Currency crises in Asia: A multivariate logit approach

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April 2004

Abstract

Indicators of financial crisis generally do not have a good track record. This paper presents an early warning system (EWS) for six countries in Asia in which indicators do work. Our binary choice model, which has been estimated for the period 1970:01–2001.12, has the following features. We compare four different currency crisis definitions, extract a full list of currency crisis indicators from the literature, apply factor analysis to combine the indicators, and introduce dynamics. We find that money growth (M1 and M2), national savings, and import growth correlate with currency crises.

Keywords: financial crises, currency crises, early warning system, panel data, multivariate logit, factor analysis
JEL-code: C33, C35, F31, F34, F47

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1 Introduction

Four waves of financial crises have hit international capital markets during the 1990s: the European Monetary System (ERM) crisis in 1992-1993, the collapse of the Mexican peso with 'tequila effects' in 1994-1995, the Asian flu of 1997-1998, and the Russia virus in 1998. These financial crises stimulated the theoretical and empirical literature on the economics of the crises in several ways, among other things on the determinants of a crisis (Kaminsky and Reinhart, 1999), its impact on domestic output (Aghion, Bacchetta and Banerjee, 2001), and policy implications (Rogoff, 1999).

In view of the large costs associated with a financial crisis, the question of how to predict a crisis has become central. This resulted in the construction of a monitoring tool, the so-called *early warning system* (EWS).[1] An EWS consists of a precise definition of a crisis and a mechanism for generating predictions of crises. Typically, an EWS has an empirical structure with indicators that contribute to a country's vulnerability to a future crisis and forecasts the likelihood of a financial crisis. EWS models differ widely in terms of the definition of financial crisis, the time span on which the EWS is estimated and attempts to forecast, the selection of indicators, and the statistical or econometric method.

The literature distinguishes three varieties of financial crises: currency crises, banking crises, and debt crises. We restrict our attention in this paper to currency crises. Several methods have been suggested for EWS models. The most popular one is used in this paper, namely qualitative response (logit

[1]For example, the IMF is putting a lot of effort in EWS models, see IMF (2002).

or probit) models. Examples are Frankel and Rose (1996), who study currency crises and Dermirgüç-Kunt and Detragiache (1997, 2000) on banking crises. Alternatives are cross-country regression models with dummy variables as put forward by Sachs, Tornell and Velasco (1996), graphical event studies as suggested by Eichengreen, Rose and Wyplosz (1995) and the signal extraction approach, a probabilistic model proposed by Kaminsky, Lizondo and Reinhart (1998). In the last method values of individual indicators are compared between crisis periods and tranquil periods. If the value of an indicator exceeds a threshold, it signals an impending crisis. A common feature of all existing EWS studies is the use of fundamental determinants of the domestic and external sectors as explanatory variables.

This paper develops an econometric EWS for six Asian countries, Malaysia, Indonesia, Philippines, Singapore, South Korea and Thailand. These countries have been selected because the Asian flu hit Thailand and spread to other countries in the region—except Singapore—almost instantaneously. We set up logit models for currency crises with indicators extracted from a broad set of potentially relevant financial crisis indicators.

The set-up of our EWS is similar to Kamin, Schindler and Samuel (2001) and Bussiere and Fratzscher (2001), who also adopt a binomial multivariate qualitative response approach. However, while the final result of their (unreported) specification search is combinations of indicators as explanatory variables, we apply factor analysis to reduce the information set. An additional novelty of our model is that we do not only include the level of the factors, but also the change therein. It can be argued that the development of the factors over time has important consequences for the probability of a currency crisis to occur. The models are estimated using panel data for the January 1970–December 2001 period. The factor analysis outcomes in combination with the estimation results allow the general conclusion that (some) indicators of financial crises do work, at least in our EWS of Asia. This finding is in contrast with IMF (2002)[2] and Edison (2003), who conclude that the performance of EWS is generally poor and at best mixed. Our method—the combination of factor analysis and logit modeling—enables us to answer the question posed by Bustelo (2000) whether additional indicators have explanatory power for financial crises. It also allows the dismissal of uninformative indicators.

Another feature of our paper is that we distinguish four currency crisis dating definitions. A priori we do not prefer one of the definitions. However, a within-sample signal extraction experiment reveals that the method of Kaminsky, Lizondo and Reinhard is superior to the other dating schemes.

The organization of the paper is as follows. Section 2 describes various methods to measure and date currency crises. The results—dummy variables indicating dates of various crises—are summarized in frequency tables which reveal information on the distribution of each type of crises over countries and over time. The dummies are used in binary choice models that explain the probability of crises. Section 3 describes our set of indicators, and presents and discusses our main results. Section 4 presents the binomial multivariate logit models for currency crises. Furthermore, we analyze the performance of the models in an in-sample experiment in Section 5. Section 6 concludes.

[2]For an assessment of the EWS models at the IMF, see Berg, Borensztein and Pattillo (2003).

