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Economics and Finance Working Paper Series

Working Paper No. 9-09

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April 2010

http://www.brunel.ac.uk/about/acad/sss/depts/economics

8th January 2010

BANKING CRISES IN ASIA AND LATIN AMERICA – A SINGLE PATTERN FOR EMERGING MARKET ECONOMIES?

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Abstract: Most extant work on prediction of banking crises has utilised global samples, which are in turn dominated by observations from middle-income countries, and rely on a single estimator, while a range of specifications is desirable to check robustness. However, economic and financial structure as well as the pattern of shocks may differ substantially across regions. Accordingly, in this paper we test the implicit pooling assumption in earlier work on Early Warning Systems using the widest range of models, by estimating logit, signal extraction and binary recursive tree specifications separately for crises in Asia and Latin America, as well as the pooled sample. Results suggest markedly different crisis determinants across regions, implying global samples are inappropriate.

Keywords: Banking crises, systemic risk, early warning systems, logit estimation, signal extraction, binary recursive tree, emerging market economies

JEL Classification: C52, E58, G21

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Introduction

The recent financial crisis has led to a renewed interest in the predictors of financial instability, so called early warning patterns. The literature has developed three distinctive approaches to development of Early Warning Systems (EWS) for banking crises, the logit (Demirguc Kunt and Detragiache 1998, 2005), the signal extraction approach (Kaminsky and Reinhart 1999) and most recently the binary recursive tree (Duttagupta and Cashin 2008). What most existing work has in common is a focus on global panels of banking crises in order to derive relevant predictors.

Recent work by Barrell, Davis, Liadze and Karim (2009) has shown that for the logit model at least, the traditional right hand side variables are not the most relevant for OECD countries once unadjusted bank capital adequacy, bank liquidity and house prices are added to the traditional variables. Earlier work by Hardy and Pararbasioglu (1998) also using logit, found some differences in predictors for Asia relative to the rest of a global sample, focusing on a unique role of foreign liabilities of banks and exchange rate depreciation.

This paper seeks to investigate further the appropriateness of aggregation by assessing whether the crises in emerging market economies of Asia and Latin America have similar precursors. Furthermore unlike earlier work cited above we use the widest variety of methodologies. We conclude that aggregation assumptions in existing work may be inappropriate. The paper is structured as follows. In Section 1 we provide an overview of the literature on banking crisis prediction. In Section 2 we reassess results for logit models using data for Asia and Latin America separately and together. Sections 3 and 4 undertake similar exercises for the signal extraction and binary recursive tree approaches, and finally Section 5 concludes.

1 Literature survey

Davis and Karim (2008b) provide an overview of the literature on EWS. Below we present a summary of the key literature and an outline of the three main methodological approaches that have been adopted in previous studies. These approaches have generally been applied to global samples of banking crises, owing in part to the relatively small number of such events. Such samples are in turn typically dominated by crises in middle-income countries such as those in Asia and Latin America.

The first methodology is the multivariate logit model, which uses macroeconomic, institutional and financial variables as inputs to calculate the probability of a banking crisis as the output via the logistic function estimator. It is suitable for answering the question “what is the likelihood of a banking crisis occurring in the next t years?” Demirguc-Kunt and Detragiache (1998) developed a parametric EWS for banking crises using this methodology using a global sample, with 31 crises. Updating their earlier work to cover 77 crises, Demirguc-Kunt and Detragiache (2005) found that they were correlated with macroeconomic, banking sector and institutional indicators. Crises occurred in periods of low GDP growth, high interest rates and high inflation, as well as large fiscal deficits. On the monetary side, the ratio of broad money to foreign exchange reserves and the credit to the private sector/GDP ratio, as well as lagged credit growth were found to be significant. Externally, there were often terms of trade shocks and depreciation prior to crises. Institutionally, countries with low GDP per capita are more prone to crises, as are those with deposit insurance.

Davis and Karim (2008a) used a similar approach with a global sample, but improved prediction by introducing more countries, crises[2] and dynamics in the macro variables; over 90% of in-sample crises were correctly identified. Barrell, Davis, Karim and Liadze (2009) utilised the logit approach solely for OECD countries, contrary to other papers and found a different set of banking crisis determinants. These are, bank liquidity, bank capital adequacy and lagged house price growth. Unfortunately one cannot conclude wholly different behaviour since these variables are generally not available for Emerging Market Economies. Hardy and Pararbasioglu (1998) as noted, found some differences in predictors for Asia relative to other regions again using logit.

The second methodology, the non-parametric signal extraction approach of Kaminsky and Reinhart (1999), tracks individual time series prior to and during crisis episodes to answer the question "is there a signal of a future crisis or not?" The logic is that if an input variable's aberrant behaviour can be quantitatively defined whenever that variable moves from tranquil to abnormal activity, a crisis is forewarned. Aberrance occurs when the variable crosses a threshold which the policy maker sets; the model then issues the output as a crisis signal, allowing preventative action to be taken. The higher the threshold, the more likely a signal is correct, so policy makers can manipulate thresholds depending on their degree of risk aversion to crisis. The Kaminsky and Reinhart study included output and stock prices as key indicators to signal a banking crisis. Borio and Lowe (2002) and Borio and Drehmann (2009) used a similar signal extraction framework, and found deviations from trend of credit growth and asset prices, to be useful predictors of banking crises. Davis and Karim (2008a) improve signal extraction for banking crisis prediction by creating composites of indicators weighted by their signalling quality, and found GDP growth and changes in terms of trade to be the most important macroeconomic indicators to monitor.

Binary Recursive Tree (BRT) partitioning is the third methodology, and it can be used to answer the question "which non-linear variable interactions make an economy more vulnerable to crisis than others?" It can be argued that liquidity, credit and market risks are all potentially non-linear (e.g. once a threshold level of credit risk is surpassed, a decline in GDP may have a heightened impact on the probability of a crisis). The estimator identifies the single most important discriminator between crisis and non-crisis episodes across the entire sample, thereby creating two nodes. These nodes are further split into sub-nodes based on the behaviour of splitter variables' non-linear interactions with previous splitter variables. This generates nodal crisis probabilities and the associated splitter threshold values. This is an innovative approach used mainly in medical research to date. The technique has been applied to systemic banking crises by Duttagupta and Cashin (2008) and Davis and Karim (2008b). The key indicators used in these studies include real interest rates, GDP growth, inflation and credit variables.

The three methodological approaches each have distinct benefits and disadvantages, suggesting that a multi-model approach may be more appropriate than working with a single model. Logistic models are ideally suited to predicting a binary outcome (1 = banking crisis, 0 = no banking crisis) using multiple explanatory variables selected on the basis of their theoretical or observed associations with banking crises. The logistic approach is also parametric, generating confidence intervals attached to coefficient values and their significance. On the other hand the logit coefficients are not intuitive to interpret and they do not reflect the threshold effects that may be simultaneously exerted by other variables.

The advantage of the signal extraction approach is that it is non-parametric; it focuses on a particular variable's association with crisis and that it can be based on high frequency data. But it may leave out important variable interactions that are captured by the logit. And indeed

[2] 105 countries are covered by data spanning 1979-2003 which yields 72 or 102 systemic banking crises depending on the crisis definition used.

on the basis of in-sample predictive ability, the multivariate logit model outperforms the signal extraction approach in terms of the percentage of crises correctly predicted (Davis and Karim 2008a). Where a signal extraction procedure is used, optimising thresholds country by country improves ability to correctly predict crises. Davis and Karim (ibid) conclude that the logit approach is the most appropriate for use as a global EWS, while signal extraction methods are more appropriate for a country-specific EWS.

The logit and BRT approaches were evaluated in predicting the subprime crisis in Davis and Karim (2008b). BRT is able to discover non-linear variable interactions, making it especially applicable to large banking crises datasets where many cross-sections are necessary to generate enough banking crisis observations, and numerous factors determine the occurrence of systemic failure. An important feature of this non-parametric technique is that no specific statistical distribution needs be imposed on the explanatory variables (Katz, 2006). It is also not necessary to assume all variables follow identical distributions or that each variable adopts the same distribution across cross-sections. Clearly, this is an advantage when analysing banking crises, since we cannot assume macro variables (such as real interest rates) and institutional variables (such as deposit insurance) follow identical distributions across time or across countries. Although logistic regression does not require variables to follow any specific distribution, in Davis and Karim (2008a) it was shown that standardising variables displaying heterogeneity across countries improved the predictive performance of logit models.

Logistic regressions are also sensitive to outlier effects (Congdon, 2003), yet it is precisely the non-linear threshold effects exerted by some variables that could generate anomalous values in the data. In low risk, stable regimes, variables may conform to a particular distribution which subsequently jumps to a regime of financial instability. Non-parametric BRTs should handle such data patterns better than logistic regressions. Finally, the BRT is extremely intuitive to interpret. The model output is represented as a tree which is successively split at the threshold values of variables that are deemed as important contributors to banking crises.

2 Data

In this paper we focus on countries in Latin America and Asia that have emerging financial systems and in most cases have suffered banking crises. It is hence a more homogenous sample than a global one including poor African countries or advanced OECD countries. The list of 20 countries is given below. It gives a total of 29 crises, 20 in Latin America and 9 in Asia, using the list given in Demirguc-Kunt and Detragiache (2005), with the total length of periods of crisis being 72.

For all three specifications we undertook estimations using all 72 crisis periods as dependent variables as shown in Table 1. Thus the crisis dummy takes a value of 1 for the duration of the crisis. This gives us early warning variables for both onset and continuance of a crisis. An alternative would have been to exclude post crisis observations. We note that Beck et al (2006) find that key results are similar across these alternatives; Barrell et al (2009) find the same outcome. Furthermore, as argued in Davis and Karim (2008a) the occurrence of a banking crisis leaves the economy vulnerable to further crises and may explain the successive crisis episodes observed in many economies. Omitting observations following crisis onset as in papers such as Demirguc-Kunt and Detragiache (2005) removes this vulnerability from the data.

Table 1: Country Sample

Region	Country	Data availability	Crisis dates
Asia	Indonesia	1981-2007	1992-5, 1997-2002
	Korea	1987-2007	1997-2002
	Malaysia	1980-2007	1985-8, 1997-2001
	Philippines	1980-2007	1981-7, 1998-2002
	Singapore	1987-2007	no crises
	Thailand	1980-2007	1983-7, 1997-2002
Latin America	Argentina	1981-2004	1980-2, 1989-90, 1995, 2001-2
	Bolivia	1985-2006	1986-8, 1994-7, 2001-2
	Brazil	1981-2006	1990, 1994-9
	Chile	1981-2006	1981-7
	Ecuador	1981-2006	1995-2002
	El Salvador	1983-2006	1991
	Guatemala	1981-2006	no crises
	Honduras	1982-2006	no crises
	Mexico	1981-2006	1982, 1994-7
	Panama	1988-2006	1988-9
	Paraguay	1988-2006	1995-9
	Peru	1981-2006	1983-90
	Uruguay	1981-2006	1981-5, 2002
	Venezuela	1981-2006	1993-7

To test for commonalities across Asia and Latin America, we employ the same set of independent variables as for Demirguc-Kunt and Detragiache (2005) noted in Section 1 (see Box 1). These variables are constructed using the IMF's International Financial Statistics (IFS) database and World Bank Development (WDI) data. We omit deposit insurance because some form of it was present throughout the data period for all the countries.

Box 1: List of Variables (with variable key)	
Variables used in previous studies: Demirguc-Kunt and Detragiache (2005); Davis and Karim (2008a).	1. Real GDP Growth (%) (YG)
	2. Real Interest Rate (%) (RIR)
	3. Inflation (%) (INFL)
	4. Fiscal Surplus/ GDP (%) (BB)
	5. M2/ Foreign Exchange Reserves (%) (M2RES)
	6. Real Domestic Credit Growth (%) (DCG)
	7. Real GDP per capita (GCAP)
	8. Domestic credit/GDP (%)
	9. Depreciation (%) (DEP)
	10. Change in Terms of Trade (%) (TOT)

3 Logit estimation

As noted in the literature survey, Demirguc-Kunt and Detragiache (1998) used the multivariate logit technique to relate the probabilities of systemic banking crises to a vector of explanatory variables. The banking crisis dependent variable, a binary banking crisis dummy, is defined in terms of observable stresses to a country's banking system, e.g. ratio of non-performing loans to total banking system assets exceeds 10%.[3] It occurs in around 5 per cent of all time and country observations in that paper. Demirguc-Kunt and Detragiache (2005) updated the banking crises list to include more years, and more crises. We use the same dependent variable in our current work.

