EUROPEAN CENTRAL BANK

WORKING PAPER SERIES

WORKING PAPER NO. 145

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* The paper was written while Matthieu Bussiere was visiting the External Developments Division of the European Central Bank. We have benefited from many discussions and would like to thank in particular Mike Artis, Anindya Banerjee, Gonzalo Camba Méndez, Søren Johansen, Helmut Lütkepohl, Rasmus Rüffer, Bernd Schnatz and the participants of two ECB seminars 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.
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ISSN 1561-0810

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Abstract

This paper develops a new Early Warning System (EWS) model for predicting financial crises, based on a multinomial logit model. It is shown that EWS approaches based on binomial discrete-dependent-variable models can be 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 32 open emerging markets from 1993 till the present, the model would have correctly predicted a large majority of crises in emerging markets. Moreover, we derive general results about the optimal design of EWS models, which allows policy-makers to make an optimal choice based on their degree of risk-aversion against unanticipated financial crises.

JEL classification: F31, F47, F30.

Keywords: currency crises; Early Warning System; crisis prediction.

Non-Technical Summary

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. As a result, international financial institutions have developed Early Warning System (EWS) models, with the aim of identifying economic weaknesses and vulnerabilities among emerging markets and ultimately anticipating such events.

The aim of this paper is to present a new EWS model that significantly improves upon existing models. First, the paper develops a different empirical methodology that corrects for what we call a *post-crisis bias*. This bias arises if 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 a post-crisis/recovery regime) constitutes a substantial improvement in the forecasting ability of EWS models.

A second aim of this paper is to test for the role of a broad set of economic and financial variables in financial crises. In particular, we test a number of contagion indicators to measure real and financial channels of transmission across economies. We find that in particular the financial contagion channel has been an important factor in explaining and anticipating currency crises for a set of 32 open EMEs for the period 1993-2001. Overall, the empirical performance of our EWS model constitutes a significant improvement in comparison to existing EWS models. Our 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.

Finally, the paper derives general results about the optimal design of EWS models for policy-makers. It shows how changes to the preferences of the policy-maker and the specification of her loss function can fundamentally alter the optimal design of the EWS model in terms of the time horizon for the model and the desired policy action. We illustrate how these choices depend crucially on the trade-off between, on the one hand, issuing many crisis alarms (hence also sending many false alarms) and, on the other hand, issuing fewer alarms at the expense of missing some crises. Hence it can be shown how the policy-maker's preferences and degree of risk-aversion about this trade-off determines the optimal design of the EWS model.

From a policy perspective, developing reliable EWS models can be of substantial value by allowing policy-makers to obtain clear signals as to when and how to take pre-emptive measures in order to mitigate or even prevent financial turmoil. Although EWS models can not replace the sound judgment of policy-makers in guiding policy, they can play an important complementary role as a neutral and objective measure of vulnerability.

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 1994-95 and the Asian crisis of 1997-98 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, Lizondo and Reinhart (1998) and by Berg and Pattillo (1999b). But also many central banks, such as the US Federal Reserve (Kamin, Schindler and Samuel, 2001, Kamin and Babson, 1999) and the Bundesbank (Schnatz, 1998, 1999), academics and various private sector institutions 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 (Berg and Pattillo, 1999a).

The aim of this paper is to develop a new EWS model that significantly improves upon existing models in three ways. First, and most importantly, the paper argues that a key weakness of existing EWS models is that they are subject to what we call a *post-crisis bias*. This bias implies that these 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.

Second, many financial crises since the 1990s have been contagious in spreading across markets. Another aim of this paper is therefore to apply to EWS models contagion indicators, developed in Fratzscher (1998, 2002), to measure real contagion channels through trade linkages (direct and indirect) and financial contagion channels via equity market interdependence. We find that in particular the financial contagion channel has been an important factor in explaining and anticipating currency crises.

Third, this paper uses a data sample of 32 EMEs, with monthly frequency, for the period 1993-2001 as the basis for the EWS model estimations. Since the aim of an EWS model is to develop a framework that allows predicting financial crises in relatively open economies in the future, it is imperative to use for the in-sample estimation only those crises and country observations that are similar to those that are likely to occur in the future. We have therefore started our sample only in 1993, excluding the 1980's and early 1990's, during which capital markets were not yet integrated and capital accounts often still closed to foreign investors, also because many countries still experienced hyperinflation in the early 1990's. Likewise, we have excluded the years immediately following the transition to a free market in the Eastern European countries.

The empirical performance of our EWS model constitutes a significant improvement in comparison to existing EWS models. In particular, the use of the multinomial logit model reduces substantially the number of false signals (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). 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.

Finally, the paper derives general results about the optimal design of EWS models. It shows how changes to the preferences of the policy-maker and the specification of her loss function can fundamentally alter the optimal design of the EWS model a policy-maker may wish to choose. On the one hand, taking pre-emptive action in response to a signal about a possible crisis is costly from a policy-maker's perspective. But on the other hand, also not receiving a signal when a crisis actually occurs can be costly if early action by the policy-maker could have helped prevent or at least lessen the impact of a crisis. We show how the policy-maker's preferences and degree of risk-aversion about this trade-off determines the optimal design of the EWS model.

The paper proceeds as follows. Section 2 starts by reviewing the two most commonly used approaches for EWS models, the leading indicator approach and the discrete-dependent variable approach. Section 3 discusses the results obtained from a simple binomial logit model. 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. Section 6 tackles the implications of the model for optimal policy design and section 7 concludes.

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, like almost all EWS models on EMEs in the literature, 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 or what has been dubbed the "twin crises" (Kaminsky and Reinhart, 1996). More specifically, our EWS model looks at successful as well as unsuccessful speculative attacks on currencies by employing a commonly used exchange market pressure ($EMP_{i,t}$) variable for defining a currency crisis for each country i and period t:

$$EMP_{i,t} = \omega_{RER}\left(\frac{RER_{i,t} - RER_{i,t-1}}{RER_{i,t-1}}\right) + \omega_r\,(r_{i,t} - r_{i,t-1}) - \omega_{res}\left(\frac{res_{i,t} - res_{i,t-1}}{res_{i,t-1}}\right) \tag{1}$$

$EMP_{i,t}$ is a weighted average of the change of the real effective exchange rate (RER), 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 is intended to account for differences in inflation rates across countries and over time. The weights ω_{RER}, 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. The relative precision is defined as the inverse of the variance of each variable for all countries over the full sample period 1993-2001.

The rationale for using a weighted average of these three variables is the following. If investors consider the underlying economic factors as unsustainable or vulnerable and attack a currency, a government essentially has two options. The first option is to abstain from defending the currency, either by abandoning a fixed exchange rate regime or by avoiding to intervene in foreign exchange markets, and to let the currency devalue and markets determine its new price. The second option is to defend the currency regime, or what is considered an appropriate exchange rate level, by raising interest rates and running down foreign exchange reserves. $EMP_{i,t}$ allows capturing both cases.

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

$$CC_{i,t} = \begin{cases} 1 & if \quad EMP_{i,t} > \overline{EMP_i} + 2\ SD(EMP_i) \\ 0 & if \quad otherwise \end{cases} \tag{2}$$

This is the definition of currency crises that will be used below in our econometric analysis. It is quite similar, though not identical, to the measures commonly used in the literature.[1]

The next crucial issue is the question of *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 crisis shows, it is already very challenging to predict reliably whether or not a crisis will occur in a particular country. Therefore, predicting not only *whether* a currency crisis happens but also the timing *when* it will happen is a highly ambitious goal and has, to our knowledge, not been undertaken so far.

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 variable Y_t, which is defined as:

$$Y_{i,t} = \begin{cases} 1 & if \quad \exists k = 1...12 \; s.t. \; CC_{i,t+k} = 1. \\ 0 & \quad otherwise \end{cases} \tag{3}$$

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. But on the other hand, from a policy-maker's perspective it is desirable to have as early an indication of economic weaknesses and vulnerabilities as possible in order to be able to take pre-emptive measures. Although other EWS models sometimes use even longer time horizons,[2] the 12-month horizon provides what we believe is a good trade-off between these two issues.

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 early signals from a range of indicators (Kaminsky and Reinhart,

[1] See for instance Schnatz (1998) for a thorough discussion.

[2] For instance, Kaminsky, Lizondo and Reinhart (1998) and Berg and Pattillo (1999b) use a 24-month horizon.

[3] These two methods use a discrete crisis index similar to ours. A third approach uses continuous indices (Sachs, Tornell and Velasco, 1996; Bussiere and Mulder, 1999). Although defining a discrete crisis index represents a

1999, Kaminsky, Lizondo and Reinhart, 1998, Goldstein, Kaminsky and Reinhart, 2000), whereas the other uses logit models (Frankel and Rose, 1996, Eichengreen, Rose and Wyplosz, 1995, Berg and Pattillo, 1999b). Let us discuss these two methods in turn.

2.2.1 The leading indicator approach

The leading indicators approach first developed by Kaminsky and Reinhart (1996), and Kaminsky, Lizondo and Reinhart (1998) considers vulnerability indicators and transforms them into binary signals: if a given indicator crosses a critical threshold, it is said to send a signal. For instance, if the current account deficit (expressed as a percentage of the GDP) falls below a given threshold, this particular indicator flashes a red light. Of course the lower the threshold, the more signals this indicator will send over time, but at the cost of more "false alarms", a particular issue that will be discussed more at length in Section 2.3. In the Kaminsky-Reinhart approach the level is chosen after a grid search that minimizes the noise-to-signal ratio.

This approach represented a major contribution to the literature when it appeared. Yet, as discussed in a book review of Goldstein, Kaminsky and Reinhart (2000), it is not without pitfalls (Bussiere, 2001). First, although it is conceivable to use a binary variable as the dependent variable if one is willing to treat crisis episodes on an equal footage, the loss of information it represents for the independent variables may be more questionable (see also Berg and Pattillo, 1999b). Thus, the current account over GDP ratio would provide the same information whether it is 1, or 5, or 10 percentage points above the critical threshold, a rather unrealistic hypothesis. Second, these various indicators do not provide a synthetic picture of the vulnerability of a given country. It is difficult to rank – in terms of vulnerability – a situation with, say, only indicators A and B in a critical zone with another situation where indicators C and D are in the red.[4]

2.2.2 The discrete-dependent-variable approach (logit and probit)

If one is willing to work with discrete choice models with continuous variables on the right-hand side, logit and probit models provide a valuable framework, especially in view of one of their characteristics that will be discussed below. Let us present the basics of the model here (see Maddala, 1989, for a detailed exposition of the model), and review linear probability models first as they provide a useful benchmark, before we turn to logit models.

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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.

[4] Although Goldstein, Kaminsky and Reinhart (2000) suggest an aggregating scheme, this scheme is open to numerous questions and concerns (see Bussiere, 2001 for further details).

a) Basic set up

We have N countries i={1,2,…N} that we observe during T periods t={1,2,…T}. For each country and each month we observe the binary dependent variable Y:

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

We want to explain the crisis index Y by a set of K independent variables X. Hence X is a KN x 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 Y. We denote γ as the vector of K marginal effects:

$$\gamma = \frac{dP}{dX'} \tag{5}$$

b) The logit model

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 defines the logit model:

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

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

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

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

$$\frac{\Omega(Y=1 \mid X_1)}{\Omega(Y=1 \mid X_0)} = e^{(X_1-X_2)\beta} \tag{9}$$

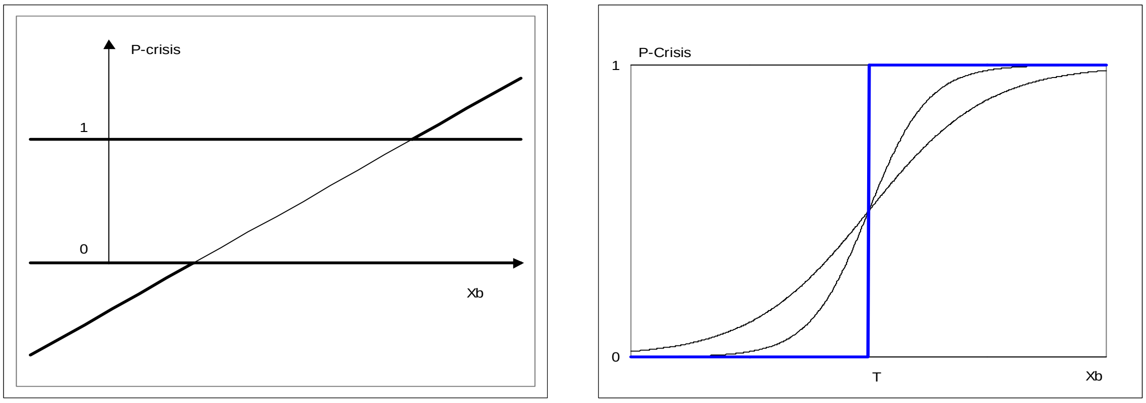
The odds ratio shows how the odds of observing Y=1 change when X moves from X_1 to X_0.

c) Discussion of the non-linear property of the model

One feature of logit models is the non-linearity of the effect of the right-hand side variables on the left-hand side index, as can be seen in Fig. 1. This is an attractive property of the model because the literature on currency crises has demonstrated that such effects are at work. To take just one example, the so-called "Greenspan-Guidotti rule", which states that the ratio of short-term debt over reserves should not be above 100, suggests that an increase of this ratio from 90 to 110 is relatively more worrying than an increase from 110 to 130. In an early indicator approach à la Kaminsky-Reinhart where the threshold would be 100, an increase from 99 to 101 would suffice to trigger a jump, whereas a linear probability model would consider that an increase of x% would have the same effect independently of the initial level. The logit model more realistically assumes that this effect takes the form of the S-shape curve, as shown in the right-hand side panel of Fig. 1.

Fig. 1: Discrete choice models

Fig. 1a: The linear probability model. Fig. 1b: The logit model.



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 predicted probability signals most reliably 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 occurred within the next 12 months (Type 1 errors). Table 1 illustrates this trade-off.

