Available online at www.sciencedirect.com
ScienceDirect
Journal of International Money and Finance 25 (2006) 953–973
Journal of International Money and Finance
www.elsevier.com/locate/jimf

Towards a new early warning system of financial crises

Matthieu Bussiere, Marcel Fratzscher*

European Central Bank, Kaiserstrasse 29, D-60311 Frankfurt, Germany

Abstract

This paper develops a new early warning system (EWS) model, based on a multinomial logit model, for predicting financial crises. It is shown that commonly used EWS approaches, which use binomial discrete-dependent-variable models, are subject to what we call a *post-crisis bias*. This bias arises when no distinction is made between tranquil periods, when economic fundamentals are largely sound and sustainable, and crisis/post-crisis periods, when economic variables go through an adjustment process before reaching a more sustainable level or growth path. We show that applying a multinomial logit model, which allows distinguishing between more than two states, is a valid way of solving this problem and constitutes a substantial improvement in the ability to forecast financial crises. The empirical results reveal that, for a set of 20 open emerging markets for the period 1993–2001, the model would have correctly predicted a large majority of crises in emerging markets.

JEL classification: F31; F47; F30

Keywords: Currency crises; Early warning system; Crisis prediction; Financial stability; Emerging markets

1. Introduction

The last decade saw a large number of financial crises in emerging market economies (EMEs) with often devastating economic, social and political consequences. These financial crises were in many cases not confined to individual economies but spread contagiously to other markets as well. In particular, the Latin American crisis of 1994–1995 and the Asian crisis of

* Corresponding author. Fax: +49 69 1344 6353.
E-mail address: marcel.fratzscher@ecb.int (M. Fratzscher).

0261-5606/$ - see front matter
doi:10.1016/j.jimonfin.2006.07.007

1997–1998 affected a wide group of countries and had systemic repercussions for the international financial system as a whole.

As a result, international organizations and also private sector institutions have begun to develop early warning system (EWS) models with the aim of anticipating whether and when individual countries may be affected by a financial crisis. The IMF has taken a lead in putting significant effort into developing EWS models for EMEs, resulting in influential papers by Kaminsky et al. (1998) and Berg and Pattillo (1999b). But also many central banks, such as the US Federal Reserve (Kamin et al., 2001; Kamin and Babson, 1999) and the Bundesbank (Schnatz, 1998, 1999), academics and various private sector institutions (JP Morgan, 1998; Goldman–Sachs, 1998; Deutsche Bank, 2000; Credit Suisse First Boston, 2001; Morgan Stanley Dean Witter, 2001) have developed models in recent years.

EWS models can have substantial value to policy makers by allowing them to detect underlying economic weaknesses and vulnerabilities, and possibly taking pre-emptive steps to reduce the risks of experiencing a crisis. The central concern is, however, that these models have been shown to perform only modestly well in predicting crises ex ante (Berg and Pattillo, 1999a).

The contribution this paper aims to make to the literature is to identify a bias in existing EWS models – what we call the *post-crisis bias* – and to develop a new type of EWS model, based on a multinomial discrete-dependent-variable approach, that solves for this bias. The post-crisis bias implies that existing EWS models fail to distinguish between tranquil periods, when economic fundamentals are largely sound and sustainable, and post-crisis/recovery periods, when economic variables go through an adjustment process before reaching a more sustainable level or growth path.

We show that making this distinction by using a multinomial logit model with three regimes (a tranquil regime, a pre-crisis regime, and post-crisis/recovery regime) constitutes a substantial improvement in the forecasting ability of EWS models. Our empirical model is based on the analysis of 20 open EMEs using a monthly frequency for the period 1993–2001. In particular, the use of the multinomial logit model reduces substantially the number of false alarms (i.e., the number of times the model indicates that a crisis is likely to occur but no crisis actually happens) and of missed crises (i.e., when the model issues no signal but a crisis occurs) as compared to the binomial logit model. Overall, the EWS model based on the multinomial logit would have predicted most EME financial crises since the early 1990s, while entirely missing a crisis only in one case (Singapore in 1997). Moreover, the out-of-sample performance of the multinomial EWS model is robust and would have allowed the correct anticipation of most emerging market crises of the 1990s.

The paper proceeds in Section 2 by outlining our definition of a financial crisis and by reviewing the two most commonly used approaches for EWS models, the leading indicator approach and the discrete-dependent-variable approach. Section 3 presents the results obtained from a simple binomial logit model, which is comparable to existing EWS models in the literature. Section 4 then discusses the post-crisis bias and the multinomial logit as a way of solving it. Section 5 presents the results from the multinomial logit and compares them with alternative models; it also presents robustness tests and out-of-sample estimates. A discussion of the findings concludes the paper in Section 6.

2. Existing methodological approaches of EWS models

2.1. What is the aim of EWS models?

There are various types of financial crises: currency crises, banking crises, sovereign debt crises, private sector debt crises, equity market crises. The EWS model in this paper focuses primarily on currency crises. Currency crises often coincide or occur in quick succession with other types of crises, for instance together with banking crises in what has been dubbed the "twin crises" (Kaminsky and Reinhart, 1999). More specifically, our EWS model employs the commonly used exchange market pressure ($\mathrm{EMP}_{i,t}$) variable for defining a currency crisis for each country i and period t:

$$\mathrm{EMP}_{i,t} = \omega_{\mathrm{REER}}\left(\frac{\mathrm{REER}_{i,t} - \mathrm{REER}_{i,t-1}}{\mathrm{REER}_{i,t-1}}\right) + \omega_{\mathrm{r}}(r_{i,t} - r_{i,t-1}) - \omega_{\mathrm{res}}\left(\frac{\mathrm{res}_{i,t} - \mathrm{res}_{i,t-1}}{\mathrm{res}_{i,t-1}}\right). \qquad (1)$$

$\mathrm{EMP}_{i,t}$ is a weighted average of the change of the real effective exchange rate (REER), the change in the interest rate (r) and the change in foreign exchange reserves (res). Taking the real variables for the exchange rate and the interest rate accounts for differences in inflation rates across countries and over time. The weights ω_{REER}, ω_{r} and ω_{res} are the relative precision of each variable so as to give a larger weight to the variables with less volatility. Precision is defined as the inverse of the variance of each variable for all countries over the full sample period 1993–2001. The key advantage of the EMP measure is that it allows capturing both successful and unsuccessful speculative attacks.

As a next step, we define a currency crisis ($\mathrm{CC}_{i,t}$) as the event when the exchange market pressure ($\mathrm{EMP}_{i,t}$) variable is two standard deviations (SD) or more above its country average EMP_i:

$$\mathrm{CC}_{i,t} = \begin{cases} 1 & \text{if } \mathrm{EMP}_{i,t} > \overline{\mathrm{EMP}_i} + 2\,\mathrm{SD}(\mathrm{EMP}_i) \\ 0 & \text{if otherwise} \end{cases}. \qquad (2)$$

This is the definition of currency crises that will be used below in our econometric analysis. It is identical or quite similar to the measures commonly used in the literature.[1] The next crucial question is *what* we are trying to predict: the timing of a currency crisis or merely its occurrence. As the state of the literature on EWS models for financial crises shows, predicting not only *whether* a currency crisis happens but also the timing *when* it will happen (the precise month) is a highly ambitious, if not unrealistic goal. The objective of our EWS is therefore not to predict the exact timing of a crisis, but to predict whether a crisis occurs within a specific time horizon. Our approach consists in transforming the contemporaneous variable CC_t into a forward-looking variable $Y_{i,t}$ which is defined as

$$Y_{i,t} = \begin{cases} 1 & \text{if } \exists\, k = 1,\ldots,12 \quad \text{s.t. } \mathrm{CC}_{i,t+k} = 1 \\ 0 & \text{otherwise} \end{cases}. \qquad (3)$$