Also following them, in this section we use the cumulative logistic distribution which relates the probability that the dummy for crises takes a value of one to the logit of the vector of n explanatory variables:

$$\Pr ob\left(Y_{it} = 1\right) = F\left(\beta X_{it}\right) = \frac{e^{\beta' X_{it}}}{1 + e^{\beta' X_{it}}} \qquad (1)$$

where Y_{it} is the banking crisis dummy for country i at time t, β is the vector of coefficients, X_{it} is the vector of explanatory variables and $F(\beta\ X_{it})$ is the cumulative logistic distribution. The log likelihood function which is used to obtain actual parameter estimates is given by:

$$Log_e\ L = \sum_{i=1}^{n}\sum_{t=1}^{T}\left[\left(Y_{it}\log_e F\left(\beta' X_{it}\right)\right) + \left(1 - Y_{it}\right)\log_e\left(1 - F\left(\beta' X_{it}\right)\right)\right] \qquad (2)$$

Although the signs on the coefficients are easily interpreted as representing an increasing or decreasing effect on crisis probability, the values are not as intuitive to interpret. Equation (2) shows the coefficients on X_{it} are not constant marginal effects of the variable on banking crisis probability since the variable's effect is conditional on the values of all other explanatory variables at time t. Rather, the coefficient $ß_i$ represents the effect of X_i when all other variables are held at their sample mean values. Whilst this makes the detection of non-linear variable interactions difficult, (the logit link function is linear), the logistic EWS has the benefit of being easily replicable by policy makers concerned with potential systemic risk in their countries.

Unlike many extant studies which use contemporaneous independent variables, we lag all independent variables so as to obtain an early warning indicator of the commencement or continuance of a crisis. We also tested down from a general equation with all variables included (left hand part of table) to the simplest equation with all remaining significant variables (right hand side of table).

Many of the variables are not significant, once we test down from the most general specification. For this combined Latin America and Asia sample, where there are 29 crises, the equation with all crisis observations includes GDP growth (crises occur in recessions), GDP per capita (crises are less common in richer countries) and the credit to GDP ratio (crises are most likely in more financially developed countries where the ratio is high). Other variables are insignificant.

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[3] Their actual criteria are: the proportion of non-performing loans to total banking system assets exceeded 10%, or the public bailout cost exceeded 2% of GDP, or systemic crisis caused large scale bank nationalisation, or extensive bank runs were visible and if not, emergency government intervention was visible.

Table 2: Regressions for Latin America and Asia – all crisis periods

Variable	Coefficient	z-Statistic	Coefficient	Z-statistic
DCRED(-1)	-0.008811	-1.60491		
GDPPC(-1)	-0.000286	-6.92365	-0.000310	-6.955853
FISCY(-1)	0.030041	1.070716		
INFL(-1)	-0.000282	-0.51922		
RIR(-1)	0.000148	0.808161		
DEPREC(-1)	-0.000387	-1.01809		
DCREDY(-1)	0.015366	4.75962	0.008273	2.906578
DTT(-1)	0.002579	0.5907		
DGDP(-1)	-0.143596	-5.60758	-0.141868	-6.005834
M2RES (-1)	-0.000135	-1.26052		
AIC	1.0128		1.0303	
Wald statistic	11.7783 (0.0000)		36.0133 (0.0000)	
Observations	503		534	

There are possible structural differences between the economies of Latin America and Asia which could predispose them to crises in different ways. For instance the Asian crises of 1997 were associated with private sector debt in foreign currency with stable currencies, followed by exchange rate depreciations and capital outflows. These were not generic features of Latin American crises. Pooling cross-sections would mask these differences. In order to assess whether Asian economies are subject to different banking crisis determinants than Latin American countries we multiply each explanatory variable by an Asian dummy and introduce it alongside the original independent counterpart.

Table 3: Including leveraged coefficients for the Asian variables in the combined sample

Variable	Coefficient	z-Statistic	Coefficient	z-Statistic
$DCRED_1$ (-1)	-0.007335	-1.29776		
δ*$DCRED_1$ (-1)	-0.026567	-1.54745	-0.036993	-2.303387
$GDPPC_1$ (-1)	-0.000358	-5.94507	-0.000246	-7.226066
δ*$GDPPC_1$ (-1)	0.000112	1.195349		
$FISCY_1$ (-1)	0.043452	1.256656		
δ*$FISCY_1$ (-1)	-0.033001	-0.43286		
$INFL_1$ (-1)	-0.000044	-0.07412		
δ*$INFL_1$ (-1)	-0.037747	-1.2113		
RIR_1 (-1)	0.000164	0.725977		
δ*RIR_1 (-1)	0.114665	2.524818	0.140847	4.161717
$DEPREC_1$ (-1)	0.000282	0.743221		
δ*$DEPREC_1$ (-1)	0.053211	2.709868	0.045997	3.264150
$DCREDY_1$ (-1)	0.013992	1.170674		
δ*$DCREDY_1$ (-1)	0.008852	0.622899		
DTT_1 (-1)	0.004688	1.02259		
δ*DTT_1 (-1)	0.002804	0.118322		
$DGDP_1$ (-1)	-0.116451	-3.98959	-0.149111	-6.110179
δ*$DGDP_1$ (-1)	-0.144915	-1.96245		
$M2RES_1$ (-1)	0.000017	0.17409		
δ*$M2RES_1$ (-1)	-0.000566	-2.14634		
AIC	0.9853		0.9921	
Wald statistic	6.5508 (0.000)		23.687 (0.0000)	
Observations	503		515	

Note: In Table 2 the coefficients and regressors can be represented as the vector βX whereas in this table the estimations can be expressed as $\beta X_1 + \delta\beta^* X_1$ where δ=0 for Latin America and δ=1 for Asia.

This generates a set of "leveraged coefficients" additional to the original coefficients, where the former illustrate the specific crisis vulnerabilities arising from Asian economy characteristics and the latter show the remaining risks that are also prevalent in Latin American economies. Our approach therefore adds to the traditional early warning literature which typically utilises large pooled samples. The results for the leveraged coefficients are shown in Table 3.

As shown in the Table, there are three variables where the leveraged coefficient is significant for the Asian countries, namely credit growth, real interest rates and depreciation. This suggests that the combined equation is not an adequate representation of the data. To show this further, we sought to undertake separate general-to-restricted estimates for Latin America and Asia. These are as shown in Tables 4 and 5.

Table 4: Regressions for Latin America – all crisis periods

Variable	Coefficient	z-Statistic	Coefficient	z-Statistic
DCRED(-1)	-0.007335	-1.297761		
GDPPC(-1)	-0.000358	-5.945074	-0.000326	-7.832812
FISCY(-1)	0.043452	1.256656		
INFL(-1)	-4.41E-05	-0.074122		
RIR(-1)	0.000164	0.725977		
DEPREC(-1)	-0.000282	-0.743221		
DCREDY(-1)	0.013992	1.170674		
DTT(-1)	0.004688	1.022590		
DGDP(-1)	-0.116451	-3.989594	-0.118849	-4.510090
M2RES(-1)	1.65E-05	0.174090		
AIC	1.0235		1.0108	
Wald statistic	9.1644 (0.0000)		47.4341 (0.0000)	
Observations	341		376	

Table 5: Regressions for Asia – all crisis periods

Variable	Coefficient	z-Statistic	Coefficient	z-Statistic
DCRED(-1)	-0.033902	-2.091298	-0.032416	-2.046609
GDPPC(-1)	-0.000246	-3.451172	-0.000235	-3.535303
FISCY(-1)	0.010451	0.153806		
INFL(-1)	-0.037791	-1.212934		
RIR(-1)	0.114829	2.528462	0.113567	2.612414
DEPREC(-1)	0.053493	2.724725	0.044323	2.712526
DCREDY(-1)	0.022844	2.971898	0.021231	2.959820
DTT(-1)	0.007492	0.322193		
DGDP(-1)	-0.261366	-3.853235	-0.276748	-4.192324
M2RES(-1)	-0.000549	-2.232728	-0.000536	-2.190088
AIC	0.9049		0.8722	
Wald statistic	3.9373		5.6055 (0.0000)	
Observations	162		162	

It is evident that, consistent with the leveraged estimate, the general to specific procedure results in quite different determinants of crises. Looking at the sample for Latin America alone, with 20 crises, the estimate includes only GDP per capita and GDP growth. The sample for Asia includes 9 crises. In this case the regression includes not only GDP per capita and GDP growth but also there is an effect of credit growth (crises are more likely when credit is already contracting), a higher real interest rate, does exchange rate depreciation, a high domestic credit/GDP ratio and, counter to intuition, a low M2/reserves ratio. The results for real interest rates, depreciation and credit growth are consistent with the leveraged results in Table 3.

We complement our statistical results with tests of performance. In terms of such performance, the standard way to assess such EWS is in terms of their ability to distinguish crisis and non crisis periods. As shown in Table 6, the performance of the leveraged equation is superior to the common coefficients, although the Hosmer-Lemeshow chi-square test of goodness of fit (HL) statistic remains unsatisfactory. Note that Demirguc-Kunt and Detragiache (2005) for their most preferred equation had a type II error of 31% (i.e. 69% of non crises correct) and a type I error of 39% (i.e. 61% of crises correct), with an overall success rate of 68% at a threshold of 0.05. Hence our work overall performs well in comparison.

Table 6: Performance of the combined Latin America and Asian equations (probability cut off = 0.5)

Regression	Latin America and Asia unrestricted (Table 2)	Latin America and Asia restricted (Table 2)	Latin America and Asia leveraged unrestricted (Table 3)	Latin America and Asia leveraged restricted (Table 3)
% crises correct	27	17	35	34
% no crises correct	96	98	96	94
% total correct	81	80	82	81
HL Stat	39.4 (0.00)	41.7(0.00)	21.9 (0.005)	30.6(0.002)

Looking at the separate equations in Table 7, the overall performance of the Asian equations is superior to the Latin American one, with a satisfactory goodness of fit statistic and around 2/3 of crises correctly classified even at a cut-off probability of 0.5, and satisfactory summary statistics as well.

Table 7: Performance of the equations for separate regions (probability cut off=0.5)

Regression	Latin America Unrestricted (Table 4)	Latin America Restricted (Table 4)	Asia Unrestricted (Table 5)	Asia Restricted (Table 5)
% crises correct	15	12	63	65
% no crises correct	99	98	90	89
% total correct	82	82	82	82
HL Stat	21.9(0.005)	34.7(0.00)	8.8(0.36)	11.3(0.18)

Table 8 constructs the results for Asia only from the Latin America and Asia combined results, and shows that without leverage compared to the separately estimated Asian results, there is a shortfall in performance in highlighting crises, which is not offset by better performance in terms of non crises. On the other hand the leveraged results are almost as good as the separately estimated ones, as might be anticipated.

Table 8: Comparing results for Asia (probability cut-off=0.5)

Regression	Latin America and Asia Unrestricted – Asia only	Latin America and Asia Restricted – Asia only	Latin America and Asia leveraged Unrestricted – Asia only	Latin America and Asia leveraged Restricted – Asia only	Asia estimate unrestricted	Asia estimate restricted
% crises correct	42	25	63	63	63	65
% no crises correct	97	99	90	90	90	89
% total correct	81	77	82	82	82	82

Overall, we conclude from the logit results that there are major differences in Asian crisis determinants that make a combined approach with Latin America inappropriate. This is shown, first, by leveraged coefficients being significant for Asia in a combined estimate second, in terms of the difference between individual equation results for the areas separately, third from the results for equation performance. In particular, the results highlight an importance of credit growth, real interest rates and depreciation in Asia that is not present for Latin America in a consistent manner.