Table 1: The trade-off problem of choosing an optimal threshold

	$S_{i,t} = 0$: No signal was issued	$S_{i,t} = 1$: Signal was issued
$Y_{i,t} = 0$: No crisis within 12 months	A Correct call of non-event	B Type 2 error - Wrong signal
$Y_{i,t} = 1$: Crisis within 12 months	C Type 1 error - Missing signal	D Correct call of crisis

Choosing a threshold level therefore requires making a judgement 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. The cost of Type 2 errors may be the cost of taking pre-emptive policy measures. By contrast, missing a crisis (which possibly could have been prevented or the effect of which could have been lowered by pre-emptive policies) has often a higher welfare cost. For instance, the high cost of financial crises have manifested themselves in the form of large output contractions, rising unemployment and poverty rates among many affected emerging markets in the 1990s. 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. Section 6 will delve further into this issue (see also Demirguc-Kunt and Detragiache, 1999, for a first discussion in the context of banking crises).

3 Estimating the Binomial Logit Model

3.1 The data

The present paper uses monthly data over the period 1993M12 to 2001M9 for a sample of 32 countries. Our country sample is similar to – although slightly larger than – most papers published on the subject and is balanced between regions as it includes 8 Latin American countries, 12 Asian countries, 11 Eastern European and accession countries, as well as South Africa (see complete country list and data sources in Appendix 1). One key assumption of the model is that the countries in the sample share common characteristics as far as openness to capital flows is concerned. This assumption is not strictly fulfilled for countries like India, Pakistan and Sri Lanka; the paper thus distinguishes a sub-group of 20 “core countries”, which analyses only the most open emerging markets and also corresponds to the two IMF models most directly related to the present study. Although results are not dramatically different between the full and the core country samples of our data set in terms of which variables are significant, results are better for the core countries in terms of prediction. Table 2 lists the right-hand side variables we have tested in the model (a star indicates the variables we keep in the final model).[5]

Table 2: Vulnerability indicators tested in the model

1. External Competitiveness	**3. Domestic Real & public Sector**	**5. Global Factors (to come)**
* REER overvaluation	* Real GDP growth rate	• GDP growth rate in G3
* Current account (%GDP)	• Fiscal stance	• US, EU interest rates
• Trade balance (%GDP)	• Public debt (p.c. GDP)	• Equity market performance in G3
• Terms of trade	• Inflation rate	• Commodity/oil price
• Export and import growth	• Domestic investment ratios	
2. External Exposure	• Real estate sector	**6. Contagion**
* Short-term debt / reserves	**4. Domestic Financial Sector**	• Trade channel
• Total debt / reserves	* Dom. Credit to private & gov. sector (level and gr. rate)	* Financial interdependence
• Debt composition (loans/bonds, misc. concepts).	• deposit / lending i.r. spreads	
• FDI, portfolio investment	• M1,M2 (% GDP, & res).	
• Total net capital inflows	equity market indices	
• Foreign exchange reserves (level and growth rate).	• Bank deposits	

3.2 Results and performance of the pooled logit model

Table 3 below presents the results using our preferred logit model with pooled data, for the full sample (all countries, period 1993-2001). All the goodness-of-fit analyses of our models below will use a probability threshold of 20% to identify crisis signals. As analyzed in detail in section 6, this threshold should be relatively close to the optimal level a policy-maker may choose. As discussed in Section 2,

[5] A complete description of the data and their source is available in the data Appendix 2. Appendix 2 provides not only a detailed definition of each of the variables together but also a discussion of how each of them affects the likelihood of and vulnerability to experiencing a financial crisis.

it is also interesting to run the same model on the restricted sample of 20 core countries (results in Table 4)[6]. Tables 5 and 6 compare the two models in terms of their predictive power. The six variables tested in the model have the correct sign and are significant at the 5% level, except the growth variable in Table 3 and financial contagion in Table 4. In terms of prediction, it is fair to say that the model estimated for the 20 core countries performs better.

Table 3: Pooled logit BF model, 32 country sample, 1993-2001

Variable	Coeff.	Std. Err.	Z	P>|z|
Overvaluation	0.128	0.009	14.26	0.000
Lending Boom	0.009	0.002	5.43	0.000
STD/res	0.002	0.000	3.89	0.000
CA/GDP	-0.045	0.0013	-3.32	0.001
Fin. Contagion	0.026	0.012	2.23	0.026
Growth	-0.023	0.017	-1.40	0.160
Const.	-2.661	0.0142	-18.70	0.000
# obs.	2080			
Pseudo R2	0.220			

Table 4: Pooled logit BF model, 20 country sample, 1993-2001

Variable	Coeff.	Std. Err.	Z	P>|z|
Overvaluation	0.163	0.012	13.980	0.000
Lending Boom	0.010	0.002	5.310	0.000
STD/res	0.003	0.001	2.450	0.014
CA/GDP	-0.046	0.015	-3.060	0.002
Fin. Contagion	0.025	0.014	1.840	0.066
Growth	-0.040	0.019	-2.110	0.034
Const.	-2.789	0.184	-15.200	0.000
# obs.	1550			
Pseudo R2	0.307			

[6] In fact the 20-country group includes lending boom data for Taiwan starting only 2001 due to data availability.

Table 5: Pooled logit BF model (32 countries)

	$S_{i,t} = 0$	$S_{i,t} = 1$	Total
$Y_{i,t} = 0$	1536	238	1774
$Y_{i,t} = 1$	129	177	306
Total	1665	415	2080

% of obs. Correctly called:	82.4
% of crises correctly called:	57.8
% of false alarms of total alarms:	57.3
% prob. of crisis given an alarm:	42.7
% prob. of crisis given no alarm:	7.7

Table 6: Pooled logit BF model (20 countries)

	$S_{i,t} = 0$	$S_{i,t} = 1$	Total
$Y_{i,t} = 0$	1140	164	1304
$Y_{i,t} = 1$	82	164	246
Total	1222	328	1550

% of obs. Correctly called:	84.1
% of crises correctly called:	66.7
% of false alarms of total alarms:	50.0
% prob. of crisis given an alarm:	50.0
% prob. of crisis given no alarm:	6.7

Table 7: IMF-DCSD model

	$S_{i,t} = 0$	$S_{i,t} = 1$	Total
$Y_{i,t} = 0$	1965	525	2490
$Y_{i,t} = 1$	167	311	478
Total	2132	836	2968

% of obs. Correctly called:	76.7
% of crises correctly called:	65.1
% of false alarms of total alarms:	62.8
% prob. of crisis given an alarm:	37.2
% prob. of crisis given no alarm:	7.8

Table 8: IMF-KLR model

	$S_{i,t} = 0$	$S_{i,t} = 1$	Total
$Y_{i,t} = 0$	1834	704	2538
$Y_{i,t} = 1$	200	298	498
Total	2034	1002	3036

% of obs. Correctly called:	70.2
% of crises correctly called:	59.8
% of false alarms of total alarms:	70.3
% prob. of crisis given an alarm:	29.7
% prob. of crisis given no alarm:	9.8

Table 9: Goldman-Sachs model

	$S_{i,t} = 0$	$S_{i,t} = 1$	Total
$Y_{i,t} = 0$	543	279	822
$Y_{i,t} = 1$	50	98	148
Total	593	377	970

% of obs. Correctly called:	66.1
% of crises correctly called:	66.2
% of false alarms of total alarms:	74.0
% prob. of crisis given an alarm:	26.0
% prob. of crisis given no alarm:	8.4

Table 10: CSFB model

	$S_{i,t} = 0$	$S_{i,t} = 1$	Total
$Y_{i,t} = 0$	1952	628	2580
$Y_{i,t} = 1$	28	44	72
Total	1980	672	2652

% of obs. Correctly called:	75.3
% of crises correctly called:	61.1
% of false alarms of total alarms:	93.5
% prob. of crisis given an alarm:	6.5
% prob. of crisis given no alarm:	1.4

Source for Tables 7-10: Berg, Borensztein, Pattillo (2001)

The main point to note is that, with a similar methodology as many other papers published on the subject, the present model performs already better in terms of prediction. Tables 5 to 10 allow a comparison of the goodness-of-fit of our pooled model with those models of previous studies on the subject.

Our model for 20 countries (Table 6) performs better in each of the five goodness-of-fit criteria than the IMF-DCSD model (Table 7), the Kaminsky-Lizondo-Reinhart model (Table 8) as well as the private sector models by Goldman-Sachs (Table 9) and Credit Suisse First Boston (Table 10).[7] Our model correctly calls the highest ratio of observations (84.1%) and of crises months (66.7%), and it gives the fewest false signals of any of the models. The *conditional* probability of having a crisis if an alarm occurred is 50%, which is much higher than any of the other models. 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 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 these models means that the variables we have been using are more reliable, and/or that the country sample and time period has been more appropriate.

3.3 Panel data analysis

One potential drawback of the model with pooled data is that it ignores some available information, namely the cross-sectional and time series dimensions of the data. It could be the case that some important information on a particular country is omitted from the pooled model. For example, the capital account of a given country may not be as open as that of other countries, which would induce the model to overestimate the probability of a crisis. Conversely, the political situation of a country could be such that we permanently underestimate this probability. Fixed and random effects are useful tools to approach these issues. In the literature on panel data it is common to distinguish between the "between" information (comparing across countries) and the "within" information (comparing the evolution of the variables with the country specific mean, ignoring inter-country comparison). Fixed effects are equivalent to country dummies: they focus on the within information only. As such, they constitute a loss of information, but the estimates are unbiased. Random effects are more efficient because they do not consider country effects as fixed but as random and combine more efficiently the between and the within information. However, they are potentially biased: random effects assume that

[7] The KLR model uses an indicator approach, as discussed in section 2.2.1, with a 2-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 (3 months for the GS model, 1 month for the CSFB model)

individual specific effects are uncorrelated with the independent variables, which may not be the case in our context (for instance, if individual effects arise because of the political setting of a given country, macroeconomic variables are likely to be also affected by the political situation). Table 22 in Appendix 3 reports the goodness of fit results for the random effect model, which faired better than using fixed effects. Still, the improvement is not very clear and the tests we have conducted deterred us from using fixed or random effects. An additional consideration was that with fixed effects non-crisis countries are excluded from the sample, which may induce a sample bias.[8]

4 A Multinomial Logit EWS Approach

4.1 Explaining the post-crisis bias

What we call the "post-crisis bias" is an important econometric problem that so far, to our knowledge, has not been addressed in the empirical literature on currency crisis models. The "post-crisis bias" implies that the econometric results of models that try to explain or predict crises can at least in part, or even fully be explained by the behavior of the independent variables during and directly after a crisis. Recall that an EWS model aims to analyze how vulnerable to a crisis the situation in a country is. The correct way of doing this is by comparing the behavior of the independent variables before a crisis with their behavior during periods when these variables are sustainable, i.e. during tranquil or "normal" times. Instead, what EWS models with two outcomes do is comparing the pre-crisis observations with the observations both during tranquil periods <u>and</u> post-crisis/recovery periods. This can lead to an important bias because the behavior of the independent variables is very different during tranquil times as compared to recovery episodes.

Table 11: Mean values of key indicators (20-country sample)

	(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	0.28	10.71	0.38	-7.50	-1.56
Lending Boom	15.24	41.55	8.15	18.38	10.70
S.Term Debt / res.	94.09	118.14	82.94	110.26	89.72
Cur. Account/GDP	-0.06	-2.66	0.37	0.46	0.39
Fin. Contagion	0.38	0.33	-0.01	1.88	0.39
Growth	4.31	3.92	5.95	-0.47	4.38

[8] The countries that never experienced a crisis in our sample are all Eastern European countries: Hungary, Lithuania, Poland, Slovakia and Slovenia.

Table 11 provides further evidence for this bias for six key leading indicators used in our benchmark model below. Recall that what an EWS model aims to test is whether we can extract information from economic variables about the sustainability and the probability of a looming currency crisis by comparing their behavior during tranquil or "normal" times as compared to pre-crisis periods. The relevant comparison therefore 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 contrast, what traditional two-state logit or probit models do is estimate the link between the pre-crisis period of column (2) with the combined tranquil and 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 should not be included in an analysis of anticipating crises because one can not extract meaningful information about the sustainability and vulnerability of a country's economic fundamentals by looking at crisis and post-crisis observations.

Further evidence for the post-crisis bias is provided by the event analysis in Appendix 5 for a set of 28 independent variables. The advantage of the event analysis is that it nicely illustrates the dynamics of the adjustment process of the independent variables before and after a crisis. Period t in the charts indicates the onset of a currency crisis. The thick line indicates the behavior of each variable from 12 months before till 12 months after the onset of the crisis. This thick line is calculated as the mean of the variable over all currency crises in our sample. The thinner, horizontal line indicates the mean of each variable during tranquil periods. The charts confirm that the behavior of most independent variables is substantially different in pre-crisis times from recovery episodes. Equally important is that most variables are substantially different in tranquil periods compared to recovery times.

Not distinguishing between tranquil and recovery periods may therefore introduce an important bias in an EWS model. Section 4.2 discusses ways of solving this bias, whereas section 5 will show that the bias is indeed important, and that solving it improves the predictive power of the EWS substantially.