2 Dating Crises

The list of studies on EWS of financial crises is long and expanding rapidly. A full list is beyond the scope of this paper. Interested readers are referred to Kaminsky, Lizondo and Reinhart (1998) for papers on currency crises prior to the East Asian crisis, and Bustelo (2000) and Bukart and Coudert (2002) on the East Asian crisis; Gonzalez-Hermosillo (1996) and Dermirgüç-Kunt and Detragiache (1997) on banking crises; and Marchesi (2003)'s survey on debt crisis.

In this paper, we identify episodes of currency crisis in East Asia using the original definitions proposed by Eichengreen, Rose and Wyplosz (ERW for short), Kaminsky, Lizondo and Reinhart (KLR), Frankel and Rose (FR) and Zhang (Z). In addition we implement our own versions of KLR and Z (LJK). All these methods employ an exchange rate market pressure index which needs to exceed a threshold to signal a crisis.[3]

Eichengreen, Rose and Wyplosz (1995) made an important early effort to develop a method to measure currency pressure and to date currency crises. Their definition of exchange rate pressure is inspired by the monetary model of Girton and Roper (1977). The exchange rate is under pressure if the value of a constructed index exceeds a certain threshold. The index consists of weighted relative changes of the nominal exchange rate, international reserves and interest rates to capture successful as well as unsuccessful speculative

[3]An alternative is the extreme value approach of Pozo and Amuedo-Dorantes (2003), which does not need thresholds. Another literature focuses on contagion and dates currency crises on the base of event studies. Examples are Granger, Huang, and Yang (2000) and Dungey and Martin (2002) who date currency crises on the basis of exchange rate jumps and news, respectively. Finally, Abiad (2003)'s Markov-switching EWS model does not require a priori crisis dates at all.

attacks. All variables in their index are relative to a reference country and their threshold is time-independent. For the dating of currency crises we set the exchange market pressure index threshold to two standard deviations from the mean.[4] To avoid potential crises that occur together, we follow Eichengreen, Rose, and Wyplosz (1995) by imposing an exclusion window of one year, six months in the future and in the past.

The method of Eichengreen *et al.* was heavily criticized which led to alternatives based on the same methodology. Kaminsky, Lizondo and Reinhart (1998) and Kaminsky and Reinhart (1999) followed the concept of Eichengreen *et al.* fairly closely, but they excluded interest rate differentials in their index and comparisons to a reference country. Lestano *et al.*(2003) have their own version of Kaminsky, Lizondo and Reinhart in which they do not exclude interest rates from the index.

Other alternatives are Frankel and Rose (1996) and Zhang (2001). Frankel and Rose (1996) excludes unsuccessful attacks from the index, since these are hard to detect. They—and also Esquivel and Larrain (1998)—drop international reserves and interest rate differentials from the exchange rate pressure index and use three years crisis window to avoid registering currency crash twice. Zhang (2001) takes the volatility of variables in the currency crisis explicitly into account ans employs time-dependent thresholds. Lestano *et al.*'s version of Zhang's method differs from the original version in two respects: the threshold differs and they include interest rates in the index.

Table 1 summarizes the distribution of the financial crises over the six

[4]See Lestano and Jacobs (2002) for a sensitivity analysis of the dating scheme to different values of the threshold. Moreover, threshold models are also sensitive to the time period considered (see Dungey *et al.*, 2003).

Asian countries in our sample. Currency crises are distributed more or less evenly over the six countries. With respect to the currency crisis definitions, ERW, FR, the original KLR and LJK's version of KLR produce more or less the same number of currency crises (around 2.5% of the months). Zhang's definition with time-varying thresholds produces nearly three times as much currency crises as ERW, FR and KLR. LJK's version of Z has even more crises dates, because they lowered the threshold.

Table 1: Currency crises: distribution over countries for various dating schemes

	ERW	KLR(org)	KLR(LJK)	FR	Z(org)	Z(LJK)
Indonesia	10 (2.60%)	7 (1.82%)	9 (2.34%)	10 (2.60%)	27 (7.03%)	44 (11.46%)
Malaysia	10 (2.60%)	11 (2.86%)	10 (2.60%)	10 (2.60%)	21 (5.47%)	31 (8.07%)
Philippines	10 (2.60%)	9 (2.34%)	12 (3.13%)	11 (2.87%)	38 (9.90%)	52 (13.54%)
Singapore	14 (3.65%)	12 (3.13%)	11 (2.86%)	11 (2.87%)	16 (4.17%)	33 (8.59%)
South Korea	7 (1.82%)	6 (1.56%)	7 (1.82%)	10 (2.60%)	21 (5.47%)	27 (7.03%)
Thailand	9 (2.34%)	10 (2.60%)	9 (2.34%)	9 (2.34%)	17 (4.43%)	22 (5.73%)
All countries	60 (2.60%)	55 (2.39%)	58 (2.52%)	61 (2.65%)	140 (6.08%)	209 (9.07%)

The number between parentheses shows the frequency of crisis occurrence which is calculated by dividing the total number of crisis months by the total number of observations. ERW, KLR, FR and Z represent currency crises dated by the method of Eichengreen, Rose and Wyplosz, Kaminsky, Lizondo and Reinhart, Frankel and Rose, and Zhang, respectively. KLR(org) and Z(org) are the original crises dating schemes, KLR(LJK) and Z(LJK) are own implementations.