4 The signal extraction approach

The signal extraction approach is a non-parametric one, which assesses the behaviour of single variables prior to and during crisis episodes. As noted in the literature survey, the logic is that if aberrant behaviour of a variable can be quantitatively defined, then whenever that variable moves from tranquil to abnormal activity, a crisis is forewarned. Let:

i = a univariate indicator
j = a particular country
S= signal variable
X = indicator

An indicator variable relating to indicator i and country j is denoted by X_i^j and the threshold for this indicator is denoted as $X{*}_i^j$ A signal variable relating to indicator i and country j is denoted by: S_i^j . This is constructed to be a binary variable where $S_i^j = \{0,1\}$. If the variable crosses the threshold, a signal is emitted and $S_i^j = 1$. This happens when

$$\{ S_i^j = 1 \} = \{ \mid X_i^j \mid > \mid X{*}_i^j \mid \} \qquad (3)$$

If the indicator remains within its threshold boundary, it behaves normally and does not issue a signal so $S_i^j = 0$,

$$\{ S_i^j = 0 \} = \{ \mid X_i^j \mid < \mid X{*}_i^j \mid \} \qquad (4)$$

Hence in a global EWS, panel data are used to derive a threshold for each variable, which distinguishes between normal and aberrant behaviour. Notice the directional sign may vary depending on whether the indicator in question has an upper or lower bound; hence the variables and thresholds in equations (3) and (4) are expressed in absolute terms. Thus for a time series of t observations for country j and indicator i we can obtain a binary time series of signal or no-signal observations. This series is then checked against actual events to construct a measure of predictive accuracy. There are four possible scenarios as shown in Figure 1:

Figure 1: Possible outcomes with the signal extraction approach

	CRISIS	NO CRISIS
SIGNAL	A	B
NO SIGNAL	C	D

If the indicator signals crisis and this correlates with an actual crisis, the outcome is denoted 'A'. If the signal is not matched by a crisis in reality, the outcome is denoted 'B'. If no signal is emitted by the indicator but there was an actual crisis, the outcome is called 'C'. If no signal is emitted and there really is no crisis, the outcome is 'D'.

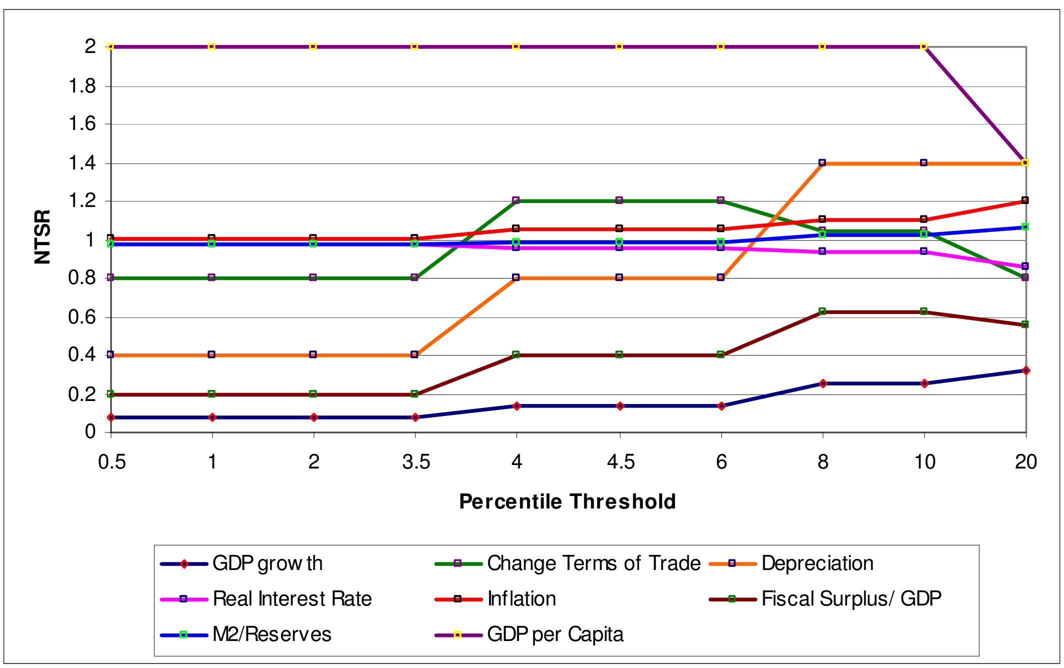
Hence a perfect indicator would produce outcomes A and D only; it would correctly call all crises and would not issue signals unnecessarily. Outcome C represents a failure to call crisis (Type I error) and outcome B generates a false alarm (Type II error). Accordingly, a measure of signalling accuracy can be constructed for each indicator, based on the proportion of false alarms and missed crises; there are various criteria (e.g. minimise Type I error only) so the chosen measure will reflect the desires of the policy maker or private institution using the EWS. This is based on the inherent trade-off between Type I and Type II errors which are functions of the threshold; changing the threshold to allow more crises to be picked up necessarily raises the likelihood of false alarms. A policy maker concerned with avoiding crises at all costs may choose to minimise Type I errors even if this entails unnecessary intervention (or at least, investigation) due to more Type II errors. Likewise, in currency crisis models, private sector investors with positions entailing a large amount of exchange rate risk may prefer wider thresholds, giving them time to take alternative investment positions. On the other hand, policy makers with relatively stable financial systems may prefer avoiding Type II errors and undue intervention.

Kaminsky and Reinhart (1999) choose to minimise the probability of failing to call crisis and the probability of false alarms simultaneously. Specifically, the Noise to Signal Ratio (henceforth NTSR) is given by (Type II error/ 1 – Type I error). As with normal hypothesis testing, changing the threshold to reduce Type I errors necessarily increases the number of Type II errors. The NTSR measure takes this trade-off into account; the optimal threshold will minimise the numerator and maximise the denominator of the NTSR. Different percentiles of the entire panel (i.e. cross-country) series are taken as thresholds and the corresponding NTSR is evaluated. The percentile that minimises the NTSR is selected and applied to each country to produce a country specific threshold which forms the benchmark for the EWS. The advantage of this non-parametric approach is that it focuses on a particular variable's association with crisis and that it can be based on high frequency data. Furthermore, it may be more comprehensible to the non-economically trained policy maker than the logit model.

In the current exercise we address the signalling properties of the variables listed in Box 1. We employ the same sample as in the logit model outlined above: Asia, Latin America and a combination of both. In assessing the performance of each indicator, we make no assumption with regards to the policy maker's relative aversion towards crisis episodes as opposed to non-crisis episodes. This means we implicitly assume the policy maker places equal weight on correctly calling both crisis and non-crisis states. Therefore, we assume a cut-off level of "noise" relative to a correct "signal" of 50% is acceptable; higher NTSRs mean the information carried in the signal is more likely to be incorrect than correct. Accordingly, in our discussion of each model below, we will focus on the top three indicators in terms of their NTSR performance, since the remaining indicators generate NTSRs above 50%.

Figure 2 shows the signalling properties of each variable in the Asian country model. The best indicator is GDP growth since it is associated with the lowest NTSR for any given threshold. This result accords with the logit results above as well as Demirguc-Kunt and Detragiache (1998, 2005) and Davis and Karim (2008) who found GDP growth to be an important leading indicator of banking crises across a heterogeneous range of countries. The procyclicality of financial instability implies GDP growth should capture boom and bust cycles and since credit risk increases during financial downturns (due to decreases in collateral values, especially property prices), recessions are associated with higher levels of non-performing loans than periods of high economic growth.

Figure 2: NTSR vs Threshold, Asia



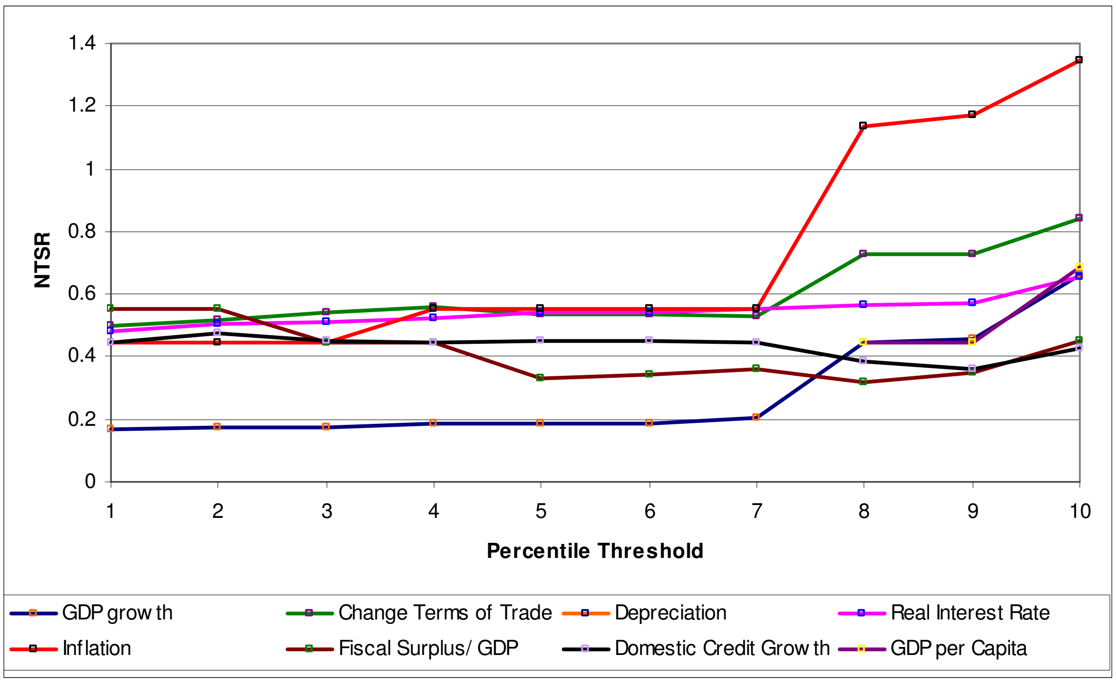
The second best predictor of the banking crises in Asia is the fiscal surplus to GDP ratio. Reinhart and Rogoff (2009) highlight the detrimental impact of banking crises on government finances so that fiscal surpluses can rapidly convert to deficits in the wake of banking crises. If countries have fiscal deficits alongside banking system vulnerability, their ability to bail out their banking systems is restricted so that systemic crises become more likely.

The third best predictor of the Asian banking crises is the percentage deprecation experienced by their currencies, which exacerbated the burden of private sector debt in foreign currency.

As we discuss below, depreciation is not one of the best performing leading crisis indicator in the Latin American countries.

Note that GDP growth, fiscal surplus/ GDP and depreciation appear to have identical optimal thresholds. Although the NTSR remains constant between the range T = 0.5 to 3.5, the optimal threshold would be 3.5 since this allows GDP growth and fiscal surpluses to deteriorate over this range before a signal is considered by the policy maker. Similarly, depreciation can worsen over the threshold range before the policy maker must accept a crisis is imminent. Since all the remaining variables generate much higher NTSRs than the three indicators discussed above, we will not rely on them as leading indicators. We next discuss the variable performances in the Latin American country model which are shown in Figure 3.

Figure 3: NTSR vs Threshold, Latin America



When considering the prediction of banking crises that occurred in Latin American countries over the years 1980 – 2007, GDP growth appears again to be important. This coincides with the Asian result for the same period, once again highlighting the importance of recessions in causing crises. The second best indicator is the fiscal surplus/ GDP. Again, this result accords with the Asian country result and therefore confirms the importance of sound government finances in mitigating the realisation of banking crises in emerging market economies.

