Towards a Unified Statistical Framework to Evaluate Financial Crises Early Warning Systems

How to evaluate an EWS?

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# Introduction

 $\rightarrow$  From the subprime crisis to currency crises

 $\rightarrow$  Early Warning Systems (EWS) set up to ring before the occurence of crises

# Introduction

#### How can we specify an EWS model?

 $\rightarrow$  Rich literature (Kaminski et al. (1998), Kumar et al. (2003), Abiad (2003), etc.)

#### How can we evaluate the predictive abilities of an EWS?

- $\rightarrow$  Kaminski et al. (1998): signalling approach
  - Threshold which minimizes the NSR criteria
  - Type I and type II errors

 $\rightarrow$  Arbitrarely chosen cut-offs (Berg and Patillo (1999), Arias and Erlandsson (2005))

# Originality

#### **Our New EWS Evaluation Method**

 $\rightarrow$  I. Optimal cut-off

# $\rightarrow$ II. Credit-scoring evaluation criteria QPS, LPS, AUC, Pietra Index, Bayesian Error, Kuiper's score

#### $\rightarrow$ III. Comparison tests

- Diebold-Mariano (1995) test for non-nested models
- Clark-West (2007) test for nested models
- Area under ROC comparison test



#### A New EWS Evaluation Method

**EWS Specification and Estimation** 

**Empirical Results** 

Conclusions

Optimal cut-off identification Performance assessment criteria Comparison tests

# Step 1. A New EWS Evaluation Method

Optimal cut-off identification Performance assessment criteria Comparison tests

# I. Optimal cut-off identification

$$C^* = \text{Arg}_{\{C\}}[\text{Sensitivity}(C) = \text{Specificity}(C)], \text{ where } C \in [0, 1]$$

#### Definition 1.

*Sensitivity* is the number of crises correctly predicted for a cutoff *C* over the total number of crises in the sample

#### Definition 2.

1 - Specificity is the number of false alarms for a cutoff *C* over the total number of non-crises in the sample

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#### **OPTIMAL CUT-OFF IDENTIFICATION (EXAMPLE)**



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#### II. Performance assessment criteria

# The Area Under the ROC Curve and the Quadratic Probability Score

What is the ROC curve? (Receiving Operating Characteristic)



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II. Performance assessment criteria

#### The Area Under the ROC Curve

$$A = \int_0^1 Sensitivity(1 - Specificity)d(1 - Specificity)$$

- Measure of the model's overall ability to discriminate between the cases correctly predicted and the false alarms
- For a perfect model AUC=1 while for a random one AUC=0.5

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#### II. Performance assessment criteria

#### The Quadratic Probability Score

$$QPS = \frac{1}{T} \sum_{t=1}^{T} 2(\widehat{I}_t - I_t)^2$$

- Comparison of forecasts  $(\hat{I}_t)$  and realizations  $(I_t)$
- The closer QPS is to 0 the better the model is

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# III. Comparison tests

- 1. Diebold-Mariano (1995) test for non-nested models
- 2. Clark-West (2007) test for nested models
- 3. Area under ROC comparison test (Delong et al. (1988))

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### III. Comparison tests

**Proposition 1**: Let us denote by *M*1 and *M*2 two EWS models, and by  $\overrightarrow{AUC_1}$  and  $\overrightarrow{AUC_2}$  the associated areas under the ROC curve.

$$H0:\widetilde{AUC_1}=\widetilde{AUC_2}$$

$$\frac{(\widetilde{AUC_1} - \widetilde{AUC_2})^2}{Var(\widetilde{AUC_1} - \widetilde{AUC_2})} \xrightarrow[T \to \infty]{d} \chi^2(1)$$

Currency crisis dating method Empirical models

# Step 2. EWS Specification and Estimation

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# To apply our evaluation methodology:

#### I. Real crisis dating method $(I_t)$

 $\rightarrow$  KLR modified pressure index - Lestano and Jacobs (2004)

 $\rightarrow$  The threshold equals two standard deviations above the mean

#### II. Crisis probabilities ( $\widehat{P}r_t$ )

 $\rightarrow$  Panel logit with fixed effects

 $\rightarrow$  Markov Switching Model with constant transition probabilities

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#### I. Currency crisis dating method

KLR modified pressure index - Lestano and Jacobs (2004)

Definition 3. The 24 months crisis variable:

$$I_{t} = C24_{n,t} = \begin{cases} 1, & \text{if } \sum_{j=1}^{24} Crisis_{n,t+j} > 0\\ 0, & \text{otherwise} \end{cases}$$