Since each method adopts a different definition of exchange rate market pressure, judging which dating system identifies currency crises best is not trivial.[5] Therefore we include all currency crises dating schemes in our model.

[5]Edison (2003) and Kamin, Schindler and Samuel (2001) reach a similar conclusion.

3 Factor analysis

This study focuses on indicators of macroeconomic development and external shocks. Worsening of these indicators affects the stability of financial system and may result in a financial crisis. The indicators are selected on the basis of economic theory as well as recent findings of empirical studies on financial crises. Another major consideration was the data availability on a monthly basis for our country coverage and sample. For convenience, the indicators are clustered into four major groups:

- *External:* Real exchange rates (REX), export growth (EXG), import growth (IMP), terms of trade (TOT), ratio of the current account to GDP (CAY), the ratio of M2 to foreign exchange reserves (MFR) and growth of foreign exchange reserves (GFR).

- *Financial*: M1 and M2 growth (GM1 and GM2), M2 money multiplier (MMM), the ratio of domestic credit to GDP (DCY), excess real M1 balances (ERM), domestic real interest rate (RIR), lending and deposit rate spread (LDS), commercial bank deposits (CBD), and the ratio of bank reserves to bank assets (RRA).

- *Domestic (real and public)*: The ratio of fiscal balance to GDP (FBY), the ratio of public debt to GDP (FBY), growth of industrial production (GIP), changes in stock prices (CSP), inflation rate (INR), GDP per capita (YPC), and growth of national saving (NSR).

- *Global*: Growth of world oil prices (WOP), US interest rate (USI), and OECD GDP growth (ICY).

The main source of all data is the International Financial Statistics of the IMF for the macroeconomic and financial indicators and the World Bank Development Indicators for the debt variables. We use monthly data, covering six Asian countries, Indonesia, Malaysia, Philippines, Singapore, South Korea and Thailand, from January 1977 to the end of 2001. Missing data are supplemented from Advance/Datastream and various reports of the country's central bank. All data in local currency units are converted into US dollars. Some annual indicators are interpolated to obtain a complete monthly database.

Table 2 lists definitions, sources and transformations of our crises indicators. Two types of transformation are applied to make sure that the indicators are free from seasonal effects and stationary, *i.e.* 12-months percentage change and deviation from linear trends. In case the indicator has no visible seasonal pattern and is non-trending, its level form is maintained. Some unavailable indicators are proxied by closely related indicators, for example OECD GDP is substituted by industrial production of industrial countries.

Table 2: Explanatory variables: definition, source, and transformation

Indicator	Code	Definition and source	Transformation
External sector (current account)			
Real exchange rate	REX	Nominal exchange rate is local currency unit (LCU) per USD, IFS-AE. The CPI is IFS-64. The real exchange rate is the ratio of foreign (US CPI) to domestic prices (measured in the same currency). Thus, REX = eP_f/P, where e = nominal exchange rate, P = domestic price (CPI), and P_f = foreign price (US CPI). A decline in the real exchange rate denotes a real appreciation of the LCU.	Deviation from trend
Export growth	EXG	IFS-70.D	12 month percentage change
Import growth	IMP	IFS-71.D	12 month percentage change)
Terms of trade	TOT	Unit value of exports divided by the unit value of imports. Unit value of exports is IFS-74.D. Import unit value for country (IFS-75.D) is not available, instead exports prices of industrialized countries is used, IFS-110.74.D.	12 month percentage change
Ratio of the current account to GDP	CAY	Current account (IFS-78AL) divided by nominal GDP (interpolated of IFS-99B).	-
External sector (capital account)			
Ratio of M2 to foreign exchange reserves	MFR	Ratio of M2 (IFS-34 plus IFS-35) and international reserves (IFS-1L.D). M2 is converted into USD.	12 month percentage change
Growth of foreign exchange reserves	GFR	IFS-1L.D	12 month percentage change

to be continued

(Table 2 continued)

Indicator	Code	Definition and source	Transformation
Financial sector			
M1 growth	GM1	IFS-34	12 month percentage change
M2 growth	GM2	IFS-35	12 month percentage change
M2 money multiplier	MMM	Ratio of M2 (IFS-34 plus IFS-35) to base (reserve) money (IFS-14).	12 month percentage change
Ratio of domestic credit to GDP	DCY	Total domestic credit (IFS-32) divided by nominal GDP (interpolated of IFS-99B).	12 month percentage change
Excess real M1 balance	ERM	Percentage difference between M1 (IFS-34) deflated by CPI (IFS-64) and estimated demand for M1. Demand for real M1 is estimated as function of real GDP, nominal interest rates (IFS-60L), and a time trend. If monthly real GDP data is not available for a country, then its annual counterpart (IFS-99BP) is interpolated to monthly data.	Based on estimated money demand equation
Domestic real interest rate	RIR	6 month time deposit (IFS- 60L) deflated by CPI (IFS-64)	-
Lending and deposit rate spread	LDS	Lending interest rate (IFS-60P) divided by 6 month time deposit rate (IFS-60L)	-
Commercial bank deposits	CBD	Demand deposit (IFS-24) plus time, savings and foreign currency deposits (IFS-25) deflated by CPI (IFS-64)	12 month percentage change
Ratio bank reserves to bank assets	RRA	Bank reserves (IFS-20) divided by bank assets (IFS-21 plus IFS-22a to IFS-22f)	-

to be continued

(Table 2 continued)