Unlike the Asian sample, however, the third best predictor of Latin American crises is the rate of domestic credit growth. This may be associated with the financial liberalisation policies of the 1980s in these countries, since such policies lead to deepening of financial markets and consequent increases in credit risk. In the Kaminsky and Reinhart (1999) sample, over 70% of banking crises were preceded by financial liberalisation within the last five years and the probability of banking crisis conditional on financial liberalisation having occurred is higher than the unconditional probability of banking crisis. Demirguc-Kunt and Detragiache (1998) also find financial liberalisation increases crisis risk within a few years of the liberalisation process.

While we will not consider the remaining indicators separately due to their relative poor performances in terms of the NTSR, it is worth noting the exceptionally inferior performance of the domestic credit to GDP ratio as a banking crisis predictor in the Latin American countries. Despite Demirguc-Kunt and Detragiache (1998, 2005) including this variable as a proxy for financial and institutional development, in our sample this variable did not signal crises (either correctly or incorrectly) at lower thresholds. However, at higher thresholds (T = 8 to T = 20) the NTSR starts to fall, indicating that credit/ GDP would have to be substantially high before any useful information on financial stability could be inferred.

Although two of the best leading indicators of Latin American crises coincide with the Asian results, the optimal thresholds for the two samples differ. In Latin America, the occurrence of banking crises is much more sensitive to reductions in GDP growth than in Asia and consequently the optimal threshold for the former is much lower (T = 0.5). The NTSR associated with the fiscal surplus/ GDP in Latin America reaches a minimum when T = 4 unlike in Asia where the same indicator has a lower optimal threshold (T = 3.5).

Figure 4: NTSR vs Threshold, Asia and Latin America

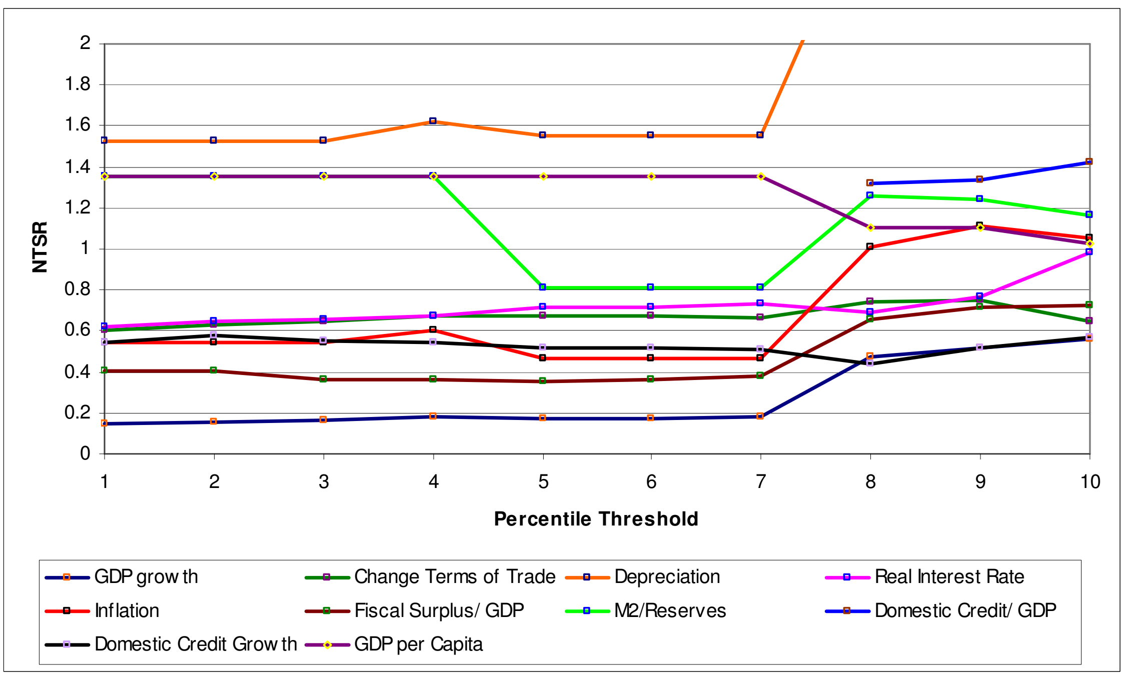


Figure 4 shows the results for the combined sample. As expected, the first and second best leading indicators in the combined sample are GDP growth and the fiscal surplus/ GDP respectively. The respective optimal thresholds are T = 0.5 and T = 4, implying that the Latin American data drives the result in the combined sample. This may explain why the third best leading indicator is inflation with an optimal threshold of T = 6 since this variable was one of the worst performers in the Asia-only sample.

Table 9 shows the in-sample performances of the best three variables for each signal extraction model. For the Asian model, the rate of real GDP growth outperforms the fiscal surplus and rate of depreciation in terms of being able to predict crises as well as in terms of being able to predict non-crisis episodes. Consequently, monitoring the rate of GDP growth in an economy should allow policy makers to discriminate between crisis and non-crisis events with 65% accuracy which is higher than the naïve success rate of 50%. However it is interesting to note the exceptionally poor abilities of real GDP growth rates, the extent of fiscal discipline and the level of real domestic credit growth to distinguish between tranquil and crisis states in the Latin American countries. Although these variables are actually better at identifying crisis episodes in Latin America than the optimal Asian variables in Asia, overall the percentage of correct predictions is much lower than Asian models. Although the univariate signal extraction approach is not directly comparable to the multivariate logit models we have estimated above, it is interesting to note that the Asian models outperform the Latin American and pooled models using both estimation techniques. Once again, our results reinforce the need to recognise regional variations in crises determinants when designing Early Warning Systems.

We note that the performance of the signal extraction model is generally inferior to that of the logit, a point also made in Davis and Karim (2008a).

Table 9: Performance of the signal extraction approach

	Asia			Latin America			Pooled		
	Real GDP Growth	Fiscal Surplus/ GDP	Deprec-iation	Real GDP Growth	Fiscal Surplus/ GDP	Real Domestic Credit Growth	Real GDP Growth	Inflation	Fiscal Surplus/ GDP
% crises correct	10	8	6	11	23	23	11	6	13
% no crises correct	99	98	98	98	93	92	98	97	95
% total correct	65	63	62	28	29	29	20	18	19

5 The binary recursive tree (BRT)

As discussed in the literature survey, the binary recursive tree is a novel approach in the financial crisis literature. Our work uses a proprietary software package known as “CART” from Salford Systems Inc. to construct the BRT. We give a brief outline of the methodology here; a fuller explanation can be found in Breimen at al (1984) and Steinberg and Colla (1995) and economic applications can be found in Duttagupta and Cashin (2008) who examined banking crises, Manasse et al (2003) who examined sovereign debt crises and Ghosh and Ghosh (2002) who examined currency crises.

The BRT process analyses a sample of data to reveal the particular value of the explanatory variable that best explains the dependent variable. Hypothetically, it could be established that the level of real GDP growth best distinguishes between crisis and non-crisis episodes across the entire sample. CART would then search for the exact threshold level of GDP growth that separates crises from tranquil periods. Assuming this “splitting value” is 4%, all data will be split into two child nodes with observations associated with GDP growth <= 4% in the left child node and remaining observations associated with GDP growth > 4% in the right child node. If low GDP growth were detrimental to banking stability, we would expect the left child node to be concentrated with banking crisis observations relative to the right node; the CART algorithm will search through all possible splitting values of all explanatory variables to find the best discriminator between crises and non-crises across the entire sample.

Once this “primary splitter” has been obtained, CART will apply the same procedure to further split the observations located in the two child nodes and in doing so will generate the BRT. This is schematically represented in Figure 5 where the primary splitter is X_1 and the corresponding threshold value is V_1^*. Subsequent splitter variables (and their threshold values) are given by X_2 (V_2) and X_3 (V_3); these values are used to partition the 72 crises in the sample.

The choice between two potential splitters is made on the basis of their comparative abilities to increase node purity, i.e. to concentrate the node further with one type of observation. The change in impurity (Δi) that arises from splitting (s) the data at a node (t) is defined as:

$$\Delta\, i(s,t) = i(t) - P_L i(t_L) - P_R i(t_R) \qquad (5)$$

where $i(t)$, $i(t_L)$ and $i(t_R)$ are the impurities associated with each existing node and the left and right child nodes respectively and P_L and P_R are the probabilities of sending an observation in the left and right nodes respectively. To quantify the degree of impurity, we use a criterion called the Gini measure, which is applicable to binary dependent variables (Steinberg and Golovnya, 2007). The Gini measure is given by:

$$i(t) = \sum_{i,\,j} c\,(i \mid j) \cdot P\,(i \mid t) \cdot P\,(j \mid t) \qquad (6)$$

where $c\,(i \mid j)$ is the cost of misclassifying a non-crisis event given that it is a crisis event, $p(j \mid t)$ is the conditional probability that an observation takes class *j* given that it lies in node t and $p(i \mid t)$ is the conditional probability that an observation takes class i given that it lies in node t (where *j* = crisis and *i* = no crisis).

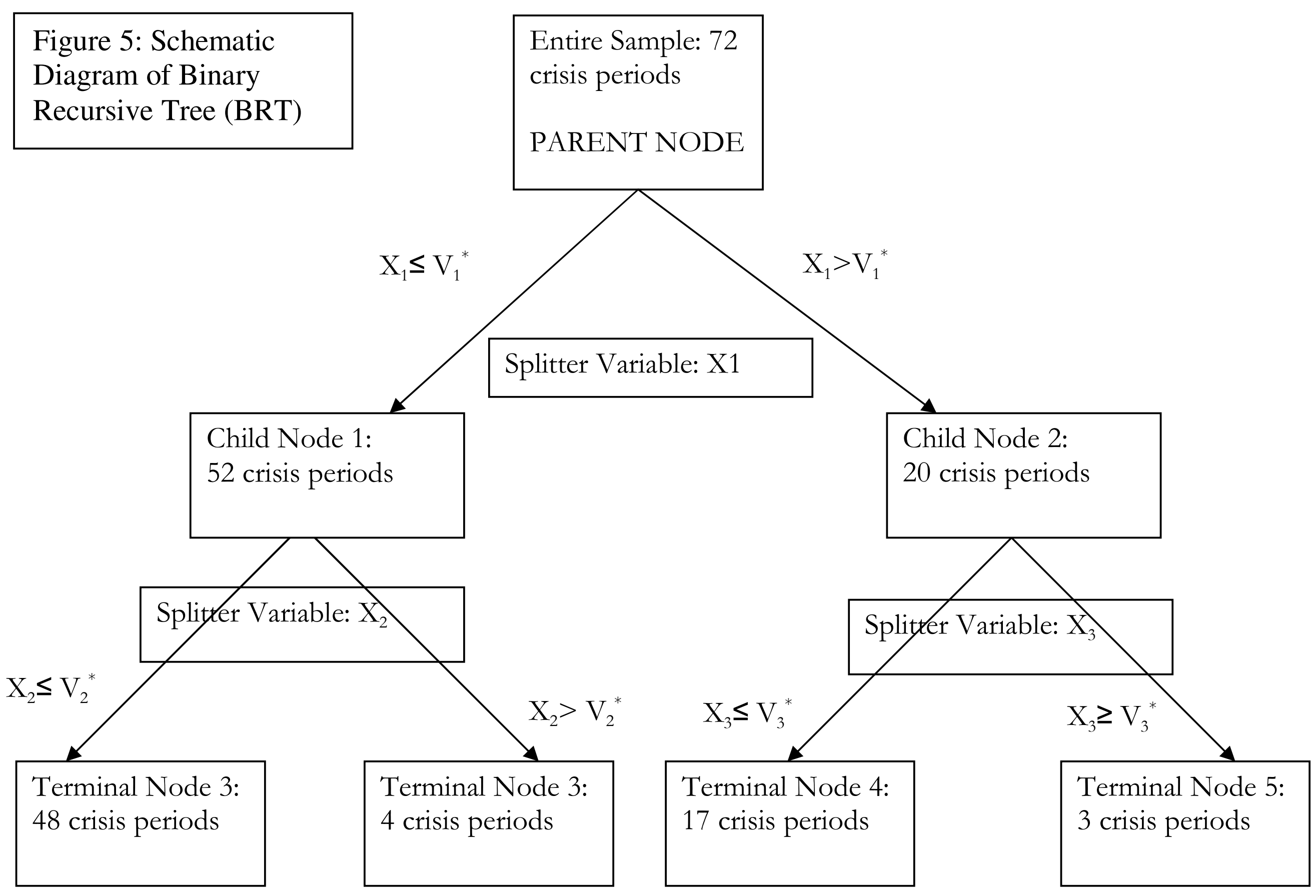


Figure 5: Schematic Diagram of Binary Recursive Tree (BRT)

