stanley Dean Witter has recently set up an Early Warning System for Currency Crises.

Goldman Sachs's GS-WATCH

IMF staff regularly tracks Goldman Sachs' GS-WATCH model and Credit Suisse First Boston's (CSFB) Emerging Markets Risk Indicator (Roy and Tudela, 2000), both of which have been in operation since 1998. GS-WATCH (Ades, Masih, and Tenengauzer, 1998) predicts the likelihood of a crisis in a three-month period, defined as a weighted average of three-month exchange rate and reserve changes. The predictions are generated through a logit regression in which most explanatory variables are converted into zero/one signals. The predictor variables include macro fundamentals such as measures of credit booms, real exchange rate misalignment, export growth, reserve growth, and external financing requirements, as well as changes in stock prices, political risk, contagion, and global liquidity. The latter two variables are measured continuously, making the overall crisis probabilities follow a smoother path. While inclusion of political risk makes sense, the simple zero/one variable (one around the time of elections, or when a revolution, coup, major riot, or strike takes place) only partially captures this type of risk. The model is estimated using monthly data, but predictions are updated weekly for inclusion in analysts' reports. On a week-to-week basis, changes in the contagion variable drive much of the movement in the crisis predictions. Contagion is measured for each country as a weighted average of the changes in the exchange rate and reserve change index for the other countries in the sample, where the weights are the historical relationships between those indices across countries.

Credit Suisse First Boston's Emerging Markets Risk Indicator (CSFB)

CSFB re-specified its model in September 2000, changing some of the predictor variables and reducing the number of variables (Roy and Tudela, 2000). A logit model predicts the one-month-ahead probability of a depreciation greater than 5 percent and at least double the preceding month's depreciation. The variables are standardized; that is, measured relative to the country-specific mean and variability for that variable. Many variables similar to those used in other models are included: real exchange rate deviations from trend; the ratio of debt to exports; growth in credit to the private sector; output changes; reserves to imports; changes in stock prices; oil prices; and a regional contagion dummy, measured simply as the number of countries in the region recently experiencing a crisis.

Deutsche Bank Alarm Clock (DBAC)

The DBAC model defines separate exchange rate and interest rate "events" as depreciations greater than a certain size (estimated separately for levels ranging from 5 percent to 25 percent) and increases in money market interest rates of more than 25 percent in a month (Garber, Lumsdaine, and van der Leij, 2000). It uses a methodology to jointly estimate the probability of these two types of events, allowing the probability of a simultaneous interest rate event to influence the likelihood of an exchange rate crisis and the probability of a depreciation event to affect the prediction of an interest rate crisis. Relatively few predictors are included in the exchange rate event model: changes in stock prices, domestic credit, industrial production, and real exchange rate deviations, as well as a contagion variable. All the investment bank models claim to demonstrate that an investor using trading strategies based on their models could earn substantial profits over a particular period. DBAC adds a twist to these calculations by proposing an "action trigger" to identify cutoff probability levels at which an alarm should be sounded and investors

should change their positions. The trigger is calculated to maximize profits, assuming a strategy in which the investor will be long in the local currency when the probability of a depreciation crisis is below the trigger and short whenever the probability crosses above the trigger.

Specification Issues

EWS models are econometric methods for generating predictions of currency crises, precisely defined. Although there have long been empirical studies of currency crises, it was not until after the 1994–95 Mexican tequila crisis that the literature focused on finding methods for predicting crises, rather than on explaining a particular set of historical crises or testing specific theories. The largely unexpected Asia crisis, however, provided the real impetus for a new wave of papers and the development of systems for a continuous monitoring of crisis vulnerabilities at various institutions.

What is being predicted?

Most would agree that a sudden, large depreciation of the exchange rate constitutes a currency crisis. Further, a situation of intense pressure on the foreign exchange market, resulting in large losses of international reserves and/or a hike in domestic interest rates can also be considered a crisis, even if a step devaluation is avoided. In any event, one may be interested in forecasting both successful (those resulting in an exchange rate depreciation) and unsuccessful attacks on the currency, so that both types of event would be considered a crisis for the purpose of a forecasting model. Box 1 discusses the difficulties involved in operationalizing the concept of currency crisis and how they are addressed in the models considered in this paper. Table A.1 lists crisis dates for the various models for the 1999–2001 period.

What variables should be included?

After identifying a set of crises, the next issue is the choice of a set of variables that may be useful in predicting crises. Berg and others (2000) survey the literature on currency crises and look for common symptoms of crises in past episodes. Drawing up a list of potential predictive variables starts with theoretical models of currency crisis. "First-generation" models focus on macroeconomic imbalances that lead to a depletion of foreign exchange reserves and make a devaluation inevitable. In second-generation models, the government weighs the cost and benefits of defending the currency. Because expectations affect the trade-off faced by the policymaker, crises may be self-fulfilling, and thus much more difficult to predict. More recent models stress elements such as market failure in international capital markets and distortions in domestic financial markets. For example, information failures can lead to investor herding behavior and contagion, and implicit government guarantees of private sector liabilities can generate moral hazard and unsustainable implicit deficits.