In other words, our model attempts to predict whether a crisis will occur during a particular period of time, in this case in the coming 12 months. Choosing the length of this period requires striking a balance between two opposite requirements. On the one hand, economic fundamentals tend to weaken the closer an economy comes to a financial crisis, and therefore a crisis can be anticipated more reliably the closer the crisis is. On the other hand, from a policy maker's perspective it is desirable to have as early an indication of economic vulnerabilities as possible in order to be able to take pre-emptive policy measures. Although other EWS models

[1] See, for instance, Schnatz (1998) for a thorough discussion of the crisis definition. Fig. 1 plots the crisis episodes for the countries in our sample.

sometimes use even longer time horizons, the 12-month horizon provides what we believe is a good trade-off between these two issues.[2]

2.2. Existing empirical models of currency crises

Previous early warning systems of currency crises have used methods that fall into two broad categories.[3] One approach extracts signals from a range of indicators (Kaminsky and Reinhart, 1999; Kaminsky et al., 1998; Goldstein et al., 2000), whereas the other uses logit or probit models (Frankel and Rose, 1996; Eichengreen et al., 1995; Berg and Pattillo, 1999b).

The leading indicators approach transforms each economic indicator into a binary signal: if a given indicator crosses a critical threshold, it is said to send a signal that a crisis is imminent. The lower the chosen threshold, the more signals this indicator will send over time, but at the cost of more "false alarms". The threshold is then chosen to minimize the noise to signal ratio, through a grid search. This approach represented a major contribution to the literature when it appeared. Yet, as discussed in Bussiere (2001), it has a number of disadvantages. Most importantly, the transformation of each independent variable into binary variables constitutes a significant loss of information compared with the discrete-dependent-variable approach (logit and probit).

Turning to the discrete-dependent-variable approach, let us present the basics of the logit model here. We have N countries $i=\{1,2,\ldots,N\}$ that we observe during T periods $t=\{1,2,\ldots,T\}$. For each country and each month we observe the binary dependent variable Y:

$$Y=\begin{cases}1 & \text{with probability } \Pr(Y=1)=P \\ 0 & \text{with probability } \Pr(Y=0)=1-P\end{cases}. \tag{4}$$

We want to explain the crisis index Y by a set of K independent variables X. Hence X is a $KN\times T$ matrix of observations. The aim of the model is to estimate the effect of the indicators X on the probability P of experiencing a crisis. We denote γ as the vector of K marginal effects:

$$\gamma=\frac{\mathrm{d}P}{\mathrm{d}X'}. \tag{5}$$

In probit and logit models the probability of a crisis is a non-linear function of the indicators:

$$\Pr(Y=1)=F(X\beta). \tag{6}$$

Using a logistic distribution function defines the logit model:

$$\Pr(Y=1)=F(X\beta)=\frac{\mathrm{e}^{X\beta}}{1+\mathrm{e}^{X\beta}}. \tag{7}$$

[2] For instance, Kaminsky et al. (1998) and Berg and Pattillo (1999b) use a 24-month horizon. A robustness check showed that the goodness-of-fit of our empirical model presented below in the paper does not change much when choosing 18-month or 24-month horizons.

[3] These two methods use a discrete crisis index similar to ours. A third approach uses continuous indices (Sachs et al., 1996a,b; Bussiere and Mulder, 1999). Although defining a discrete crisis index represents a loss of information as it treats all crises equally, it allows considering non-linear effects in a logit model, which a linear regression does not.

In the logit model the effect of the indicators on the odds is then defined as

$$\Omega(Y=1|X) = \frac{P}{1-P} = e^{X\beta}. \tag{8}$$

The effect of the indicators on the odds ratio, given two realizations of X, e.g., X_1 and X_0, is

$$\frac{\Omega(Y=1|X_1)}{\Omega(Y=1|X_0)} = e^{(X_1-X_0)\beta}. \tag{9}$$

The odds ratio shows how the odds of observing $Y=1$ change when X moves from X_1 to X_0. A key property of discrete-dependent-variable models, such as the logit model, is their non-linearity. This implies, as the odds ratio of Eq. (9) indicates, that the marginal effect of a change in the independent variables on the probability of the outcome Y is not constant but depends on the precise state of the independent variable X.

2.3. Evaluating the performance of EWS models: the trade-off problem

To evaluate the performance of EWS models, one ideally would like to compare the predicted probability of a crisis obtained from the EWS model with the actual probability. Since the latter is not directly observable, one needs to compare the predicted probability with the actual occurrence of crises. As the predicted probability is a continuous variable, a necessary step consists in defining a probability level above which the probability signals most reliably predicted that a crisis is about to occur. In other words, one needs to specify a cut-off or threshold probability above which the predicted probability can be interpreted as sending a signal of a pending crisis.

The key issue to be solved is what the ‘‘optimal’’ threshold level is. The lower it is chosen, the more signals the model will send, but having the drawback of also raising the number of wrong signals (Type 2 errors). By contrast, raising the threshold level reduces the number of wrong signals, but at the expense of increasing the number of missing crisis signals, i.e., the absence of a signal when a crisis actually occurs within the next 12 months (Type 1 errors).

Choosing a threshold level therefore requires making a judgment on the relative importance of Type 1 errors versus Type 2 errors. In general, Type 2 errors may be less worrisome from a policy maker's perspective for two reasons. First, Type 2 errors tend to be less costly from a welfare perspective than Type 1 errors. Second, Type 2 errors may not always be due to the predictive failure of the model, but simply reflect the fact that although fundamentals were indeed vulnerable, appropriate policy initiatives were taken to improve the resilience of the economy and prevent a crisis. We therefore choose for all our models a probability threshold of 20%. This is clearly an ad hoc choice, as any threshold choice depends on the preferences of the modeler. We choose this relatively low threshold level because we are interested in the analysis from the perspective of a policy maker, hence giving a relatively large weight to avoiding Type 1 errors.[4]

[4] A robustness check using different probability thresholds showed that the relative performance of the models analyzed did not change when using different thresholds. For a detailed simulation exercise comparing the trade-off using different thresholds and time horizons in EWS models, see Bussiere and Fratzscher (2002).

3. The binomial logit model

3.1. Data issues and comparability to alternative EWS models

The paper uses monthly data over the period 1993M12–2001M9 for a sample of 20 emerging markets. Our country sample is similar to that of many papers published on the subject and is balanced between regions as it includes six Latin American countries, nine Asian countries, four Eastern European and accession countries and Turkey (see Appendix A). The central motivation for choosing this country sample and time period is to construct a model that will help us anticipate future currency crises in emerging markets. Given this motivation, we include only open emerging markets in our EWS models. This implies that we exclude countries with relatively closed financial accounts, such as India, Pakistan and Sri Lanka.[5] It also implies looking only at the 1990s, rather than going back to the 1970s as other models do (e.g., Kaminsky et al., 1998), because financial flows were much more subdued and few emerging markets sufficiently open to capital flows in the 1970s and 1980s. Moreover, we do not include developed economies in our EWS model because currency crises in these countries tend to be of a fundamentally different nature than those in emerging markets.[6]

The choice of our independent variables is similar to those commonly used in EWS models. After testing for a broad set of fundamentals (see Table 11 in Appendix A for the full list of right-hand side variables tested) we include six independent variables in our EWS model: the degree of the overvaluation of the exchange rate, the current account (as a percentage of GDP), the short-term debt to reserves ratio, domestic credit growth or ‘‘lending boom’’ as a measure of financial sector vulnerability, real GDP growth and financial sector contagion. Appendix A provides detailed definitions. The main reason for including only six variables is to keep the model as simple and tractable as possible and also to allow a more direct comparison with other EWS models. Moreover, although some other variables, such as the fiscal deficit, have a significant coefficient when included in the model, adding these variables does not improve the overall predictive power of the model, i.e., it neither increases the number of anticipated crises nor significantly reduces the false alarms.