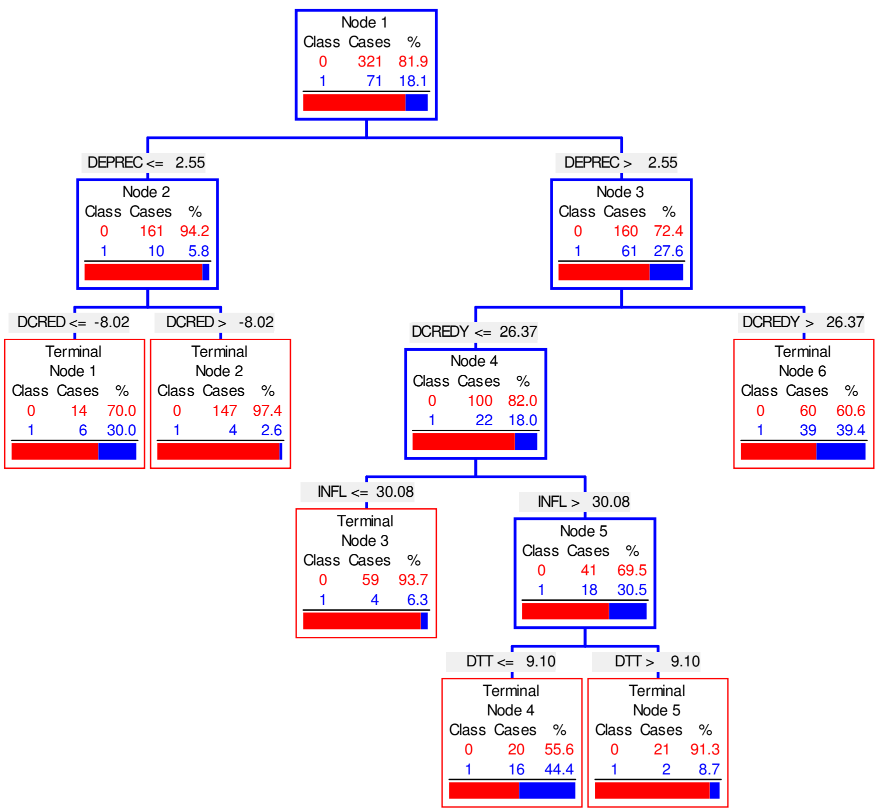
In this section we employ the tree for the Asian and Latin American samples separately, and then go on to do a joint estimate for both together as with the logit and signal extraction approaches.

Figure 6 displays the tree based on the Latin American countries only. Across the entire Latin American sample, the main discriminator between crisis and non-crisis states is the degree of currency depreciation. Specifically, depreciation in excess of 2.55% increases the probability of banking crisis to 28% compared to a 6% crisis probability for less severe deprecations.

Crisis probability may substantially worsen if currency depreciation in excess of 2.6% occurs in the presence of high levels of banking intermediation; if domestic credit/ GDP exceeds 26%, it is possible that higher levels of foreign currency borrowing make bank balance sheets riskier. In this case, the probability of crisis rises to 39%.

Alongside high currency depreciation, levels of domestic credit/ GDP below 26% result in a banking crisis probability of 18%. However, this probability almost doubles (30.5%) if inflation also exceeds 30%, whereas if inflation is contained, crisis probability falls to 6.3%. In the presence of high inflation, a significant improvement in the terms of trade (above 9%) is required to mitigate the probability of crisis, otherwise the likelihood of crisis increases to 46%.

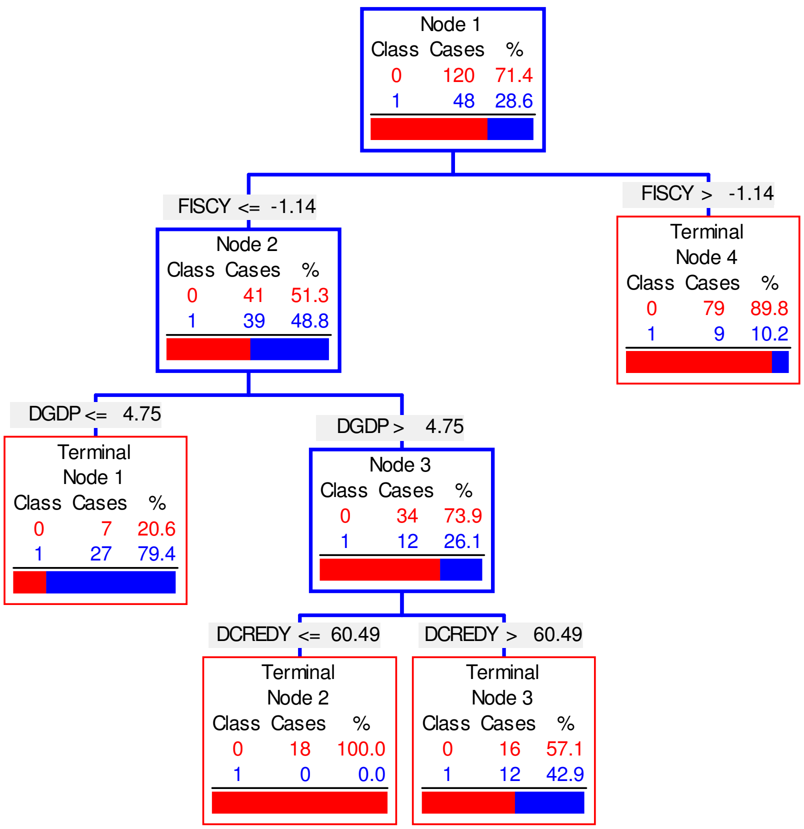
Figure 6: Splitting Variables and Thresholds for the Latin American Countries



In cases where depreciation is less than 2.55%, the rate of domestic credit growth is the next most important determinant of banking crises. A credit crunch, where the contraction in domestic credit supply is more than 8% raises the crisis probability five fold from 5.9% to 30%. On the other hand, if the credit contraction is less severe and borrowers are able to refinance their debt, then the banking system is less prone to crises with an associated probability of 2.7%.

Turning next to the model based on the sub-sample of Asian countries, we note that the degree of fiscal discipline, GDP growth and credit/ GDP are the primary factors associated with the Asian banking crises, as shown in Figure 7.

Figure 7: Splitting Variables and Thresholds for the Asian Countries



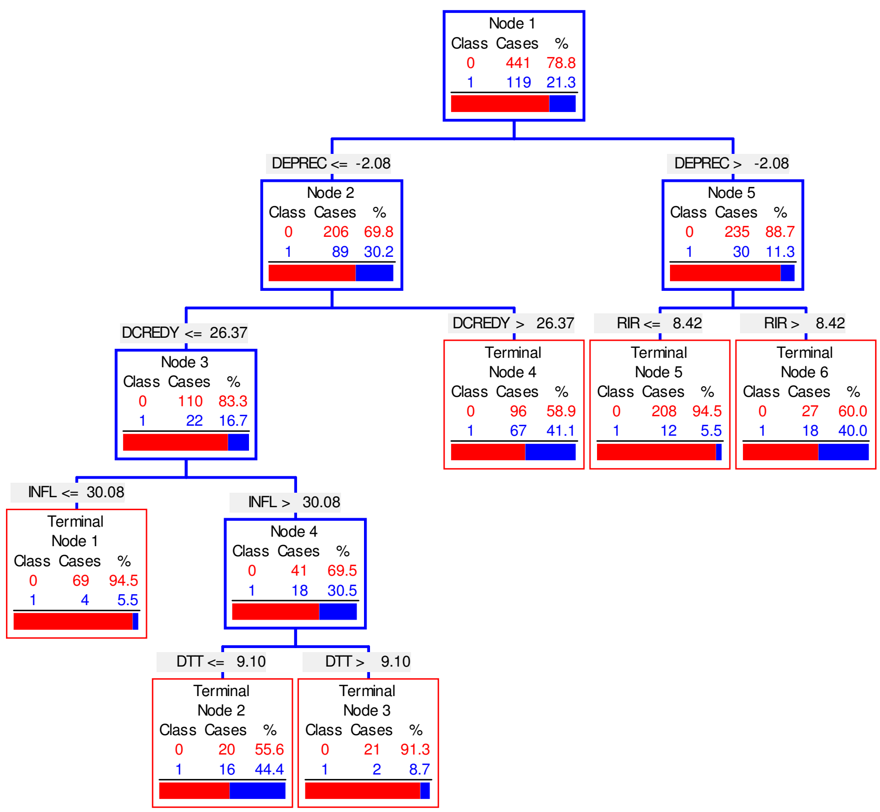
Across the Asian sample, the budget surplus/GDP ratio is the primary splitter; a threshold value of -1.14% is the single most important discriminator between crisis and non-crisis episodes. Governments that ran deficits of more than 1.14% of GDP put their banking systems in a riskier position (48.8% crisis probability) than those that maintained moderate deficits or surpluses (10.2% crisis probability). This accords with our signal extraction model for Asia; a healthy fiscal position allows governments more flexibly to deal with systemic banking distress – fiscal laxity may also fuel a boom that leads to a banking crisis.

In the presence of fiscal indiscipline, crisis probabilities are elevated if GDP growth is low. The threshold level of 4.75% GDP growth implies that in Asian economies, approximately 5% of GDP growth is required to counteract the fiscal deficits which impede bank bailouts. If GDP growth is below 4.75%, the lack of public financial support to the banking system and the level of non-performing loans put the banking system under stress and the probability of crisis rises to 79.4%.

In contrast, if GDP growth exceeds 4.75%, the probability of crisis is much lower at 26.1%. This is further reduced if the level of domestic credit/ GDP is lower than 60.49% since in such cases, a lesser degree of banking intermediation is associated with lower levels of risky bank lending; if banks do supply higher levels of credit relative to GDP, the lack of public financial support raises crisis probability to 42.9%.

Figure 8 shows the tree based on the combined sample where the two major branches essentially track the regional crises separately: the left part describes the Latin American crises[4] whilst the right side of the tree describes the Asian crises. The primary splitter across the entire sample is the rate of depreciation although the threshold value differs from that of the Latin American tree due to the Asian crises which were associated with currency depreciation. Consequently, the main discriminator between crisis types is whether a country experienced depreciation in excess of -2.08% (i.e. currency appreciation) or a depreciation of less that -2.08% (i.e. marginal appreciations or actual declines in currency value). There were fewer Asian crises in the sample compared to Latin American crises; appreciation is therefore associated with a lower crisis probability in node 5 (11%) than depreciation (30%, in node 2).

Figure 8: Splitting Variables and Thresholds for the Asian and Latin American Countries



[4] Hence the similarity between the left side of the tree and the tree based on the Latin American sample.

For banking systems in economies where the currency appreciated by more than 2.08%, real interest rate movements become critical. Interest rates in excess of 8.42%, possibly linked to overvalued exchange rates, would reduce banks' interest margins, raise the level of non-performing loans and consequently, raise the risk of a banking crisis to 40%. Conversely, the banking system would be less likely to collapse if the currency appreciation was not accompanied by high real interest rates; in this case the probability of crisis falls to 5.5%.