4.2 How to address the post-crisis bias

There are at least two ways of tackling the post-crisis bias. The first, crudest way would be to drop out all post-crisis observations from the data and then to estimate the standard two outcome discrete-dependent-variable model, as done for example in Demirguc-Kunt and Detragiache (1998).[9] The drawback of such a method is that it ignores data that potentially could provide valuable information,

[9] The paper by Demirguc-Kunt and Detragiache (1998) is otherwise very distinct from ours in that it looks at a different type of crisis (banking crises) and in particular some specific events.

for instance on how the economic variables behave during recoveries and when or whether economic variables return to levels of tranquil or “normal” times. A second and our preferred alternative is a discrete-dependent-variable approach with more than two outcomes, in our case a multinomial logit model. For the case of the EWS model, we construct a multinomial logit model with three outcomes:

$$Y_t^i = \begin{cases} 1 \quad if\ \exists k = 1...12\ s.t. \quad CC_{t+k}^i = 1, \\ 2 \quad if\ \exists k = 1...12\ s.t. \quad CC_{t-k}^i = 1, \\ 0 \qquad otherwise \end{cases} \tag{10}$$

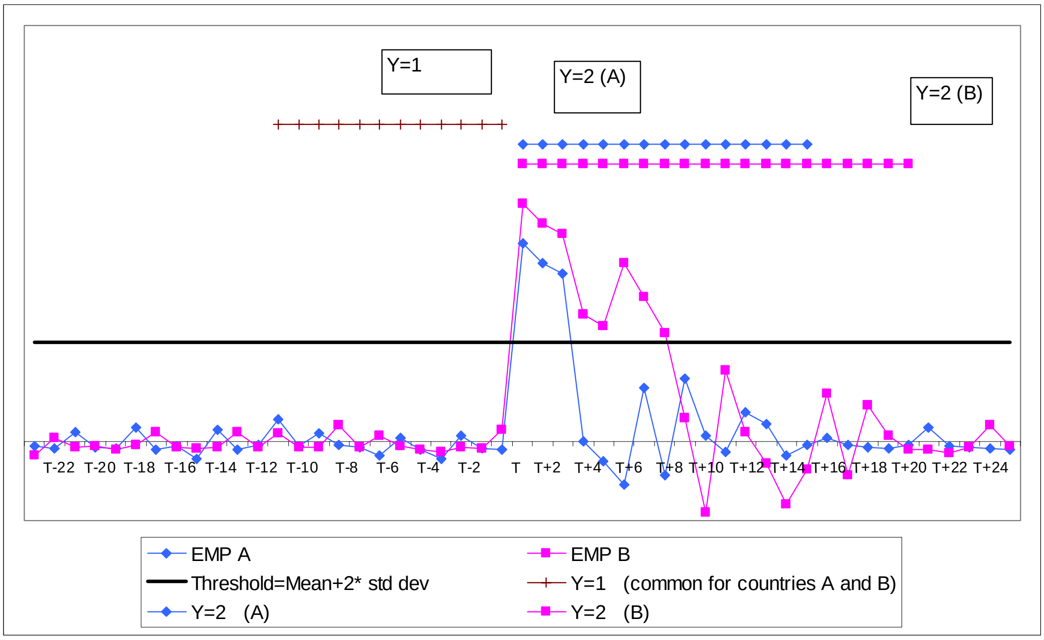
i.e. a pre-crisis regime for the 12 months prior to the onset of a crisis ($Y_{i,t} = 1$), a post-crisis/recovery regime for the crisis itself and 12 months following the end of the crisis ($Y_{i,,t} = 2$), and a tranquil regime for all other times ($Y_{i,,t} = 0$). Let us delve further into these definitions. The regime that corresponds to Y=1 announces a crisis in the next 12 months. Forwarding the left-hand side variable and using it on contemporaneous right-hand side variables allows a considerable simplification of the notation: otherwise we would need to include in the right-hand side all 12 lags of the six variables, i.e. 72 variables. Above all, it directly follows from the approach outlined in the definition: the present paper does not try to predict the timing of a crisis exactly k months ahead, which would be the outcome of a model in which right-hand side variables show up at lag k. Instead, the model tells us whether a crisis can happen *any time* in the following 12 months. The fact that the left-hand side variable is a forward variable ensures that the same variables (the exchange rate and the level of reserves) never simultaneously appear on both sides of the equation: the statement yielded by the model is that a low level of reserves (compared to debt) and an overvalued exchange rate *now* are likely to trigger a further drop in reserves and/or a devaluation of the exchange rate *later*.

The definition of the regime corresponding to Y=2 follows a similar logic. Once a country has experienced a crisis, it will take some time before it recovers. This time can considerably vary from one country to the next. In parallel with the definition of regime 1 announcing a crisis, regime 2 announces a recovery. We based our definition of regime 2, again, on the EMP, as Fig. 1.c below exemplifies. This figure represents the EMP of two fictitious countries that underwent a crisis at the same time, T. Consequently, their discrete crisis indices coincide in the pre-crisis period for which Y=1. However, the post-crisis/recovery period varies for these two countries. For country A the crisis is relatively short and the EMP returns to “normal” (i.e. a mean slightly below zero and low variance) relatively quickly. For country B the crisis is deeper and more protracted; recovery is then longer than for country A. As a consequence the period for which Y=2 is longer for country B than for country A. To date the end of regime 2, we used a strong empirical observation for the countries included in the sample: the return to normal generally occurred 12 months after the last observation for which the

EMP index was above the critical threshold. It is this observation that led us to define outcome 2 as of equation (10)[10]

Although the introduction of a second state Y=2 stemmed from a 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. For instance in Russia our EMP measure exceeded the critical threshold during only one month (1998M8); in Korea the EMP index stood above the threshold for three months, for Malaysia and Indonesia six months. 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 stroke the markets. The asymmetry between the two movements results in the shape of the distribution of the EMP, strongly skewed to the left.

Fig. 1.c: EMP and crisis index, an illustrative example



[10] This empirical regularity could be given a more rigorous definition is a regime-switching model, where the definition of the regimes would be based on the first two moments of the distribution of the EMP, which we hope to implement in future work. For the time being the definition employed in the present paper closely corresponds to the stylized facts observed in our sample.

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:

$$\Pr(Y_{i,t}=0)=\frac{1}{1+e^{(X_{i,t-1}\beta^1)}+e^{(X_{i,t-1}\beta^2)}}$$

$$\Pr(Y_{i,t}=1)=\frac{e^{(X_{i,t-1}\beta^1)}}{1+e^{(X_{i,t-1}\beta^1)}+e^{(X_{i,t-1}\beta^2)}} \tag{11}$$

$$\Pr(Y_{i,t}=2)=\frac{e^{(X_{i,t-1}\beta^2)}}{1+e^{(X_{i,t-1}\beta^1)}+e^{(X_{i,t-1}\beta^2)}}$$

This implies that β^1 measures the marginal 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 marginal 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:

$$\frac{\Pr(Y_{i,t}=1)}{\Pr(Y_{i,t}=0)}=e^{(X_{i,t-1}\beta^1)} \tag{12}$$

$$\frac{\Pr(Y_{i,t}=2)}{\Pr(Y_{i,t}=0)}=e^{(X_{i,t-1}\beta^2)}$$

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 marginal effects β^1 and β^2. The relevant information we are 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 is of much less value for an EWS of predicting financial crises because it provides information about whether an economy is still in a recovery state or if it has already returned to a tranquil regime. Section 5 below will show that empirically there is indeed a substantial difference between the two models.

5 Multinomial Logit EWS Model: Results and Robustness Tests

5.1 Results and performance of the multinomial logit model

Table 12 summarizes the results obtained from the multinomial logit 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 a correct sign and are significant at the 1% 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 are the results for the post-crisis period ($Y_{i,t}$=2) in the second panel of Table 12. Here the coefficients are not only substantially different from the pre-crisis period but 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 13 shows the goodness-of-fit of the multinomial logit model. Our model fares much better than other existing models and than our pooled model of Tables 4-5. Moving from the simple logit to the multinomial logit helps increase the percentage of correctly predicted crises from to 66.7% to 73.7% while reducing false alarms from 50% to 44.1%. Similarly, the conditional probability of experiencing a crisis when an alarm was issued rises from 50% to 55.9%.

Table 12: 12-month multinomial logit model, 20 core countries, 1993-2001.

Variable	Coeff.	Std. Err.	Z	P>|z|
		Pre-crisis period $Y_{i,t}$ = 1		
Overvaluation	0.161	0.013	12.870	0.000
Lending boom	0.013	0.002	6.300	0.000
STD/res	0.004	0.001	3.610	0.000
CA/GDP	-0.055	0.017	-3.220	0.001
Fin. contagion	0.039	0.015	2.560	0.011
Growth	-0.060	0.023	-2.620	0.009
Const.	-2.866	0.215	-13.330	0.000

Post-crisis period $Y_{i,t} = 2$				
Overvaluation	-0.078	0.010	-8.230	0.000
Lending boom	0.010	0.002	4.620	0.000
STD/res	0.004	0.001	4.210	0.000
CA/GDP	0.018	0.010	1.740	0.083
Fin. contagion	0.052	0.012	4.430	0.000
Growth	-0.235	0.018	-13.010	0.000
Const.	-1.183	0.135	-8.760	0.000
# obs	1549			
Pseudo R2	0.333			

Table 13: Multinomial logit model (20 countries), goodness of fit.

	$S_{i,t} = 0$	$S_{i,t} = 1$	Total
$Y_{i,t} = 0$	853	135	988
$Y_{i,t} = 1$	61	171	232
$Y_{i,t} = 2$	297	32	329
Total	1211	338	1549

% of obs. correctly called:	83.9
% of crises correctly called:	73.7
% of false alarms of total alarms:	44.1
% prob. of crisis given an alarm:	55.9
% prob. of crisis given no alarm:	6.7

5.2 *Discussion of results*

Let us now turn to analyzing the order of magnitude of importance of each variable. As explained in Section 2.2.2, the logit model is non-linear, so the coefficients reported in Table 12 cannot be interpreted as marginal effects: marginal effects must be computed at a certain value. This way, a 10% increase of one variable has a different effect depending on the reference point. Another fact to consider is that a 10% increase in one variable is not necessarily comparable with the same increase in another variable, as should be clear by comparing, say, the current account and short-term debt.[11]

Table 14 presents the effect on the predicted probability under various scenarios, based on equation (11). The first row of the table gives the expected probability of a crisis when all right-hand side variables equal their average in tranquil times, as of Table 11 (above), column (3). In this case, a country has a 5.45% risk to have a crisis in the next 12 months. If all right-hand side variables jump to their pre-crisis average level, as of Table 11, column (2), this probability increases to 41.75%. Which

[11] Another complication arises as we have here 3, not 2 states: even is both β^1 and β^2 are positive, an increase in a variable may reduce the predicted probability that outcome 1 appears if β^2 is larger than β^1.

variables have the strongest effect? The subsequent rows answer this question by letting all variables equal to their tranquil average, except one that is allowed to vary to isolate its effect on the probability.

The exchange rate overvaluation has a strong weight in the crisis probability. A one- percent increase of the exchange rate above its trend increases the probability of a crisis by 1 point, a 2% increase by 2 points, a 5% increase by 6.3 points, and a 10% increase by 17.9 points at 23.36%. This may seem to be a lot but a word of caution is in order: these numbers do not refer to absolute exchange rate appreciation, but to an appreciation *above trend*.

Row 7 gives the crisis probability that results from an increase of the short-term debt to reserves ratio to its average pre-crisis level (120 %). Such a rise increases the probability of a crisis by almost one point. The same magnitude is attained if the current account deficit jumps to its average pre-crisis level (-2.67 % of the GDP, row 8). When the contagion variables equals 10% (see row 10), the crisis probability increases by almost two points at 7.41%. Row 11 shows that when growth slows down to 2%, the crisis probability increases by only half a point.

Table 14: Effect on the probability of a crisis under given scenarios

Scenario	Crisis probability	Change in probability
1. All variables at mean of tranquil time – as of Table 11 (3)	5.45 %	- (benchmark)
2. All variables at mean of pre-crisis time, as of Table 11 (2)	41.75 %	+ 36.30 pts
All variables at mean of tranquil time –as of Table 11, (3)- except:		
3. Exch. Rate +1%	6.39 %	+ 0.93 pts
4. Exch. Rate +2%	7.47 %	+ 2.01 pts
5. Exch. Rate +5%	11.76 %	+ 6.30 pts
6. Exch. Rate +10%	23.36 %	+ 17.91 pts
7. S.-term debt /reserves = 120%	6.24 %	+ 0.79 pts
8. CA / GDP = -2.67%	6.34 %	+ 0.89 pts
9. Contagion =5%	6.39%	+0.94 pts
10. Contagion = 10%	7.41 %	+ 1.96 pts
11. Growth = 2 %	5.97 %	+ 0.52 pts

5.3 Robustness tests

A number of robustness tests were undertaken: we excluded from the model the most important variables, and we tested alternative variables that have been found significant in other papers.

- ***Excluding the real effective exchange rate variable***

One key variable in our model is the deviation of the real effective exchange rate from its trend. To check that this variable does not entirely drive the results, we ran the same estimation excluding it from the right-hand side. Reassuringly, all the other variables retain their significance in the new equation, and their predicting power is still very high. We conclude that the real effective exchange rate is an important variable to consider, but that the other variables are also essential to predict crises.

- ***Testing alternative variables***

Table 16 shows results obtained when alternative variables are included in the model.[12] It presents regression results, but also the effect on the percentage of crises correctly predicted and the number of false alarms: some alternative variables can enter the equation significantly but contribute little to the predictive power of the model. Another motivation for whether to include a variable or not depends on its availability for the present sample, which is why the tables also include the number of observations. A strong increase in the predictive power sometimes simply comes from the fact that up to 50% of the observations were dropped for reasons of data availability: as this excludes some countries and some particular years, this is likely to induce a bias in the results.

Let us briefly discuss the key findings here:

- *Government deficit*

The government deficit, expressed as a percentage of the GDP, enters the equation with a positive sign and is significant at the 1% level. This counter-intuitive result is now well documented in the literature: many of the countries hit by a crisis actually ran a fiscal surplus, noticeably Mexico in 1994 and the Asian countries in 1997. This fact led many authors to reject “first generation models of currency crises” (Krugman, 1979) for more elaborate models in which moral hazard plays a role (a country with a government surplus is more likely to bail out risky investment projects).