To assess the quality of our binomial EWS model, we compare our model with four prominent models in the literature. Two of the three models are IMF models – the one by Kaminsky et al. (KLR, 1998) and the other by Berg and Pattillo (DCSD, 1999b) – as well as two private

[5] The reason for including China, which is rather closed to portfolio flows though not to direct investment flows, is that it has been argued that China’s devaluation in 1994 may have been the ‘‘first domino’’ for inducing the Asian crisis in 1997–1998 – see Fernald et al. (1999) for a thorough discussion. Excluding China from the sample, however, does not significantly change the overall results.

[6] One key reason to exclude industrial countries from the sample is that industrial countries generally have much more developed financial markets. In addition, it has often been argued that the reasons behind the 1992–1993 ERM crisis in Europe were very different from the crises that occurred in EMEs in the 1990s. For instance, Krugman (1998) underlines that ‘‘although there had been some slowdown in growth in 1996, the Asian victims did not have substantial unemployment when the crisis began. There did not, in other words, seem to be the kind of incentive to abandon the fixed exchange rate to pursue a more expansionary monetary policy that is generally held to be the cause of the 1992 ERM crises in Europe. (And of course the aftermath of devaluation has involved dramatic economic contraction, not expansion.)’’

sector models – by Goldman–Sachs (GS, 1998) and by CSFB (2001).[7] Although our country sample and definitions of dependent and independent variables are very similar to most of these models, it should be stressed that they are not directly comparable as our EWS model starts only in the early 1990s.

A key difference of our EWS model to those four alternative models is the definition of exchange rate overvaluation. Most of the alternative models define exchange rate overvaluation as the deviation of the real or real effective exchange rate (REER) from its long-term trend over the *full* sample period. For instance, what this implies is that the degree of overvaluation in, e.g., 1996 is measured as the deviation of the REER in 1996 from its trend over the full sample period, e.g., 1980–2002. However, in 1996 there was obviously no information about exchange rate developments in 1997–2002 so that the trend can be estimated only ex post but not ex ante. This is less problematic if the aim is to simply explain past crises. In EWS models, however, the goal is to forecast future crises and the out-of-sample performance of the model is an important benchmark for evaluating the EWS model. The measure of overvaluation we use in our EWS model is therefore the change of the REER over the past two years. A detailed definition is given in the data appendix. In our previous work (Bussiere and Fratzscher, 2002), we show that the overvaluation measure based on the deviation from the long-term trend yields a better performance of the EWS model. Using the percent change definition instead of the more common deviation from trend may therefore introduce a bias against our EWS model and in favor of the alternative models.

However, it should be emphasized that the main objective is not to show that using different variable definitions, time periods or country samples helps improve the performance of EWS models. The key objective is to illustrate that accounting and solving for the post-crisis bias in the predominant EWS methodology based on binomial discrete-dependent-variable models constitutes a significant improvement in the predictive power of EWS models.

3.2. Performance and robustness of the binomial logit model

Tables 1 and 2 present the results using our binomial logit model. Table 1 indicates that the six variables tested in the model have the correct sign, most of them being significant at the 1% level. Table 2 shows the performance of our binomial logit model: the percentage of observations and crises correctly called, the percentage of false alarms and other relevant ratios.

Table 4 presents these goodness-of-fit criteria for the four above-mentioned alternative models. The main point to note is that, mostly with a similar methodology, our binomial EWS model (Table 2) performs already somewhat better in terms of prediction than three out of the four of the alternative models (Table 4), with the exception of the IMF–DCSD model. The *conditional* probability of having a crisis if an alarm occurred is 35%. This number may not seem high, but it is still reasonably good when comparing it to the *unconditional* probability of experiencing a crisis, which is in our model 15.8% (i.e., 246 months out of a total of

[7] The KLR model uses an indicator approach and the DCSD model a probit model, as discussed in Section 2.2, both with a two-year forecast horizon. The Goldman–Sachs and the CSFB models also use a logit methodology, although they partly have a longer sample period but fewer countries and different forecast horizons (three months for the GS model, one month for the CSFB model).

Table 1
Estimation results of binomial logit model

Variable	Coefficient	Standard error	Z	$P > \|z\|$
Overvaluation	0.062	0.006	9.92	0.000
Lending boom	0.006	0.001	4.11	0.000
STD/res	0.004	0.001	5.21	0.000
CA/GDP	−0.075	0.015	−4.87	0.000
Financial contagion	0.014	0.012	1.15	0.250
Growth	−0.001	0.015	−0.05	0.960
Constant	−2.917	0.173	−16.89	0.000
No. of observations	1550			
Pseudo R^2	0.171			

1550 months were months for which a crisis followed within the subsequent 12 months). The better performance of our pooled model using the same methodology as most of the models suggests that the variables we have been using are more reliable, and that the country sample and time period have been more appropriate.

Table 4 shows that the main reason why our binomial EWS model performs worse than the IMF−DCSD model is the different definition for the overvaluation variable. Table 3 indicates that the performance of the model improves significantly when the deviation from the country-specific trend is used, and that our binomial EWS model then outperforms the IMF−DCSD model. However, as stressed above it makes sense to stick to our previous overvaluation definition for the purpose of the out-of-sample analysis, and we proceed by using this measure only.

We conduct several sensitivity tests to check for the robustness of the results of our binomial logit model. In particular, one potential drawback of the model with pooled data is that it ignores the cross-sectional and time series dimensions of the data. It could be the case that some important information for a particular country is omitted from the pooled model. For example, the political situation or the legal system of a country could be such that we permanently underestimate the probability of a crisis. Panel data models with fixed and random effects are useful tools to address these issues. To test whether such country-specific information are important, we estimate the binomial logit model using fixed effects and random effects. The results show that the random effects model fared better than the fixed effects model. However, overall the improvement using the panel data models is rather small.

Table 2
Performance of binomial logit model

	$S_{i,t}=0$	$S_{i,t}=1$	Total
$Y_{i,t}=0$	1049	255	1304
$Y_{i,t}=1$	106	140	246
Total	1155	395	1550
% of observations correctly called			76.7
% of crises correctly called			56.9
% of false alarms of total alarms			64.6
% probabilities of crisis given an alarm			35.4
% probabilities of crisis given no alarm			9.2

Table 3
Performance of binomial logit model with alternative overvaluation definition

	$S_{i,t}=0$	$S_{i,t}=1$	Total
$Y_{i,t}=0$	1140	164	1304
$Y_{i,t}=1$	82	164	246
Total	1222	328	1550
% of observations correctly called			84.1
% of crises correctly called			66.7
% of false alarms of total alarms			50.0
% probabilities of crisis given an alarm			50.0
% probabilities of crisis given no alarm			6.7

Note: Overvaluation is defined as the deviation of the REER from its country-specific trend over the full sample period. See Appendix A for a detailed discussion.