In the cases associated with minor currency appreciation or actual depreciation, the level of financial intermediation becomes important. Higher levels of intermediation raise the probability of crisis to 41%. If financial intermediation, as measured by credit/ GDP ratio, is lower than 26.37%, then a crisis is less probable: 16.7%. In such cases however, crises can become more likely if authorities do not sufficiently manage inflation. When inflation is controlled to rates below 30.08%, the probability of a crisis actually drops to 5.5%. However, excessive inflation (above 30%) almost doubles the chances of a systemic banking crisis materialising so the probability rises to 30.5%. This probability is worsened even further if the terms of trade do not improve in line with the rise in inflation: a change in the terms of trade of less than 9.1% raises the probability of crisis to 44.4%. On the other hand, if the high inflation is associated with an improvement in export volumes relative to total trade, the crisis probability drops to 8.7%.

As noted above, pooling the Latin American and Asian data seems to generate few benefits in terms of the identification of a universal set of variables that are determinants of banking crises. The tree itself disaggregates the crises according to region suggesting that the interplay of factors that caused the crises in Latin America and Asia were indeed different. This implies that the use of large cross-country datasets may not be the best approach to identifying potential crisis episodes. To further this point, we next compare the in-sample performances of the regional models against the pooled model.

Table 10: Performance of the Separate Tree Models

	Asia Only Tree	Latin America Only Tree	Pooled Sample Tree
% crises correct	46	14	0
% no crises correct	90	92	100
% total correct	84	65	62

Table 10 shows the accuracy of each BRT model in terms of its ability to correctly identify both crisis and non-crisis episodes. Because the tree essentially generates a discrete crisis probability distributions based on all the nodes, a cut-off probability has to be selected according to the nodal probabilities. To make our model assessment stringent, we choose to set the cut-off probability for each model as the highest probability of all the nodes in that model assuming the probabilities do not exceed 50%. If any nodal probabilities exceed 50%, then 50% is used as the cut-off in line with the logit models described above.

The Asian model is able to classify crisis episodes with the most accuracy but even then, only 46% of the Asian crisis observations were classified as such. The Latin America model performs even worse in terms of crisis prediction, with a success rate of 14%, suggesting these crises were more heterogeneous than the Asian crises and that common determinants are harder to isolate. Consequently, pooling the Asian and Latin American crises together results in no crises being correctly identified. Since this model classes most observations as a non-crisis episode, it has 100% accuracy in predicting tranquil periods. For similar reasons, the regional models also have good abilities to catch tranquil periods which therefore increase the overall predictive accuracy of the models. This is however, not of assistance in an exercise aimed at capturing the incidence of banking crises.

The charts showing in sample tree prediction for each country, which are summarised in Table 10, are included in an Appendix to the paper.

Conclusion

Summarising our results, Table 11 shows the contrasting leading indicators of banking crises according to the logit, signal extraction and BRT specifications across different regions. There are some common patterns, notably GDP growth is an extremely important crisis determinant since it is picked up by virtually all model specifications, irrespective of the geographic location of the banking crisis. The fiscal surplus/ GDP ratio also appears to be important in mitigating financial instability since the signal extraction model picks this variable up in the Asian, Latin American and combined models, whilst the BRT model also uses the variable as a splitter in the Asian model. Both the logit and BRT specifications highlight the association between the scale of financial intermediation and potential related risk taking by banks and the emergence of crises, since either domestic credit/ GDP are highlighted by at least two models in each regional sample.

Table 11: Leading Indicator Selection by Model Type and Sample

	Asia			Latin America			Combined		
	Logit	Signal Extraction	Tree	Logit	Signal Extraction	Tree	Logit	Signal Extraction	Tree
Real GDP Growth	✓	✓	✓	✓	✓		✓	✓	✓
Real Interest Rate									
Inflation						✓		✓	
Fiscal Surplus/ GDP		✓	✓		✓			✓	
M2/ Foreign Exchange Reserves	✓								
Real Domestic Credit Growth	✓				✓	✓			
Real GDP per capita	✓			✓			✓		✓
Domestic credit/GDP	✓		✓			✓	✓		✓
Depreciation	✓	✓				✓			
Terms of Trade	✓	✓				✓			
Current account/GDP									
External short term debt /GDP									

Further commonalities beyond those discussed above are absent. Some variables such as depreciation are detected by different models in different regions (signal extraction and logit for Asia and BRT for Latin America), whilst others are highlighted in specific regions and by different models (terms of trade and inflation in Latin America). These results therefore appear to be underpinned by the different nature of crises in Latin America compared to Asia: the Asian crises are linked to financial variables and currency issues whereas the Latin American crises are underpinned by financial variables with inflationary and trade issues. Pooling is hence seen as inappropriate.

The estimators themselves differ across regions in the variables they highlight, which may link in turn to their differing statistical characteristics. Of the three specifications, logit is the only parametric estimator such that confidence intervals can be attached to the ranking of leading indicators. Moreover, the logit and BRT models are the only ones that are multivariate; logit detects the interactions of variables with each other when deciding on the best crisis predictors, whilst the BRT model takes this one step further by using non-linear variable interactions to map the dynamics of crises. The signal extraction approach isolates the behaviour of individual variables in the run-up to a crisis. Nevertheless it is telling that for each model, the predictors differ between regions, and that the performance of the combined model is inferior to the regional ones in each case.

For policy purposes, we contend that, in the light of the different variables highlighted for each region, as well as the poor overall performance of the combined model, it would appear best to estimate the regions separately with all three approaches providing complementary warning signals.

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Appendix:

Figure A1: In Sample Tree Predictions: Asia

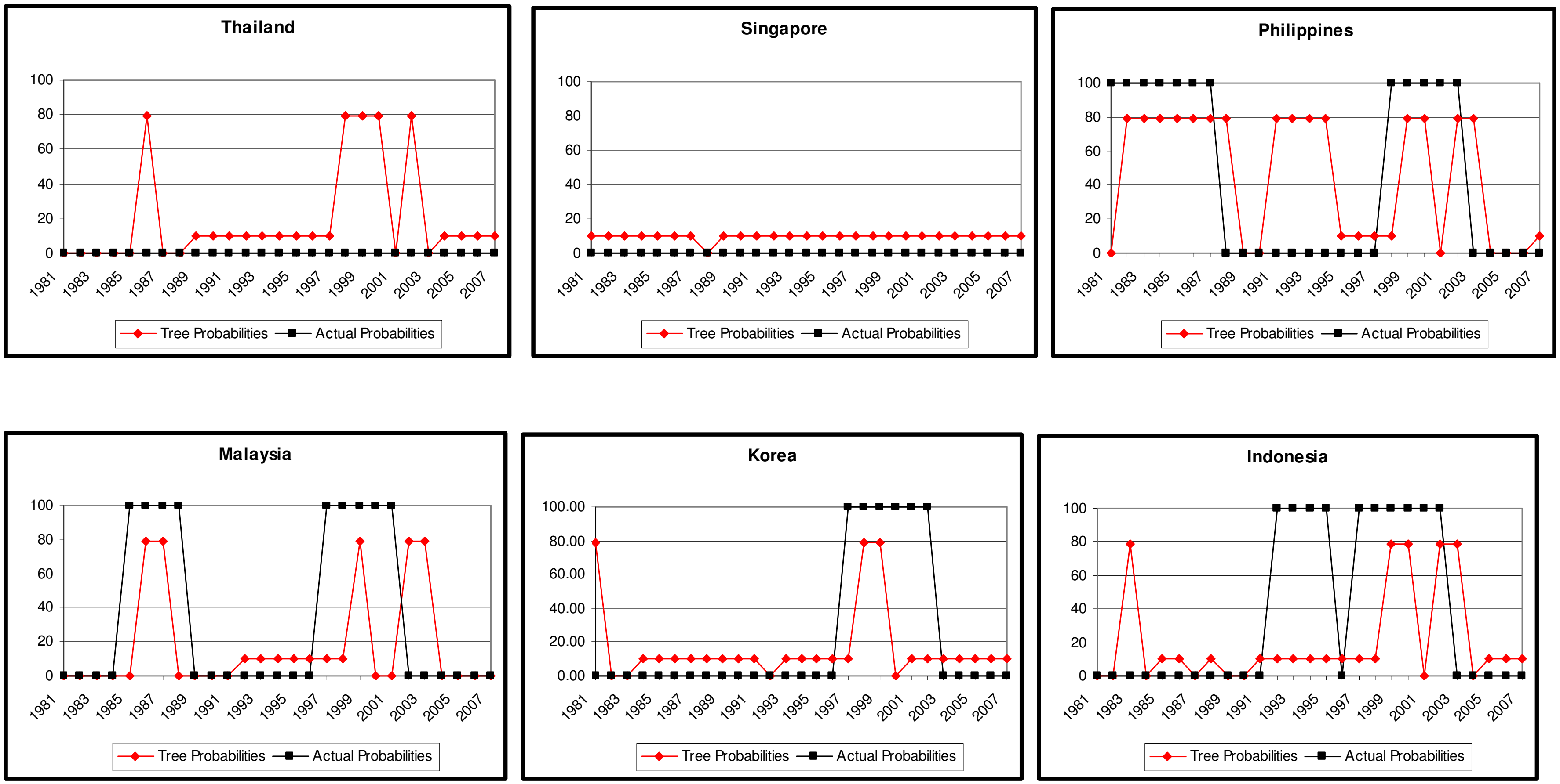
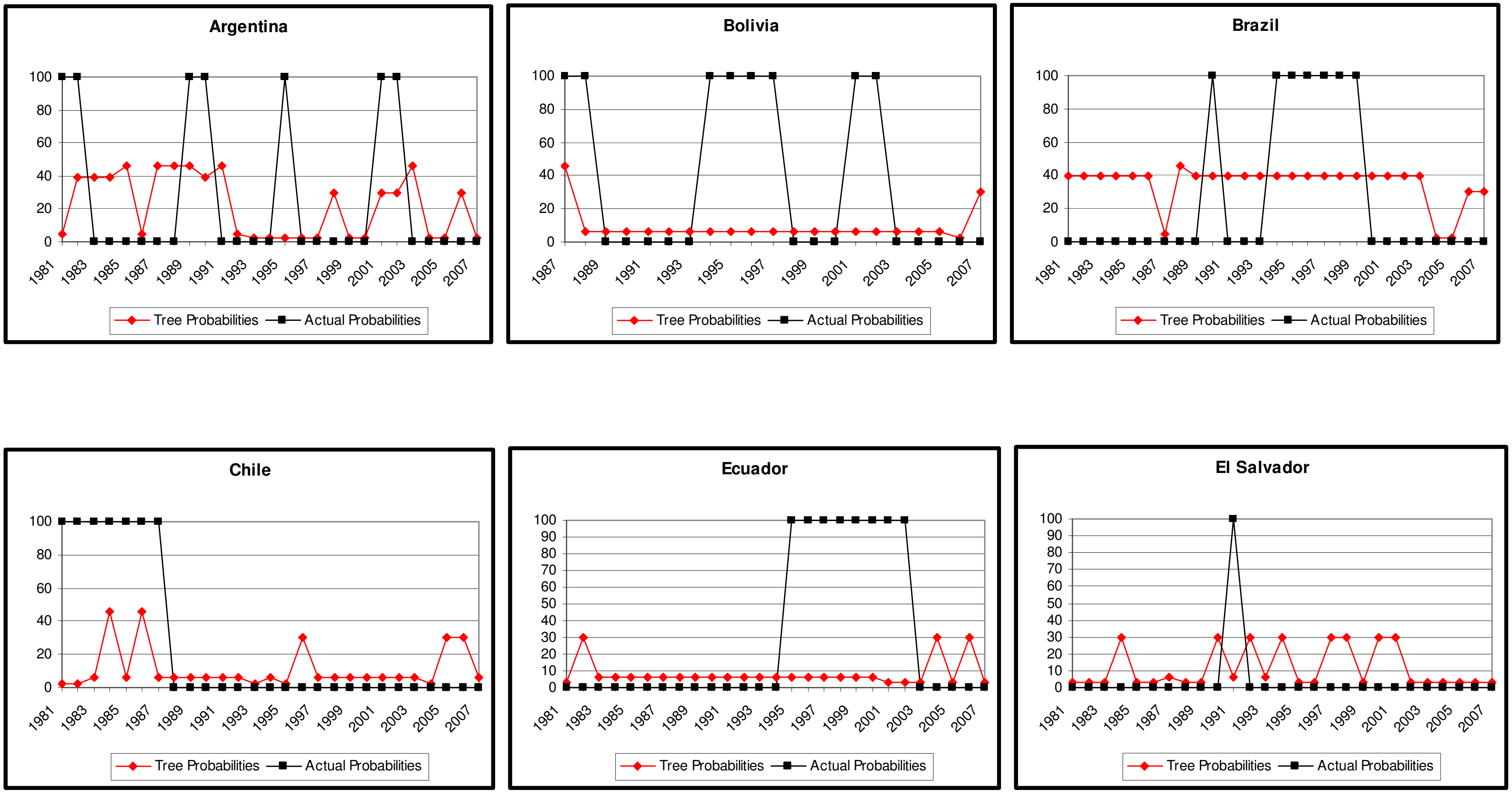
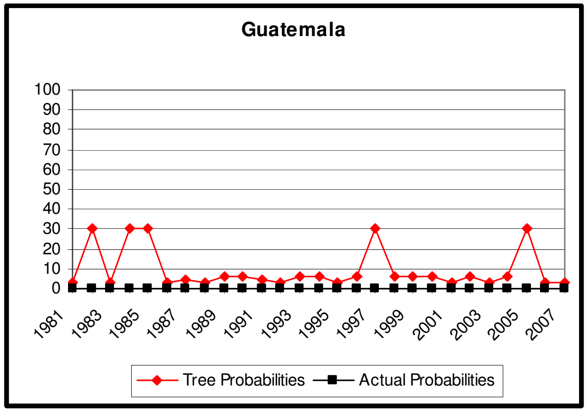
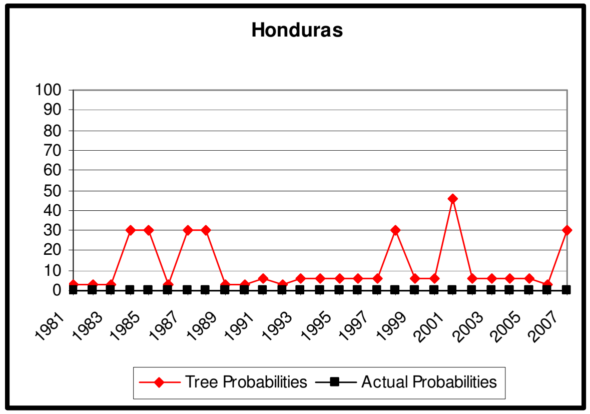
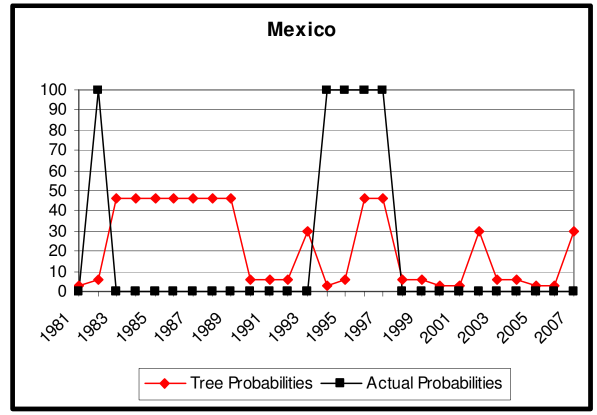