Indicator	Code	Definition and source	Transformation
Domestic real and public sector			
Ratio of fiscal balance to GDP	FBY	Government budget balance (IFS-80) divided by nominal GDP (interpolated IFS-99B).	-
Ratio of public debt to GDP	PBY	Public and publicly guaranteed debt (World Bank) divided by nominal GDP (interpolated IFS-99B).	-
Growth of industrial production	GIP	Industrial production index for Country is not available, then index of primary production (crude petroleum, IFS.66AA) is used	12 month percentage change
Changes in stock prices	CSP	IFS-62	12 month percentage change
Inflation rate	INR	IFS-64.	12 month percentage change
GDP per capita	YPC	GDP (interpolated IFS-99B) divided by total population (interpolated IFS-99Z).	12 month percentage change
National savings	NSR	public (IFS-91F) and private consumption (IFS-96F) subtracted from GDP (interpolated IFS-99B).	12 month percentage change
Global economy			
Growth of world oil prices	WOP	IFS-176.AA	12 month percentage change
US interest rate	USI	US treasury bill rate (IFS-111.60C)	12 month percentage change
OECD GDP growth	ICY	Proxied by industrial production (IFS-66).	12 month percentage change

As already mentioned in the Introduction, the aim of this paper is to construct a model that calculates the probability of a currency crisis. To do so we use a binomial multivariate qualitative response approach. However, the set of economic indicators that may contain information on whether or not a crises will occur is huge. It is not feasible to include all indicators in the logit model because of too few observations and multicollinearity among the indicators. So, for each country we reduce the information set into a limited number of factors using factor analysis. These factors are then used as explanatory variables in the logit model.

Technically speaking, factor analysis transforms a set of random variables linearly and orthogonally into new random variables.[6] The first factor is the normalized linear combination of the original set of random variables with maximum variance; The second factor is the normalized linear combination with maximum variance of all linear combinations uncorrelated with the first factor; and so on. By construction factors are uncorrelated. The eigenvalue for a given factor measures the variance in all the variables which is accounted for by that factor. A factor with a low eigenvalue may be ignored, because other factors are more important in explaining the variance in the set of variables under consideration.

Unfortunately, there is no "best" criterion for dropping the least important factors. The so-called Kaiser criterion drops all factors with eigenvalues below one. The Cattell scree test is a graphical method in which the eigenvalues are plotted on the vertical axis and the factors on the horizontal axis.

[6] For a detailed exposition of factor analysis including references see *e.g.*, Venables and Ripley (2002, Chapter 11).

The test suggests to select the number of factors that corresponds to the place of the curve where the smooth decrease of eigenvalues appears to level off to the right of the plot. In general, the scree test provides a lower bound on the number of relevant factors. In this paper we use the Kaiser criterion.

For most countries, eight factors emerge with an eigenvalue above unity.[7] Table 3 lists eigenvalues and the total variance explained by the factors for each country.

Table 3: Eigenvalues and the cumulative proportion of the variance explained by the factors (h^2)

Eigenvalues	Indonesia	Malaysia	Philippines	Singapore	South Korea	Thailand
factor 1	5.93	7.79	5.58	7.88	7.55	6.69
factor 2	3.40	3.19	3.71	3.28	3.37	3.96
factor 3	2.84	2.38	2.60	2.78	2.60	3.37
factor 4	2.01	2.15	2.41	1.91	1.85	2.22
factor 5	1.91	1.93	1.72	1.66	1.63	1.72
factor 6	1.46	1.34	1.52	1.37	1.39	1.42
factor 7	1.20	1.12	1.11	1.01	1.25	1.34
factor 8	1.06	1.05	1.05	0.92	1.10	0.78
h^2	0.76	0.81	0.76	0.83	0.80	0.83

4 Logit model

Since our dependent variable is a binary variable (0=no crisis and 1=crisis) we use a binary choice model. Two popular versions are the probit and the logit model. The major difference is that the probit model is based on the normal distribution , whereas the logit model uses an S-shaped logistic

[7]For Singapore and Thailand we use also eight factors although only seven factors have an eigenvalue above unity.