This confirms that ignoring fixed and random effects does not constitute a bias in the estimation.[8]

4. The post-crisis bias and the multinomial logit EWS approach

4.1. What is the post-crisis bias?

What we call the ‘‘post-crisis bias’’ implies that the econometric results of binomial logit EWS models are at least in part explained by the behavior of the independent variables during and directly after a crisis. Recall that the aim of an EWS model is to analyze the vulnerability of a country to a crisis. The correct way of doing this is by comparing the behavior of fundamentals before a crisis with their behavior during periods when these variables are sustainable, i.e., during tranquil or ‘‘normal’’ times. Instead, what binomial EWS models do is to compare the pre-crisis observations with the observations both during tranquil periods *and* crisis/post-crisis periods. This can lead to an important bias because the behavior of the independent variables is very different during tranquil times as compared to crisis/recovery periods.

Table 5 illustrates the existence of the post-crisis bias for the six fundamentals of our benchmark EWS model. As argued above, the correct comparison is between column (2), which shows the means of these indicators in the pre-crisis period, and column (3), which corresponds to what we define as ‘‘normal periods’’ by excluding the period during and immediately after a crisis. By contrast, what traditional two-state logit or probit models do is estimate the relationship between the pre-crisis period of column (2) with the combined tranquil and crisis/post-crisis episodes shown in column (5). As column (4) reveals, crisis and post-crisis/recovery periods are often disorderly and volatile corrections towards longer-term equilibria. They therefore should not be included in an analysis of anticipating crises because one cannot extract meaningful information about the sustainability and vulnerability of a country's economic fundamentals by looking at crisis/post-crisis observations.

[8] Other robustness tests conducted, which are consistent with these results, were to exclude China – which is the country with the least open financial account in our sample – as well as to exclude countries that never experienced a crisis (Hungary and Poland). The results were very robust to these exclusions and did not yield significant changes in the parameter estimates or the goodness-of-fit. Results are available upon request.

Table 4
Performance of alternative models

Models	IMF–DCSD	IMF–KLR	Goldman–Sachs	CSFB
% of observations correctly called	76.7	70.2	66.1	75.3
% of crises correctly called	65.1	59.8	66.2	61.1
% of false alarms of total alarms	62.8	70.3	74.0	93.5
% probabilities of crisis given an alarm	37.2	29.7	26.0	6.5
% probabilities of crisis given no alarm	7.8	9.8	8.4	1.4

Source: Berg et al. (2004).

4.2. How to address the post-crisis bias

There are at least two ways of tackling the post-crisis bias. The first and the crudest way is to drop all crisis/post-crisis observations from the data and then to estimate the standard binomial discrete-dependent-variable model, as done for example in Demirguc-Kunt and Detragiache (1998) in the context of banking crises. The drawback of such a method is that it ignores data that could provide valuable information, in particular on how fundamentals behave during recoveries and when or whether economic variables return to levels of tranquil or "normal" times. The second and our preferred alternative is a discrete-dependent-variable approach with more than two outcomes, in our case a multinomial logit model with three outcomes:

$$Y_{i,t} = \begin{cases} 1 & \text{if } \exists\, k = 1, \ldots, 12 \quad \text{s.t. } \mathrm{CC}_{i,t+k} = 1, \\ 2 & \text{if } \exists\, k = 0, \ldots, p \quad \text{s.t. } \mathrm{CC}_{i,t-k} = 1, \\ 0 & \text{otherwise} \end{cases} \tag{10}$$

i.e., a pre-crisis regime for the 12 months prior to the onset of a crisis ($Y_{i,t} = 1$), a post-crisis/recovery regime for the crisis itself and till return to the tranquil period p months after the crisis ($Y_{i,t} = 2$), and a tranquil regime for all other times ($Y_{i,t} = 0$).

The key difference is that what used to be the tranquil period definition ($Y_{i,t} = 0$) in Eq. (3) is now split into a crisis/post-crisis regime ($Y_{i,t} = 2$) and a *new* tranquil regime ($Y_{i,t} = 0$). The logic for the definition of the crisis/post-crisis regime ($Y_{i,t} = 2$) in Eq. (10) is the following. Once a country experiences a crisis, it will take some time before it recovers. This time can vary considerably from one country to the next. We use two complementary methods to define the end p of the crisis/post-crisis regime ($Y_{i,t} = 2$). First, we use a regime-switching model, previously developed in Fratzscher (2003), in which a Markov-switching model is used for each country to

Table 5
Mean values of key indicators

	(1) Average, all periods	(2) Average, year preceding crisis ($Y = 1$)	(3) Average, normal periods ($Y = 0$)	(4) Average, year following crisis ($Y = 2$)	(5) Average, $Y = 0$ or $Y = 2$
Overvaluation	3.06	13.30	4.36	−8.07	1.25
Lending boom	15.24	41.55	8.15	18.38	10.70
STD/res	94.09	118.14	82.94	110.26	89.72
CA/GDP	−0.06	−2.66	0.37	0.46	0.39
Financial contagion	0.38	0.33	−0.01	1.88	0.39
Growth	4.31	3.92	5.95	−0.47	4.38

define the end of the crisis/post-crisis regime. The regime in this model is defined as a shift in the level of the exchange market pressure variable $EMP_{i,t}$ of Eq. (1) and the variance. Hence, the end of the crisis/post-crisis regime ($Y_{i,t}=2$) is reached when the exchange market pressure and its variance return to the tranquil regime. Second, we check this definition visually by charting the EMP_i variable for each country and analyze whether the end of the crisis/post-crisis regime ($Y_{i,t}=2$) based on the regime-switching model coincides with our intuition.

Although the introduction of a state $Y_{i,t}=2$ stemmed from the concern that the post-crisis observations may affect the ability of the model to predict crises, it also provides some interesting indications on the unfolding of and recovery from a crisis. For some of the countries in the sample the crisis was violent and sudden, lasting no more than a couple of months, whereas for others it was more protracted. Thus, the present model not only investigates whether a set of fundamentals can predict currency crises, but also whether the *same* fundamentals can predict the end of the crisis as well. Intuitively, if a high debt ratio can trigger a crisis, the return of this ratio to a sustainable level may signal for investors the end of the crisis and induce them to return to the country. Although there is a resemblance between the two impacts, the effect is probably not exactly symmetric: it may take longer for the investors to return than it took them to leave when panic hit the markets.

Just as for the binomial discrete-dependent-variable logit model, we chose the tranquil regime ($Y_{i,t}=0$) as the base regime in order to provide identification for the logit model:

$$\begin{aligned}
\Pr(Y_{i,t}=0) &= \frac{1}{1+e^{\left(X_{i,t-1}\beta^1\right)}+e^{\left(X_{i,t-1}\beta^2\right)}}\\
\Pr(Y_{i,t}=1) &= \frac{e^{\left(X_{i,t-1}\beta^1\right)}}{1+e^{\left(X_{i,t-1}\beta^1\right)}+e^{\left(X_{i,t-1}\beta^2\right)}}\\
\Pr(Y_{i,t}=2) &= \frac{e^{\left(X_{i,t-1}\beta^2\right)}}{1+e^{\left(X_{i,t-1}\beta^1\right)}+e^{\left(X_{i,t-1}\beta^2\right)}}.
\end{aligned} \tag{11}$$

This implies that β^1 measures the effect of a change in the independent variable $X_{i,t-1}$ on the probability of being in a pre-crisis period *relative* to the probability of being in the tranquil regime. Accordingly, β^2 measures the effect of a change in the independent variable $X_{i,t-1}$ on the probability of being in a recovery period *relative* to the probability of being in the tranquil regime:

$$\begin{aligned}
\frac{\Pr(Y_{i,t}=1)}{\Pr(Y_{i,t}=0)} &= e^{\left(X_{i,t-1}\beta^1\right)}\\
\frac{\Pr(Y_{i,t}=2)}{\Pr(Y_{i,t}=0)} &= e^{\left(X_{i,t-1}\beta^2\right)}.
\end{aligned} \tag{12}$$

The key advantage of the multinomial logit is that it allows an explicit modeling of and distinction between the three different regimes, and thus it enables us to distinguish between the different effects β^1 and β^2. The information we are particularly interested in for our EWS model is β^1, i.e., whether an economy is in a pre-crisis state facing a crisis within the next 12 months or whether it is still in a tranquil state in which economic fundamentals are sustainable. β^2 provides information about whether an economy will still be in a recovery state or will return to a tranquil regime.

