

Early Warning Systems: Theory and Practice

CARIBBEAN CENTRE FOR MONEY AND FINANCE
ASSESSING MACRO-PRUDENTIAL VULNERABILITIES AND POLICYFRAMEWORKS
IN A REGIONAL CONTEXT

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Introduction

- Recent sub-prime crisis has renewed policy makers' interest in crisis prediction models
- Previous research into Early Warning Systems (Kaminsky and Reinhart, 1999 and Demirguc-Kunt and Detragiache, 1998) has since been refined further by Barrell et al (2010, 2013).
- I will review our latest crisis prediction model alongside brief reviews of alternative techniques for macroprudential surveillance that are used by policymakers and IFIs.

Outline:

- Early Warning Systems (EWS):
 - (i) Signal Extraction
 - (ii) Binary Recursive Tree (BRT)
 - (iii) Logit Models
- Variables to be watched
- Evaluation using Macro Models

Traditional EWS Design

- A set of models have been explicitly used to predict systemic banking problems: logit, SE and BRT
- Such estimators have become popular because:
 - (i) Computationally easy
 - (ii) Intuitive to interpret
 - (iii) Utilise aggregate data
- SE is the easiest to execute and interpret followed by logit, followed by BRT
- Given our extensive research into logit EWS we focus on these but will outline the SE and BRT methodologies first.

Signal Extraction

- non-parametric approach which assesses the behaviour of single variables prior to and during crisis episodes.
- Logic: if aberrant behaviour of a variable can be quantitatively defined then whenever that variable moves from tranquil to abnormal activity, crisis is forewarned
- Note it is essentially a univariate approach (can create composites, see Borio and Lowe, 2002)

Signal Extraction contd.

- Let , i = a univariate indicator, j = a particular country, S = signal variable, X = potential financial stress variable
- An indicator variable relating to indicator i and country j is denoted by X_{ij} and the threshold for this indicator is denoted as X^*_{ij}
- Let signal variable relating to indicator i and country j is denoted by: S_{ij}
- This is a binary variable where $S_{ij} = \{0,1\}$
- If the variable crosses the threshold, a signal is emitted and $S_{ij} = 1$

$$\{ S_{ij} = 1 \} = \{ | X_{ij} | > | X^*_{ij} | \} \dots\dots\dots(1)$$

Signal Extraction contd.

- If the indicator remains within its threshold boundary, it behaves normally and does not issue a signal so $S_{ij} = 0$

$$\{ S_{ij} = 0 \} = \{ | X_{ij} | < | X^*_{ij} | \} \dots \dots \dots (2)$$

- 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
- Note this time series will change as we vary the threshold (X^*_{ij})
- For the risk averse PM (low X^*_{ij}) signals will be issued often (and vice versa)

Signal Extraction contd.

- Check this series against a banking crisis dummy to assess in sample performance (require min NTSR)

$$NTSR = \frac{\frac{B}{B+D}}{\frac{A+C}{A+B+C+D}} = \frac{\text{Type II}}{1 - \text{Type I}}$$