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#### II. Empirical models

Model 1. Panel and time-series logit model

$$\mathsf{Pr}(C24_{nt}=1) = rac{\exp(eta' x + f_n)}{1 + \exp(eta' x + f_n)} \ \forall n \in \Omega_h,$$

where

- *f<sub>n</sub>* represents the fixed effects
- x is the matrix of economic variables
- n is the country identifier
- Ω<sub>h</sub> is the h<sup>th</sup> cluster

Optimal country clusters: (Kapetanios procedure (2003))

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### II. Empirical models

Model 2. Markov model - Hamilton (1995)

$$KLRm_t = \mu_t(S_t) + \beta(S_t)x_t + \epsilon_t(S_t),$$

where

- KLRmt is the pressure index vector
- x<sub>t</sub> represents the matrix of economic variables
- S<sub>t</sub> follows a two states Markov chain

$$\mathcal{S}_t = egin{cases} 1, ext{if there is a crisis at time } t \ 0, ext{if not} \end{cases}$$

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# II. Empirical models

**Definition 4. The 24 months ahead forecasts** (Arias and Erlandson (2005)):

$$\Pr(S_{t+1...t+24} = 1 | \Omega_t) = 1 - \Pr(S_{t+1...t+24} = 0 | \Omega_t)$$

$$= 1 - \{ [P_{10}P_{00}^{(23)} \Pr(S_t = 1 | \Omega_t)] + [P_{00}^{24} \Pr(S_t = 0 | \Omega_t)] \},\$$

where P<sub>10</sub> and P<sub>00</sub> are elements of the transition probability matrix

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## II. Empirical models

#### From crisis probabilities to crisis forecasts

$$\widehat{l}_t = egin{cases} 1, \textit{if } \Pr(\textit{C24}_t = 1) > \textit{C}^* \ 0, \textit{otherwise} \end{cases},$$

where  $C^*$  is an **optimal cut-off** (see section 1)

Dataset Optimal country clusters Comparison tests Cut-off identification and performance assessment criteria

# **Empirical Results**

Dataset Optimal country clusters Comparison tests Cut-off identification and performance assessment criteria

# **Empirical Results**

- I. Dataset
- II. Optimal country clusters
- III. Comparison tests
- IV. Optimal model: cut-off identification and performance assessment criteria

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# I. Dataset

 $\rightarrow$  Monthly data in US dollars for the period 1985-2005 (6 Latin-American and 6 South-Asian Countries)

- $\rightarrow$  Market expectation (m.e.) variables:
  - Yield spread
  - Growth of stock market price index
- $\rightarrow$  Macroeconomic variables: Jacobs et al. (2003)

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# II. Optimal country clusters

#### Kapetanios procedure (2003)

- 1. Argentina, Brazil, Mexico, Venezuela
- 2. Peru, Uruguay
- 3. Korea, Malaysia, Taiwan
- 4. Philippines, Thailand
- 5. Indonesia

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# III. Comparison tests

#### Testing strategy

- 1. Logit with market-expectation variables vs. simple logit
- 2. Markov with market expectation variables and spread switching vs. Markov with market expectation variables
- 3. Best logit vs. best Markov specification

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#### III.1. Logit with m.e. variables vs. simple logit

	ROC		Clark-West		
Country	test statistic	p-value	test statistic	pvalue	
Argentina	0.0301	0.8622	0.1372	0.4454	
Brazil	5.7105	0.0169	3.4901	0.0002	
Indonesia	7.9917	0.0047	4.4332	0.0000	
Korea	4.5357	0.0332	3.7746	0.0001	
Malaysia	0.3859	0.5345	0.3288	0.3711	
Mexico	< 0.001	1.0000	0.6869	0.2460	
Peru	0.0028	0.9577	2.1634	0.0153	
Philippines	0.8738	0.3499	0.8709	0.1919	
Taiwan	10.475	0.0012	3.5603	0.0002	
Thailand	6.9801	0.0082	4.5964	0.0000	
Uruguay	0.7443	0.3883	0.6656	0.2528	
Venezuela	6.6647	0.0098	-2.0740	0.9810	

\* The coefficients significant at a 5% level are in bold

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# III.2. Markov with m.e. variables and spread switching vs. Markov with m.e. variables

	ROC		Clark-West		
Country	test statistic	p-value	test statistic	pvalue	
Argentina	10.930	0.0009	-6.7740	1.0000	
Brazil	19.200	<0.001	8.0833	<0.001	
Indonesia	36.319	<0.001	19.003	<0.001	
Korea	4.8024	0.0284	-0.7131	0.7621	
Malaysia	0.0064	0.9361	4.8475	<0.001	
Mexico	0.0001	0.9930	-26.953	1.0000	
Peru	6.9116	0.0086	9.7281	<0.001	
Philippines	0.0906	0.7634	11.102	<0.001	
Taiwan	0.5000	0.4795	1.4058	0.0799	
Thailand	6.5530	0.0105	-7.7623	1.0000	
Uruguay	111.15	<0.001	8.1857	<0.001	
Venezuela	0.0691	0.7927	17.209	<0.001	