function to constrain the probabilities to the [0,1] interval. Predicted probabilities calculated by these models in practice only slightly differ. We opt for the logit model. Suppose the probability model is specified as

$$P = F(Z) = \frac{1}{1 + e^{-Z}} = \frac{1}{1 + e^{-(\alpha + \beta X)}}, \tag{1}$$

where P is the probability that Z takes the value 1 and F is the cumulative logistic probability function; X is the set of regressors and α and β are parameters. It can be shown that the regression equation is equal to

$$\ln \frac{P}{1 - P} = Z = \alpha + \beta X. \tag{2}$$

In our model, the vector of explanatory variables X consists of the eight factors rather than the huge list of economic indicators themselves. Since the change in the factors may affect the probability of a currency crisis to occur, we also include differences in the factors.[8] Note that including differenced factors reduces the number of observations for each country by one. Finally, testing for fixed effects rejects the null of common effects in all models except the ERW and FR types of currency models. The results are presented in Table 4. Note that intercepts and country-specific intercepts (fixed effects) are not reported.

If we look at the likelihood ratio tests presented in Table 4, we conclude that—excpet for the FR currency model—all variables (factors in levels and in differences) contribute significantly to the explanation of the variation in

[8]It should be noted that it would not be correct to include factors and lagged factors because of significant temporal dependence in the factors.

the crises dummies. Also, testing (not reported) whether the differences in the factors contribute significantly to the explanation of the variation in the crises dummies, leads us to conclude that this indeed is the case for all but the FR-type of currency crisis models.

The estimation results presented in Table 4 gives rise to a number of conclusions. First, factor 1 has the biggest impact on the predicted probability of a currency crises. Moreover factor 1 is significant at 1% in all but one (FR) currency crises models. We will examine this factor in some more detail below. Second, factor 8 is significant at 1% in the KLR versions of currency crises models. Third, at a 1% significance level, only factor 4 adds to explain crises probabilities in the FR currency model. Fourth, factors 3 and 4 are significant at 1% in the Z currency crises models.

Factor 1 by far shows the biggest contribution to predicting crises probabilities. Although interpretation of the estimated coefficients in terms of the underlying indicators is not trivial, it is informative to examine the eigenvector of factor 1. Factor 1 is a linear combination of the indicators with weights given by the first eigenvector. These weights are presented in Table 5. The biggest weights in factor 1 are related to the growth of money (M1 and M2)—supporting Kamin, Schindler and Samuel (2001)—,the growth of national saving, the rate of growth of GDP per capita, and import growth. These variables are dominant for all countries in our sample. Other variables that have an impact in some countries are commercial bank deposits, growth of foreign exchange reserves, export growth, and to a lesser extent domestic real interest rate, terms of trade, and growth of world oil prices.

Table 4: Estimation results of the binomial logit model (fixed effects not reported) with Huber-White robust standard errors.

	ERW		KLR(org)		KLR(LJK)	
	Coefficient	z-statistic	Coefficient	z-statistic	Coefficient	z-statistic
factor 1	−0.22	−3.94	−0.41	−4.80	−0.27	−4.14
Δ(factor 1)	−1.07	−4.76	−1.79	−5.32	−1.78	−7.03
factor 2	0.05	0.52	0.05	0.41	0.09	0.80
Δ(factor 2)	−0.06	−0.17	−0.22	−0.73	−0.52	−1.71
factor 3	0.09	1.04	0.12	0.92	0.22	2.03
Δ(factor 3)	−0.23	−0.75	0.36	1.11	−0.13	−0.39
factor 4	0.22	2.10	0.33	2.38	0.39	3.31
Δ(factor 4)	0.15	0.55	0.64	2.31	0.15	0.58
factor 5	0.17	1.74	0.14	0.93	0.19	1.67
Δ(factor 5)	0.60	1.84	0.34	0.96	0.53	1.63
factor 6	0.08	0.74	0.04	0.25	0.07	0.50
Δ(factor 6)	0.11	0.42	0.44	1.14	0.60	2.22
factor 7	−0.04	−0.44	0.16	1.26	0.14	1.22
Δ(factor 7)	0.17	0.62	−0.12	−0.42	0.06	0.24
factor 8	0.16	1.28	−0.16	−0.82	−0.10	−0.61
Δ(factor 8)	0.45	2.33	0.80	3.48	0.8	3.83
McFadden R^2		0.18		0.42		0.38
Observations with Dep=1		60		55		58
Likelihood ratio statistic, χ^2(16 d.f.)		100.31		216.99		202.66