5. Multinomial logit EWS model: results and robustness tests

5.1. Results and in-sample performance of the multinomial logit model

Table 6 summarizes the results obtained from the multinomial logit model and Fig. 1 charts the predicted probabilities obtained from the model. The first panel shows the coefficients for the six benchmark variables comparing the probability of being in a pre-crisis ($Y_{i,t}=1$) with that of being in a tranquil period ($Y_{i,t}=0$). All variables enter the equation with the correct sign and are significant at the 5% level. A positive deviation of the real effective exchange rate from its trend, a rapid increase of the credit to the private sector ("lending boom"), a high ratio of short-term debt to reserves, and financial contagion from closely integrated countries all increase the probability of a crisis. Conversely, a high current account surplus and a rapid growth rate decrease the probability of a crisis, hence a negative sign on these variables (which means also that a deep current account deficit and decelerating growth make a country more vulnerable to crises).

An interesting finding that underlines the relevance of the post-crisis bias is the result for the post-crisis period ($Y_{i,t}=2$) in the second panel of Table 6. Here the coefficients are not only substantially different from the pre-crisis period but also they change their sign in some cases. Again, the results are intuitively convincing and are as expected. For instance, the current account usually improves significantly during post-crisis periods and the exchange rate falls below its trend, therefore we find a positive coefficient for these variables.

In terms of predictive power, Table 7 shows the goodness-of-fit of the multinomial logit model. Our model fares better than all four of the alternative models in Table 4 and than the binomial model presented in Table 2. Moving from the simple logit to the multinomial logit helps increase the percentage of correctly predicted crises from 56.9% to 65.5% while reducing

Table 6
Estimation results of multinomial logit model

Variable	Coefficient	Standard error	Z	$P>\|z\|$
Pre-crisis period $Y_{i,t}=1$				
Overvaluation	0.050	0.007	7.24	0.000
Lending boom	0.011	0.002	5.59	0.000
STD/res	0.005	0.001	5.95	0.000
CA/GDP	−0.073	0.016	−4.58	0.000
Financial contagion	0.027	0.013	2.06	0.040
Growth	−0.041	0.019	−2.19	0.028
Constant	−2.576	0.192	−13.41	0.000
Post-crisis period $Y_{i,t}=2$				
Overvaluation	−0.042	0.005	−7.55	0.000
Lending boom	0.010	0.002	5.04	0.000
STD/res	0.003	0.001	3.20	0.001
CA/GDP	0.010	0.010	1.00	0.319
Financial contagion	0.052	0.011	4.46	0.000
Growth	−0.243	0.018	−13.50	0.000
Constant	−0.862	0.136	−6.35	0.000
No. of observations	1549			
Pseudo R^2	0.250			

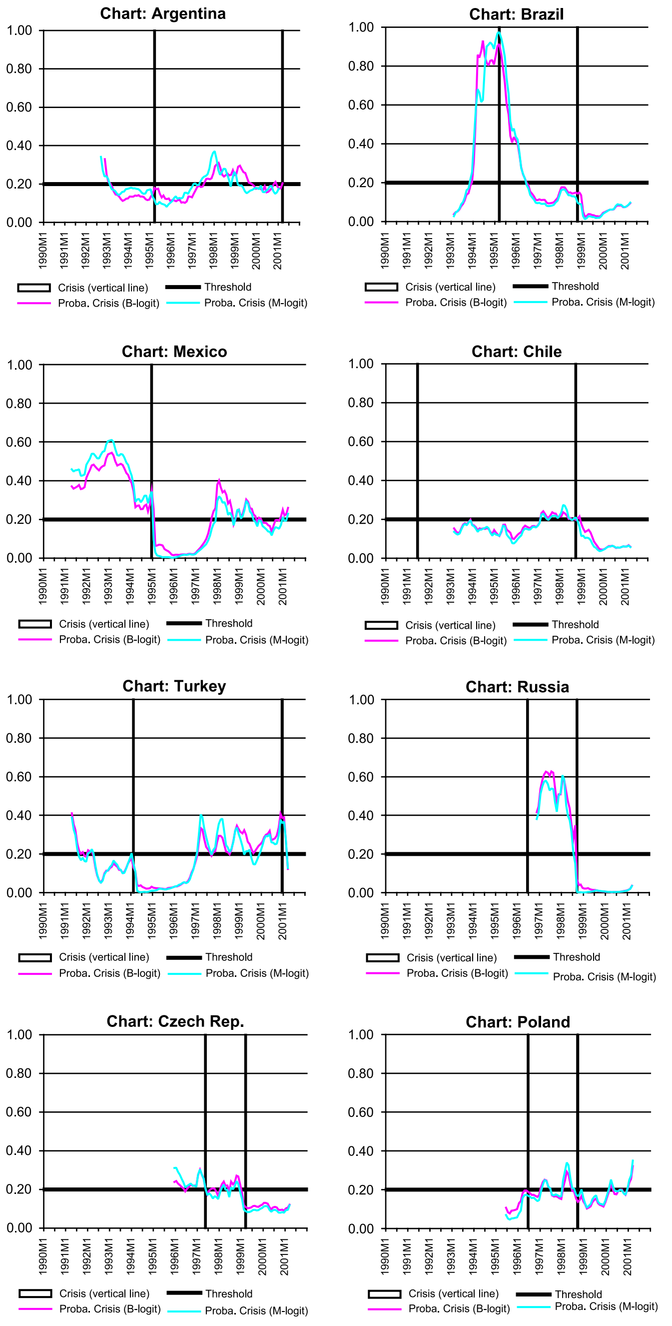

Fig. 1. Predicted probabilities.