\* The coefficients significant at a 5% level are in bold

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# III.3. Logit with m.e. variables vs. Markov with m.e. variables and spread switching

	ROC	;	Diebold-Mariano		
Country	test statistic	p-value	test statistic	pvalue	
Argentina	62.678	<0.001	12.965	<0.001	
Brazil	9.7859	0.0018	8.783	<0.001	
Indonesia	46.529	<0.001	29.244	<0.001	
Korea	9.8754	0.0017	12.207	<0.001	
Malaysia	21.455	<0.001	17.066	<0.001	
Mexico	17.829	<0.001	50.850	<0.001	
Peru	45.942	<0.001	12.164	<0.001	
Philippines	7.4266	0.0064	9.7129	<0.001	
Taiwan	34.195	<0.001	16.591	<0.001	
Thailand	45.902	<0.001	18.281	<0.001	
Uruguay	125.00	<0.001	12.877	<0.001	
Venezuela	17.351	<0.001	9.4665	<0.001	

\* The coefficients significant at a 5% level are in bold

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# Comparison tests

#### Remarks

 $\rightarrow$  The panel logit model with market expectation variables works better than the Markov specifications

 $\rightarrow$  The introduction of market expectation variables has a positive effect on the forecasting performance of an EWS.

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#### Best model - Optimal cut-off

	Accuracy measures		Kaminski et al. (1998) NSR criteria				
Country	Cut-off	Sensitivity	Specificity		Cut-off	Sensitivity	Specificity
Argentina	0.300	82.76	82.61		0.620	41.38	100.0
Brazil	0.160	100.0	69.47		0.880	7.69	100.0
Indonesia	0.200	96.97	96.20		0.930	72.73	100.0
Korea	0.206	85.71	90.96		0.930	14.29	100.0
Malaysia	0.380	93.10	93.97		0.730	65.52	100.0
Mexico	0.379	100.0	99.15		0.390	75.00	100.0
Peru	0.260	100.0	82.72		0.940	12.90	100.0
Philippines	0.346	67.95	68.35		0.730	20.51	100.0
Taiwan	0.160	94.12	65.17		0.670	17.65	98.31
Thailand	0.120	90.32	61.29		0.321	25.81	96.24
Uruguay	0.119	93.33	75.73		0.900	50.00	100.0
Venezuela	0.225	85.71	67.90		0.330	64.29	77.78

• Optimal cut-off:  $C \leq 0.38$ 

Crisis and calm periods: correctly identified

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#### Best model - Evaluation criteria

Country	AUC	Kuiper score	Pietra index	Bayesian error rate	QPS	LPS
Argentina	0.898	65.37	0.235	0.132	0.215	-0.325
Brazil	0.907	69.47	0.249	0.132	0.202	-0.311
Indonesia	0.996	93.17	0.330	0.0138	0.034	-0.058
Korea	0.920	76.67	0.273	0.0780	0.135	-0.228
Malaysia	0.985	87.07	0.311	0.048	0.083	-0.131
Mexico	0.998	99.15	0.350	0.008	0.011	-0.023
Peru	0.947	82.72	0.292	0.107	0.166	-0.266
Philippines	0.739	36.30	0.163	0.235	0.368	-0.558
Taiwan	0.739	36.30	0.163	0.235	0.368	-0.558
Thailand	0.811	51.61	0.192	0.138	0.218	-0.348
Uruguay	0.939	69.06	0.257	0.105	0.165	-0.246
Venezuela	0.777	53.61	0.189	0.257	0.370	-0.530

Performance assessment criteria: close to the optimal values

Robustness of the model to sensitivity analysis

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#### Conclusion

# Conclusions

**Objective:** Developing a new EWS evaluation framework based on optimal cut-offs, credit-scoring criteria and comparison tests

 $\rightarrow$  Substantial improvement of the predictive power of EWS

 $\rightarrow$  Markov models are not as efficient as panel logit model with market expectation variables

# Conclusions

#### The optimal model

 $\rightarrow$  Predicts well most currency crises in the specified emerging markets

 $\rightarrow$  Robust to some sensitivity analysis

#### Extensions

- $\rightarrow$  Markov switching model with time varying probabilities
- $\rightarrow$  Other market expectation variables
- $\rightarrow$  A more consistent database (a longer period, more countries)
- $\rightarrow$  Out of sample validation