- *Alternative liquidity ratios*

The question of which liquidity ratio to focus on is of crucial importance for reserve managers. The present paper chose to use the ratio of short-term debt to reserves, in view of growing empirical evidence in support of the Greenspan-Guidotti rule (see for instance Bussiere and Mulder, 1999, 2001). Testing for the growth rate of reserves and the ratio of reserves to exports, to GDP or to monetary aggregates (M1 and M2) led either to non-significant coefficients, or to significant results without a clear increase in the predictive power of the model.

One exception is worth noting however: the rate of growth of reserves does seem to play an important role, either measured as a percent change of the level or of the level expressed in percentage of exports.

[12] For space reason we only report the coefficient and the standard error on the additional variable and the goodness of fit here; complete estimation results are available upon request.

- *Short-term debt over GDP*

To check that the short-term debt to reserves ratio is not significant simply because the denominator diminishes before a crisis, we tested the level of short-term debt measured as a percentage of GDP. The result is conclusive: this variable is significant and contributes to the predictions in an important way as well. Both in view of the importance of the Greenspan-Guidotti rule and to avoid potential multicollinearity with the current account (if both are scaled with GDP), we decided to scale short-term debt with reserves.

- *Current account items*

The present model uses the current account over GDP ratio. As the trade balance would be an obvious alternative, we tested it, separately and together with the current account. When the trade balance is included alone it is significant with the correct sign; when it is tested together with the current account it is no longer significant, from which we conclude that the current account is a preferable indicator, probably because it incorporates more information. Interestingly, the growth rate of exports has the expected negative sign and helps predict slightly more crises. Openness of the country, measured as the sum of imports and exports over GDP, is not significant: more open countries do not expose themselves to a higher risk.

- *FDI and portfolio investment*

It has sometimes been argued that the size and the nature of capital flows matters for currency crises, in particular, there is a general perception that FDI is a better investment than portfolio investment for the domestic economy. To investigate this issue, we included in the equation FDI and portfolio investment, both as a level of the net value (expressed in percent of GDP) and as a growth rate. As can be seen on Table 16d, the variables on the levels did not enter the specification significantly. On the other hand, it is interesting to note that the growth rate of FDI inflows comes close to the 10% threshold: it seems that an increase in FDI inflows has some effect in avoiding currency crises.

To summarize, in order to keep the model tractable and as simple as possible we limited ourselves to a relatively small number of variables. However, other variables may be included in an extended model and are certainly worth monitoring in an extended model: the growth rate of reserves, both as a level and as a percentage of exports, the market index of domestic banks, and the growth rate of FDI inflows.

5.4 Out-of-sample performance

Since the important contribution of Berg and Pattillo (1998) on the frequent failure of models to predict crises in subsequent episodes, out-of-sample forecasts have become the corner-stone of testing the goodness-of-fit of EWS models. Indeed, in-sample properties do not ensure that the model can predict future crises if the causes of currency crises drastically vary from one episode to the next. To check that our model is also able to predict crises out-of-sample, we estimate the model on restricted periods and computed the probability of a crisis in the following 12 months.

We conduct the out-of-sample test for three episodes: for the Asian crisis of 1997, for various emerging market crises in 1998 (including Russia and Brazil), and for the recent crises in Turkey and Argentina in 2001. Note that the out-of-sample models include the same six key variables from our benchmark model above. This is not strictly "out-of-sample" as some included variables may not be significant for the shorter out-of-sample models whereas other, excluded variables may have been significant for the shorter out-of-sample model periods. The reason for restricting the model to the six key variables is to obtain a comparison between the in-sample and the out-of-sample performance of our benchmark model. Table 17 shows the estimation results for the various sub-samples that are used to generate the out-of-sample forecasts.

The 1997 Asian Crisis: Out-of-sample forecast in December 1996

For predicting the Asian crisis, Table 17 shows that both the short-term debt to reserves ratio and the current account deficit lose their significance if the model is estimated ending in December 1996. However, these results are intuitively convincing: it is well know that a high level of short term debt was one of the key factors that had made Asian countries vulnerable in 1997. Excluding the Asian crisis episode from the estimation therefore can render the short-term debt variable insignificant.

The important question is whether our model would have predicted the Asian crisis in late 1996, even as some of the important underlying factors (i.e. the large share of short-term debt) could not yet be identified as relevant factors. Table 18 shows that indeed our model would nevertheless have predicted quite accurately which countries were most vulnerable and experienced a crisis. Table 18 shows the probabilities of a crisis as of 1996M12, predicted by the model estimated until 1996M12 only - the second column indicates the starting point of the crisis. For Indonesia, Malaysia, the Philippines and Thailand, probabilities are above 20%, clearly signaling an imminent crisis. For Hong Kong, Korea, and Singapore on the other hand, predicted probabilities reach a more modest 16%. The relative failure to predict the Korean crisis comes from the importance of the level of short-term debt relative to reserves in the unfolding of the crisis. Last, the model sends two important "false-alarms", or more accurately “too early alarms”: the predicted probability of a crisis in Russia and Colombia is very high, whereas these countries were hit by a crisis only in 1998.

This exercise sheds an interesting light on the Asian crisis. As widely documented, short-term debt was a key factor of the crisis, but what the results show is that other variables, such as the lending boom, contagion, and overvalued exchange rates are essential for understanding the crisis. What this suggests is that the Asian crisis had multiple causes and can not be narrowed down to a single factor.

The 1998 Brazil/Russia Crisis: Out-of-sample forecasts in December 1997

In 1998 many countries were hit by a crisis, most prominently Russia in October and Brazil one month later. The variables in our model shed an interesting light on these two crises. In Russia the short-term debt to reserves ratio had risen above 200%, whereas the real effective exchange had significantly deviated from trend (more than 20%), in a context of negative growth rate. For Brazil evidence of contagion is overwhelming: the exchange rate showed only moderate signs of overvaluation (4%), short-term debt was only slightly above the level of international reserves, and the current account deficit (4% of the GDP) was not in itself worrying. The contagion variable however rose as high as 20% on the eve of the crisis because of Russia’s turmoil – levels above 20% have been reached only by some of the Asian countries in 1997.

Crises in 2001, Turkey and Argentina: Out-of-sample forecasts in December 2000

The year 2001 saw two emerging market crises in Turkey and Argentina. The estimation results obtained when the sample is interrupted in 2000M12 are actually very close to the full model. Would the model have predicted these crises, out-of-sample, in December 2001? Table 18 provides a clear answer to this question. The Turkish crisis was unambiguously signaled, as the probability of a crisis reached 91%. In fact the model sent a signal by crossing the 20% line as early as November 1999. For Argentina, the predicted probability of a crisis in December 2000 was not very high. As the chart in Appendix 6 demonstrates, the probability of a crisis in Argentina stayed at levels approaching the 20% level during the previous two years, but crossed the threshold only in July. The reason why the model does not call the Argentine crisis well is that one key underlying cause of the crisis was the large share of government debt servicing and the large premium it had to pay on its debt. Both of these factors are only indirectly captured in our benchmark model. This would provide a rationale for using an extended EWS model adding a broader variety of variables.

Table 17: Estimation results, out-of-sample forecasts

Model	Benchmark	End point: 1996M12	End point: 1997M12	End point: 2000M12
Over-	***0.161	***0.120	***0.135	***0.167
valuation	(0.013)	(0.021)	(0.015)	(0.013)
Lending	***0.013	***0.016	***0.018	***0.013
Boom	(0.002)	(0.003)	(0.003)	(0.002)
STD/res	***0.004	-0.001	**0.002	***0.004
	(0.001)	(0.002)	(0.001)	(0.001)
CA/GDP	***-0.055	-0.008	0.002	***-0.055
	(0.017)	(0.029)	(0.019)	(0.017)
Financial	***0.039	*0.063	***0.084	***0.044
Contagion	(0.015)	(0.038)	(0.031)	(0.015)
Growth	***-0.060	*-0.067	-0.040	**-0.054
	(0.023)	(0.040)	(0.034)	(0.023)
Constant	***-2.866	***-2.015	***-2.345	***-2.866
	(0.215)	(0.394)	(0.337)	(0.221)
# obs	1549	590	818	1501
Pseudo R2	0.333	0.317	0.308	0.344

Table 18: 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
Argentina	0.038	No	0.151	No	0.134	2001M3
Brazil	0.121	No	0.362	98M10	0.065	No
Chile	0.111	No	0.368	98M9	0.011	No
China	0.088	No	0.191	No	0.053	No
Colombia	0.685	No	0.422	98M9	0.002	No
Czech Rep.	0.141	97M5	0.03	No	0.030	No
H.-Kong	0.164	No	0.711	98M8	0.013	No
Hungary	0.063	No	0.036	No	0.002	No
Indonesia	0.480	97M8	0.004	No	0.014	No
Korea	0.167	97M11	0.002	No	0.080	No
Malaysia	0.305	97M7	0.031	No	0.028	No
Mexico	0.003	No	0.036	No	0.555	No
Philippines	0.680	97M10	0.125	No	0.001	No
Poland	0.114	No	0.120	No	0.090	No
Russia	0.329	No	0.881	98M9	0.026	No
Singapore	0.167	97M10	0.179	No	0.008	No
Thailand	0.340	97M7	0.002	No	0.018	No
Turkey	0.010	No	0.166	No	0.914	2000M12
Venezuela	0.001	No	0.111	No	0.172	No

Note: For Turkey the predicted probability of a crisis actually passed 20% in 1999M11.

6 Policy Relevance of the Multinomial Logit EWS Model

The purpose of this section is to show how changes to the preferences of the policy-maker and the specification of the loss function and its parameters can fundamentally alter the design of the optimal type of model a policy-maker may wish to choose.

Tables 12 and 13 above shows the results of the multinomial logit EWS model for a time horizon of 12 months prior to a crisis and at a probability threshold of 20%. However, the time horizon and the probability threshold are endogenous choices that a policy-maker can decide. These choices depend on the loss function of the policy-maker, i.e. how she weights the benefit from receiving a correct signal about a pending crisis relative to the cost of sending a wrong signal and the cost of missing a crisis. For a decision-maker, taking pre-emptive action in response to a signal about a possible crisis is costly. But also not receiving a signal when a crisis actually occurs can be costly if early action by the policy-maker may could have helped prevent or at least lessen the impact of a crisis.

6.1 Loss function for the policy-maker

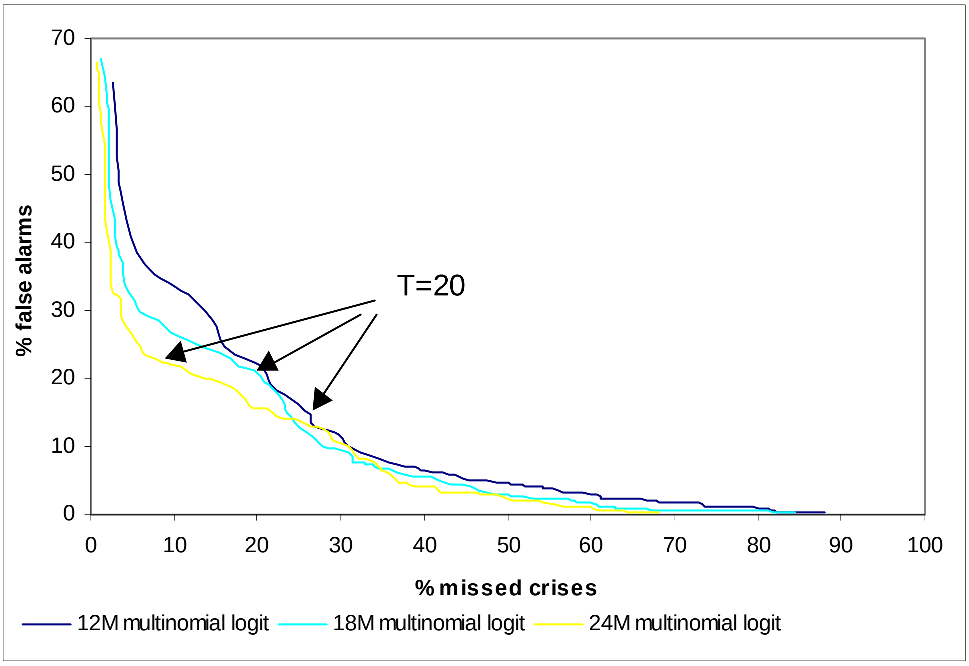
As discussed briefly in section 2.3, the first difficult choice for a policy-maker is which objective function to optimize. Clearly, a policy-maker wishes to extract as many correct signals as early in advance as possible about the occurrence of a crisis. On the contrary, she would like to minimize the number of false alarms (i.e. when the model issues a signal but no crisis occurs) and the number of missed crises (when the model yields no signal but a crisis ensues). The difficulty with the latter is that there is a trade-off between the number of false alarms and the number of missed crises: raising the probability threshold T and lengthening the time horizon length H reduces the number of false alarms, but at the cost of raising the number of missed crises months. Lowering the threshold T and shortening the time horizon length H will accordingly lead to the opposite trade-off. Figure 2 illustrates this trade-off for all thresholds T and for three time-horizon models (12 months, 18 months and 24 months).

Which of the models and thresholds a policy-makers wishes to choose depends on the form of her objective function. Assume that missing a crisis as well as issuing a signal that requires taking pre-emptive action both have a cost for the policy-maker, which she wants to minimize. Therefore the loss function of the policy-maker is formulated as

$$L(T) \equiv \theta \quad prob^{NS/C}(T) + (1-\theta) \quad prob^{S}(T) \tag{13}$$

with $prob^{NS/C}$ as the probability of a missed crisis, i.e. the joint probability that the EWS model issues no signal and a crisis occurs, and $prob^{S}$ as the probability of issuing a signal that a crisis will occur. θ can be interpreted as the relative cost of missing a crisis, or the policy-maker's degree of relative risk-aversion, whereas (1 - θ) can analogously be understood as the cost of taking pre-emptive action. Note that when talking below about θ as the degree of a policy-maker's "risk aversion", the strict meaning is the policy-maker's risk aversion *towards missing a crisis*.