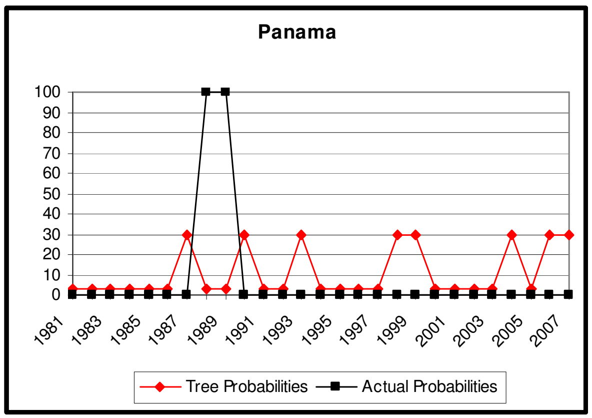
Figure A2: In Sample Tree Predictions: Latin America

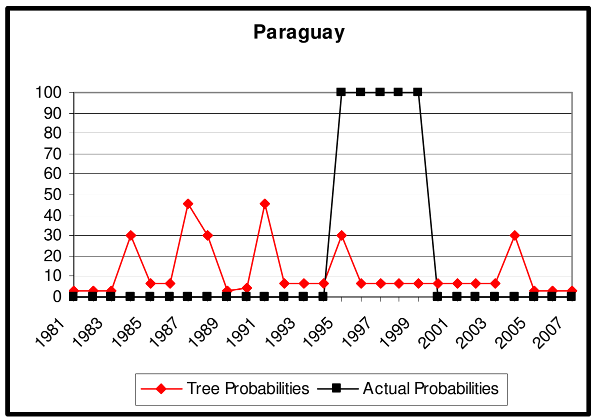


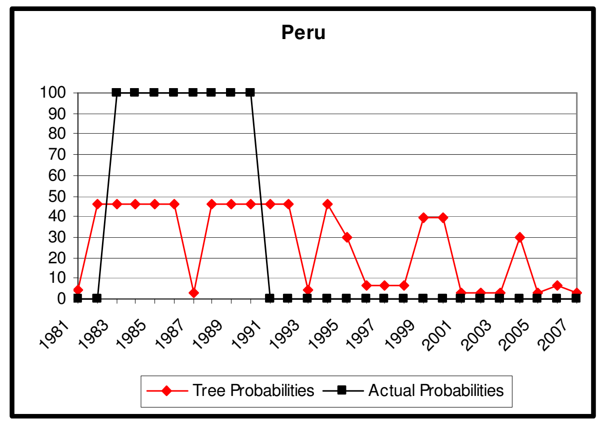

Guatemala
Tree Probabilities
Actual Probabilities


Honduras
Tree Probabilities
Actual Probabilities


Mexico
Tree Probabilities
Actual Probabilities


Panama
Tree Probabilities
Actual Probabilities


Paraguay
Tree Probabilities
Actual Probabilities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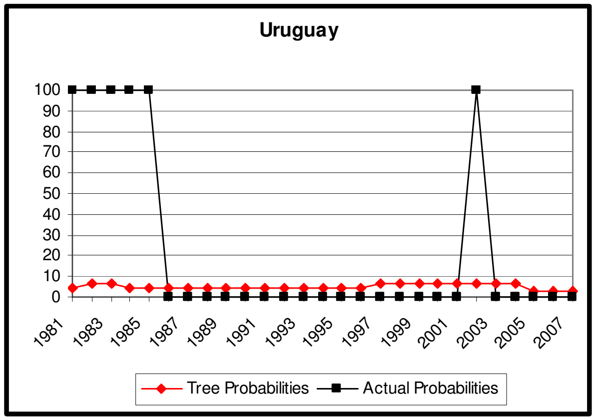
Tree Probabilities
Actual Probabilities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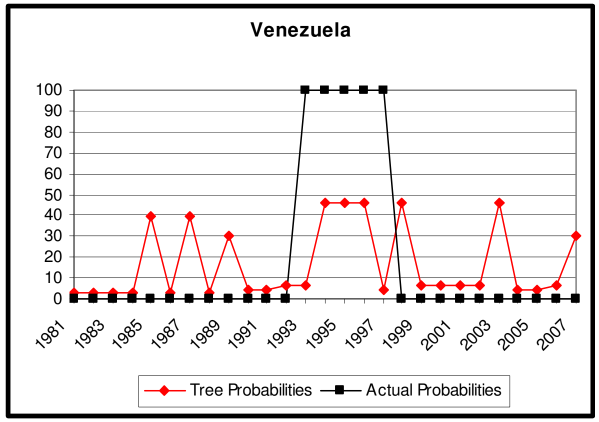
Tree Probabilities
Actual Probabilities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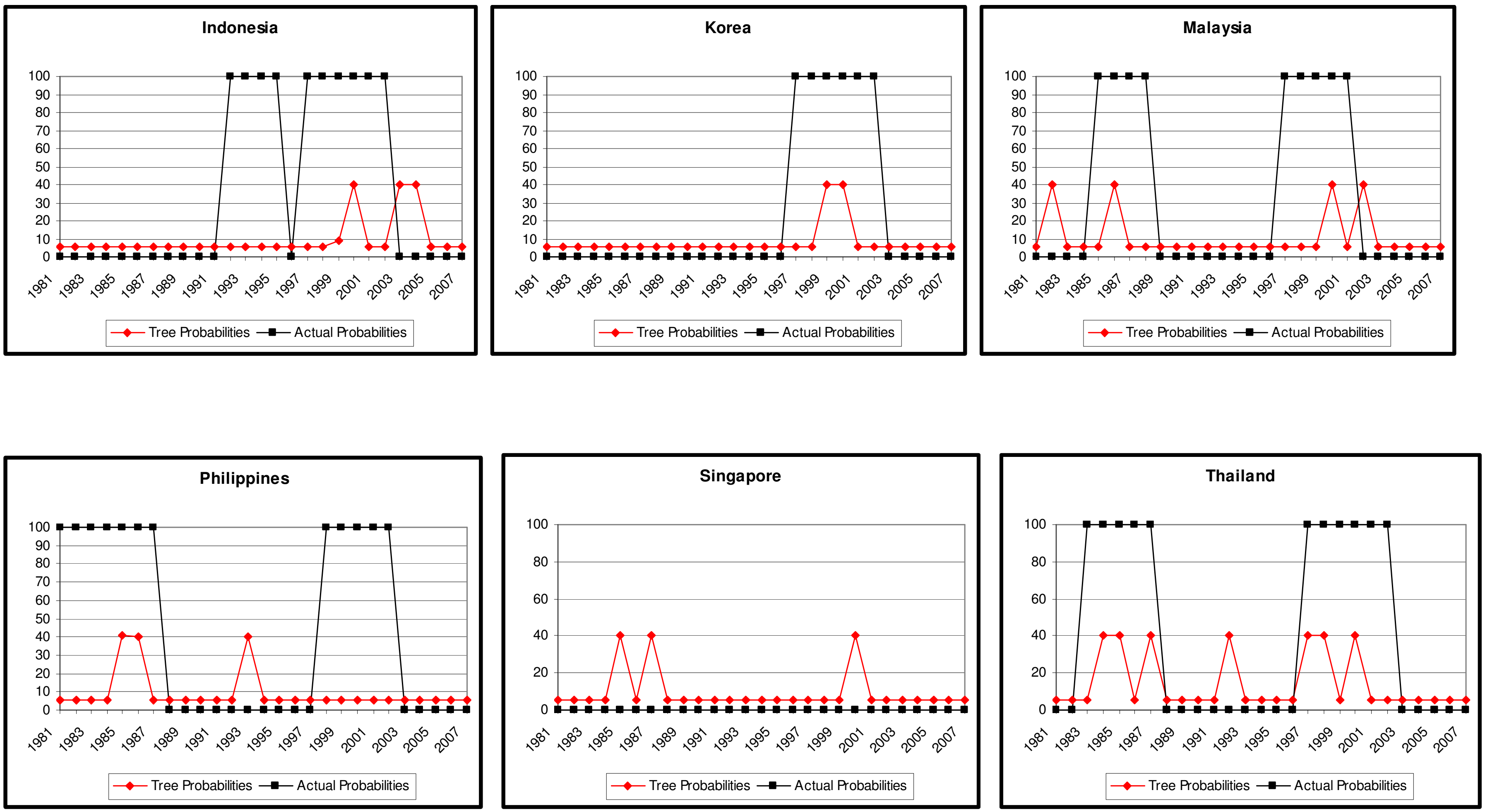
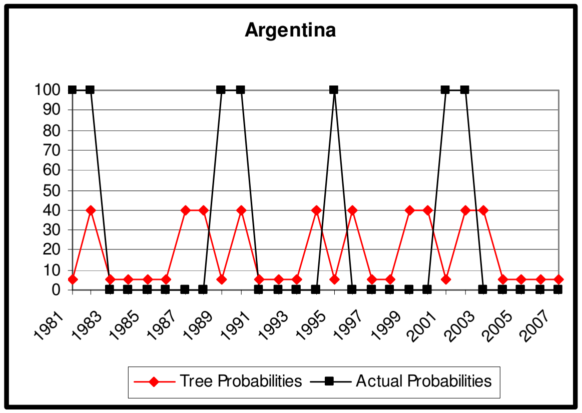
Tree Probabilities
Actual Probabilities