	FR		Z(org)		Z(LJK)	
	Coefficient	z-statistic	Coefficient	z-statistic	Coefficient	z-statistic
factor 1	−0.02	−0.44	−0.13	−2.87	−0.06	−1.73
Δ(factor 1)	0.02	0.09	−1.38	−7.60	−0.97	−6.58
factor 2	−0.04	−0.50	0.12	2.05	0.07	1.40
Δ(factor 2)	−0.45	−1.73	−0.15	−0.77	−0.13	−0.70
factor 3	−0.02	−0.28	0.10	1.62	0.15	3.09
Δ(factor 3)	−0.46	−1.84	0.65	3.02	0.31	1.71
factor 4	0.26	3.45	0.20	3.09	0.17	2.87
Δ(factor 4)	0.05	0.22	0.60	2.99	0.42	2.39
factor 5	0.06	0.50	0.03	0.41	0.06	0.88
Δ(factor 5)	0.38	1.45	−0.05	−0.24	0.04	0.20
factor 6	0.09	0.75	0.17	2.37	0.16	2.58
Δ(factor 6)	0.08	0.30	−0.17	−0.80	−0.05	−0.30
factor 7	−0.04	−0.38	0.15	1.72	0.07	1.00
Δ(factor 7)	0.31	1.70	−0.14	−0.66	−0.22	−1.24
factor 8	0.13	0.92	0.09	0.80	0.10	1.29
Δ(factor 8)	0.13	0.57	0.24	1.57	0.24	1.76
McFadden R^2		0.04		0.19		0.11
Observations with Dep=1		59		140		209
Likelihood ratio statistic, χ^2(16 d.f.)		20.63		199.56		148.04

ERW, KLR, FR and Z represent currency crises dated by the method of Eichengreen, Rose and Wyplosz, Kaminsky, Lizondo and Reinhart, Frankel and Rose, and Zhang, respectively. KLR(org) and Z(org) are the original crises dating schemes, KLR(LJK) and Z(LJK) are versions of Lestano, Jacobs and Kuper.

Critical values of the z-statistic at the 1% and 5% level are 2.57 and 1.96, respectively. The critical value of the likelihood ratio test at 1% (16 d.f.) is 32.00.

Table 5: Weights of the first factor

Indicator	Indonesia	Malaysia	Philippines	Singapore	South Korea	Thailand
CAY	0.01	0.00	0.00	0.01	0.04	0.00
CBD	0.02	0.08	0.06	0.07	0.01	0.05
CSP	0.01	0.05	0.00	0.00	0.00	0.02
DCY	0.01	0.05	0.01	0.00	0.00	0.02
ERM	0.01	0.00	0.01	0.01	0.01	0.02
EXG	0.07	0.06	0.09	0.03	0.08	0.06
FBY	0.01	0.01	0.00	0.02	0.00	0.02
GFR	0.06	0.03	0.03	0.00	0.02	0.07
GIP	0.03	0.07	0.02	0.00	0.05	0.04
GM1	0.11	0.09	0.09	0.12	0.06	0.09
GM2	0.10	0.10	0.09	0.12	0.06	0.10
ICY	0.01	0.04	0.02	0.01	0.01	0.01
IMP	0.05	0.07	0.08	0.09	0.08	0.09
INR	0.01	0.00	0.03	0.00	0.07	0.02
LDS	0.00	0.00	0.00	0.00	0.04	0.01
MFR	0.00	0.00	0.00	0.00	0.00	0.01
MMM	0.00	0.04	0.01	0.00	0.02	0.01
NSR	0.09	0.11	0.10	0.13	0.10	0.12
PBY	0.06	0.00	0.01	NA	0.00	0.02
REX	0.00	0.01	0.02	0.06	0.02	0.04
RIR	0.03	0.01	0.05	0.01	0.05	0.02
RRA	0.04	0.03	0.01	0.00	0.08	0.00
TOT	0.07	0.01	0.05	0.05	0.02	0.01
USI	0.02	0.03	0.04	0.05	0.04	0.02
WOP	0.06	0.01	0.04	0.06	0.03	0.03
YPC	0.10	0.10	0.10	0.13	0.10	0.12
Total	1.00	1.00	1.00	1.00	1.00	1.00

5 Signaling crises

The logit models discussed above estimate probabilities of crises to occur. High probabilities signal crises. But the model might also give false signals, *i.e.*, a crisis does not take place despite the logit model producing a high probability. There are four possibilities. A model may indicate a crisis (high estimated probability) when a crisis indeed occurs ($P(1,1)$) or it may indicate a crisis when no crisis actually takes place ($P(1,0)$). It is also possible that the model does not signal a crisis (low estimated probability) where in fact a crisis does occur ($P(0,1)$). The final possibility ($P(0,0)$) is a situation in which the model does not predict a crisis and no crisis occurs. Table 6 lists the four possibilities.

Table 6: The probabilities of right and wrong crisis predictions

		Crisis ($Z=1$)	No crisis ($Z=0$)
Estimated probability	high	$P(1,1)$	$P(1,0)$
	low	$P(0,1)=1-P(1,1)$	$P(0,0)=1-P(1,0)$

The model signals a crisis when the estimated probability is high. We calculate the probability in periods detected as crises as:

$$P(1,1)=\frac{\sum_t \hat{P}_t Z_t}{\sum_t Z_t}, \tag{3}$$

where $\hat{P}_t$ is the estimated probability from the logit model at time t and Z_t is the crisis index dummy which equals one if a crisis occurs at time t, and zero otherwise. The probability in periods not detected as crises is denoted as $P(1,0)$:

$$P(1,0) = \frac{\sum_t \hat{P}_t(1 - Z_t)}{\sum_t(1 - Z_t)} \tag{4}$$

which produces a false signal or noise. Note that $P(0,1) = 1 - P(1,1)$ is also a false signal: the estimated probability is low, whereas a crisis did occur. Similarly, $P(0,0) = 1 - P(1,0)$ is a correct signal, since the estimated probability is low and there is no crisis.