Figure 2: Trade-off between false alarms and missed crises

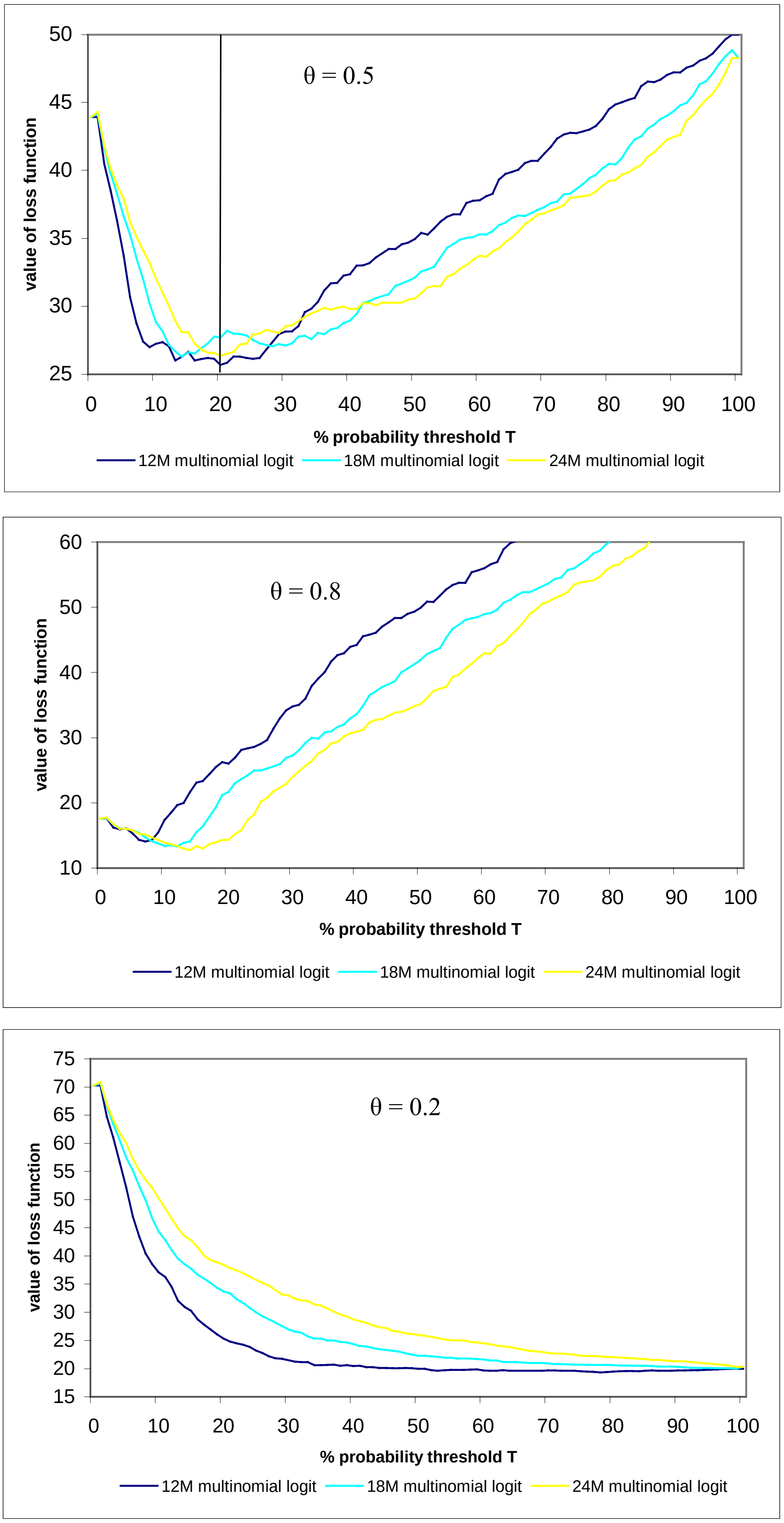


6.2 Solving for the optimal threshold and time horizon

Given this loss function, what threshold T and time horizon H should the policy-maker choose? Figure 3 illustrates for our multinomial logit model of section 4 that the choice of T and H is determined by θ, i.e. by the relative importance the policy-maker attaches to missing a crisis. For θ=0.5, the best model (i.e. the model that produces the lowest value of the loss function L) is the 12-month multinomial logit model with a threshold of T=20. This implies that at T=20, and given θ=0.5, the 12-month multinomial logit model provides the best achievable trade-off between missing crises and issuing wrong signals (Figure 3, first panel). On the one hand, lowering T raises the number of false alarms disproportionally more than the number of correctly anticipated crises. On the other hand, raising T reduces the number of false alarms, but which is more than outweighed by raising the number of missed crises.

By contrast, a highly risk-averse policy-maker with θ = 0.8 prefers the 24-month multinomial logit model with a threshold of T=14 (Figure 3, second panel), whereas a policy-maker with θ = 0.2 chooses the 12-month multinomial logit model with a threshold of T=78 (Figure 3, third panel).

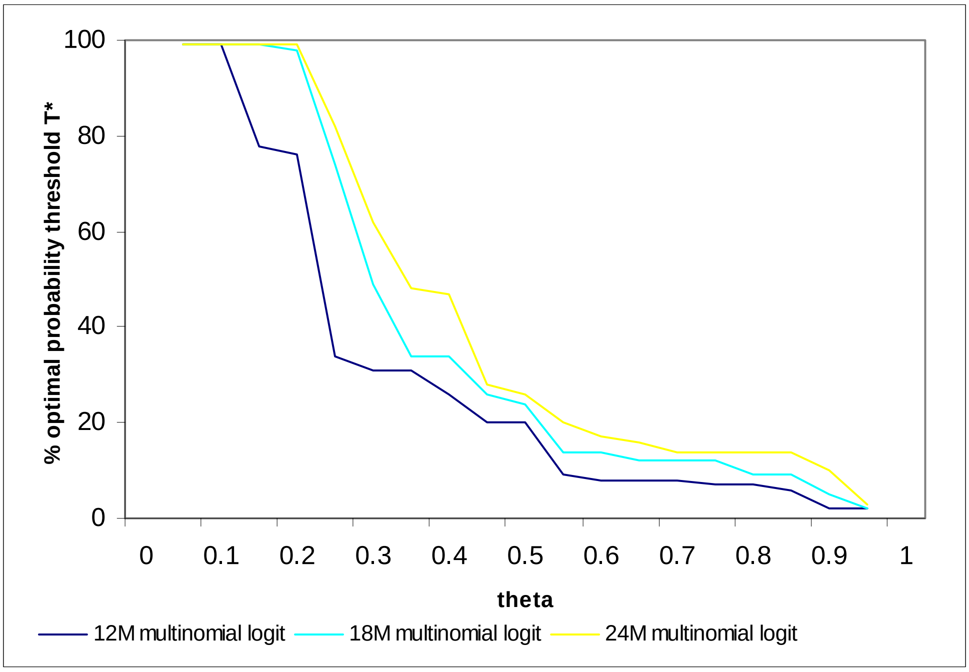
Figure 3: Comparing differences in risk-aversion in loss functions



Estimating our multinomial model for all possible degrees of risk aversion θ, for all possible thresholds T and for all time horizons H between one month and 24 months, allows us to derive three general results:

Result 1: For any given model with time horizon H, raising the degree of risk aversion θ leads to a lower optimal threshold level T* (see Figure 4).[13] The intuition is that the higher the weight a policy-maker puts on not missing a crisis, the lower she will wish to set the threshold T of the model in order to raise the number of correct crisis signals.

Figure 4: Determining the optimal threshold T*

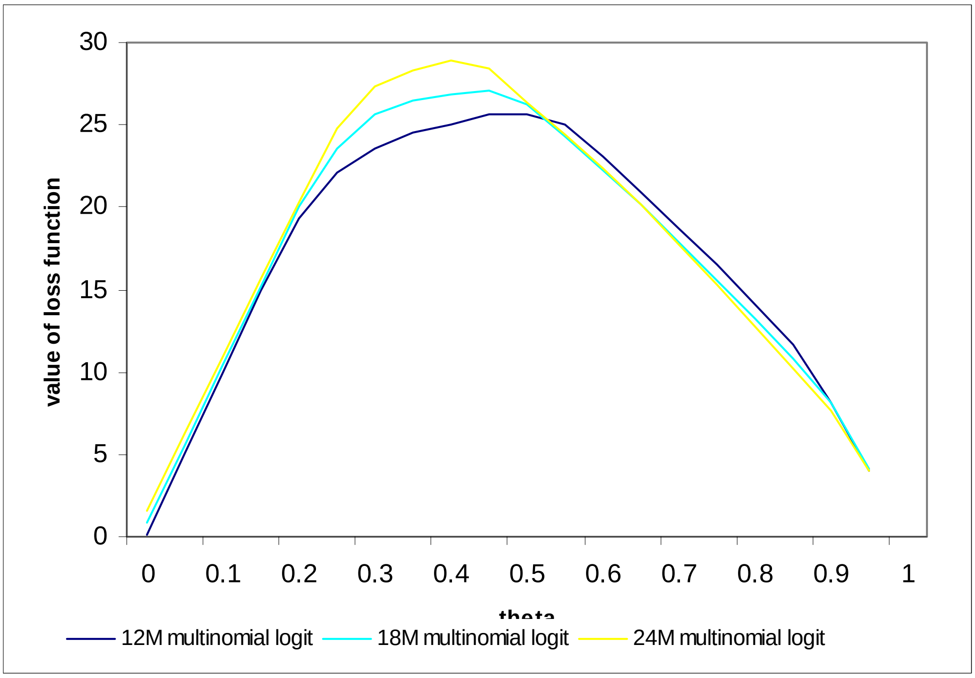


Result 2: For any given degree of risk aversion θ, the larger the time horizon H* of the optimal (loss function minimizing) model, the larger is the optimal threshold T* (see Figure 4). The reasoning is that at any given threshold T, models with a longer time horizon H produce a relatively higher proportion of false alarms than correct signals. Therefore, a higher time horizon H requires also the raising of the threshold T in order to minimize the loss function at any given θ.

[13] T* is determined by estimating each multinomial logit model with time horizon H over all $\in [0,1]$ and over all thresholds $T \in [0,1]$. The optimal threshold T* that minimizes the loss function at each θ is then graphed in Figure 4.

<u>Result 3:</u> The lower the policy-maker's degree of risk aversion θ, the lower is the optimal time horizon of the EWS model she wishes to choose (see Figure 5). The intuition is that a longer time horizon H allows a policy-maker to miss fewer crises, which outweighs the fact that choosing a longer time horizon H also raises the number of alarms that the EWS model sends. In the example with three time horizons (H = 12, H = 18, H = 24), the multinomial logit EWS model with H = 12 performs best for $0 \leq \quad < 0.55$, the EWS model with H = 18 is best for $0.55 \leq \quad < 0.65$, and the EWS model with H = 24 is the preferred model for $0.65 \leq \quad < 1$.

Figure 5: Determining the optimal time-horizon H*

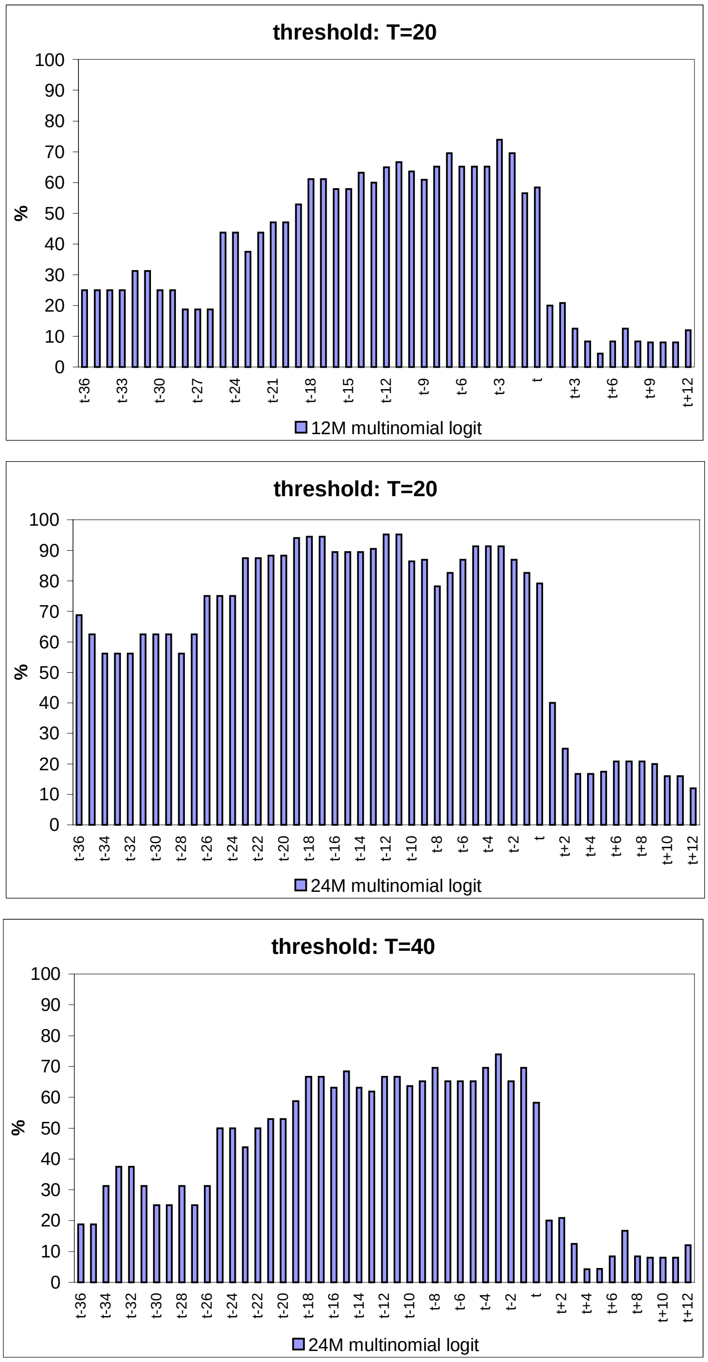


6.3 Illustrating the signal distribution for time-horizon models

An important consideration is that the timing of *when* a false signal or a missed crisis occurs can be of relevance when evaluating the quality of an EWS model. For instance, false signals in a model with a 12-month prediction horizon may be less worrisome if these false signals occur immediately before the start of the 12-month window. Similarly, missing a crisis signal in one particular month may be less of a concern if the model issues many signals during the months before the start of a crisis.