Figure A3: In Sample Tree Predictions: Pooled Data

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Tree Probabilities
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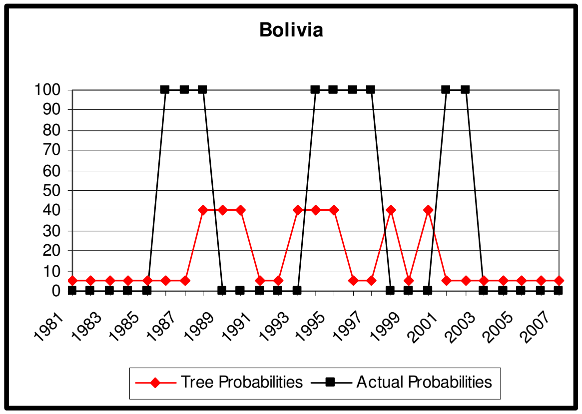
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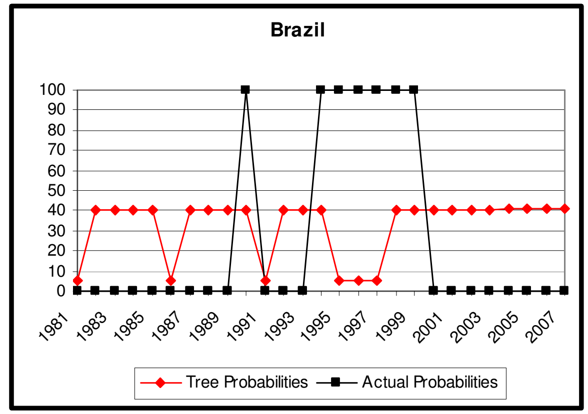
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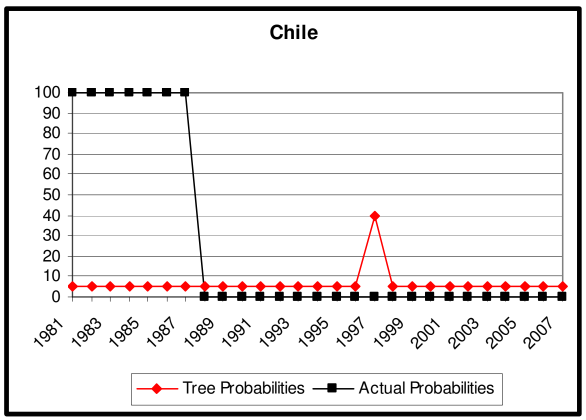
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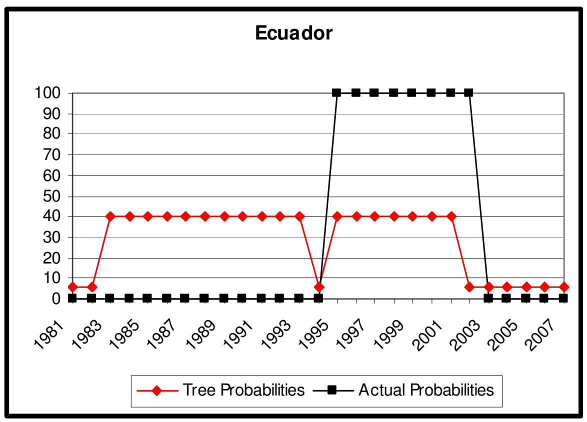
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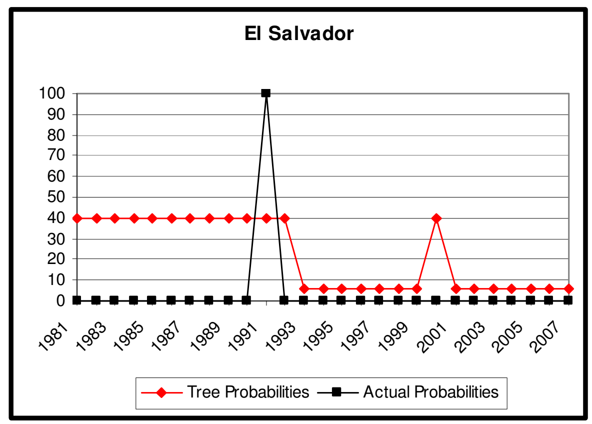
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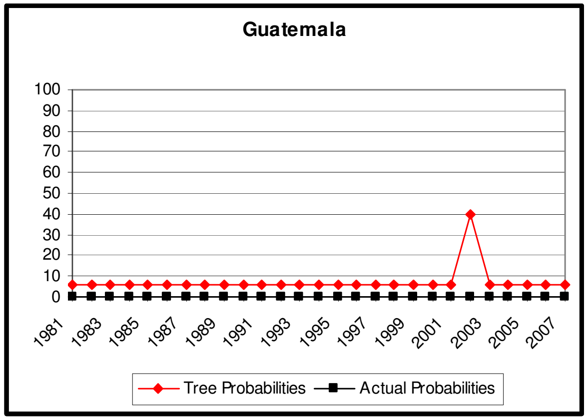
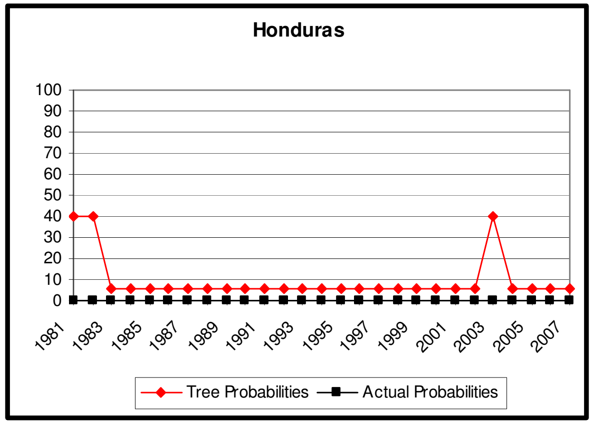

Guatemala
Tree Probabilities
Actual Probabilities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Tree Probabilities
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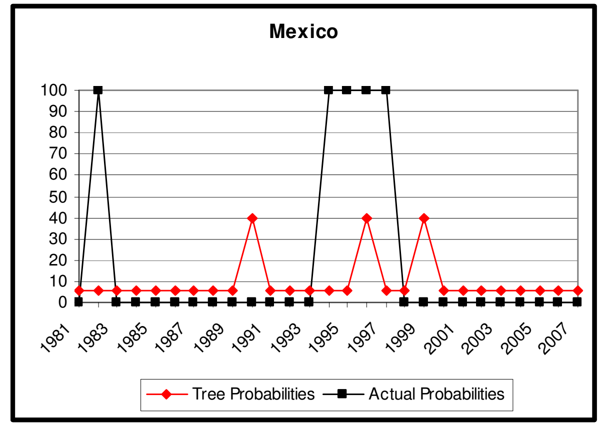
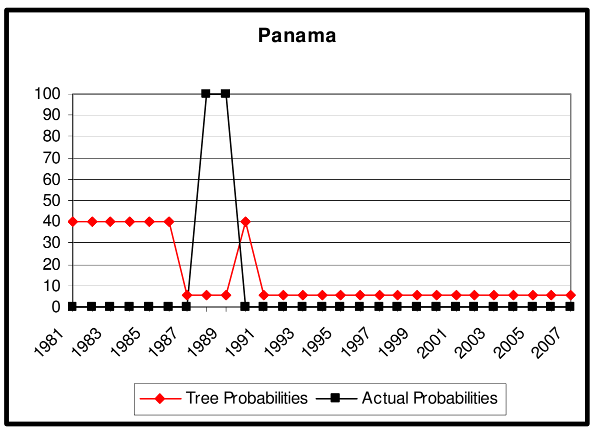
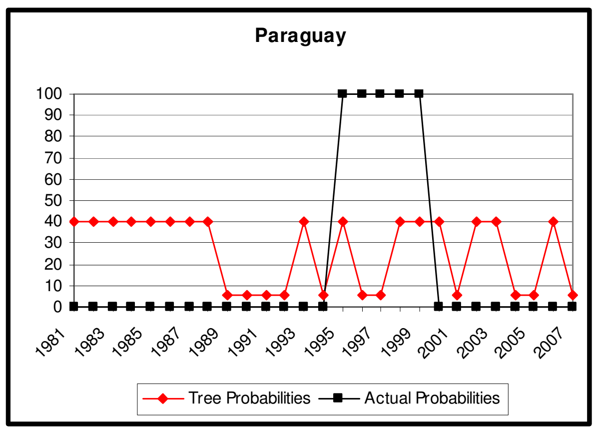
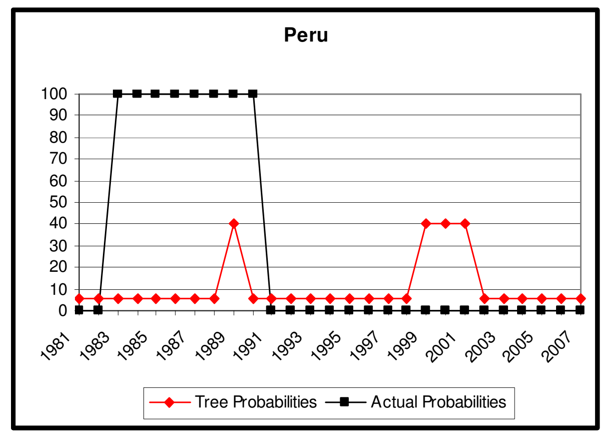
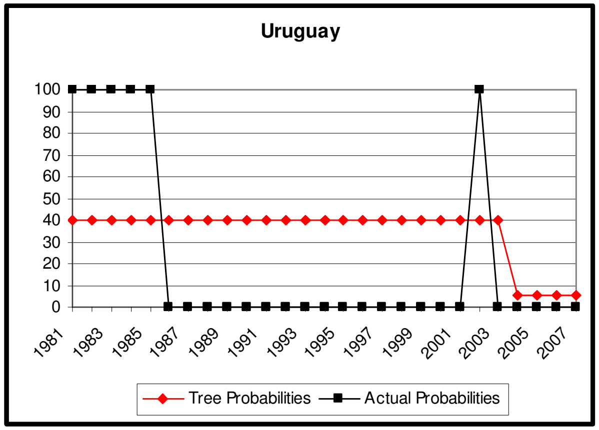

Mexico
Tree Probabilities
Actual Probabilities


Panama
Tree Probabilities
Actual Probabilities


Paraguay
Tree Probabilities
Actual Probabilities


Peru
Tree Probabilities
Actual Probabilities



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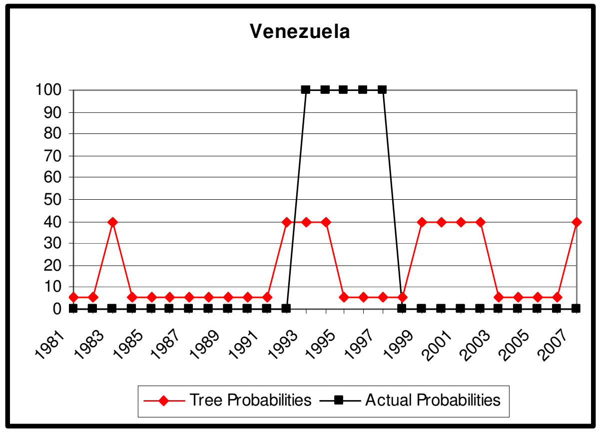

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