	CRISIS	NO CRISIS
SIGNAL	A	B
NO SIGNAL	C	D

Type II error

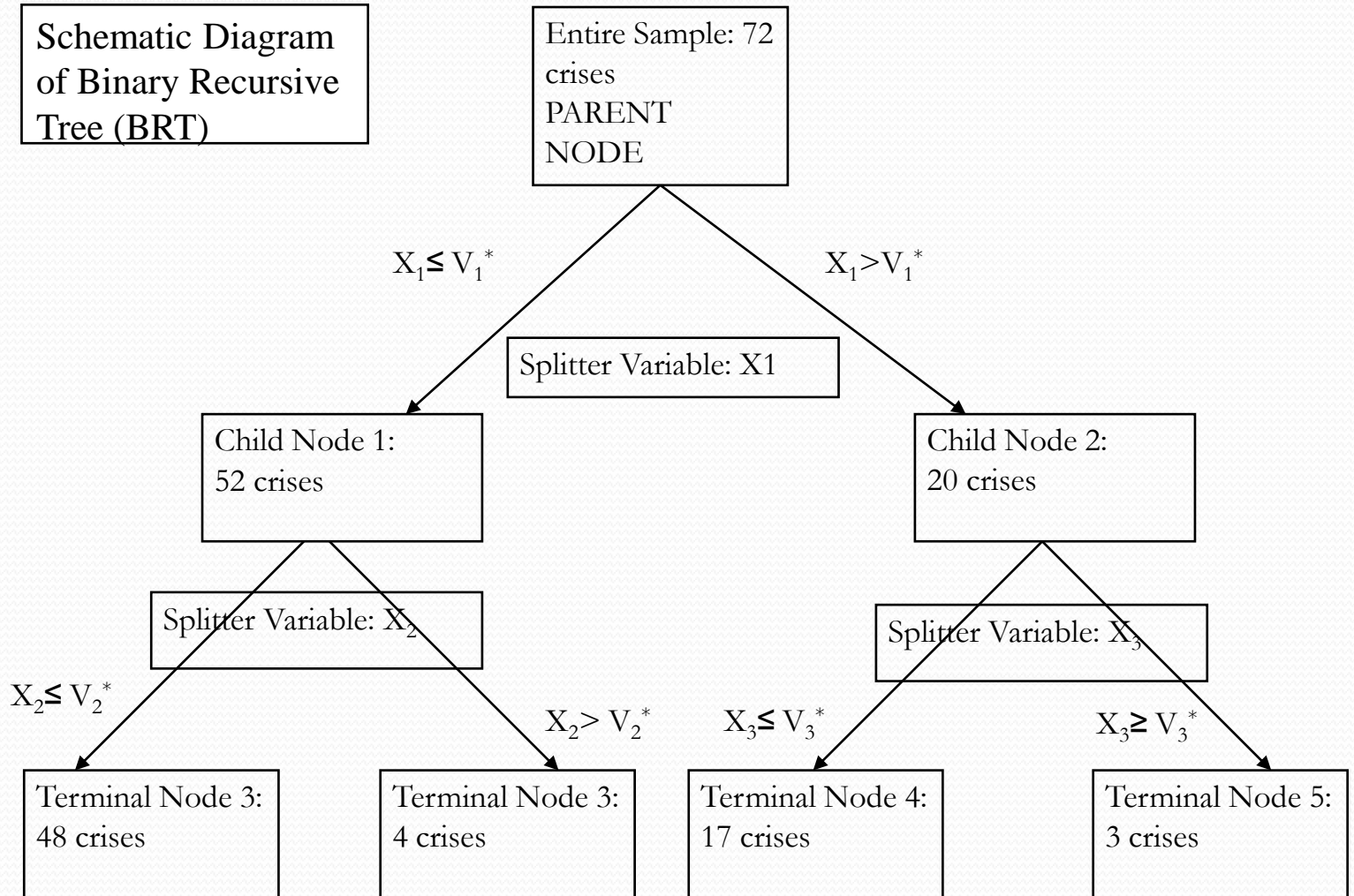
Type I error

Binary Recursive Tree (BRT)

- Duttagupta and Cashin (2008) – banking crises
- Ghosh and Ghosh (2002) - currency crises
- Roubini et al. (2003) – sovereign debt crises
- Davis, Karim and Liadze (2011) – LA vs. Asia
- The BRT process analyses a set of variables to reveal a particular value of the explanatory variable that best explains crises.
- Once this primary splitter is identified, BRT ranks the next best explanatory variable and so on.
- No underlying distributions need be satisfied: non-parametric
- In successively splitting the data BRT constructs a “tree”.

BRT contd

Schematic Diagram of Binary Recursive Tree (BRT)



Node 1			
CREDG <= -3.91			
Class	Cases	%	
0	2138	97.0	
1	67	3.0	

CREDG <= -3.91

Terminal Node 1			
Class	Cases	%	
0	465	94.3	
1	28	5.7	

CREDG <= -3.91

Node 2			
RIR <= 14.12			
Class	Cases	%	
0	1673	97.7	
1	39	2.3	

RIR <= 14.12

Node 3			
DEP <= -39.05			
Class	Cases	%	
0	1503	98.3	
1	26	1.7	

RIR <= 14.12

Node 6			
GDPCAP <= 806.86			
Class	Cases	%	
0	170	92.9	
1	13	7.1	

DEP <= -39.05

Terminal Node 2			
Class	Cases	%	
0	80	89.9	
1	9	10.1	

DEP <= -39.05

Node 4			
INF <= 6.66			
Class	Cases	%	
0	1423	98.8	
1	17	1.2	

GDPCAP <= 806.86

Terminal Node 6			
Class	Cases	%	
0	60	100.0	
1	0	0.0	

GDPCAP <= 806.86

Terminal Node 7			
Class	Cases	%	
0	110	89.4	
1	13	10.6	

INF <= 6.66

Terminal Node 3			
Class	Cases	%	
0	667	99.4	
1	4	0.6	

INF <= 6.66

Node 5			
DEP <= 6.48			
Class	Cases	%	
0	756	98.3	
1	13	1.7	

DEP <= 6.48

Terminal Node 4			
Class	Cases	%	
0	698	98.9	
1	8	1.1	

DEP <= 6.48

Terminal Node 5			
Class	Cases	%	
0	58	92.1	
1	5	7.9	

Advantages of BRT

- Able to detect non-linear variable interactions
- Able to identify explanatory variable effect conditional on other variables' behaviour
- Can identify threshold effects
- Does not assume any specific variable distributions within countries or across countries