Figure 6 illustrates the distribution of crisis signals in our multinomial EWS model between 36 months before until 12 months after the onset of the crisis in period t. The first panel of Figure 6 for our preferred 12-month multinomial logit EWS model with T=20 shows that each of the 12 months before a crisis had about 70% of correct crisis signals. This ratio falls steadily to about 45% for the period of 12 to 24 months before the crisis and then drops further to about 20% for up to 36 months. This finding implies that what one may classify as false signals in this model are often signals that occur just before the onset of the 12 months period to a crisis.

Figure 6: Signal distribution (% of signals to crises)



By contrast, the 24-month multinomial logit EWS model with T=20 has a higher ratio of correct signals in the 24 months before the crisis, but also the number of false signals stays very high for most of the sample period, often also following a crisis (see second panel of Figure 6). Hence a signal is not nearly as reliable and it may be preferable to impose a higher threshold T. By contrast, at a threshold of T=40, the 24-month model performs similarly to the 12-month EWS model with T=20 (see third panel of Figure 6).

7 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 three areas. First, it discussed what we call the “post-crisis” bias in the existing binomial discrete-dependent-variable EWS models and showed that failing to distinguish between pre-crisis and post-crisis periods may introduce a bias in the estimation results. By contrast, the use of a multinomial logit allows the distinction between more than two regimes and allows solving for this type of bias.

The second area is that our EWS model employs a number of relevant economic variables that have not been used before for the purpose of EWS models. In particular, we find that the use of contagion variables, which takes into account that crises are often not isolated events but interconnected across economies, helps improve the predictive power of EWS models. And third, the paper developed a framework that allows policy-makers to design the features of their EWS model according to their preferences and degree of risk-aversion.

The paper showed that taking into account these methodological issues can indeed help improve the performance of EWS models substantially. In particular, moving from a binomial logit model to a multinomial logit model with three regimes improves the predictive power of the EWS. 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 only two of the emerging market crises in our sample. For the out-of-sample estimation, the model for instance would have anticipated correctly most of the countries that succumbed to the Asian crisis.

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 in the future. 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, developing Early Warning System (EWS) models that help to reliably anticipate financial crises could become an even more important tool for policy-makers in the future. 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 clear signals when and how to take pre-emptive measures in order to mitigate or even prevent financial turmoil. It should be stressed that EWS models can not replace the sound judgment of the policy-maker to guide policy, but it can play an important complementary role as a neutral and objective measure of vulnerability.

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Appendix

Appendix 1: Country list and data sources

Table 19: Country list

Latin America	Asia	Eastern Europe	Others
* Argentina	* China	Bulgaria	South Africa
* Brazil	* Hong Kong	* Czech Rep.	* Turkey
* Chile	India	Estonia	
* Colombia	* Indonesia	* Hungary	
Ecuador	* Korea	Latvia	
* Mexico	* Malaysia	Lithuania	
Peru	Pakistan	* Poland	
* Venezuela	* Philippines	* Russia	
	* Singapore	Slovak Rep.	
	Sri Lanka	Slovenia	
	* Taiwan		
	* Thailand		

A star * indicates the 20 countries of the core group.

- ***Source of the raw data***

The data appendix reviews, indicator by indicator, the raw data sources, and, when relevant, the interpolation technique. We used 5 different sources for the macro and financial variables: the IMF International Financial Statistics (IFS), the IMF-World Bank-OECD-BIS joint table for the debt statistics available on-line (BIS), the World Market Monitor from DRI-WEFA (WMM), J.P. Morgan (JPM), and Datastream (DS) for the market indices. When multiple sources have been chosen we checked the consistency of the definition. Data relative to Taiwan were all taken from WMM as they are not included in IFS; original data come from Central Bank of China and Directorate General Of Budget. Data are retrieved on a monthly (M), quarterly (Q), semi-annual (SA) or yearly (Y) basis and linearly interpolated when necessary.

- ***Raw data used to compute EMP***

The EMP index is computed from the real exchange rate (using end-period exchange rate, IFS line AE and CPI line 64), international reserves (IFS line 1L), and a short-term interest rate (discount rate, IFS line 60, money market rate, IFS line 60B, deposit interest rate IFS line 60L, lending interest rate IFS line 60P).

The default is the money market rate (IFS line 60b), we used the lending rate (IFS Line 60P) for Chile, China, the deposit rate (IFS line 60L) for Colombia, the Czech Rep., Ecuador, Hungary, Peru, Philippines, Slovakia, and Venezuela.

We transformed the raw EMP using a three-month moving average with weights 3/6, 2/6 and 1/6 for time t, t-1 and t-2 respectively. This transformation is similar to Schnatz (1998, 1999) who used geometric weights, to which we refer for a detailed discussion of methodological issues in the design of the crisis index.

- ***Real effective exchange rate***

For Chile, China, Col., Czech Rep., Ecuador, Estonia, Hungary, Korea, Malaysia, Mexico, Pakistan, Philippines, Poland, Russia, Slovak Republic, South Africa, Turkey, data were taken from WMM and for Argentina, Brazil, Bulgaria, Hong Kong, India, Indonesia, Peru, Singapore, Slovenia, Taiwan, Thailand, from JPM. The data from WMM come from IMF (see Desruelles and Zanello, 1997 for a presentation of the IMF definition of the REER) or closely follow this methodology.

- ***GDP***

Nominal and real GDP were taken from WMM and interpolated from Q data. For Pakistan and Sri Lanka data are from IFS line 99b (A frequency).

- ***Current account items***

Exports are taken from IFS line 70 and imports from IFS line 71. Current account was taken from WMM and linearly interpolated from Q to M frequency , except for China (IFS, A frequency). Ratio's are expressed in percentage of the GDP using the nominal monthly exchange rate. The series were transformed using a 12 month moving average with equal weights: this allowed to remove seasonality and sometimes strong volatility, and in addition it allows a more reliable assessment of the situation by looking at flows on the past year instead of the last month.

- ***Government deficit***

The government deficit is available at a monthly frequency from IFS line 80. Exception were Chile, China, Estonia, India, Indonesia, Pakistan, Slovak Republic, Sri Lanka, Turkey (A), for Hong Kong, Malaysia, Poland data were taken from WMM (Q). The same transformation as for the current account was undertaken.

- ***Monetary variables***

Source is IFS line 34 for M1 and line 35 for quasi-money (M2 is obtained adding line 34 and line 35). Domestic credit is taken from IFS line 32, credit to the government sector (central government) from line 32an, credit to the private sector from line 32b.

- ***Financial account capital flows***

WMM was the source for foreign direct investment, exports, imports, and net flows, for portfolio investment, assets, liabilities, and net flows.

- ***Debt statistics***

The BIS database on debt statistics includes the following series that we downloaded: bank loans (BIS Line A), Brady Bonds (Line C), liabilities within one year (Line G), total liabilities, locational concept (Line J), total liabilities, consolidated concept (Line K).

- ***Trade data***

Bilateral trade data come from the World Trade Analyzer.

Appendix 2: Discussion of definition and explanatory power of independent variables

• ***Current account items***

CAGDP. The level of the current account expressed as a percentage of the GDP as a vulnerability indicator has been analyzed extensively in Milesi-Ferretti and Razin (1996). The higher the deficit (i.e., the current account being defined as negative when in deficit, the lower the ratio), the less likely a country will be able to generate external revenue to finance a balance of payments problem. We tested other similar variables like trade balance over GDP, which proved to be also significant but to carry less information as the full current account. The rate of growth of exports and imports was not significant.

• ***Debt and liquidity ratios***

STDR. The ratio of short-term debt to reserves is a key vulnerability indicator, and as a rule of thumb known as the Greenspan-Guidotti rule should be smaller than 100: reserves should cover at least the level of short-term debt. Other liquidity ratios were tested but found insignificant: M1 and M2 to reserves, total debt to reserves, debt (short and long) to GDP, reserves to imports and to exports, as well as the variation of reserves over the preceding year.

• ***Overvaluation of the exchange rate***

REERCH. An overvalued exchange rate is often perceived by the market as an indication that the country will have to devalue. The real effective exchange rate, as defined in Desruelle and Zanello (1997) is a valuable concept to look at since it takes into account the competitiveness of the home country, as well as competition in third countries. One key question in the measurement of the overvaluation is which benchmark should be taken for the comparison. Overvaluation is often taken as a percent change over a given period (the last 2 or 4 years), e.g.:

$$REERCH_t^i = \frac{REER_t^i - REER_{t-48}^i}{REER_{t-48}^i} * 100 \tag{A.1}$$

However this measure is not satisfying in the present context for the following reason: if a country devalues at time t, its currency will appear severely overvalued at time t+48 only because of the base effect. To avoid this caveat we define overvaluation as deviation from a linear trend (it also makes sense to consider a trend for emerging markets whose currencies are expected to appreciate over time, reference here).

$$REERDEV_t^i = \frac{\left(REER_t^i - TREND_t^i\right)}{TREND_t^i} * 100 \tag{A.2}$$

• ***Real variables***

GROWTH. The rate of growth of real output can play an important role is avoiding crises for two reasons: first it will generate with more difficulty the revenues necessary to pay back the debt burden and second a government may be more reluctant to implement stabilization programs if output is already slowing down.

• ***Financial sector fragilities***

As the Twin crises argument has met a lot of empirical support since it was started by Kaminsky and Reinhart (1996), EWS models have given an increasing importance to financial sector fragility. The presence of bad loans in the banking sector has often been put forward as a key determinant of the Asian crisis (references). Such variables are however more difficult to collect than the other variables listed above because they are not directly observable. Bad loans for instance are subject to notorious under-reporting. Four types of variables have been considered as proxies:

a) Lending boom index

The increase of the credit to the private sector can give an indication that a country is over-heating. If the progression of these credits is too rapid, one can suspect that a lot is going to dubious projects. Empirical evidence so far was not conclusive: earlier contributions (Sachs, Tornell, and Velasco, 1995) were later contradicted by studies pointing out that lending booms can also act as contra-indicators, noticeably in the case of Russia (Bussiere and Mulder, 1999). The present results should then be qualified: in many cases a lending boom led to a crisis, but a sharp decrease can also be a sign of weakness (as exemplified recently in Argentina). This issue deserves further investigation to fix the debate.

b) Banking sector stock index

The banking sector stock index could proxy banking sector imbalances, assuming that these imbalances are perfectly evaluated by the markets – an admittedly bold assumption. In fact the coefficient on this variable turned up to be significant at the 5% level, with the correct sign. However, we decided not to keep this variable in the model for two reasons: first its contribution to the predictive power of the model was not conclusive and second problems of comparability across countries can be more important for this variable as for the others as not all countries have a fully developed and transparent market where bank indices are freely quoted.

c) Lending/deposit interest rate spread

As the revenue of banks arises from a difference between lending and deposit interest rates, the measurement of this spread is a direct measure of profitability. However, this would assume the existence of one lending interest rate and one deposit interest rate, whereas in reality there are different products on different markets. In this sense, the synthetic interest rates given in IFS, that we have used as proxies, are not perfect, which may explain why the spreads did not enter the equation significantly.

• ***Contagion variables***

Next, we considered testing for various contagion channels. There is now clear face value evidence of contagion across countries (in Latin America in 1995 with the so-called "Tequila effect", in Asia in 1997, and in the Russia/Brazil crisis of 1999). The literature has attempted to distinguish between various contagion channels. Fratzscher (1998) proposed a methodology that we follow here. Two particular channels were considered: trade and financial linkages. We only briefly present the contagion measures here. For a more detailed account, see Fratzscher (1998).

The trade channels attempts to capture the fact that if two countries are competing strongly in third markets or are trading a lot with each other, then a crisis may be more likely to spread among these two countries. The measure of this real linkage is the following:

$$REAL_{ij} = \sum_{c} \sum_{d} \left(\frac{X^{c}_{jd}}{X^{c}_{\cdot d}} \times \frac{X^{c}_{id}}{X_{i\cdot}} \right) + \sum_{c} \left(\frac{X^{c}_{ij} + X^{c}_{ji}}{X^{c}_{\cdot i} + X^{c}_{i\cdot}} \right) \tag{A.3}$$

with X_{id} as exports from country i to region d. The first of the two terms therefore measures how strong a competitor country j is for economy i in all regions d. The second term then calculates the bilateral trade share.

We use the correlation of equity market return residuals μ_t during tranquil periods as our measure for financial market contagion across two markets i and j. The idea is that a higher degree of financial market integration means that a crisis is more likely to spread across markets in subsequent months. We first obtain the return residuals for each individual country by regressing equity market returns $r_{i,t}$ on relevant country-specific fundamentals:

$$r_{i,t} = \ {}_{1} + \ {}_{2}TB_{i,t} + \ {}_{3}i_{i,t} + \ {}_{4}P_{i,t} + \ {}_{5}S_{i,t} + \ {}_{6}GRET_{t} + \ {}_{i,t} \tag{A.4}$$

with the independent variables as the trade balance (*TB*), the change in a country's interest rate (*i*), the rate of inflation (*P*) and the spot exchange rate (*S*) for each country *i*. markets, and a global equity market return (*GRET*). We then measure the degree of financial interdependence as the cross-country correlations of the residuals μ, which should provide a reasonably good proxy about the true financial interdependence of various emerging stock markets:

$$FINCONT1_{ij} = CORREL\ \mu_{i,t}, \mu_{j,t} \tag{A.5}$$

As a final step, the measures of real or financial interdependence for each country is interacted with the degree of exchange market pressure (EMP) during the past six months in each of the other countries. Moving to a longer lag was not found to be more significant as contagion tends to occur within a few months. The intuition of these contagion measures is that if a country experiences a crisis, the crisis is more likely to spread to those countries that are more interdependent with the crisis country.