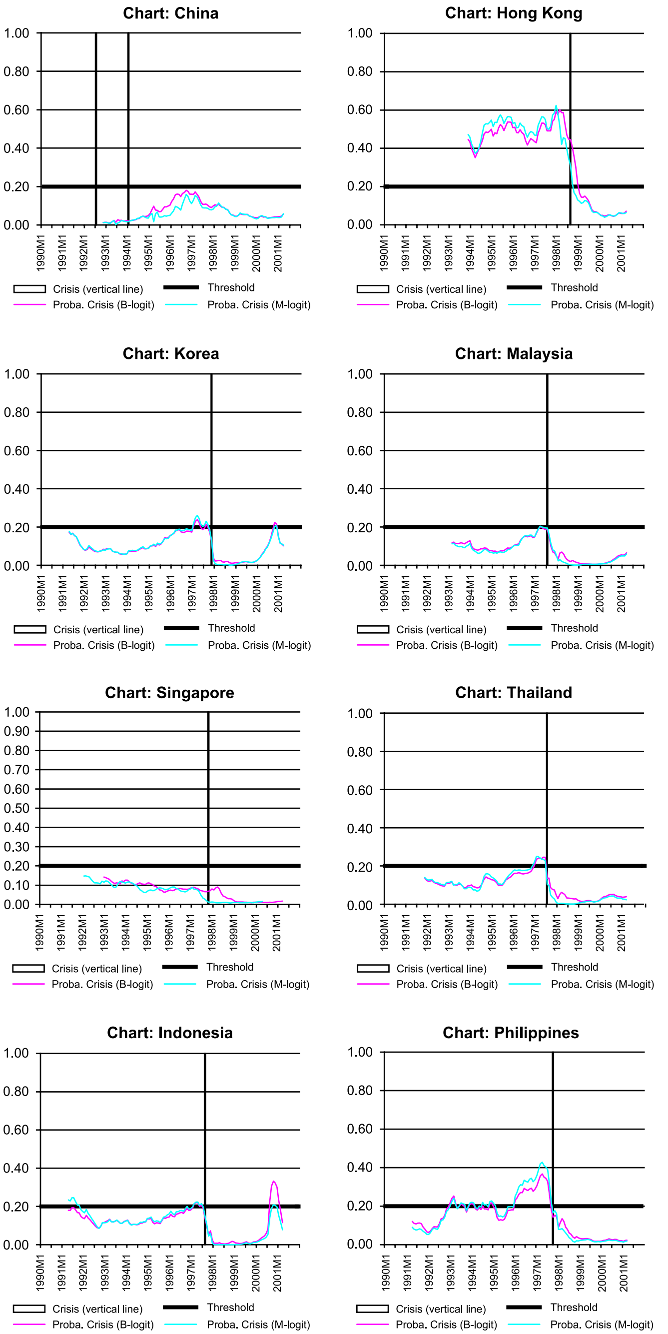

Fig. 1 (*continued*).

Table 7
Performance of multinomial logit model

	$S_{i,t}=0$	$S_{i,t}=1$	Total
$Y_{i,t}=0$	781	207	988
$Y_{i,t}=1$	80	152	232
$Y_{i,t}=2$	291	38	329
Total	1152	397	1549
% of observations correctly called			76.5
% of crises correctly called			65.5
% of false alarms of total alarms			57.7
% probabilities of crisis given an alarm			42.3
% probabilities of crisis given no alarm			9.3

false alarms from 64.6% to 57.7%. Similarly, the conditional probability of experiencing a crisis when an alarm was issued rises from 35.4% to 42.3%.

Before turning to robustness checks, it is useful to briefly analyze the magnitude of importance of each variable. As the logit model is non-linear, the coefficients reported in Table 6 cannot be interpreted as marginal effects: marginal effects must be computed at a certain value of the independent variable. One way to assess the weight of the different variables is to imagine a fictitious country where all variables are equal to their tranquil average as in Table 5, column (3). Next, assuming that only one of the variables jumps to its crisis level (column 2), while all five other variables stay at their tranquil level, one can compute the ceteris paribus increase in the probability of a crisis due to a change in this variable. On this basis, the exchange rate overvaluation has the highest weight: the crisis probability increases by 5% when the overvaluation measure jumps from 4.4% to 13.3%. It is followed by the lending boom variable (probability increase of 3%), the debt and the current account (2% each), while the contagion and the growth variables have the smallest weights.

A final robustness test is to compare the multinomial logit EWS model with a binomial logit model in which all crisis/post-crisis observations are dropped from the model, as described in Section 4.2 (see results in Table 8). The estimates of the two models as well as the goodness-of-fit are very similar, with the multinomial logit model performing significantly better. The percentage of observations correctly predicted in the binomial logit where $Y=2$ observations have been dropped reaches only 58%, against 76.5% in the multinomial logit.

Table 8
Robustness test on binomial logit, dropping observations $Y=2$

Variable	Coefficient	Standard error	Z	$P>\|z\|$
Overvaluation	0.055	0.008	7.00	0.000
Lending boom	0.014	0.003	5.17	0.000
STD/res	0.005	0.001	5.81	0.000
CA/GDP	−0.061	0.016	−3.85	0.000
Financial contagion	0.020	0.013	1.48	0.139
Growth	−0.030	0.019	−1.58	0.115
Constant	−2.712	0.211	−12.86	0.000
No. of observations	1221			
Pseudo R^2	0.178			

The similarity of the parameters was to be expected because the relationship between the pre-crisis regime ($Y_{i,t}=1$) and the tranquil regime ($Y_{i,t}=0$) should not be affected by whether or not there is also an additional regime ($Y_{i,t}=2$) included in the model. In the microeconometric literature, this point is referred to as the *independence from irrelevant alternatives* (IIA) assumption. For the EWS models, we formally check whether IIA holds by running a Hausman test for the equality of the parameters in the two models. The equality of parameters is confirmed, showing that IIA holds and thus that the multinomial logit model is valid and unbiased.[9]

Overall, we conclude that the multinomial logit EWS model is a valid way to solve for the post-crisis bias and that it is a superior solution because it also has the advantage of allowing to analyze also the crisis/post-crisis period and to anticipate when an economy may return to a tranquil regime.

5.2. Out-of-sample performance of the multinomial logit model

Since the important contribution of Berg and Pattillo (1999a) on the failure of models to predict crises in subsequent episodes, out-of-sample forecasts have become the cornerstone of testing the goodness-of-fit of EWS models. To check whether our model is able to predict crises out-of-sample, we estimate the model on restricted periods and compute the probability of a crisis in the following 12 months.

We conduct the out-of-sample test for three episodes: for the Asian crisis in 1997, for the Russia/Brazil crisis in 1998, and for the crises in Turkey and Argentina in 2001. For this purpose, we estimated the model over three periods ending at the end of 1996, 1997 and 2000, respectively (see results in Table 9). These regressions can also be seen as robustness tests on the stability of parameters over time, although the shortness of the time dimension, especially for the first estimation (ending in 1996, i.e., over two years only) prevents such interpretation. Interestingly, estimating the model at the end of 1996 would have led one to conclude that the debt ratio is not significant. This stems from the fact that many Asian countries had accumulated large amounts of short-term debt and had not experienced (at that time) a crisis.

The out-of-sample probabilities of the multinomial and binomial models are presented in Table 10. Overall, both models fare relatively well, even out-of-sample, predicting most crises in Asian countries in 1997, the Russian crisis in 1998 (which spread to several Latin American countries), and the crises in Argentina and Turkey in 2001.[10] Still, they failed to predict the crisis in Singapore in 1997, while the predicted probabilities for Indonesia and Korea were rather low for that year. Both models incorrectly sent a signal for Mexico and the Czech Republic in 1998 and for Indonesia in 2000. However, the multinomial model fares significantly better than the binomial, in particular by sending far less false alarms. For instance, the multinomial model returned a substantially lower probability for China and Russia in 1997, for the Czech Republic, Hungary, Mexico and Singapore in 1998, or for Indonesia in 2000 (all these countries did not experience a crisis in those years).

[9] See Hausman and McFadden (1984) for a detailed account of the IIA issue and the formulation and application of the Hausman principle to formally test for IIA. For space reason, results of neither the binomial logit model without $Y_{i,t}=2$ nor the Hausman tests are reported, but they are available from the authors upon request.