Now, we can calculate the signal-to-noise ratio S/N as a measure of performance of the model:

$$\frac{S}{N} = \frac{P(1,1) + P(0,0)}{P(1,0) + P(0,1)}. \tag{5}$$

A value below one indicates that the model gives more false than right signals. The higher the signal-to-noise ratio, the better the model performs. A number like 2 indicates that the model indicates a signal level which is 100% above the noise level. In other words, the model produces twice as many signals then noise.

Table 7 lists the good ($P(1,1)$) and bad ($P(1,0)$) crisis signals and the signal to noise ratio for the various types of financial crises and the six Asian countries in our sample. From the signal-to-noise ratio it is easily seen that the currency crisis models based on the dating methodology of Kaminsky, Lizondo and Reinhart (KLR) outperform the other models. The FR-type of currency model performances poorly. This is not surprising since the factors identified in this paper hardly help to explain the probability of currency crises as dated by Frankel and Rose.

Table 7: Signalling crises

		ERW	KLR(org)	KLR(LJK)	FR	Z(org)	Z(LJK)
Indonesia	$P(1,1)$	0.07	0.26	0.26	0.03	0.19	0.18
	$P(1,0)$	0.02	0.01	0.02	0.03	0.06	0.11
	S/N	1.10	1.65	1.64	1.01	1.30	1.17
South Korea	$P(1,1)$	0.24	0.45	0.36	0.03	0.24	0.18
	$P(1,0)$	0.02	0.01	0.01	0.02	0.04	0.06
	S/N	1.57	2.61	2.05	1.02	1.50	1.27
Malaysia	$P(1,1)$	0.15	0.35	0.33	0.03	0.18	0.16
	$P(1,0)$	0.02	0.02	0.02	0.02	0.05	0.07
	S/N	1.31	1.97	1.90	1.02	1.31	1.19
Philippines	$P(1,1)$	0.31	0.54	0.41	0.04	0.28	0.26
	$P(1,0)$	0.02	0.01	0.02	0.03	0.08	0.12
	S/N	1.82	3.21	2.26	1.03	1.52	1.35
Singapore	$P(1,1)$	0.08	0.21	0.19	0.04	0.10	0.13
	$P(1,0)$	0.03	0.03	0.02	0.03	0.04	0.08
	S/N	1.11	1.45	1.40	1.03	1.13	1.11
Thailand	$P(1,1)$	0.27	0.44	0.40	0.03	0.30	0.20
	$P(1,0)$	0.02	0.02	0.01	0.02	0.03	0.05
	S/N	1.66	2.45	2.26	1.01	1.73	1.36

ERW, KLR, FR and Z represent currency crises dated by the method of Eichengreen, Rose and Wyplosz, Kaminsky, Lizondo and Reinhart, Frankel and Rose, and Zhang, respectively. KLR(org) and Z(org) are the original crises dating schemes, KLR(LJK) and Z(LJK) are versions of Lestano, Jacobs and Kuper.

$P(1,1)$=the estimated probability is high and a crisis does occur; $P(1,0)$=the estimated probability is high and a crisis does not occur; S/N is the signal-to-noise ratio; – means no crisis observations.

6 Conclusion

This paper builds an econometric EWS of six Asian countries, Malaysia, Indonesia, Philippines, Singapore, South Korea and Thailand. We set up qualitative choice—in our case logit—models for different versions of currency crises. From the literature we extract a broad set of potentially relevant financial crisis indicators which are combined into factors using factor analysis. These factors are used as explanatory variables in a panel covering the period January 1970–December 2001.

The factor analysis in combination with the estimation results of the logit model allows the general conclusion that (some) indicators of financial crises do work, at least in our EWS of Asia. We find that the rates of growth of money (M1 and M2), GDP per capita, national savings, and import growth correlate with all definitions of currency crises. So, our method offers a solution to the bad (mixed and weak in timing of crisis) performance of EWS as noted by IMF (2002) and Edison (2003). A second, important conclusion is that first differences in indicators add to explaining probabilities of currency crises. Including dynamics in the factors improves the specification of EWS models and makes it a more powerful surveillance instrument for policy makers.

Existing EWS models differ in terms of crises definitions and in the way crises periods are identified. An additional feature of our paper is the distinction between different currency crisis dating definitions, which are evaluated in terms of the power of signaling crises. A within-sample signal extraction experiment reveals that the method of Kaminsky, Lizondo and Reinhart is superior to the dating schemes of Eichengreen, Rose and Wyplosz, Frankel and Rose, and Zhang.