In the empirical estimations, only the financial contagion channel appeared to play a significant role in our EWS models, the coefficient on our trade variable had the correct sign but it was not always significant.

Appendix 3: Estimation results with alternative models

Table 20: 24-month multinomial logit model, 20 core countries, 1993-2001.

Variable	Coeff.	Std. Err.	Z	P>|z|
	Pre-crisis period $Y_{i,t} = 1$			
Overvaluation	0.230	0.015	14.940	0.000
Lending boom	0.017	0.002	6.910	0.000
STD/res	0.006	0.001	6.310	0.000
CA/GDP	-0.049	0.013	-3.630	0.000
Fin. Contagion	-0.030	0.014	-2.140	0.033
Growth	-0.080	0.020	-4.030	0.000
Const.	-2.272	0.186	-12.240	0.000
	Post-crisis period $Y_{i,t} = 2$			
Overvaluation	-0.061	0.010	-6.150	0.000
Lending boom	0.013	0.002	5.540	0.000
STD/res	0.005	0.001	4.850	0.000
CA/GDP	0.015	0.010	1.480	0.140
Fin. Contagion	0.039	0.012	3.330	0.001
Growth	-0.244	0.019	-13.080	0.000
Const.	-1.061	0.140	-7.600	0.000
# obs	1551			
Pseudo R2	0.379			

Note: Tranquil period Y=0 is the comparison group

Table 21: Multinomial logit (20 countries)

	$S_{i,t} = 0$	$S_{i,t} = 1$	Total
$Y_{i,t} = 0$	699	128	827
$Y_{i,t} = 1$	83	312	395
$Y_{i,t} = 2$	289	40	329
Total	1071	480	1549

% of obs. correctly called:	82.7
% of crises correctly called:	79.0
% of false alarms of total alarms:	29.1
% prob. of crisis given an alarm:	70.9
% prob. of crisis given no alarm:	10.6

Note: observations Y=2 are not included in the computation of the ratio's because they cannot be classified as correct or wrong signals in this framework.

Table 22: Random effect logit model (20 countries)

	$S_{i,t} = 0$	$S_{i,t} = 1$	Total
$Y_{i,t} = 0$	1147	157	1304
$Y_{i,t} = 1$	79	167	246
Total	1226	324	1550

% of obs. correctly called:	84.8
% of crises correctly called:	67.9
% of false alarms of total alarms:	48.5
% prob. of crisis given an alarm:	51.5
% prob. of crisis given no alarm:	6.4

Appendix 4: Robustness tests and sensitivity analysis

Table 15: Goodness of fit when REER is excluded from the model 20 core countries, 1993-2001.

Variable	Coeff.	Std. Err.	Z	P>|z|
	Pre-crisis period $Y_{i,t} = 1$			
Overvaluation	-	-	-	-
Lending boom	0.012	0.002	6.640	0.000
STD/res	0.004	0.001	5.080	0.000
CA/GDP	-0.071	0.015	-4.850	0.000
Fin. Contagion	0.031	0.013	2.450	0.014
Growth	-0.056	0.018	-3.080	0.002
Const.	-1.990	0.158	-12.620	0.000
	Post-crisis period $Y_{i,t} = 2$			
Overvaluation	-	-	-	-
Lending boom	0.009	0.002	4.830	0.000
STD/res	0.005	0.001	5.130	0.000
CA/GDP	0.028	0.010	2.770	0.006
Fin. Contagion	0.047	0.011	4.240	0.000
Growth	-0.257	0.017	-15.250	0.000
Const.	-0.984	0.128	-7.670	0.000
# obs	1549			
Pseudo R2	0.192			

Note: Tranquil period Y=0 is the comparison group

	$S_{i,t} = 0$	$S_{i,t} = 1$	Total
$Y_{i,t} = 0$	818	170	988
$Y_{i,t} = 1$	121	111	232
$Y_{i,t} = 2$	272	57	329
Total	1211	338	1549

% of obs. Correctly called:	76.15
% of crises correctly called:	47.84
% of false alarms of total alarms:	60.50
% prob. of crisis given an alarm:	39.50
% prob. of crisis given no alarm:	12.89

Table 16a: Testing the impact of the government deficit and of alternative reserve ratio's

Variable	Benchmark	Government Deficit	12M Reserves Growth Rate	Reserves/ Exports, Growth Rate, 12M
Coefficient on	-	***0.188	***-1.636	**-0.011
Additional variable		(0.043)	(0.451)	(0.004)
# obs	1549	1485	1549	1541
Pseudo-R2	0.333	0.348	0.350	0.345
Predicted Crises, %	73.7	73.76	76.29	75.43
False alarms, %	44.1	40.43	37.79	37.61

Table 16b: Current account items and alternative debt ratio

Variable	Exports, 12 Months Growth Rate	Trade Balance, % GDP	Openness	ST Debt / GDP
Coefficient on	-0.009	-0.025	0.001	***0.008
Additional variable	(0.006)	(0.016)	(0.001)	(0.002)
# obs	1541	1538	1538	1549
Pseudo-R2	0.338	0.335	0.338	0.333
Predicted Crises, %	74.14	74.14	73.71	74.57
False alarms, %	39.59	39.88	39.05	39.88

Table 16c: Financial variables

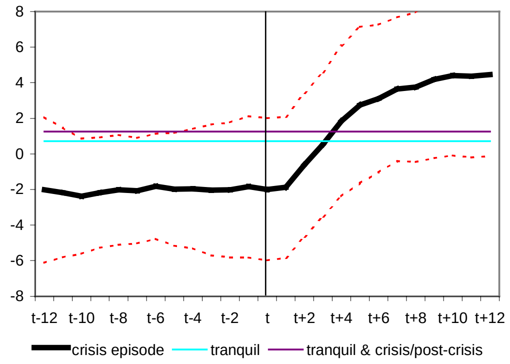
Variable	Interest Rate Spread	DS Index, Banks	DS Index, Fin. Instit.	DS Index, Total Market
Coefficient on	0.012	*-0.003	-0.002	0.0001
Additional variable	(0.009)	(0.002)	(0.001)	(0.001)
# obs	1428	1268	1268	1339
Pseudo-R2	0.342	0.383	0.383	0.351
Predicted Crises, %	69.57	75.56	75.00	74.73
False alarms, %	47.90	45.10	45.26	45.36

Table 16d: Capital flows

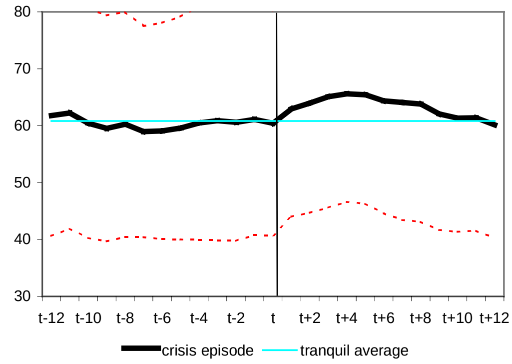
Variable	Net FDI Flows (% GDP)	FDI Inflows, 12 months p.c.	Net Portfolio Flows (% GDP)	Portfolio liabilities., 12 month p.c.
Coefficient on	0.013	-0.056	-0.023	-0.0002
Additional variable	(0.047)	(0.035)	(0.038)	(0.0002)
# obs	999	1053	852	1049
Pseudo-R2	0.360	0.415	0.502	0.425
Predicted Crises, %	79.53	84.62	82.24	81.87
False alarms, %	39.24	35.57	33.33	37.33

Appendix 5: Event Analysis

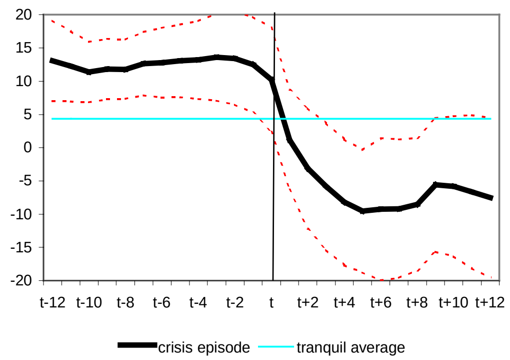
Current account to GDP ratio (in %)



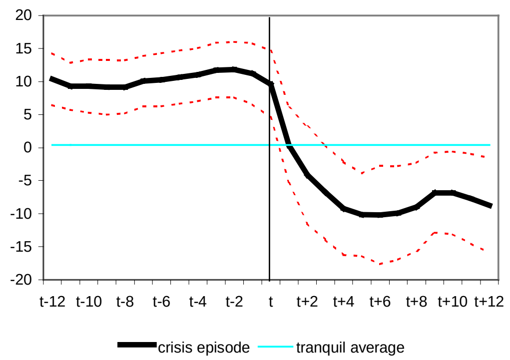
Domestic credit to GDP ratio (in %)



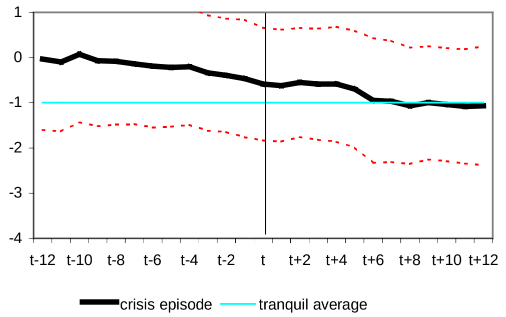
REER change over past two years (in %)



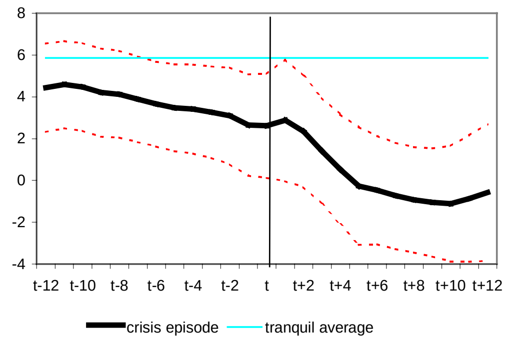
REER deviation from linear trend (in %)

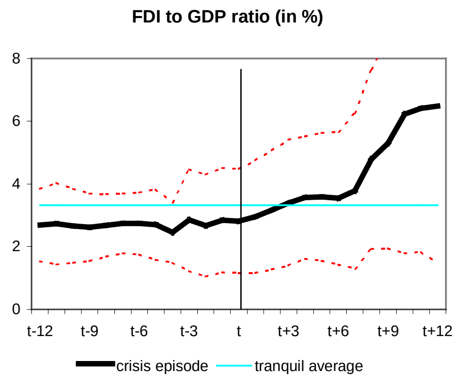


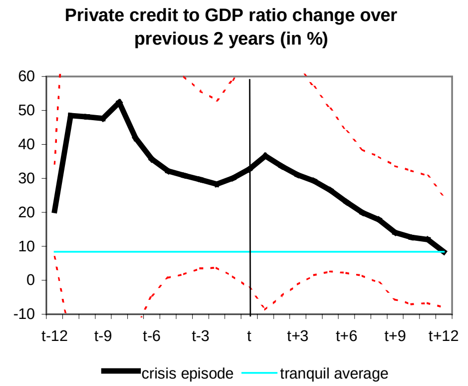
Government deficit to GDP ratio (in %)

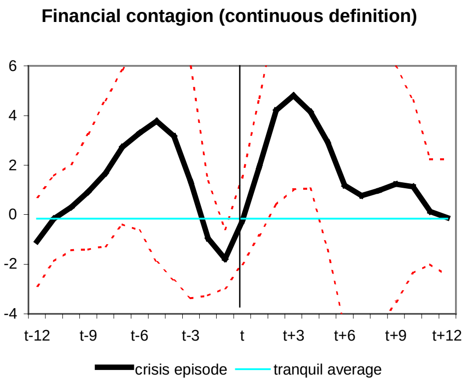


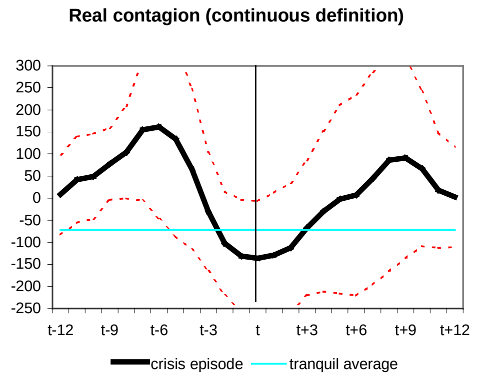
Annualised GDP growth rate (in %)

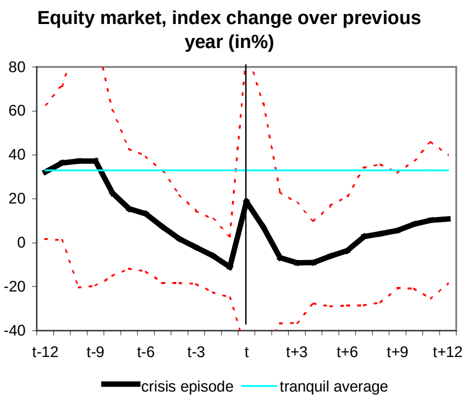


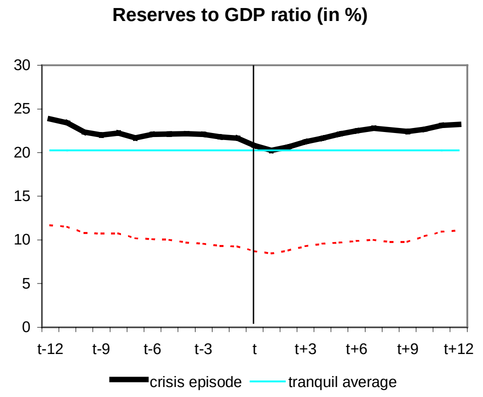

FDI to GDP ratio (in %)
8
6
4
2
0
t-12
t-9
t-6
t-3
t
t+3
t+6
t+9
t+12
crisis episode
tranquil average