The theoretical literature suggests classifying variables into three groups: first, macroeconomic fundamentals such as measures of real exchange rate overvaluation, the fiscal deficit, excess money growth, terms of trade, domestic credit, the current account deficit, and output growth; and second, variables that gauge a country's vulnerability to attacks, if, given relatively weak fundamentals, an attack were to take place. These include measures of the adequacy of international reserves relative to possible short-run liabilities of external and domestic origin, external financing needs, and soundness of the financial sector.

The third group of variables is composed of indicators of market expectations or sentiment, such as interest rate differentials, bond spreads, the forward exchange rate, the number of crises elsewhere or other contagion channels, and variables representing investors' "risk appetite."

Table A.1. Crisis Dates According to Different Models

DCSD/KLR Crisis Dates (Jan. 1999–Mar. 2003)	
Brazil	Jan 99
Colombia	Aug 99; Jul 02
South Africa	Dec 01
Turkey	Feb 01
Uruguay	Jul 02
Venezuela	Feb 02
Zimbabwe	Aug 00
GS Crisis Dates (Jul. 1998–Apr. 2001)	
Brazil	Jul 98–Jan 99; Jun–Jul 99; Mar–May 00; Sep 00; Jan–Apr 01
Bulgaria	Jan–Apr 99; Jan–Feb 00; Feb 01
Chile	Jun–Aug 99; Mar–Apr 01
China	Jul–Aug 98
Colombia	Jul–Aug 98; Mar–Jul 99; Mar–May 00
Czech Republic	Nov 98–Jan 99
Ecuador	Jul–Aug 98; Nov 98–Feb 99; Apr–May 99; Jul–Nov 99; Jan 01
Egypt	Jul 99; Sep–Oct 00
Hong Kong SAR	Jul–Sep 98; May–Jul 99
Hungary	Jul 98
India	May 00
Indonesia	Dec 98; Jun–Jul 99; Mar–May 00; Jan–Mar 01
Israel	Jul–Sep 98; Jul 99
Korea, Rep. of	Sep–Nov 00
Malaysia	Aug 00
Mexico	Jul 98
Peru	Jul–Nov 98; Jul 99; Nov 00
Philippines	Jul 98; Jun–Jul 99; May–Oct 00
Poland	Nov 98; Jul 99; Mar 00
Russia	Jul–Nov 98; Jul–Aug 99
South Africa	Sep–Oct 00
Singapore	Oct 98; Mar 01
Taiwan Province of China	Sep–Nov 00; Apr 01
Thailand	Jun–Jul 99; Feb–Aug 00
Turkey	Sep–Nov 98; Nov 00–Mar 01
CSFB Crisis Dates (Jul. 1998–Aug. 2001)	
Brazil	Mar 99
Colombia	Nov 98; Sep 99
Croatia	Apr 99
Czech Republic	Apr 99
Ecuador	Mar–Apr 99; Aug 99; Nov–Dec 99; Feb 00
Indonesia	Jul 98; Mar 99; Oct 99; Jan 00; Nov 00; Jun 01
Israel	Dec 98
Korea, Rep. of	Feb 01
Mexico	Oct 98
Nigeria	May 99; May 01
Pakistan	Nov 00
Philippines	Dec 00
Poland	Apr 99
Russia	Oct–Nov 98; Feb 99; Jun 99; Mar 00
South Africa	Aug 98
Slovak Republic	Oct 98; Jul 00

Table A.1. *(Concluded)*

Sri Lanka	Aug 00; Mar 01
Thailand	Aug 98; Nov 99
Turkey	Jan 99; Apr–May 01; Aug 01
Zimbabwe	Jul 98; Oct 98; Mar 99; Oct 00

Source: Authors' calculations.

Note: KLR: Kaminsky, Lizondo, and Reinhart (1998); DCSD: Developing Country Studies Division of the IMF (Berg and others, 2000); GS: Goldman Sachs (Ades, Masih, and Tenengauzer, 1998); CSFB: Credit Suisse First Boston (Roy and Tudela, 2000).

The task of specifying a model with variables that are useful predictors of crisis does not involve simply assembling all the a priori plausible variables. There is significant danger of "overfitting" a model by adding more and more variables through "data mining." Typically, such a model will explain a particular historical episode of crisis very well, but will have little power in forecasting the next set of crises. Finding the best method to forecast crisis probabilities argues for a parsimonious model: a robust set of variables useful for predicting both past and future crises. There is a deeper problem associated with the statistical one. If the nature of crises changes from one episode to the next, how can a model be robust to those changes? The answer is to focus on the symptoms that may be common to all external crisis episodes, even when the ultimate causes of those crises are different.