Acknowledgements

The present version of the paper benefited from comments received at the NAKE Research Day, Amsterdam, October 2002, the SOM Brown Bag Seminar, University of Groningen, November 2002, the Workshop on Southeast Asia, University of Groningen, May 2003, the NAKE Research Day, Amsterdam, October 2003, and discussions with Mardi Dungey.

References

Abiad, A. (2003), "Early warning systems: a survey and a regime-switching approach", *IMF Working Paper* 32, International Monetary Fund, Washington, D.C.

Aghion, P., P. Bacchetta, and A. Banerjee (2001), "Currency crises and monetary policy in an economy with credit constraints", *European Economic Review*, **45**(7), 1121–1150.

Berg, A., E. Borensztein and C. Pattillo (2003), "Assessing early warning systems: how have they worked in practice?", *IMF Working Paper*, International Monetary Fund, Washington, D.C., forthcoming.

Burkart, O. and V. Coudert (2002), "Leading indicators of currency crises for emerging countries", *Emerging Markets Review*, **3**(2), 107–133.

Bussiere, M. and M. Fratzscher (2002), "Towards a new early warning system of financial crises", *Working Paper* 145, European Central Bank, Frankfurt am Main, Germany.

Bustelo, P. (2000), "Novelties of financial crises in the 1990s and the search for new indicators", *Emerging Markets Review*, **1**(3), 229–251.

Dermirgüç-Kunt, A. and E. Detragiache (2000), "Monitoring banking sector fragility: a multivariate logit approach", *World Bank Economic Review*, **14**(2), 287–307.

Dungey, M., R. Fry, B. Gonzalez-Hermosillo, and V.L. Martin (2003), "Empirical modelling of contagion: a review of methodologies", *Working Papers* 8, Cambridge Endowment for Research in Finance, Cambridge.

Dungey, M. and V.L. Martin (2002), "Measuring contagion in the East Asian currency crisis", *Mimeo*, The Australian National University, Canberra, Australia.

Edison, H. J. (2003), "Do indicators of financial crises work? An evaluation of an early warning system", *International Journal of Finance and Economics*, **8**(1), 11–53.

Eichengreen, B., A.K. Rose, and C. Wyplosz (1995), "Exchange rate mayhem: the antecedents and aftermath of speculative attacks", *Economic Policy*, **21**, 251–312.

Frankel, J.A. and A.K. Rose (1996), "Currency crashes in emerging markets: an empirical treatment", *Journal of International Economics*, **41**(3-4), 351–366.

Girton, L. and D. Roper (1977), "A monetary model of exchange market pressure applied to the postwar Canadian experience", *American Economic Review*, **67**(4), 537–548.

Gonzalez-Hermosillo, B. (1996), "Banking sector fragility and systemic sources of fragility", *IMF Working Paper* 12, International Monetary Fund, Washington, D.C.

Granger, C.W.J., B.W. Huang and C.W. Yang (2000), "A bivariate causality between stock prices and exchange rates: evidence from recent asian flu", *Quarterly Review of Economics and Finance*, **40**(3), 337–354.

International Monetary Fund (2002), *Global Financial Stability Report*, A Quarterly Report on Market Developments and Issues, International Monetary Fund, Washington, D.C.

International Monetary Fund (2003), *International Financial Statistics CD-Rom*, International Monetary Fund, Washington, D.C.

Kamin, S.B., J.W. Schindler, and S.L. Samuel (2001), "The contribution of domestic and external sector factors to emerging market devaluations crises: an early warning systems approach", *International Finance Discussions Papers* 711, Board of Governors of the Federal Reserve System, Washington, D.C.

Kaminsky, G.L., S. Lizondo, and C.M. Reinhart (1998), "Leading indicators of currency crisis", *IMF Staff Papers* 45/1, International Monetary Fund, Washington, D.C.

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

Lestano and J.P.A.M. Jacobs (2002), "Dating Asian currency crises 1970-2002: a comparison of method", *Mimeo*, Department of Economics, University of Groningen, Netherlands.

Lestano, J.P.A.M. Jacobs and G.H. Kuper (2003), "Indicators of financial crises do work! An early-warning system for six Asian countries", *CCSO Working Paper* 13, Department of Economics, University of Groningen, The Netherlands.

Pozo, S. and C. Amuedo-Dorantes (2003), "Statistical distributions and the identification of currency crises", *Journal of International Money and Finance*, **22**(4), 591–609.

Rogoff, K. (1999), "International institutions for reducing global financial instability", *Journal of Economic Perspectives*, **13**(4), 21–42.

Sachs, J.D., A. Tornell, and A. Velasco (1996), "Financial crises in emerging markets: the lessons from 1995 (with comments and discussion)", *Brookings Papers on Economic Activity*, **1**, 147–198.

Venables, W.N. and B.D. Ripley (2002), *Modern applied statistics with S*, 4th edition, Springer, New York, Berlin, Heidelberg.

World Bank (2002), *World Development Indicators CD-Rom*, World Bank, Washington, D.C.

Zhang, Z. (2001), "Speculative attacks in the Asian crisis", *IMF Working Paper* 189, International Monetary Fund, Washington, D.C.