Private credit to GDP ratio change over previous 2 years (in %)
60
50
40
30
20
10
0
-10
t-12
t-9
t-6
t-3
t
t+3
t+6
t+9
t+12
crisis episode
tranquil average

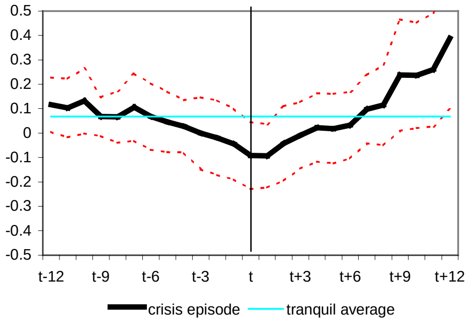

Financial contagion (continuous definition)
6
4
2
0
-2
-4
t-12
t-9
t-6
t-3
t
t+3
t+6
t+9
t+12
crisis episode
tranquil average


Real contagion (continuous definition)
300
250
200
150
100
50
0
-50
-100
-150
-200
-250
t-12
t-9
t-6
t-3
t
t+3
t+6
t+9
t+12
crisis episode
tranquil average

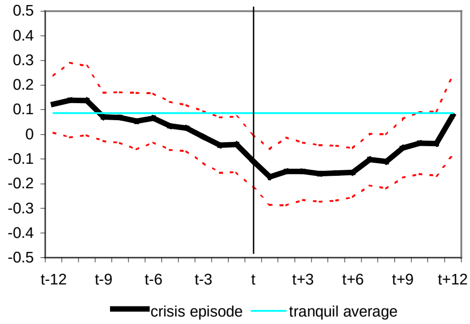

Equity market, index change over previous year (in%)
80
60
40
20
0
-20
-40
t-12
t-9
t-6
t-3
t
t+3
t+6
t+9
t+12
crisis episode
tranquil average


Reserves to GDP ratio (in %)
30
25
20
15
10
5
0
t-12
t-9
t-6
t-3
t
t+3
t+6
t+9
t+12
crisis episode
tranquil average

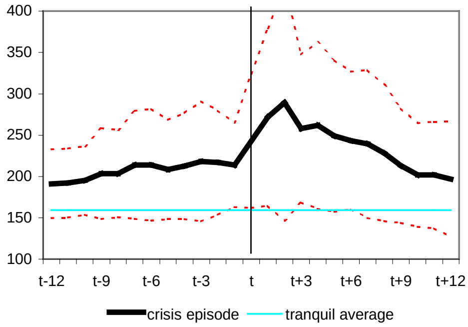
Reserves to import ratio, growth rate over previous year (in %)



Reserves to export ratio, growth rate over previous year (in %)



Total consolidated external debt to reserves ratio (in %)



Short-term external debt to reserves ratio (in %)

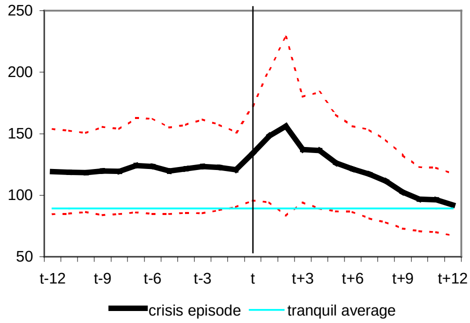


Fig. X: Trade balance to GDP ratio (in %)

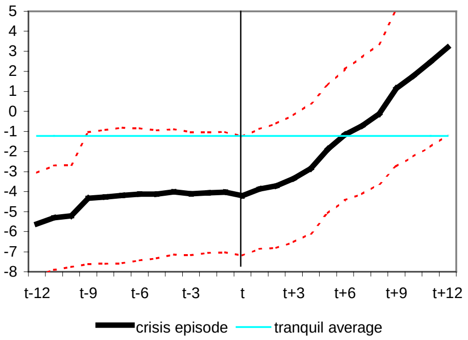
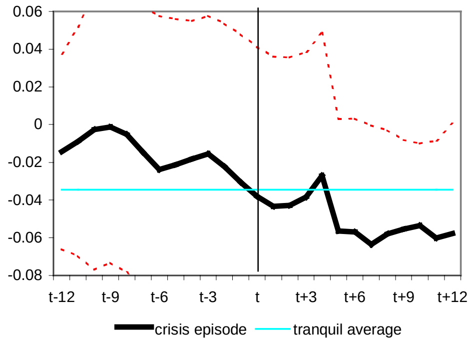


Fig. X: Terms of trade change over previous two years (in %)



Appendix 6: Predicted probabilities and signal extraction

Chart: Argentina

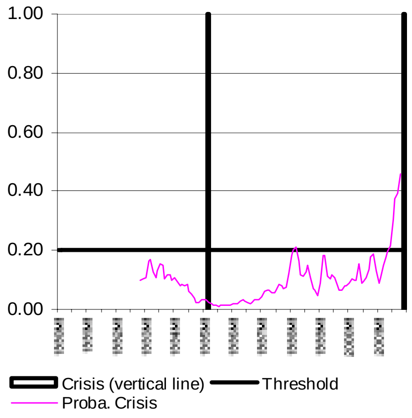


Chart: Brazil

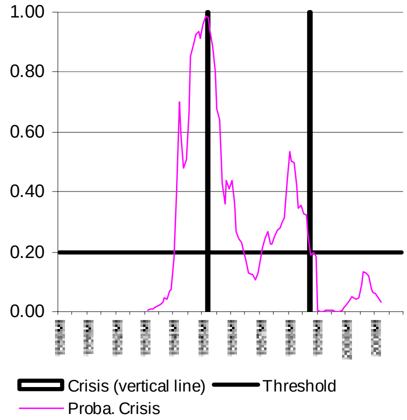


Chart: Mexico

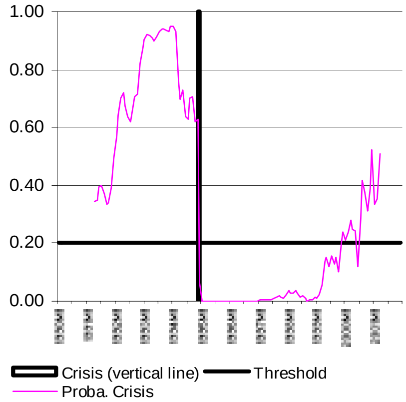


Chart: Chile

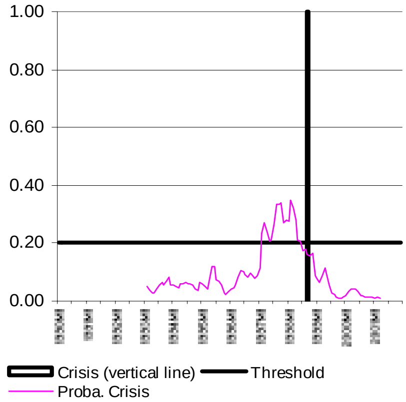


Chart: Turkey

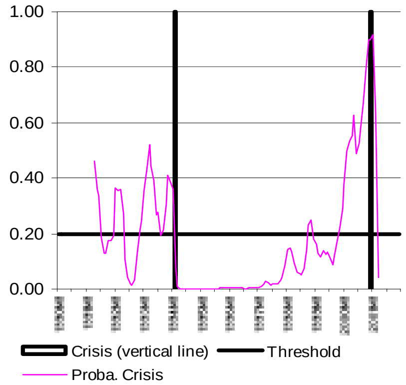


Chart: Russia

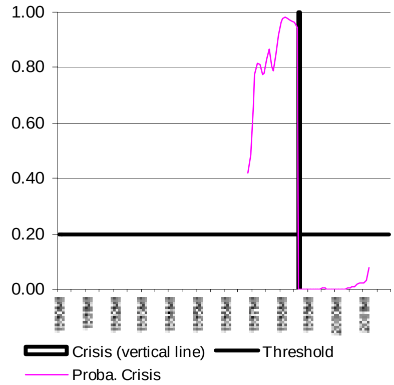


Chart: Poland

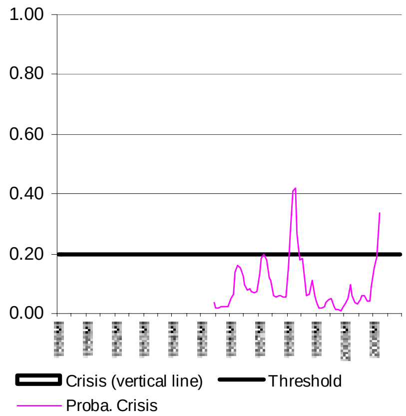


Chart: Czech Rep.

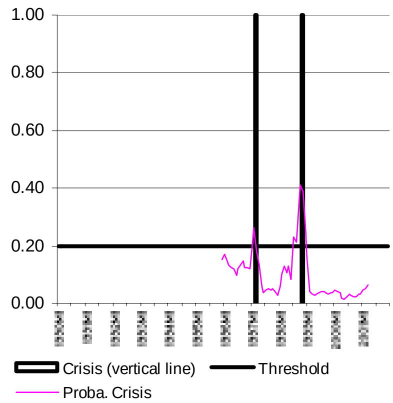


Chart: Thailand

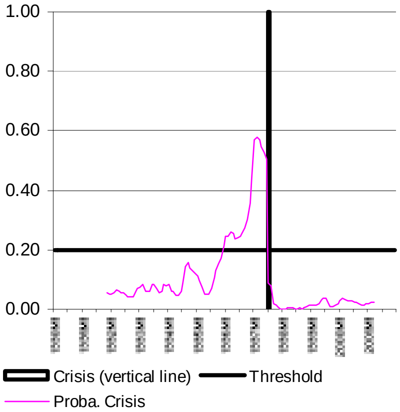


Chart: Singapore

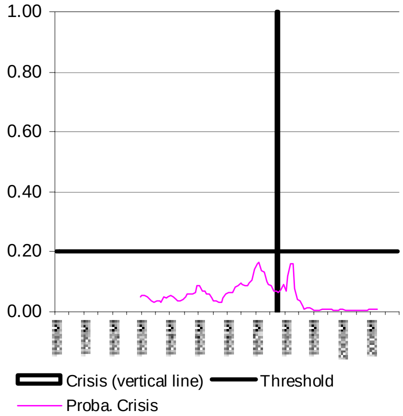


Chart: Malaysia

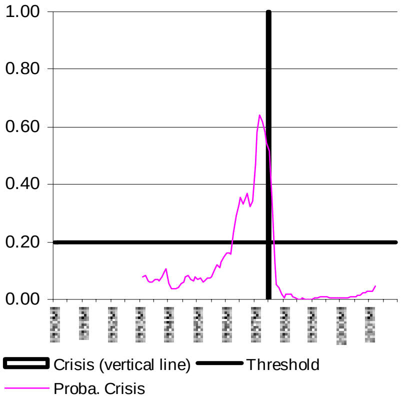


Chart: Indonesia

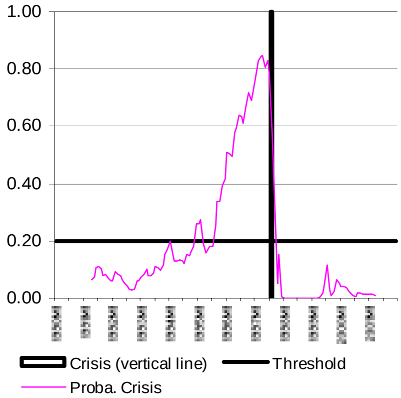


Chart: Korea

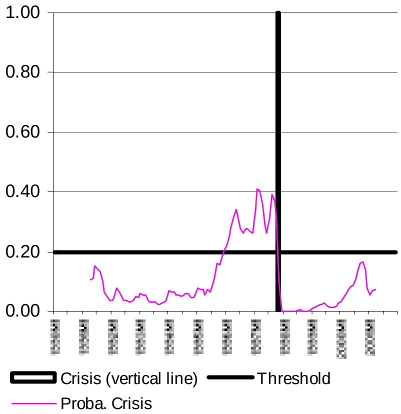


Chart: Philippines

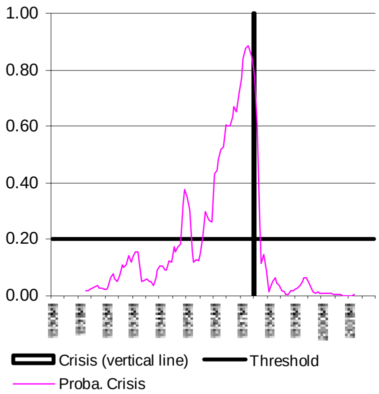


Chart: Hong Kong

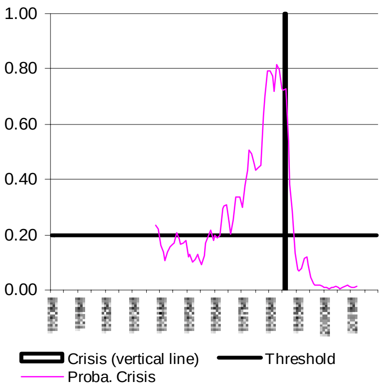
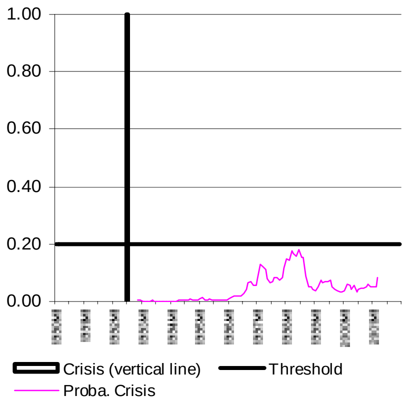


Chart: China



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