[10] Although the out-of-sample predicted probability of a crisis in Argentina was below the 20% threshold in December 2000, the model was signaling an imminent crisis as this probability was quickly rising.

Table 9
Estimation results, m-logit model, out-of-sample forecasts

Model	Benchmark	End point: 1996M12	End point: 1997M12	End point: 2000M12
Overvaluation	0.050*** (0.007)	0.050*** (0.013)	0.038*** (0.009)	0.050*** (0.007)
Lending boom	0.011*** (0.002)	0.014*** (0.003)	0.017*** (0.003)	0.011*** (0.002)
STD/res	0.005*** (0.001)	0.000 (0.001)	0.002*** (0.001)	0.005*** (0.001)
CA/GDP	−0.073*** (−0.016)	−0.031 (0.029)	−0.006 (0.018)	−0.072*** (0.016)
Financial contagion	0.027** (0.013)	0.048 (0.035)	0.057** (0.028)	0.032** (0.013)
Growth	−0.041** (0.019)	−0.056* (0.033)	−0.058** (0.028)	−0.040** (0.019)
Constant	−2.576*** (0.192)	−1.962*** (0.0375)	−1.750*** (0.029)	−2.522*** (0.195)
No. of observations	1549	590	818	1501
Pseudo R^2	0.250	0.241	0.220	0.254

Note: Standard errors in parentheses. ***, **, * indicate statistical significance at the 99%, 95% and 90% levels, respectively.

Overall, therefore, the superior performance of the multinomial logit model is evident both in its in-sample performance as well as in the out-of-sample ability to anticipate financial crises.

6. Conclusions

This paper developed a new early warning system (EWS) model for predicting financial crises, based on a multinomial logit model approach. Its main difference to existing EWS models and its intended contribution to the literature focused on the identification and solution of what

Table 10
Predicted probabilities, out-of-sample forecasts

Country	Out-of-sample end date: 1996M12		Crisis in 1997	Out-of-sample end date: 1997M12		Crisis in 1998	Out-of-sample end date: 2000M12		Crisis in 2001
	M-logit	B-logit		M-logit	B-logit		M-logit	B-logit	
Argentina	0.093	0.096	No	0.254	0.263	No	0.143	0.169	01M3
Brazil	0.087	0.110	No	0.134	0.169	98M10	0.076	0.067	No
Chile	0.178	0.173	No	0.272	0.263	98M9	0.062	0.055	No
China	0.084	0.275	No	0.151	0.164	No	0.040	0.039	No
Colombia	0.327	0.396	No	0.292	0.275	98M9	0.025	0.024	No
Czech Republic	0.228	0.250	97M5	0.143	0.197	No	0.084	0.086	No
Hong Kong	0.211	0.245	No	0.474	0.554	98M8	0.067	0.059	No
Hungary	0.077	0.094	No	0.039	0.223	No	0.016	0.129	No
Indonesia	0.113	0.115	97M8	0.013	0.039	No	0.211	0.322	No
Korea	0.103	0.106	97M11	0.043	0.044	No	0.159	0.153	No
Malaysia	0.160	0.142	97M7	0.086	0.079	No	0.053	0.052	No
Mexico	0.015	0.017	No	0.250	0.410	No	0.224	0.262	No
Philippines	0.368	0.300	97M10	0.195	0.178	No	0.017	0.017	No
Poland	0.203	0.227	No	0.268	0.217	No	0.215	0.197	No
Russia	0.267	0.416	No	0.460	0.494	98M9	0.011	0.009	No
Singapore	0.065	0.076	97M10	0.100	0.190	No	0.014	0.013	No
Thailand	0.179	0.165	97M7	0.008	0.074	No	0.034	0.035	No
Turkey	0.181	0.157	No	0.427	0.327	No	0.370	0.421	00M12
Venezuela	0.036	0.103	No	0.200	0.172	No	0.078	0.090	No

Note: M- and B-logit stand for multinomial and binomial logit models, respectively.

we call the *post-crisis bias* in existing binomial discrete-dependent-variable EWS models. The paper illustrated that failing to distinguish between tranquil periods and crisis/post-crisis episodes may introduce an important bias in the estimation results and thus worsen our ability to anticipate financial crises.

The paper showed that moving from a binomial logit model to a multinomial logit model with three regimes improves the predictive power of the EWS substantially. Overall, the EWS based on the multinomial logit model predicts well most currency crises in emerging markets during the 1990s, both in-sample as well as out-of-sample. For the in-sample estimation, the model fails to anticipate entirely only one of the emerging market crises in our sample. For the out-of-sample estimation, we find that the model would have anticipated correctly most of the countries that succumbed to the Asian crisis in 1997–1998 as well as the Russian and Brazilian crises in 1998 and the Turkish crisis in 2001.

It should be emphasized that the EWS model developed in this paper does certainly not constitute the final step towards a comprehensive EWS model of financial crises. However, we believe that by outlining existing methodological difficulties and by suggesting a new method to solve some of these problems, the paper constitutes a further step towards developing an EWS model that could become an even more powerful tool for policy makers. Future research on EWS models may focus on adding dynamic components to EWS models, and in particular by addressing the current endogeneity of the choice of the timing and the length of different regimes. This may be accomplished, for instance, by utilizing regime-switching models that have already been employed successfully in other areas of economic forecasting.

From a policy perspective, EWS models that help to reliably anticipate financial crises constitute an important tool for policy makers if they are employed carefully and sensibly. Many financial crises over the past few decades had devastating social, economic and political consequences. Developing reliable EWS models therefore can be of substantial value by allowing policy makers to obtain clearer signals about when and how to take pre-emptive action in order to mitigate or even prevent financial turmoil. It should be stressed that EWS models cannot replace the sound judgment of the policy maker to guide policy, but they can play an important complementary role as a neutral and objective measure of vulnerability.

Acknowledgements

We have benefited from many discussions and would like to thank in particular Mike Artis, Anindya Banerjee, Gonzalo Camba-Méndez, Søren Johansen, François Laisney, Helmut Lütkepohl, Rasmus Rüffer, Bernd Schnatz, as well as two anonymous referees. We are also grateful to the participants of seminars at the European Central Bank, the 13th World Congress of the International Economic Association, Free University of Berlin, the Royal Economic Society Annual Conference 2003, ZEW-University of Mannheim, the Bundesbank and the Bank of Canada for their comments and suggestions. The views expressed in this paper are those of the authors and do not necessarily reflect those of the European Central Bank.

Appendix A. Country list

Latin America: Argentina, Brazil, Chile, Colombia, Mexico, and Venezuela.

Asia: China, Hong Kong, Indonesia, Korea, Malaysia, Philippines, Singapore, Taiwan, and Thailand.

Eastern Europe and others: Czech Republic, Hungary, Poland, Russia, and Turkey.

Table 11
Independent variables

1. External Competitiveness
* REER overvaluation
* Current account (%GDP)
• Trade balance (%GDP)
• Terms of trade
• Export and import growth
2. External Exposure
* Short-term debt/reserves
• Total debt/reserves
• Debt composition (loans/bonds, locational and consolidated concepts, short and long terms)
• FDI, portfolio investment (%GDP)
• Total net capital inflows
• Foreign exchange reserves (level and growth rate, as a % of GDP and exports)
3. Domestic Real and Public Sector
* Real GDP growth rate
• Fiscal stance
• Public debt (%GDP)
• Inflation rate
• Domestic investment ratios
• Real estate sector
4. Domestic Financial Sector
* Domestic credit to private and government sector (level and growth rate)
• Deposit/lending interest rate spreads
• M1, M2 (as a % of GDP and as a % of reserves)
• Equity market indices
• Bank deposits
5. Contagion
• Trade channel
* Financial interdependence

Only the variables with a star in Table 11 are included in the final benchmark EWS models and will be described below.