It should also be kept in mind that the different indicators are interrelated, so that the inclusion of all of them is not necessary. The indicators may be covered indirectly, in that the variables employed in the model may capture many of the important manifestations of these other problems. For example, a large fiscal deficit and high inflation may contribute to the risk of crisis, but may be already accounted for in a model that includes real exchange rate overvaluation and the current account deficit.

Finally, there are the issues of availability of consistent data over time and across countries, and at a desirably high frequency. Data on the health of the financial sector, such as rates of nonperforming loans, is an important example of factors that do not meet those standards. Political risk is another example of a factor that is intrinsically difficult to measure consistently. In addition, some variables may not fit well into the structure of a given model. A good example is the phenomenon of contagion. The transmission of crises from country to country, particularly if the mechanism operates through financial channels, seems to occur quite rapidly. Thus, it is difficult to incorporate contagion in models attempting to predict the likelihood of crisis over a longer horizon, such as the next two years. Also, there are other idiosyncratic variables (for example, oil prices) that, while particularly important for some countries, may have insignificant or contrary effects in other emerging markets.

How do you generate predictions?

Two conceptual questions underlie the choice of a methodology that uses the variables to predict the crises. First, how should the information content of each explanatory variable be assessed? One option is the "signaling" approach, in which each indicator is said to issue a signal of impending crisis when its value exceeds a particular threshold. For example, if the country-specific threshold for the ratio of the current account deficit to GDP is 3 percent, a ratio below 3 percent would not contribute to the risk of crisis, while ratios above 3 percent would contribute equally to the probability of a crisis. A second option is to introduce the variables

continuously so that, for example, any small increase in the current account/GDP ratio could marginally increase the crisis prediction.

It is also necessary to decide how the variables should be measured. Some models include the variables in raw form, often in growth rates or ratios. Alternatively, the variables could be measured relative to their history for each country. For example, what matters in the DCSD model is not the level of the current account deficit per se but whether the deficit corresponds to a high percentile, relative to the history of the current account deficit in each country considered individually.

The second question is how to aggregate the information from the different variables into a single prediction. A method associated with the signaling approach is the calculation of a composite probability as the weighted sum of the number of indicators that are signaling, where each indicator is weighted by its reliability in predicting crises.[28] An alternative is to use a probit (or logit) regression; that is, a regression in which the dependent variable takes the value of one when there is a crisis and zero otherwise.[29]

What are the relative advantages and disadvantages of each approach? The indicator approach is a popular one, because the framework of monitoring key variables for signs of "unusual" behavior accords well with the intuition of early warning. But, by evaluating each variable separately, the method does not consider how an interrelated set of conditions could make an economy more vulnerable to crisis. A practical difficulty with the indicator approach is that the crisis probabilities tend to be "jumpy," as variables move in and out of the signaling territory, making interpretation difficult.[30] A probit regression addresses many of the problems with the indicator approach: it generates predictions taking into account the correlation among all the predictive variables, and allows testing of the statistical significance of individual variables. However, because the probit is a nonlinear model, the contribution of a particular variable depends on the magnitude of all the other variables. This means that the relationship between changes in the variables themselves and changes in their contribution to the crisis prediction is not always transparent. In the final analysis, the relative merits of the two approaches are decided by one key factor: how successful is each method in predicting crises?

Forecasting horizon

Another important design issue for models that attempt to predict both the cross-country incidence and timing of crises is how far in advance the prediction is to be made. Neither the KLR nor the DCSD model attempts to predict the exact timing of the crisis (which may be much harder or impossible), but rather the likelihood that a crisis will occur sometime in the following 24 months. The relatively long prediction window could be useful for the IMF because it would permit sufficient lead time for the authorities to make some policy adjustments. In fact, research on the DCSD model has shown relatively little difference in the estimated model using any horizon between nine months and two years.

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[28]The Bank for International Settlements adopts a less common approach, in which, after each variable is converted to a score from a set scale, the scores are aggregated by summing, using judgmental weights.

[29]There are also a number of new approaches that are being explored in the literature. For example, Burkart and Coudert (2000) use linear discriminant analysis; Vlaar (2000) and Fratzscher (2003) develop switching regime models; and Osband and Van Rijckeghem (2000) use non-parametric methods to identify safe zones.

[30]The Goldman Sachs GS-WATCH model also uses predictive indicators in zero/one form, but these are used as regressors in a logit model. Therefore, the probabilities are less "jumpy" than in the KLR indicators model.