Logit EWS

- The multivariate logit estimator relates the likelihood of banking crisis occurrence to a vector of explanatory variables:
- Probability that the banking dummy takes a value of one (crisis occurs) at time t is given by the value of the logistic cumulative distribution evaluated for the data and parameters at time t:

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

Evolution of Logit EWS: D&D(1998) to Barrell et al (2010)

- Seminal work by Demirguc-Kunt and Detragiache (1998): 65 countries; 31 crises; 1980 – 94.
- However used a heterogeneous mix of developed and developing economies and thus banking systems
- Used mix of macro + financial variables; no bank specific variables.
- Used contemporaneous variables, \therefore not true EWS

Evolution of Logit EWS: D&D(1998) to Barrell et al (2010) contd

- Davis, Karim and Liadze (2010): used updated DD(98) + current account + short term debt on 14 Latin American and 6 Asian economies; 1980-2008

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)

Evolution of Logit EWS: D&D(1998) to Barrell et al (2010) contd

- Findings: heterogeneous countries should NOT be pooled: crisis determinants differ by region

Crisis Determinants by Region	Pooled	Asia	Latin America
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			

Evolution of Logit EWS: D&D(1998) to Barrell et al (2010) contd

- Barrell et al (2010 a,b): all logit models based on 14 OECD economies:
Belgium, Canada, Denmark, Finland, France, Germany , Italy, Japan, Netherlands, Norway, Sweden, Spain, UK and the US; 1980-2007; 14 crises
- Barrell et al (2010a)
- Barrell et al (2010b)

Evolution of Logit EWS: D&D(1998) to Barrell et al (2010) contd

- Given the difference in crisis determinants across regions.....
- ❖ Barrell et al (2010a)
 - Tested OECD banking crisis determinants: traditional DD(98) variables + new additions: capital adequacy, liquidity, real property price growth
 - Result: Traditional variables drop out! → only the new additions remain → capital adequacy, liquidity, real property price growth are main OECD crisis determinants

Evolution of Logit EWS: Variables to be Watched

- ❖ Barrell et al (2010b)
 - Re-estimated 2010a model but added variable that was associated with sub-prime: current account deficit (% of GDP)
 - Final 2010b specification:

Variable	Coefficient	z-Statistic
LEV(-1)	-0.342	-4.1
NLIQ(-1)	-0.113	-3.3
RHPG(-3)	0.079	2.4
CBR(-2)	-0.236	-2.8

	Dep=0	Dep=1	Total
P(Dep=1)≤C	247	5	252
P(Dep=1)>C	97	15	112
Total	344	20	364
Correct	247	15	262
% Correct	71.80	75.00	71.98
% Incorrect	28.20	25.00	28.02

Evolution of Logit EWS: Variables to be Watched contd

- 2010b specification out-of-sample performance:

	2004	2005	2006	2007	2008
BG	0.003	0.008	0.015	0.031	0.043
CN	0.014	0.021	0.015	0.019	0.023
DK	0.021	0.013	0.020	0.011	0.051
FN	0.000	0.001	0.001	0.002	0.002
FR	0.019	0.034	0.072	0.154	0.180
GE	0.010	0.013	0.003	0.003	0.003
IT	0.016	0.026	0.021	0.037	0.013
JP	0.002	0.001	0.000	0.001	0.001
NL	0.047	0.013	0.007	0.007	0.002
NW	0.001	0.001	0.001	0.000	0.000
SD	0.006	0.001	0.003	0.003	0.002
SP	0.033	0.066	0.232	0.531	0.637
UK	0.077	0.142	0.217	0.228	0.229
US	0.070	0.042	0.052	0.069	0.091

Note: BG-Belgium, CN-Canada, DK-Denmark, FN-Finland, FR-France, GE-Germany, IT-Italy, JP-Japan, NL-Netherlands, NW-Norway, SP-Spain, SD-Sweden, UK-United Kingdom, US-USA.

Conclusion

- Alternative ways to construct EWSs but practical considerations should dominate choice:
 - (i) computational ease: how easy is it to re-estimate on a rolling bases; changing/ new desk officers need to be able to replicate
 - (ii) data availability
 - (iii) out-of-sample performance
- Also need to consider invertability of estimator for practical policy use: once variable impacts are known can we work backwards to deduce necessary regulatory adjustments?
- Beneficial to have confidence intervals for the above: non-parametric signal extraction and BRT do not provide this
- Therefore ideal approach would use a mix of estimators
- However Barrell et al (2010b) is most parsimonious, robust and effective OECD crisis predictor.
- If resource constraints, then this approach can be used as a starting point for desk officers wishing to develop EWS further