A1. Current account to GDP ratio

Sources: IMF International Financial Statistics (IFS). Data are quarterly and have been transformed into monthly frequency by taking a moving average.

A2. Short-term debt to reserves ratios

Sources: IMF IFS for reserves and the IMF–World Bank–OECD–BIS joint table for the debt statistics for short-term debt. Data are mostly quarterly and have been transformed into monthly frequency by taking a moving average.

A3. Overvaluation of the exchange rate

Sources: IMF and JP Morgan. The real effective exchange rate (REER) is a valuable concept to look at since it takes into account the competitiveness of the home country, as well as competition with third countries. One key question in the measurement of the overvaluation is which benchmark should be taken for the comparison. A first option is to take as a percent change over a given period (e.g., over the past 24 months):

$$\mathrm{REERCH}_t^i = \frac{\left(\mathrm{REER}_t^i - \mathrm{REER}_{t-24}^i\right)}{\mathrm{REER}_{t-24}^i} \times 100. \tag{A.1}$$

One potential bias of this measure is that if a country devalues at time t, its currency will appear severely overvalued at time $t+24$ only because of the base effect. One option is to smooth the base by taking an average of the year preceding observation $t-24$, i.e., to compute the percent change between time t and the average of REER computed over the period between time $t-24$ and $t-36$. This is the measure employed in our EWS model, as shown in Tables 2 and 7. Yet, even this average may not completely offset the base effect. As an alternative definition of overvaluation, we use the REER deviation from a linear trend computed over the full sample period for each country i separately:

$$\mathrm{REERDEV}_t^i = \frac{\left(\mathrm{REER}_t^i - \mathrm{TREND}_t^i\right)}{\mathrm{TREND}_t^i} \times 100. \tag{A.2}$$

This is the measure used for Table 3. The motivation for using such a trend as the benchmark is that one would expect the currencies of emerging markets to appreciate over time due to the Balassa–Samuelson effect. However, a potential problem arising from this definition is that the trend is strongly influenced by the first few and last few observations in the sample.

A4. Real GDP growth

Source: IMF (IFS). Data are quarterly and have been transformed into monthly frequency by taking a moving average.

A5. Financial sector fragilities

Source: IMF (IFS). We use the measure first suggested by Sachs et al. (1996a,b), who define a lending boom index in a country as the growth rate of domestic credit to the private sector over the past four years. Similarly as for the measure of exchange rate overvaluation, we take the percentage change between month t and the average computed over the months $t-24$ and $t-36$ to avoid base effects.

A6. Contagion variables

Sources: IMF (IFS), World Trade Analyzer, Thomson Financial Datastream. The contagion variables are defined following Fratzscher (1998, 2003). The contagion channel based on financial linkages uses the correlation of weekly equity market returns across a country-pair during tranquil periods, controlling for similarities in fundamentals, as our measure of financial interdependence. The financial contagion variable for country i is then measured as the sum of financial interdependence multiplied with the exchange market pressure EMP_j of each partner country in any given month, as defined in Eq. (1). For a more detailed account, see Fratzscher (1998, 2003).

References

Ades, A., Masih, R., Tenengauzer, D., December 1998. GS-Watch: a new framework for predicting financial crises in emerging markets. Goldman–Sachs.

Berg, A., Borensztein, E., Pattillo, C., 2004. Assessing early warning systems: how have they worked in practice? IMF Working Paper 04/52.

Berg, A., Pattillo, C., 1999a. Are currency crises predictable? A test. IMF Staff Papers 46 (2), 107–138.

Berg, A., Pattillo, C., 1999b. Predicting currency crises: the indicators approach and an alternative. Journal of International Money and Finance 18 (4), 561–586.

Bussiere, M., 2001. Book review, assessing financial vulnerability: an early warning system for emerging markets, by Goldstein, M., Kaminsky, G., Reinhart, C. International Journal of Finance and Economics 6 (2), 185.

Bussiere, M., Fratzscher, M., May 2002. Towards a new early warning system of financial crises. ECB Working Paper No. 145.

Bussiere, M., Mulder, C., 1999. External vulnerability in emerging market economies: how high liquidity can offset weak fundamentals and the effects of contagion. IMF Working Paper, WP/99/88.

Demirguc-Kunt, A., Detragiache, E., March 1998. The determinants of banking crises in developing and developed countries. IMF Staff Papers 45 (1).

Eichengreen, B., Rose, A., Wyplosz, C., 1995. Exchange market mayhem: the antecedents and aftermaths of speculative attacks. Economic Policy 21, 249–312.

Fernald, J., Edison, H., Loungani, P., 1999. Was China the first domino? Assessing links between China and other Asian economies. Journal of International Money and Finance 18 (4), 515–535.

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

Fratzscher, M., 1998. Why are currency crises contagious? A comparison of the Latin American crisis of 1994–1995 and the Asian crisis of 1997–1998. Weltwirtschaftliches Archiv/Review of World Economics 134 (4), 664–691.

Fratzscher, M., 2003. On currency crises and contagion. International Journal of Finance and Economics 8 (2), 109–130.

Garber, P., Lumsdaine, R., van der Leij, M., October 2000. Deutsche Bank alarm clock (DBAC): forecasting exchange rate and interest rate events in emerging markets. Deutsche Bank.

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

Hausman, J., McFadden, D., 1984. A specification test for the multinomial logit model. Econometrica 52, 1219–1240.

Kamin, S., Babson, O., September 1999. The contribution of domestic and external factors to Latin American devaluation crises: an early warning systems approach. International Finance Discussion Papers Number 645. Board of Governors of the Federal Reserve System.

Kamin, S., Schindler, J., Samuel, S., 2001. The contribution of domestic and external factors to emerging market devaluation crises: an early warning systems approach. International Finance Working Paper No. 711. Board of Governors of the Federal Reserve System.

Kaminsky, G., Lizondo, S., Reinhart, C., 1998. Leading indicators of currency crises. IMF Staff Papers 45 (1), 1–48.

Kaminsky, G., Reinhart, C., 1999. The twin crises: the causes of banking and balance-of-payments problems. American Economic Review 89 (3), 473–500.

Kimbrough, K., Li Jen, S., July 2001. An early warning system for currency crises. Morgan Stanley Dean Witter.

Krugman, P., 1998. What happened to Asia? MIT Mimeo.

Persaud, A., May 1998. Event Risk Indicator Handbook. J.P. Morgan.

Roy, A., Tudela, M., February 2001. Emerging market risk indicator (EMRI): re-estimated version, September 2000. Credit Suisse First Boston (CSFB).

Sachs, J., Tornell, A., Velasco, A., 1996a. The Mexican peso crisis: sudden death or death foretold? Journal of International Economics 41, 265–283.

Sachs, J., Tornell, A., Velasco, A., 1996b. Financial crises in emerging markets: the lessons from 1995. Brookings Papers on Economic Activity 10 (1), 147–198.

Schnatz, B., May 1999. The sudden freeze of the Asian miracle: the role of macroeconomic fundamentals. Asia Pacific Journal of Finance 2 (1).

Schnatz, B., September 1998. Macroeconomic determinants of currency turbulences in emerging markets. Discussion Paper 3/98. Economic Research Group of the Deutsche Bundesbank.