Private sector models tend to attempt to predict the probability of a crisis over a shorter horizon, from one to three months. Some investment banks provide weekly updates of crisis predictions to their clients, although only a small subset of the variables changes at this frequency. This prediction horizon clearly relates to these firms' objectives of providing advice to clients participating mainly in foreign exchange markets, who may use shifting short-term forecasts to continually adjust their portfolios or hedge their positions. Different sets of variables may be important predictors at short horizons. For example, the three private sector models tracked by the IMF staff all include a measure of contagion in the model, reflecting the fact that contagion can occur relatively rapidly in emerging markets. Changes in stock prices and domestic credit to the private sector have also been found to be important predictive variables in all three private sector models.

APPENDIX II

Meaning of In-Sample and Out-of-Sample Periods in Early Warning System (EWS) Models

The text emphasizes the distinction between in-sample and out-of-sample performance. This appendix defines these terms and explains their implementation in this paper. The designer of an EWS chooses the variables and estimates the parameters of the model in a way that best fits the observations in a particular sample (the estimation sample). In-sample testing measures how well the models fit the crises in a particular sample. Good in-sample testing is a sign of a useful model but must be interpreted cautiously. Good in-sample performance may be a coincidence, perhaps resulting from a search through a large number of specifications until a good fit occurs by chance. Moreover, the determinants of crises may vary over time.

In out-of-sample testing, the predictions of an existing model are compared with a new set of observations not belonging to the estimation sample. An unavoidable difficulty with out-of-sample testing is that a forecast can be properly judged only after the entire forecast window has closed. This paper examines the forecasts through June 1999 of the Kaminsky-Lizondo-Reinhart (KLR) and Developing Country Studies Division (DCSD) models, since it is too early to fully judge more recent forecasts. A prediction of risks as of August 1999, for example, cannot be fully judged until September 2001. Before then, it cannot be known whether August 1999 was in fact a pre-crisis or a tranquil month, since it would not yet be known whether a crisis followed within 24 months. Given the two-year model horizon, these forecasts apply to the two-and-a-half-year period through July 2001. For the private sector Goldman Sachs (GS) and Credit Suisse First Boston (CSFB) models, which have three-month and one-month horizons, respectively, it is possible to look at goodness of fit through April and August 2001.[31]

Out-of-sample testing should mimic the way a forecasting model would be used in practice. In the strictest and most interesting form of out-of-sample testing, the modeler has no knowledge of the out-of-sample observations when generating the forecasts to be tested. Sometimes, in contrast, the modeler may withhold the most recent observations from the estimation sample, using them for subsequent out-of-sample testing. The modeler may nonetheless use information from these observations to create the model. For example, the DCSD model was estimated over the pre–Asia crises period and used to predict the Asia crises out of sample in Berg and others (2000). However, the authors created the model in 1998, after the Asia crises, and they added the

[31]Similarly, in-sample estimation periods for KLR and DCSD must end some 24 months before the model is estimated. For example, the in-sample period for the DCSD model in Berg and others (2000) ended in May 1995, so that the estimation did not reflect knowledge of the Asia crises that began in July 1997.

Table A.2. Model Samples

	Sample
Asia crisis	
In sample	
KLR/DCSD	Dec. 1985 to Apr. 1995
Out of sample	
KLR/DCSD	May 1995 to Dec. 1996
Recent experience	
In sample	
KLR/DCSD	Dec. 1985 to May 1997
GS	Jan. 1996 to Dec. 1998
CSFB	Jan. 1994 to Jul. 2000
Out of sample	
KLR/DCSD	Jan. 1999 to Dec. 2000
GS	Jan. 1999 to Apr. 2001
CSFB	Aug. 2000 to Aug. 2001

Source: Authors' calculations based on models.

Note: KLR: Kaminsky, Lizondo, and Reinhart (1998); DCSD: Developing Country Studies Division of the IMF (Berg and others, 2000); GS: Goldman Sachs (Ades, Masih, and Tenengauzer, 1998); CSFB: Credit Suisse First Boston (Roy and Tudela, 2000).

short-term debt and reserves variable because they knew it was likely to be important in explaining the Asia crises.

The start dates for the out-of-sample periods examined in this paper were chosen because they followed the dates at which they could have informed the estimation of the models. The KLR and DCSD forecasts examined here, for the period of January 1999 to December 2000, correspond to the versions used for the "official" internal July 1999 forecasts and subsequent internal forecasts. The model specifications were finalized in late 1998. The GS out-of-sample forecasts come directly from contemporary monthly publications over the period of January 1999 to April 2001, so they could not have reflected out-of-sample information. The CSFB out-of-sample estimates for the April 2000 to June 2001 period were produced in August 2001 using the model as it had been estimated a year earlier, so in principle they should not have been influenced by out-of-sample events.

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